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Research Paper

Brand Hate: Decoding Emotional Trends in the Indian Telecommunication Industry Through Sentiment Analysis

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ABSTRACT

The growing number of brand hate cases in the competitive market is gaining the attention of researchers and making a call for studies to explore the concept of brand hate thoroughly. Moreover, the application of cutting-edge technologies in emotion detection is also growing rapidly. This study used the vast capabilities of Python's rich ecosystem of natural language processing (NLP) libraries and machine learning frameworks in the business domain to investigate a real-world brand hate incident that occurred in the Indian telecommunication industry and explore customers' opinions and sentiments for telecom brands. It primarily aims to explore the brand hate of customers by using the sentiment analysis approach to identify their hidden emotions. Qualitative data, scraped from Facebook comments posted by the general public, was analyzed to examine the customers' hidden sentiments. The study's result shows how an unfavorable action taken by the company caused hate among the customers and influenced them to take action. Customers expressed unfavorable emotions and aggression toward the company using negative words in social media comments that fluctuate over the period. Those who voiced aggression further expressed their intention to switch to another telecom operator. The insights of the study can assist businesses in understanding their customers' behaviour and aid management in devising actionable strategies to resolve customer hate issues and improve consumer-brand relationships.

Keywords: *Brand Hate, Switching, Consumer-Brand Relationship, Telecommunication, Sentiment Analysis, Python*

In the dynamic panorama of human progress, from the beginning of the Industrial Revolution to the current digital era, technological advancements have emerged as a driving force that has transformed all aspects of human existence (Shrivastava, 2024). From enabling online purchases through e-commerce sites to facilitating digital payments, technology has transformed the industry landscape and revolutionized how people connect, communicate, learn, and interact globally (Suherlan & Okombo, 2023). Advancements in the field of ICT, such as the emergence of 4G and 5G networks, improved bandwidth, and internet speed, have enabled people worldwide to build instant virtual connections with others using various communication tools like emails and messaging apps (Abdel-Aziz et al., 2016). Social media sites like Facebook, WhatsApp, Instagram, Twitter, etc. have

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allowed people to publicly express their thoughts, feelings, opinions, and reviews about various topics. (Shahzad et al., 2023). Despite its numerous benefits, social media also presents various challenges that impact individuals, organizations, and society. According to the recent transition observed, people have started using social media to present negative emotions toward others through negative comments, messages, and hateful speech (Castaño-Pulgarín et al., 2021). They have started using social media to share their negative thoughts, opinions, and awful past experiences with others (Joshi & Yadav, 2021). This behavior fosters negative attitudes among both existing and potential consumers towards brands, leading to the emerging issue of brand hate (Şişli & Ülker, 2024). This transition could be hazardous, as hate can potentially damage the image of any individual, organization, firm, or brand (Curina et al., 2020). It influences individuals' perceptions and consequently impacts their purchase decisions (Balaji et al., 2016).

In the Indian context, its recent example was seen in the telecommunication industry when a renowned Indian telecom brand raised its tariffs. The Indian telecommunication sector, which is regulated by the Telephone Regulatory Authority of India (TRAI), has emerged as the fastest-evolving sector globally with the highest mobile data usage per subscriber (Telecom Regulatory Authority of India, 2020). This explosive growth in the telecommunication sector brings several challenges before TRAI, such as managing continuous development, ensuring good infrastructure, fair competition, and fostering the growth of the telecom sector. According to a recent survey report, the most critical challenge is understanding customers' opinions and views about a telecom service provider in the context of their tariffs and service quality (Telecom Regulatory Authority of India, 2020). Moreover, recently, this sector has faced an emerging issue of hate among its customers caused by the aggressive pricing action taken by the telecom giant Reliance Jio. The issue gained traction on social media when users denigrated companies' actions and called for alternate service providers. Meanwhile, another rival company, BSNL, came forward with a positive growth rate as discontented customers expressed a positive tendency towards BSNL (D'Cruze, 2024). Soon after the company’s price hike announcement, people began sharing negative comments and opinions about this action. The impact was so severe that hashtags such as #BoycottJio, #BSNLKiGharWapsi, and #SwitchToBSNL became trending on social media (Upadhayay, 2024; Banerjee, 2024; D'Cruze, 2024). Targeting this incident, this research attempts to analyze the emotions of the actual as well as potential customers of these companies, using a sentiment analysis approach, by evaluating their opinions posted in the form of comments on a popular social media platform, Facebook. The issue must be analyzed thoroughly, as brand hate can have severe negative consequences for businesses. According to a study conducted by Verhagen et al. (2013), negative online word-of-mouth communications in the telecommunications industry significantly impact the behavior of other consumers and influence their switching and repatronage intentions. Moreover, Alqatan (2025) conducted a study to examine the impact of boycott movements on companies' financial performance. The findings of his study reveal that companies suffering from boycott movements face substantial reputational risks and need urgent financial and operational strategies to mitigate the adverse effects of these movements.

