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# Brand Reputation and Trust: The Impact on Customer Satisfaction and Loyalty for the Hewlett-Packard Brand

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**Abstract:** Reputation is shaped depending on factors such as the quality of products and services offered by a brand to its stakeholders, its reliability, and its innovative aspect in the eyes of stakeholders. The sustainability of a brand reputation depends on the brand creating a positive perception by fulfilling its social responsibilities and maintaining this perception in the long term. In this study, the brand reputation of Hewlett-Packard (HP) computers is evaluated through customer reviews. The data set in the study consists of 2012 customer reviews obtained from Hepsiburada, one of the most widely used e-commerce platforms in Turkey. Sentiment analysis and text mining artificial intelligence methods were used in the study. For sentiment analysis, the Naive Bayes method, which is one of the machine learning methods, was used, and the comments were divided into three groups as positive, negative, and neutral. In the study, 82% of the customer comments were positive, 11% were negative, and 7% were neutral. The fact that most of the comments consist of positive sentiments shows that HP Computer has a positive reputation in the eyes of stakeholders consisting of customers. Comments consisting of negative and neutral emotions show the aspects that the brand needs to improve. In the study, the text mining method emphasises the prominent features of the brand in the comments. This study makes an important contribution to the reputation assessment of brands and to ensuring sustainable brand reputation.

**Keywords:** sustainable reputation; e-commerce; public relations; sentiment analysis machine learning; text mining

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## 1. Introduction

In today's increasingly competitive world, a brand's sustainable success depends on its reputation in the eyes of stakeholders. As a matter of fact, in today's conditions, where it is extremely easy to imitate products and services, corporate reputation, which represents only the values of the organisation, cannot be imitated by competitors and is the main element in its differentiation [1].

Both changes in competition conditions and changes in the target audience are the keys to sustainable success for companies. Hall (1993) states that reputation, which is an intangible value for organisations, provides sustainable competitive advantage to organisations [2]. Corporate reputation, which provides a great competitive advantage to companies, offers unique opportunities to leave a positive impression on the target audience by fulfilling its social responsibility [3]. Reputation management, which was previously carried out with classical public relations methods, is now supported by dialogic-based

communications in online environments. Indeed, thanks to the change in and development of technology, the online world has become very important in building and maintaining positive brand reputations [4].

Stakeholders can easily get information about brands through internet portals and express their positive or negative opinions about brands [5]. These evaluations can spread very quickly and have a direct impact on brand reputation. At this point, it is critical for brands to act more meticulously to ensure customer satisfaction [6]. Especially prioritising customer satisfaction by caring about customers is important for a sustainable brand reputation. Based on the importance of customer reviews for brand reputation, this study aims to contribute to the literature and practice by revealing the effect of customer reviews on brand reputation in the context of e-commerce platforms.

In this context, five computer products of the HP brand with the highest number of customer reviews on the Hepsiburada platform were evaluated. The evaluations were created by analysing 2012 customer reviews obtained from the Hepsiburada online shopping site by using text mining techniques.

While the results of the study provide important information about how a global brand such as HP is perceived in the local market, it also emphasises the need for effective analysis of customer feedback.

## 2. Literature

Brand reputation reflects all the impressions created by your products or services in the perception of consumers. Brand reputation can be positive, or it can be affected by a negative image. Reputation is a set of values that your brand has in the eyes of consumers, customers, and investors [7,8]. Brand reputation is a general image of a brand that is formed in the minds or eyes of consumers. This perception consists of various elements such as the quality of the products and services offered by the brand, customer feedback, social and environmental responsibilities, and online and offline comments about the brand [9,10]. Brand reputation is a critical factor that affects consumers' emotional attachment and loyalty levels towards the brand. In this context, brand reputation is considered one of the key elements that determine a brand's competitiveness in the market, consumer preferences, and the long-term success of the brand in general.

Brand reputation is generally defined as the sum of positive and negative characteristics of a brand. These attributes include elements such as the extent to which the brand fulfils its promises, its success in meeting customer expectations, its participation in social responsibility projects, and its perception in the public [11]. Brand reputation is shaped over time and is considered an element that increases the brand's resilience in crisis situations as well as providing a sustainable competitive advantage.

Brand reputation reflects many characteristics of the brand, such as quality, reliability, innovation, and usability. A good reputation is important for brands because a brand with a good reputation increases consumer loyalty and can become indispensable for the consumer. A bad brand reputation, on the contrary, can affect the market share of the brand and the rate of preference, and directly affect the brand's revenue. Brand reputation determines the general perception of consumers about the brand, and this perception directly affects the impact of the brand on customer satisfaction and loyalty. Credible and reputable brands gain the trust of their customers, which strengthens the brands' positions in the market [11].

Brand reputation management is the term given to studies planned and implemented to increase the reliability, value, and recognition of brands. Brand reputation is an important concept that measures how strong a brand's perceived value is. Brands need to understand the importance of brand reputation to gain the trust of their customers and increase the likelihood that they will purchase their brand's products and services. Ensuring brand reputation is important for improving trust between the brand's existing and potential customers and increasing the value of the brand [12]. To manage brand reputation, brand employees need to be trained on brand-related issues and share brand-related

messages correctly with a specific target audience. In addition, to increase brand reputation, it is also important to fulfil customers' expectations by improving the quality of products and services and to increase customers' loyalty to the brand. An effective social media strategy is also important to engage with the consumer and make the brand stand out.

A positive brand reputation builds loyalty and increases customer confidence in your brand and product, which leads to an increase in sales. A good brand reputation means that consumers trust your company and feel good about buying your products or services. Lack of brand reputation management can seriously damage your brand and cause damage which takes much time, money, and effort to repair.