Hence, a detailed investigation of the brand hate incident that occurred in the Indian telecom industry becomes crucial. Prior research investigating the adverse aspects of the consumer-brand relationship has concentrated on the conceptualization of the brand hate construct (Fournier, 1988), identified its distinct categories (Kucuk, 2019; Zarantonello et al., 2016), and examined various antecedents and consequences of brand hate (Hegner et al., 2017;

Farhat & Chaney, 2021). Nonetheless, to achieve a more profound understanding of consumer behavior, it is essential to address the gap in identifying and analyzing genuine brand hatred occurrences. This study aims to fill this gap by contributing significantly to the academic literature on brand hate, particularly within the Indian context, by analyzing a real-life incident of brand hate and cautioning industry stakeholders about the increasing consumer negativity towards their brands. The primary aim of this research is to assist the stakeholders in understanding the consumers' emotions and behavior in the telecommunication industry by answering the following research questions associated with this incident:

- **RQ.1.** What was the frequency of negative comments from customers, and how did they fluctuate over the period?
- **RQ.2.** What were the most frequently used words by customers to express their emotions toward both companies following the price increase?
- **RQ.3**. What type of sentiments did consumers express through their comments, and what were their switching intentions?
- **RQ.4.** Among the four prominent classifiers utilized in the study to analyze the data, which one brings the most accurate prediction of negative sentiment in customer comments?

To answer these questions, this study used a unique methodology, dividing it into different segments. The first part depicts the frequency of comments posted by the public on the company's official page over various days. The next part presents word clouds, showcasing the negative words the public used to express their emotions. After that, data depicting the type of consumers' sentiments for both companies is presented through tables and graphs. A comparative analysis of sentiments for both companies was also provided. Finally, the study presents the comparative performance analysis of four different classifiers used to analyze consumers' sentiments for both companies. Discussion over the findings of the study, along with the implications and suggestions for future research (i.e., limitations of the current study), was given in the last segments. Through its findings, the study will contribute to the academic literature by providing factual data related to a real-world brand hate incident. It will assist the management practitioner in formulating actionable coping strategies to mitigate the customers' aggression and help them devise an effective mechanism to redress their grievances. It will result in better customer satisfaction and ultimately lead to the formation of a positive consumer-brand relationship by improving consumers' experiences and fostering brand loyalty.

LITERATURE REVIEW

Brand Hate

Emotion is often considered a crucial, well-studied phenomenon in psychology (Farhat & Chaney, 2021), neuroscience (Zeki & Romaya, 2008), and consumer behavior (Graham et al., 2008). However, most existing literature explores the positive aspects of consumers' emotions. The darker side of consumers' sentiments, which has a stronger impact than the positive one, is under-explored (Kucuk, 2019). According to Romani et al. (2012), anger, hatred, sadness, and dissatisfaction towards an object are some examples of negative emotions. In the context of service brands, when customers experience service failure and have bad experiences with brands, they become angry or hateful and tend to form negative opinions about them (Farhat & Chaney, 2021). Customers induced by such anger may resort to coping mechanisms like retaliation, switching, complaining, or spreading negative word of mouth to others (Fetscherin, 2019).

The term brand hate has been defined by different authors in different ways (Zarantonello et al., 2016). Gregoire et al. (2009) conceptualized it as a desire for revenge and avoidance, which expresses the passion of a customer to harm and punish the faulty brand and withdraw any further interaction with it. Alba & Lutz (2013) defined brand hate as true brand disgust, a circumstance in which the customer is "held hostage" by the business due to exorbitant switching costs, a local monopoly, or other forms of exit obstacles. The outcome of this animosity is social media manifestations of consumer annoyance and spreading negative word of mouth to other customers. Curina, et al. (2021) found that brand hate influences people to spread negative word of mouth, make online complaints, and convince them not to purchase again from the same brand. However, despite being a critical factor in the growth of a business, the brand hate concept is still underrated and least explored, particularly in the context of service brands (Roy et al., 2022). In the Indian context, studies related to customers' hate for brands are also scant. Research conducted so far has also highlighted the need for further exploration of the concept of brand hate, particularly in the context of products and services, across different industries, cultures, and geographical locations (Aziz & Rahman, 2022).

Sentiment Analysis

Sentiment Analysis, often considered opinion mining, is a technique used to identify hidden sentiments in a text (Khan et al., 2024). It is a popular technique widely used in various domains like social media monitoring, customer feedback, and market research to analyze people's opinions about a specific topic or issue expressed in the form of public tweets or comments (Kaur & Sharma, 2020). Text is extracted from tweets or comments and classified as positive, negative, or neutral sentiments that are further analyzed using different machine-learning techniques to identify the true emotion or sentiment it conveys (Gupta et al., 2017). It is one of the most preferred techniques used in various domains like marketing, social media analysis, and customer services to understand consumers' desires and preferences by using different approaches such as machine learning algorithms and deep learning models (Gupta & Kumar, 2023).

Python

Python, a high-level programming language, was created by Guido van Rossum in the late 1980s (Diyasa et al., 2021). It is a well-known interpreted programming language with greater reliability and short code length (Gupta et al., 2017). The language provides ease of reading through its extensive standard library that allows its users to perform various functions such as data analysis, machine learning, and natural language processing to achieve different objectives (Sharov et al., 2024; Gupta et al., 2017). The current study used this approach for decoding consumers' true emotions, as Python is a highly preferred language used to analyze sentiments, which allows users to easily create and modify sentiment analysis models to meet their requirements. Khan et al. (2024) in their study identified it as a powerful tool for determining sentiment polarity and assessing the sentiment of Facebook posts. As the study used a unique combination of machine learning technologies with the business domain, providing advanced analytical power through Python, it allows a deeper and more comprehensive understanding of consumers' emotions and behavior (Sharma et al., 2024).

METHODOLOGY

As the study targeted customers' sentiments, data about their emotions was gathered through their social media activities. Facebook has been utilized for data collection, as Shahzad et al. (2023) in their study consider Facebook as a widely accepted social networking site used frequently by users to share content as well as their emotions related to different objects and events. The data has been gathered for a period ranging from 3rd July 2024 to 18th July 2024, i.e., from the date of the announcement of tariff hiking by the company till the date of authoring this paper. Public comments left beneath all the posts shared by the company during this period on its official page have been gathered for this paper.

Table No.1 shows the number of comments captured from the company's Facebook page. A total of 2051 comments were initially retrieved from the public comments. The information was raw in form and included impurities such as comments in languages other than English, stop words, numbers, emojis, URLs, special characters, etc. After cleaning the data, 1688 comments were left.

Table 1: Number of Comments Collected

NUMBER OF INITIAL COMMENTS	2051
NUMBER OF ACHIEVED COMMENTS	1688

Before preprocessing, the data were analyzed daily to identify the frequency of comments posted by the public during the selected duration. Figure 1 shows the day-wise classification of the number of comments posted on each day between the 3rd to 18th of July 2024:

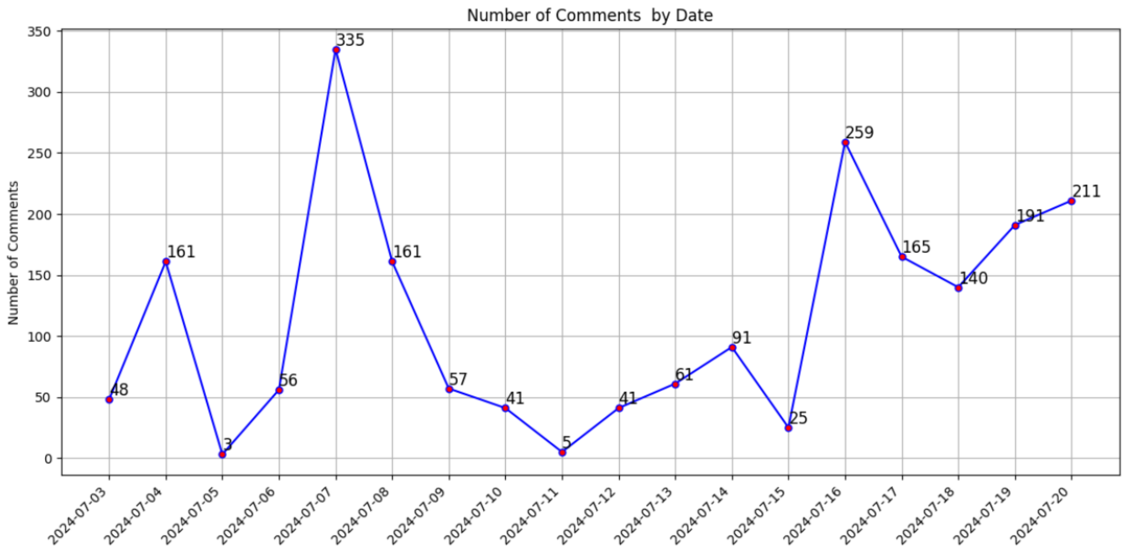

Fig.1 Frequency of Comments Per Day

Fig.1 shows the graph of comments portraying customers' opinions about the tariff hike done by the company through the comments posted by the public below the official posts of the company on different days. As per the graph, the maximum number of comments, i.e., 335 comments, were posted on 7th July, four days after the incident, which could be the sudden shock effect, followed by 259 comments on 16th July and 140 comments on 18th July. After this period, a gradual increase was seen in the frequency of comments. People started spreading negative word of mouth about the company, and soon various hashtags such as #BoycottJio and #SwitchToBSNL became trending on different social media platforms.

DATA ANALYSIS

The achieved comments were further analyzed, and word clouds (the graphical representation of the words in the text) were formed from the dataset using Python. Fig.2 depicts the most frequently used words adopted by the customers to express their negative sentiments for Reliance Jio as most of the comments contain words like 'Boycott Jio', 'poor plan', 'worst network', 'port, complaint', 'Worst service', 'pathetic services', etc.

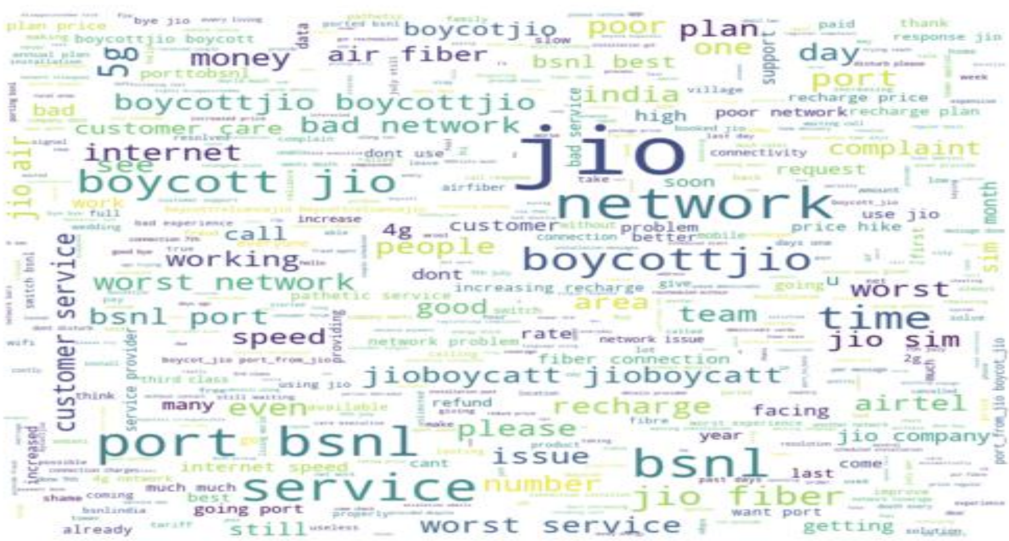

Fig.2 Word Cloud for Reliance Jio

Moreover, Fig.3 portrays the negative emotions of people along with their intention to switch to another telecom brand. Customers' sentiments towards BSNL were presented through this word cloud, as another trending hashtag during this period was #SwitchToBSNL. Those who expressed their negative emotions and hate against Reliance Jio also expressed their positive emotions towards rival brand BSNL. People use words like 'BSNL', 'Switch to BSNL', 'Port to BSNL', 'ported', etc., and show their switching intentions caused by their hate for Jio.