Corporate reputation is shaped because of the perceptions formed during direct interactions between businesses and their stakeholders [13]. Therefore, the impact of stakeholder comments is highly decisive for the creation of a sustainable brand reputation. Especially for businesses offering online services, positive or negative comments made by customers about products and services directly affect brand reputation. As a matter of fact, while positive customer comments spread rapidly and contribute positively to the brand, negative comments can damage the brand by spreading at the same speed. For this reason, it is important to analyse each comment well and to continuously increase customer satisfaction by providing the necessary improvements. There are many studies emphasising this importance in the literature.

Hennig-Thurau et al. (2004) explain how online reviews shape brand perceptions and affect consumer behaviour [14]. In Kayakuş et al. (2024), customer comments on the iPhone 11 phone received through Trendyol online shopping site were analysed by sentiment analysis and machine learning methods. The results of the study reveal that 85 percent of the customers share that they are satisfied with the iPhone 11, but also reveal which aspects of the brand customers like and which aspects they do not like [9]. Lucini et al. analysed online customer reviews to provide guidelines to increase the competitiveness of airline companies by using text mining methods in their study in 2020 and achieved an accuracy of 79.95% [15].

Chevalier and Mayzlin (2006) examined the effect of word-of-mouth advertising on the relative sales of books on Amazon.com and Barnesandnoble.com. The authors found that reviews were mostly positive on both sites and that for most cases, the effect of one-star reviews was greater than the effect of five-star reviews, indicating that customers read the text of reviews rather than relying solely on summary statistics [16]. Ordenes et al. (2014) proposed a model that offers a holistic approach to analysing feedback, facilitated a deeper analysis of customer feedback experiences by covering three value creation elements: activities, resources, and context [17]. Park (2023) proposed a new methodology that combines data envelopment analysis with text mining to analyse online textual reviews. To demonstrate the effectiveness and applicability of the proposed approach, Park conducted an empirical case study, applying it to the world's top 20 airlines in 2020 [18].

Kim and Chun (2019) examined consumer reviews of three different competitive car brands using text mining and association rule methods and analysed the advantages and disadvantages of each vehicle. The paper provides detailed insights into the advantages and disadvantages of each brand and consumers' perceptions of the cars [19]. Kumar et al. (2023) utilised a text mining approach to discover the determinants of grocery mobile app satisfaction using online customer reviews. The results obtained from the study provide guidance to the operators of grocery mobile applications on customer satisfaction management [20]. Joseph and Varghese (2019) analysed Airbnb user reviews using text mining methods. The study aims to develop a new understanding of the tourism and hospitality industry by presenting a case of big data analyses in Airbnb user reviews [21].

Two separate studies were conducted to understand consumers' attitudes towards brand extensions, i.e., the use of a brand name in a new product category. The first study analysed 20 brand extension concepts identified with the names of six well-known brands. The second study evaluated the effectiveness of different positioning strategies for these extensions. The empirical data suggest that negative associations in consumer perception

can be more effectively changed by presenting the characteristics of the brand extension in detail rather than by reminding them of positive perceptions of the original brand [22].

A new approach based on social media shows that brand equity is linked to various brand rankings performed by marketing agencies in their measurement processes. At the same time, some of the indicators were found to have a significant relationship with the stock market performance of the company. As a result, a new and valid measure of brand equity created with the help of social media that simultaneously addresses both consumer and financial perspectives has emerged [23].

As can be seen in the examples above, when the relevant literature is examined, it is seen that there are many studies that address the impact of customer reviews on brand reputation from various perspectives. In this context, this study extends the existing literature and analyses how customer reviews of HP computers are analysed using sentiment analysis and text mining methods.

## 3. Materials and Methods

In this study, the sustainable brand reputation of the HP brand in the computer category is analysed through customer reviews. For this purpose, comments on the five most evaluated HP computers on Hepsiburada, one of Turkey's largest e-commerce platforms, were used. The Naive Bayes method, one of the machine learning methods, was used for emotion analysis. The comments were categorised as positive, negative, and neutral according to their sentiment. Word frequency was calculated using text mining methods, and the prominent features of the comments were identified. To make the analysis results more readable and understandable, word clouds were created using data visualisation techniques.

### *3.1. Data Set*

There are many e-commerce sites in Turkey. In the study, Hepsiburada, one of the e-commerce sites with the highest number of users and sales in Turkey, was preferred. The main reason for choosing Hepsiburada as the source of the data set is that it is one of the largest and most widely used e-commerce platforms in Turkey. This platform has a wide range of products and appeals to a strong customer base in the electronics category. The fact that Hepsiburada has the highest number of comments for HP-branded computers shows that customers actively share their experiences about the products on this platform. Therefore, it provides a wide and comprehensive data source for analyses based on customer reviews. In addition, the popularity and reliability of Hepsiburada ensure that the data obtained has a high representativeness [24].

The HP (Hewlett-Packard) brand was preferred for brand reputation analysis. HP was chosen for the brand reputation analysis because, as a global leader in the technology sector, it has a wide range of products and a significant market share. HP's globally recognized and widely used computer and printer products offer customers a variety of experiences. It receives feedback that directly affects the brand's customer satisfaction and reputation.. Having a significant presence in the Turkish market, HP is known for its high-performance products and customer service. In this context, HP's broad customer base and various product categories provide in-depth and representative data for brand reputation analysis. For these reasons, HP is an appropriate and meaningful choice for brand reputation analysis [25].

The data set of the study consists of 2012 customer reviews for the five most reviewed HP-branded computers in Hepsiburada [26]. The 2012 customer reviews in the data set are an important sample group representing customer experiences and feedback about HP computers. This quantity of reviews provides a suitable data set to understand the positive, negative, and neutral emotional states of customers and to effectively apply text mining and sentiment analysis techniques. This is a sufficient size to conduct a comprehensive analysis on a specific product or product line. The sample size ensures the

accuracy of the analyses and supports the consistency of the findings obtained with extended data sets. Table 1 provides information about the computers that make up the data set.

**Table 1.** Computers in the data set [26].

| Features | Computer-1 | Computer-2 | Computer-3 | Computer-4 | Computer-5 |
|---|---|---|---|---|---|
| Number of comments | 537 | 487 | 386 | 311 | 291 |
| Score | 4.7 | 4.6 | 4.5 | 4.7 | 4.6 |
| Number of question-answers | 101 | 53 | 60 | 68 | 50 |
| Processor Type | Intel i5 | AMD Ryzen 7 | AMD Ryzen 5 | Intel Core i5 | AMD Ryzen 5 |
| Ram | 16 GB | 16 GB | 8 GB | 16 GB | 16 GB |
| Hard disc | 512 GB SSD | 512 GB SSD | 512 GB SSD | 512 GB SSD | 512 GB SSD |
| Price (USD) | 497 | 497 | 430 | 363 | 758 |

When the characteristics of the five HP computers with the highest number of comments in Hepsiburada are analysed in Table 1, it is observed that the products have some common characteristics. The numbers of comments are 537, 487, 386, 311, and 291, respectively, and the customer scores vary between 4.5 and 4.7. The number of questions and answers between the products varies between 50 and 101. Processor types vary between the Intel i5 (Intel, Santa Clara, CA, USA) and AMD Ryzen series, with the Ryzen 5 and Ryzen 7 (AMD, Santa Clara, CA, USA) models being particularly preferred. In terms of RAM capacity, four models have 16 GB of memory, while one model has 8 GB of RAM. All products have a 512 GB SSD storage unit. These data reveal that these computers, which offer high performance and are positively evaluated by customers, are similar in critical hardware features such as processor and storage. The wide popularity of these five HP computers is supported by the large number of user reviews. However, the extent to which consumer reviews are influenced by the price of the computers requires careful analysis. Looking at the prices, the lowest priced computer is priced at USD 363, while the highest is priced at USD 758. The differences indicate a significant price range. This diversity suggests that prices may influence consumer evaluations. For example, more affordable computers may appeal to a wider range of users, leading to more reviews. On the other hand, expensive computers may cause users to have high expectations, which may lead to differences in evaluations. Considering that computers are not in the same price range, it becomes important to understand the relationship between market positioning and consumer evaluations. Lower-priced PCs may be preferred and evaluated by more users because they are more accessible, while more expensive models may have fewer users but hav more in-depth and expectant reviews.

Consumers, especially when purchasing technology products, pay attention to the extent to which they get what they pay for. When the price of a computer is not in line with its features, performance, and long-term durability, fluctuations in consumer satisfaction may occur. At this point, when there is a mismatch between consumer expectations and the actual performance of the computer, negative reviews and low satisfaction rates can be observed. While a lower-priced computer may be considered 'cost-effective' by the user and receive favourable reviews, an expensive computer may disappoint consumers if its performance is not commensurate with its price.

A sample data set is given in Table 2.

**Table 2.** Sample data set [26].

| Comments | Emotional State |
|---|---|
| Product HP quality is very good, speed, etc. Everything is good, and the cargo came fast. | Positive |
| The best among those that can be bought at this price is a complete price performance product suitable for office and homework. | Positive |
| The product is good for its price, but it heats up very quickly. There is a heating problem, and I think it will be necessary to add an additional fan. | Negative |
| I am not very satisfied with the product; there is constant fan noise, more than medium level, not smooth according to 16 GB of RAM. | Negative |
| Hello; I received the product yesterday and started using it. Cargo delivery and box contents were complete and trouble-free. A more than sufficient and quality product for daily work and office environments | Positive |
| I bought it for my brother for homework. I found it very successful; he likes to use it himself. The speaker, the keyboard, and the screen display are quite good compared to other products. | Positive |
| Extreme quality, but the packaging was not solid at all. | Neutral |
| Quality brand price is very affordable, nice appearance, carefully shipped | Positive |
| I like it very much. I recommend it to everyone. It came a little late, but it is worth the wait. | Positive |
| The product is very good, but the packaging is terrible; there is a slight damage to the product. | Negative |

### *3.2. Machine Learning*

Machine learning is a field of artificial intelligence that enables computers to learn from experience or data and use this learning to make future predictions or decisions. Machine learning is used to recognise complex patterns, especially in large data sets, and to generalise these patterns [27]. Machine learning is basically divided into two categories: supervised and unsupervised, according to learning methods. The most important point in the supervised learning algorithm is the use of a labelled data set. In other words, since it is known which data correspond to which information, it is a machine learning model used to take a known input set and the corresponding outputs and produce the most appropriate outputs for new data that the algorithm has never seen before (not used in training). In unsupervised learning, there is unlabelled data. By trying to find the hidden structure or pattern between these unlabelled data, self-learning is exhibited. While supervised learning is generally applied to regression and classification problems, unsupervised learning is applied to clustering and association problems.

Naive Bayes Method

The Naive Bayes method is a probabilistic machine learning model used for the classification task. The Naive Bayes method is named after Thomas Bayes, an English mathematician who lived in the 17th century. Given a class variable, it calculates the probability of the class variable using the Bayes rule for each variable. It predicts the class variable with the highest posterior probability [28]. Based on this conditional probability function, the Naive Bayes algorithm allows tthe prediction of new and unlabelled observations with the same logic by using the feature information of labelled observations. This algorithm has been successfully used not only on numerical data but also on non-numerical textual data.

Based on conditional probabilities, this algorithm analyses the probability of a certain value in the target class and predicts the value of the target class based on this probability [29].

$$P(A|B) = \frac{P(A|B) \cdot P(B)}{P(B)} \quad (1)$$

P(A|B) is the probability that A is true when B is known to be true. P(B|A) is the probability of B when A is known to be true. P(A) is the probability that A happens, and P(B) is the probability that B happens.

There is a strong assumption in this method. Each variable is conditionally independent given the class variable. What is meant by independence is probabilistic independence [30]. The Naive Bayes method can be used with continuous and discrete data and can work well with little data. It can work well with high dimensional data [31].