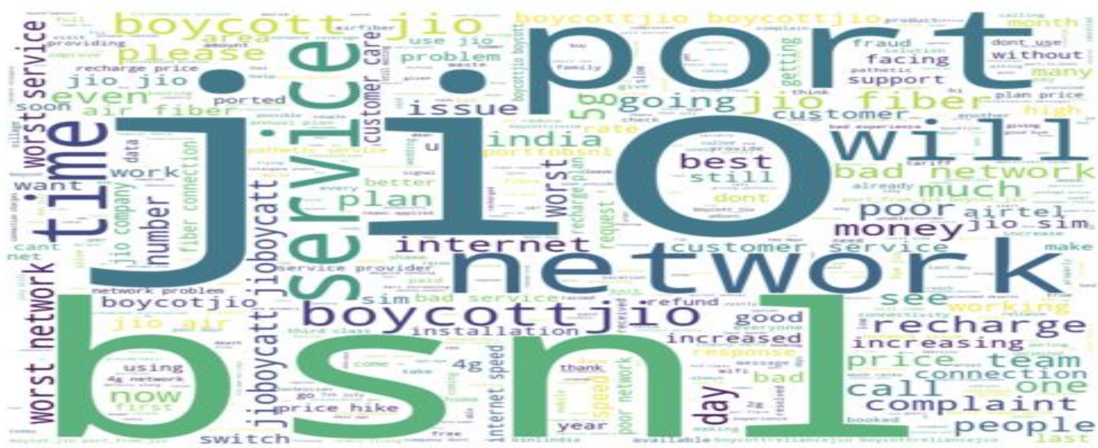

Fig.3 World Cloud for BSNL

1. Preprocessing
Data collected in the form of comments was raw and contained impurities. Hence, it was required to purify it through preprocessing and cleaning steps. It is a stage in which unwanted data, such as stop words, URLs, numbers, emojis, etc., were removed so that true sentiments can be analyzed. Only the comments posted in the English language were included in the data set for analyzing the sentiments of the customers. Text was extracted from these comments and converted into data frames using the following steps for cleaning:

- Converting the text from upper case to lower case
- Removal of stop words
- Removal of URLs from the comments
- Removal of hashtags
- Removal of numbers
- Removal of usernames and mentions
- Removal of unnecessary space
- Removal of punctuation marks and symbols

After cleaning the impurities, the data were prepared for further analysis. Table 2 presents the text extracted before and after cleaning the comments:

Table 2: Preprocessing of Comments

Comments Before Cleaning
"Jio is the worst service   provider!!!!! #BoycottJio "
Comments After Cleaning
"jio worst service provider boycottjio"

2. Model building
Once the cleaning and preprocessing of the data were completed, the text was labeled using a machine-learning algorithm. The text was labeled using different classifications, namely Positive, Negative, and Neutral. Table 3 indicates the classification of comments. This paper aims to identify the consumers' sentiments toward Reliance Jio and BSNL and to check their behavioral responses through their switching intentions. The total comments were segregated into two different categories, namely 'Sentiments for Reliance Jio' and 'Sentiments for BSNL', to analyze the consumers' sentiments for both categories separately.

Table 3: Classification of Comments

COMMENTS	**SENTIMENT FOR JIO**	**SENTIMENT FOR BSNL**
NEGATIVE	1603	4
NEUTRAL	56	1201
POSITIVE	29	483
TOTAL	1688	1688

A total of 1688 comments after cleaning were thoroughly analyzed and classified based on sentiment as 'Negative', 'Neutral', and 'Positive'.