### *3.3. Text Mining*

Text mining is a discipline that aims to extract meaningful information from large amounts of text data. Text and data mining can be defined as the process of discovering previously unknown information from unstructured texts [32]. The basis of text mining studies begins with the collection of large data sets. Text data are collected from sources such as the Internet, social media platforms, documents, and articles. The collected text data are subjected to a preprocessing step. In this step, texts are cleaned and tokenised, stop-words and unnecessary characters are removed, and this is followed by normalisation operations. The texts are made processable by machine learning algorithms. At this stage, the texts are converted into vectors, and a numerical representation is obtained. This process allows text data to be processed mathematically. In the final stage, text data are analysed, and meaningful information is extracted. Methods such as text classification, sentiment analysis, and topic modelling are used to make sense of text data.

In recent years, the term text and data mining has also been used to describe the mining of scientific content such as journal articles, books, book chapters, or conference proceedings. Text mining saves time and resources. By automating the processes, the results obtained from text mining models can be used to solve specific problems [33].

Text preprocessing is a necessary step for text analysis processes. It is the stage of making the input data consistent to facilitate the digitisation of the text. Traditional text preprocessing methods are word separation and stop word extraction. Stop word extraction is the process of creating a list of words that are meaningless on their own and extracting them from the text. In this step, frequently occurring words in common usage (e.g., 'and', 'this', 'with') that have no meaningful contribution to the analysis are removed from the data set. This allows the model to focus its attention on meaningful words that need to be analysed. Stemming is the process of reducing the derived word to root or stem form. Tokenisation can be defined as breaking words into their smallest meaningful expressions. The first step in text processing is to break the character stream into words or tokens. The process of breaking the text into simpler units is called tokenisation. Tokenisation is the process of separating the text into words or meaningful parts (tokens). In this step, texts are divided on a word-by-word basis, and each word is made analysable [34]. These processes constitute the first steps towards cleaning the data set and extracting meaningful information.

Text mining creates terms or sentences according to the frequency and distribution of words in the texts. It creates a document term matrix according to these terms. In this way, important information in the texts is stored and can be used for later analysis. To distinguish the meaning and relationships in the underlying content, we need to perform operations such as clustering, classification, and association, and these are the basic operations of machine learning [35].

### *3.4. Sentiment Analysis*

Sentiment analysis is the process of determining how a statement contains a feeling through text analysis. Generally, statements are analysed in three groups: positive, negative, or neutral [36,37]. Sentiment analysis use cases are when marketing and customer service teams frequently use social media platforms to help identify their customers' emotions and ideas [38,39].

Sentiment analysis is a field where we try to use natural language processing for text analysis to identify sentiments for a service, product, or entity. Sentiment analysis is the computational study of people's opinions, evaluations, attitudes, and emotions. There are two generally recognised types of sentiment classification methods. These are dictionary-based approaches and machine learning approaches. The most preferred technique in sentiment classification is the supervised machine learning method. This technique uses vocabulary and sentiment dictionaries to understand the meaning of words and expressions in the text. Sentiment dictionaries measure the emotional values of words and classify these values as positive, negative, or neutral [39].

Many brands focus on solving problems by prioritising negative reviews to improve their products or services through user feedback. In addition, fast and accurate classification of customer feedback is a prerequisite for all these efforts. Sentiment analysis not only facilitates customer feedback management but also contributes to longer-term analyses and enables the improvement of customer service operations.

## 4. Results

In this study, the brand reputation of HP-branded computers was evaluated. For this purpose, 2012 customer reviews from Hepsiburada, one of the largest e-commerce platforms in Turkey, were analysed. The Python (version 3.13.0) programming language, text mining, sentiment analysis, and machine learning methods were used in the study.

The initial stage of the study is the data cleaning process, which involves preparing the data for analysis. To extract meaning from unstructured data, unnecessary data were extracted, missing data were completed, and texts were made analysable. In the second stage, the word stemming process was applied. Word stemming is the process of reducing the words in the texts to their basic roots and provides more accurate and efficient results in text mining applications. This process is especially critical in areas such as summarising texts, sentiment analysis, and topic modelling.

The methods used for stemming on comments include dictionary-based, statistical, and mixed methods. In this study, the most appropriate methods were selected to reach the correct roots of the words. In supervised machine learning, the data set is divided into two, as training and testing sets. Training data are used to determine the parameters of the machine learning method, while test data are used to learn the success of the model. There is no definite method for dividing the data set into training and testing sets. The data set is divided into two because of trial operations. In this study, various ratios (60–40%, 70–30%, 80–20%) were tried, and the most successful result was a 70% training and 30% testing ratio. Thus, 1408 of the 2012 comments were allocated for training and 604 for testing. To increase the reliability of data selection, the data were divided into two by using the random method.

The Naive Bayes method, one of the machine learning methods, was used to classify customer comments as positive, negative, and neutral according to their emotional states. Precision, recall, accuracy, and F1 score metrics were used to measure the accuracy and success of the model.

Precision is the ratio of how many of the positively predicted samples are correctly predicted. This metric plays a critical role in situations where false positive errors need to be limited [40].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Here, TP (true positives) represents the number of true positive predictions, and FP (false positives) represents the number of false positive predictions.

Sensitivity (recall) is a metric that measures how many true positive samples the model can correctly predict. This metric is important when the cost of false negatives is high [41].

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

FN (false negatives) refers to the number of false negative predictions.

Accuracy is a metric that measures the proportion of all instances correctly predicted by the model in the total predicted instances [42]. Although accuracy is frequently used to evaluate overall performance, it can give misleading results in imbalanced data sets.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4}$$

Here, TN (true negatives) represents the number of true negative predictions, while TP, FP, and FN are defined as described above.

The F1 score balances these two metrics by taking the harmonic mean of precision and sensitivity. It plays an important role in measuring classification performance by considering both precision and sensitivity together, especially in imbalanced data sets [43].

$$\text{F1} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Precision} + \text{Recall}} \tag{5}$$

These metrics are used to comprehensively evaluate the performance of the classification model. While precision, sensitivity, and the F1 score generally produce more meaningful results on imbalanced data sets, the accuracy metric is used to evaluate the overall success of the model. The importance of each metric varies depending on the application area and the nature of the data set. Table 3 shows performance measurement of the model.

**Table 3.** Performance Measurement.

| Metrics | Value |
|---|---|
| Precision | 0.928 |
| Recall | 0.929 |
| Accuracy | 0.885 |
| F Score (F1) | 0.928 |

As a result of the sentiment analysis, the classification performance metrics obtained for the brand reputation of the HP brand are quite successful. The precision value was determined as 0.928. This value shows that 93 out of every 100 comments are classified correctly. The recall value of 0.929 indicates that 93% of the positive examples are correctly predicted. Accuracy was calculated as 0.885. This shows that 88.5% of all predictions are correct. The F1 score of 0.928 shows that precision and recall metrics show a balanced performance. All these results show that Naive Bayes, used in the study, gives high success and reliable results in classification.

These results provide important information to understand the overall reputation of the HP brand and its reputation in the eyes of customers. According to these results, the HP brand will be able to perform brand reputation management successfully. Table 4 shows the sentiment classification of customer reviews using Naive Bayes.

**Table 4.** Sentiment statistics.

| Sentiment | Comment Count |
|---|---|
| Positive | 1660 |
| Negative | 212 |
| Neutral | 140 |

As seen in Table 2, 1660 (82.5%) of the total comments were classified as positive, 212 (10.53%) as negative, and 140 (6.97%) as neutral. These data show that most of the customer comments on the HP computer brand consist of positive comments. This shows

that the brand meets customer needs and creates a positive impression on the brand. This situation reveals that HP keeps customer satisfaction at a high level and draws a positive picture in terms of brand reputation. On the other hand, although negative comments constitute only 11% of the total comments, these comments need to be analysed carefully. Negative feedback provides an opportunity to identify and resolve problems that may exist with the brand's products or services. Neutral comments, on the other hand, do not show a clear positive or negative tendency towards the brand but rather provide informative and objective feedback. Overall, it appears that the HP brand has a positive reputation, and that customer feedback is largely positive; however, efforts to improve negative reviews could have an even more positive impact on the brand's reputation.

Figure 1 shows the distribution of customer comments about HP-branded computers according to their emotional states. When the graph is analysed, it is seen that 82% of the comments are positive, 11% are negative, and 7% are neutral. This distribution shows that HP computers generally generate strong satisfaction among customers. Most positive comments indicate that HP has a high reputation for product quality, performance, and customer experience. The 11 percent of negative reviews indicate problems or dissatisfaction with the product experienced by some customers, while the 7 percent of neutral reviews indicate that customers offer unbiased and balanced opinions about the product. The data in Figure 2 give an idea about the issues that the HP brand can do to increase the brand reputation of negative and neutral customer reviews.

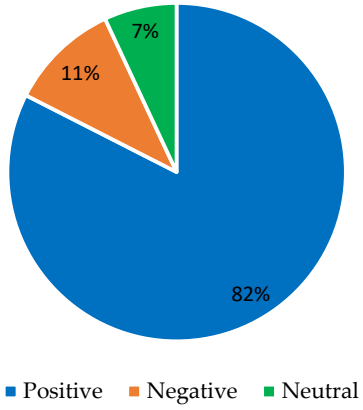


**Figure 1.** Graphical representation of customer comments.




**Figure 2.** Word cloud of positive customer reviews.

N-gram models are used in areas such as probability and statistical natural language processing, which examine and model the probability of certain sequences. An N-gram consists of n consecutive characters. When the N-gram model is used in natural language processing, the independence assumption is applied, with the words preceding the n-1st row. The probability of the word depends only on the preceding n-1 words. The unigram model depends on the order of 0 words before it. The bigram model depends on the preceding one word, while in the trigram model, the word depends on the last two words before it. N-gram models are used for prediction of letter order in speech recognition problems [44].

TF-IDF is a weight factor calculated by statistical method showing the importance of a term in a document. Term Frequency (TF) is a method used to calculate term weights in a document. Inverse Document Frequency (IDF) tries to understand whether this word is a term or a conjunction by finding the number of occurrences of the word in more than one document. As the frequency of the word increases, it is possible to say that the word is more relevant to that document. The weight of a term in a document is proportional to the term frequency. IDF determines how rare or common a term is. Rare terms receive a higher weight, while common terms receive a lower weight. This is usually calculated by the ratio between the number of all documents and the number of documents containing a particular term [45]. Table 5 shows the most frequently mentioned words in customer comments according to the sentiment.

**Table 5.** Word frequency list.

| Positive | Negative | Neutral |
|---|---|---|
| Product (1087) | Product (82) | Product (57) |
| Bought (584) | HP (68) | Install (44) |
| Good (503) | Computer (55) | Arrived (29) |
| Computer (435) | Wrong (53) | Problems (25) |
| Price (394) | Service (42) | Reached (17) |
| Recommend (340) | Seller (39) | Use (16) |
| Installed (313) | Broken (28) | Price–performance (14) |
| Quality (272) | Price–performance (26) | Need (13) |
| Performance (268) | Technician (25) | Freedos (13) |
| Screen (203) | HDD (23) | Play (11) |

The words in the positive comments in Table 5 can be evaluated in three groups. The words in the comments can be grouped as general statements about the product, technical terms, statements about price and quality, and usage experience. Negative comments can be grouped into five categories: general statements about the product, negative situations and problems, statements about the seller and service, delivery and time, and technical problems. Neutral comments can be grouped into four categories: general statements about the product, delivery and time, problems and complaints, and verbal statements and comments.

Data visualisation is the expression of a body of information or data using a graphical or other visual representation. This is done by establishing a systematic relationship between graphical representations and data [46]. Seaborn is a data visualisation library based on and complementary to Matplotlib. Matplotlib is a core library for data visualisation in Python, and Seaborn builds on this core library. Seaborn extends the capabilities of Matplotlib and makes it easier to use [47].

In this study, the word cloud technique was used to visualise the data obtained from content analysis to make it more understandable. The word cloud is a special visualisation technique that expresses the frequency of repeated words in the analysed data. Thus, the

researcher can present the data obtained within the scope of his research and the results of his analyses to the readers with much more understandable visual-based content [48].

Figure 2 shows the word cloud created from the positive customer reviews of HP-branded computers on the Hepsiburada platform. When the word cloud is analysed, it is seen that the expressions 'product', 'performance', 'recommend', 'price', 'quality' are large. The prominence of these words indicates customer satisfaction in terms of product and performance. This situation indicates that the products produced by the brand and included in the review meet user expectations in terms of price–performance. On the other hand, the density of words such as 'fast', 'arrived', 'nice', 'computer' and 'laptop', which stand out in the word cloud, indicates the general satisfaction of customers with the delivery processes and products.

Figure 3 shows the word cloud created from neutral customer reviews of HP-branded computers on the Hepsiburada platform. These expressions express neutral and emotionless descriptions rather than containing a positive or negative emotion. When the word cloud is analysed, it is seen that the sizes of the expressions 'product', 'performance', 'computer', 'laptop', 'quality', and 'price' are large. These expressions include customers' unbiased evaluations of the performance, price, and quality of the products. Expressions such as 'arrived', 'bought', 'installed', and 'using', which have high intensity among the comments, indicate that users focus on installation and usage along with the delivery processes.




**Figure 3.** Word cloud of neutral comments.

Figure 4 shows the word cloud created from negative customer reviews of HP-branded computers on the Hepsiburada platform. When the high-dimensional words in the word cloud are analysed, the words 'product', 'performance', 'computer', 'arrived', 'bought', and 'quality' stand out. These words show that customers have negative opinions and thoughts about the products and their performance. Expressions such as 'install', 'screen', 'price', and 'graphics', which gain intensity in the word cloud, show that customers are dissatisfied with issues such as installation and screen quality. The fact that the word densities in the word cloud are different reveals that the areas where customers are dissatisfied vary.




**Figure 4.** Word cloud of negative customer reviews.

## 5. Discussion

This study, in which HP brand reputation is evaluated with sentiment analysis using text mining and machine learning methods, is supported by data visualisation methods. There are many studies on brand reputation and corporate reputation in the literature. In addition, studies using sentiment analysis and text mining methods are frequently encountered. This study differs from similar studies in terms of using artificial intelligence techniques in the measurement of brand reputation. In addition, the results are well above average success compared to similar studies.

There are studies measuring brand reputation in different fields in the literature. One of them is Kim and Ko (2012), who analysed the impact of social media on the reputation of a luxury automotive brand. In the study, an evaluation was made based on the comments of people using social media. Similarly, in this article, the brand reputation of the HP brand was evaluated through customer comment [42]. In another study, Singh and Kaur (2020) determined that positive customer comments about mobile phones positively affect brand reputation [49].

In the literature, there are studies using sentiment analysis and text mining in brand reputation measurement. Metaxas and Mustafaraj (2010) determined brand reputation through social media data [50]. In this study, the brand reputation of the HP brand was determined by sentiment analysis and text mining in the same way as in the literature. While price–performance expectation was effective on the brand reputation of the HP brand, in another study in the literature, customer satisfaction and product quality were effective [51].

In the studies in the literature, customer comments on e-commerce sites have an important place as a data set. There are studies like this study. Chevalier and Mayzlin (2006) examined the effect of book reviews on sales on Amazon and Barnes & Noble e-commerce sites. The results show that as the number of positive reviews increases, book sales increase [16]. This situation is also valid for HP-branded computers. As the number of positive comments increases, the reputation of the brand also increases. While the quality and aesthetic features of the products are at the forefront in similar studies, price–performance is effective in HP-branded computers [52].

Research results provide an opportunity for companies like HP to develop more effective management strategies and marketing approaches by analysing customer feedback. Using sentiment analysis and text mining, the findings clarify which product

features customers are satisfied with and which areas they complain about. This information can increase customer satisfaction by enabling the product development process to focus on specific features. Furthermore, analysing negative comments can be used to address or reposition these weak points in marketing strategies. Thus, companies can improve both product quality and customer relations while becoming more responsive to customer demands.

As a general evaluation, HP computers show similarities with similar studies in the literature and reveal that positive customer reviews increase brand reputation. While price–performance is the main factor determining brand reputation, it is observed that the expectation changes according to the quality of the product in the studies in the literature.

## 6. Conclusions

In this study, customers' comments on HP computers on the Hepsiburada e-commerce site were analysed in terms of brand reputation. Machine learning, text mining, and sentiment analysis were used as methods in the study, which was evaluated over a total of 2012 comments.

Sentiment analysis shows that 82% of the comments are positive, 11% are negative, and 7% are neutral. In general, it shows that customers are satisfied with HP computers. The fact that positive comments have a very high percentage compared to negative and neutral comments indicates that the products of the brand have a good reputation with customers in terms of quality and performance. This data also reveal that the brand is successful in meeting customer expectations and requests. On the other hand, this high satisfaction rate may be a sign that the brand focusses on customer satisfaction.

Compared to positive comments, the rate of negative comments is reported to be low. However, the presence of negative comments may be an indication of possible problems with the products and services of the brand. As a matter of fact, analysing negative comments well provides opportunities to strengthen the brand's reputation and increase customer satisfaction. For this reason, it is critical to identify these areas correctly to carry out the necessary improvement works in a healthy way.

Brand-neutral customer comments are important because they contain objective experiences towards HP products. These comments, which do not contain any emotion, point out the points that the brand should focus on because they are impartial and informative.

The Unigram method and TF-IDF techniques used in the text mining process were effective in determining the keywords and themes in the comments. Word frequencies and TF-IDF analyses provided important information to better understand the content of customer comments and to identify the strengths and areas that need to be developed. Word clouds created with the Seaborn library visualised the most frequently used terms and provided a visual summary of the overall content of the reviews.

The fact that this study focuses on a single brand, HP, raises the need to question the adaptability of the model to other computer brands or a wider range of smart devices. Since the sentiment analysis and text mining methods used are basically brand-independent, similar methods can be easily applied to other computer brands. However, considering that each brand has a different customer base and market strategy, the model may need to be adapted to these different conditions.

Future studies can contribute to the brand reputation literature and application area by providing comparative and more comprehensive analyses of different brands. In addition to the methods used in this study, by using more advanced techniques such as deep learning and machine learning algorithms, customer comments can be analysed in more depth and more comprehensive data can be obtained. Unlike this study, evaluating the product categories separately by segmentation will provide more detailed information in terms of reputation. Such studies to be carried out in the future will contribute to the creation of brand strategies more effectively and to move the reputation of the brand to a positive point in the eyes of all customers.

As a result of the study, it is possible to say that the customer satisfaction of the HP brand is high, and this emphasises the positive reputation. On the other hand, negative and neutral comments are important in terms of providing the brand with areas that need to be improved in terms of customer satisfaction. Regardless of the field of activity, it is important for brands to analyse customer complaints, expectations, and requests correctly to create a positive reputation and make it sustainable in today's competitive conditions. In this context, sentiment analysis techniques offer opportunities to provide insight to brands.

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## References

1. Fombrun, C.; Van Riel, C. The Reputational Landscape. In *Revealing the Corporation: Perspectives on Identity, Image, Reputation, Corporate Branding, and Corporate-Level Marketing*; Balmer, J., Greyser, S., Eds.; Routledge: London, UK, 2003; pp. 223–233.
2. Hall, R. A framework linking intangible resources and capabiliites to sustainable competitive advantage. *Strateg. Manag. J.* **1993**, *14*, 607–618.
3. Roper, S.; Davies, G. The corporate brand: Dealing with multiple stakeholders. *J. Mark. Manag.* **2007**, *23*, 75–90.
4. Cantoni, L.; Tardini, S. Communicating in the Information Society: New tools for new practices. In *Digital Literacy: Tools and Methodologies for Information Society*; IGI Global: Hershey, PA, USA, 2008; pp. 26–44.
5. Cho, M.; Furey, L.D.; Mohr, T. Communicating corporate social responsibility on social media: Strategies, stakeholders, and public engagement on corporate Facebook. *Bus. Prof. Commun. Q.* **2017**, *80*, 52–69.
6. Kim, E.-G.; Chun, S.-H. Analyzing online car reviews using text mining. *Sustainability* **2019**, *11*, 1611.
7. Pruzan, P. Corporate reputation: Image and identity. *Corp. Reput. Rev.* **2001**, *4*, 50–64.
8. Jiang, S.; Xiao, F. How Teachers Contribute to the Sustainability of the University Brand: Evidence from China. *Sustainability* **2024**, *16*, 3793.
9. Kayakuş, M.; Yiğit Açikgöz, F.; Dinca, M.N.; Kabas, O. Sustainable Brand Reputation: Evaluation of iPhone Customer Reviews with Machine Learning and Sentiment Analysis. *Sustainability* **2024**, *16*, 6121.
10. Ahmadi, A.; Ataei, A. Emotional attachment: A bridge between brand reputation and brand advocacy. *Asia-Pac. J. Bus. Adm.* **2024**, *16*, 1–20.
11. Carroll, A.B.; Shabana, K.M. The business case for corporate social responsibility: A review of concepts, research and practice. *Int. J. Manag. Rev.* **2010**, *12*, 85–105.
12. Kim, H.B.; Gon Kim, W.; An, J.A. The effect of consumer-based brand equity on firms' financial performance. *J. Consum. Mark.* **2003**, *20*, 335–351.
13. Deephouse, D.L. Part IV: How do reputations affect corporate performance?: The effect of financial and media reputations on performance. *Corp. Reput. Rev.* **1997**, *1*, 68–72.
14. Hennig-Thurau, T.; Gwinner, K.P.; Walsh, G.; Gremler, D.D. Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *J. Interact. Mark.* **2004**, *18*, 38–52.
15. Lucini, F.R.; Tonetto, L.M.; Fogliatto, F.S.; Anzanello, M.J. Text mining approach to explore dimensions of airline customer satisfaction using online customer reviews. *J. Air Transp. Manag.* **2020**, *83*, 101760.
16. Chevalier, J.A.; Mayzlin, D. The effect of word of mouth on sales: Online book reviews. *J. Mark. Res.* **2006**, *43*, 345–354.
17. Ordenes, F.V.; Theodoulidis, B.; Burton, J.; Gruber, T.; Zaki, M. Analyzing customer experience feedback using text mining: A linguistics-based approach. *J. Serv. Res.* **2014**, *17*, 278–295.

18. Park, J. Combined Text-Mining/DEA method for measuring level of customer satisfaction from online reviews. *Expert Syst. Appl.* **2023**, *232*, 120767.
19. King, R.A.; Racherla, P.; Bush, V.D. What we know and don't know about online word-of-mouth: A review and synthesis of the literature. *J. Interact. Mark.* **2014**, *28*, 167–183.
20. Kumar, A.; Chakraborty, S.; Bala, P.K. Text mining approach to explore determinants of grocery mobile app satisfaction using online customer reviews. *J. Retail. Consum. Serv.* **2023**, *73*, 103363.
21. Joseph, G.; Varghese, V. Analyzing Airbnb Customer Experience Feedback Using Text Mining. In *Big Data and Innovation in Tourism, Travel, and Hospitality: Managerial Approaches, Techniques, and Applications*; Springer: Amsterdam, The Netherlands, 2019; pp. 147–162.
22. Aaker, D.A.; Keller, K.L. Consumer evaluations of brand extensions. *J. Mark.* **1990**, *54*, 27–41.
23. Clément, A.; Robinot, É.; Trespeuch, L. What if brand equity was alive? Proposal of a dynamic measure through social networks. *Int. J. Internet Mark. Advert.* **2023**, *19*, 369–387.
24. Hepsiburada. Corporate. Availabe online: https://kurumsal.hepsiburada.com/ (accessed on 9 September 2024).
25. HP. About Us. Availabe online: https://www.hpstore.com.tr/hakkimizda (accessed on 26 July 2024).
26. Hepsiburada. HP Laptop. Availabe online: https://www.hepsiburada.com/hp/laptop-notebook-dizustu-bilgisayarlar-c-98?siralama=yorumsayisi (accessed on 9 September 2024).
27. Kabas, O.; Ercan, U.; Moiceanu, G. Critical Drop Height Prediction of Loquat Fruit Based on Some Engineering Properties with Machine Learning Approach. *Agronomy* **2024**, *14*, 1523.
28. Sibyan, H.; Svajlenka, J.; Hermawan, H.; Faqih, N.; Arrizqi, A.N. Thermal comfort prediction accuracy with machine learning between Regression Analysis and Naïve Bayes Classifier. *Sustainability* **2022**, *14*, 15663.
29. Flach, P.A.; Lachiche, N. Naive Bayesian classification of structured data. *Mach. Learn.* **2004**, *57*, 233–269.
30. Rish, I. An empirical study of the naive Bayes classifier. In Proceedings of the IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence, Seattle, WA, USA, 4 August 2001; pp. 41–46.
31. Panda, M. Developing an efficient text pre-processing method with sparse generative Naive Bayes for text mining. *Int. J. Mod. Educ. Comput. Sci.* **2018**, *10*, 11–19.
32. Kayakuş, M.; Yiğit Açıkgöz, F. Classification of news texts by categories using machine learning methods. *Alphanumeric J.* **2022**, *10*, 155–166.
33. Archer, D. Data mining and word frequency analysis. In *Research Methods for Reading Digital Data in the Digital Humanities*; Edinburgh University Press: Edinburgh, Scotland, 2016; pp. 72–92.
34. Kayakuş, M.; Yiğit Açıkgöz, F. Fake News Detection on Twitter with Machine Learning Methods. *J. Abant Soc. Sci.* **2023**, *23*, 1017–1027.
35. Alfarizi, M.I.; Syafaah, L.; Lestandy, M. Emotional text classification using tf-idf (term frequency-inverse document frequency) and lstm (long short-term memory). *JUITA J. Inform.* **2022**, *10*, 225–232.
36. Bilgin, U.; Soner Kara, S. Identification of Perceived Challenges in the Green Energy Transition by Turkish Society through Sentiment Analysis. *Sustainability* **2024**, *16*, 3367.
37. Song, R.; Shi, W.; Qin, W.; Xue, X.; Jin, H. Exploring Passengers' Emotions and Satisfaction: A Comparative Analysis of Airport and Railway Station through Online Reviews. *Sustainability* **2024**, *16*, 2108.
38. Nandwani, P.; Verma, R. A review on sentiment analysis and emotion detection from text. *Soc. Netw. Anal. Min.* **2021**, *11*, 81.
39. Jeong, N.; Lee, J. An Aspect-Based Review Analysis Using ChatGPT for the Exploration of Hotel Service Failures. *Sustainability* **2024**, *16*, 1640.
40. Baldi, P.; Brunak, S.; Chauvin, Y.; Andersen, C.A.; Nielsen, H. Assessing the accuracy of prediction algorithms for classification: An overview. *Bioinformatics* **2000**, *16*, 412–424.
41. Kuhn, M.; Johnson, K.; Kuhn, M.; Johnson, K. Measuring performance in classification models. In *Applied Predictive Modeling*; Springer: Amsterdam, The Netherlands, 2013; pp. 247–273.
42. Jierula, A.; Wang, S.; Oh, T.-M.; Wang, P. Study on accuracy metrics for evaluating the predictions of damage locations in deep piles using artificial neural networks with acoustic emission data. *Appl. Sci.* **2021**, *11*, 2314.
43. Xu, S.; Song, Y.; Hao, X. A comparative study of shallow machine learning models and deep learning models for landslide susceptibility assessment based on imbalanced data. *Forests* **2022**, *13*, 1908.
44. Awwalu, J.; Bakar, A.A.; Yaakub, M.R. Hybrid N-gram model using Naïve Bayes for classification of political sentiments on Twitter. *Neural Comput. Appl.* **2019**, *31*, 9207–9220.
45. Yun-tao, Z.; Ling, G.; Yong-cheng, W. An improved TF-IDF approach for text classification. *J. Zhejiang Univ. Sci. A* **2005**, *6*, 49–55.
46. Sinar, E.F. Data visualization. In *Big Data at Work*; Routledge: London, UK, 2015; pp. 115–157.
47. Waskom, M.L. Seaborn: Statistical data visualization. *J. Open Source Softw.* **2021**, *6*, 3021.
48. Ibrahim, V.; Bakar, J.A.; Harun, N.H.; Abdulateef, A.F. A word cloud model based on hate speech in an online social media environment. *Baghdad Sci. J.* **2021**, *18*, 0937.
49. Kaur, A.; Singh, B. Disentangling the reputation–performance paradox: Indian evidence. *J. Indian Bus. Res.* **2020**, *12*, 153–167.
50. Mustafaraj, E.; Metaxas, P. From obscurity to prominence in minutes: Political speech and real-time search. In Proceedings of the Web Science Conference 2010, Raleigh, NC, USA, 26–27 April 2010.

51. Godes, D.; Mayzlin, D. Using online conversations to study word-of-mouth communication. *Mark. Sci.* **2004**, *23*, 545–560.
52. Park, C.; Lee, T.M. Information direction, website reputation and eWOM effect: A moderating role of product type. *J. Bus. Res.* **2009**, *62*, 61–67.

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