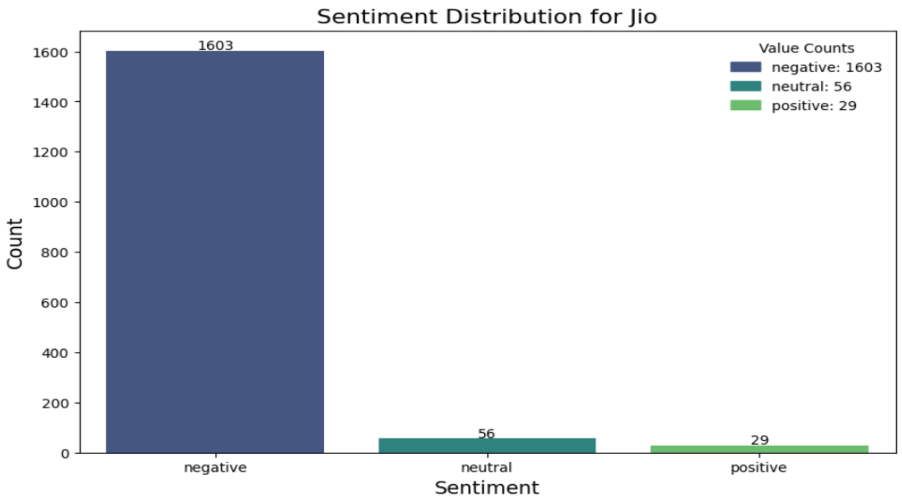

Fig.4 Classification of Sentiments for Reliance Jio

As shown in Fig.4, out of 1688 public comments, 1603 comments expressed the negative sentiments of the customers for Reliance Jio, whereas 29 comments show the positive sentiments. However, out of a total of 1688 comments, 56 comments were of the neutral category, which means consumers expressed neither negativity nor positivity for Reliance Jio. The number of negative comments (approximately 95%) was high, indicating that consumers were deeply affected by the company's price hike action, which prompted them to express their dissatisfaction through negative word of mouth on social media platforms.

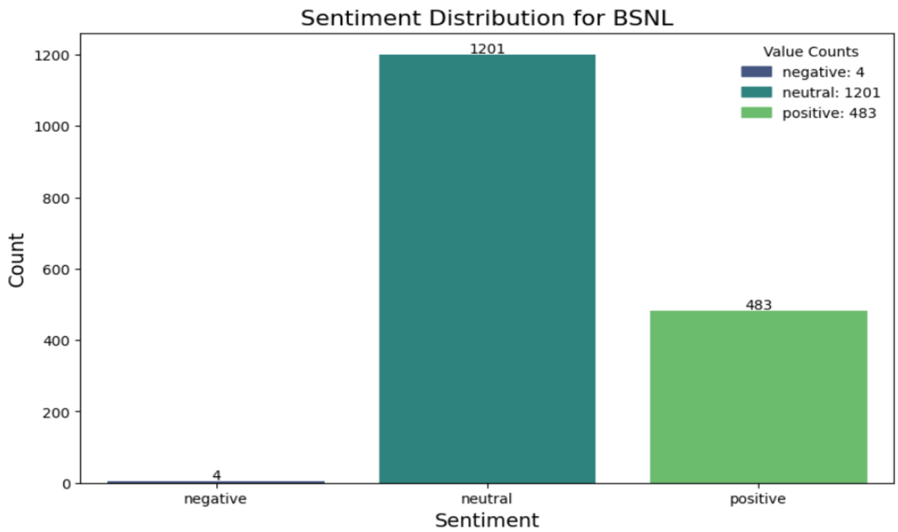

Fig.5 Classification of Sentiments For BSNL

Those who were in a rage with Jio further expressed their affection for BSNL. As shown in Fig.5, out of 1688 comments, 483 comments (i.e., 29% of the total) showed the positive emotions of furious customers for BSNL. Though the number of neutral comments was high in the case of BSNL, i.e., 1201 comments (71% of the total), #Switch to BSNL was trending during this period. The reason behind this is that this paper focuses on analyzing the sentiments of only those customers who expressed their negative emotions toward Jio on their official Facebook page. However, people used multiple social media platforms to express their aggression. The number of negative comments for BSNL is nominal.

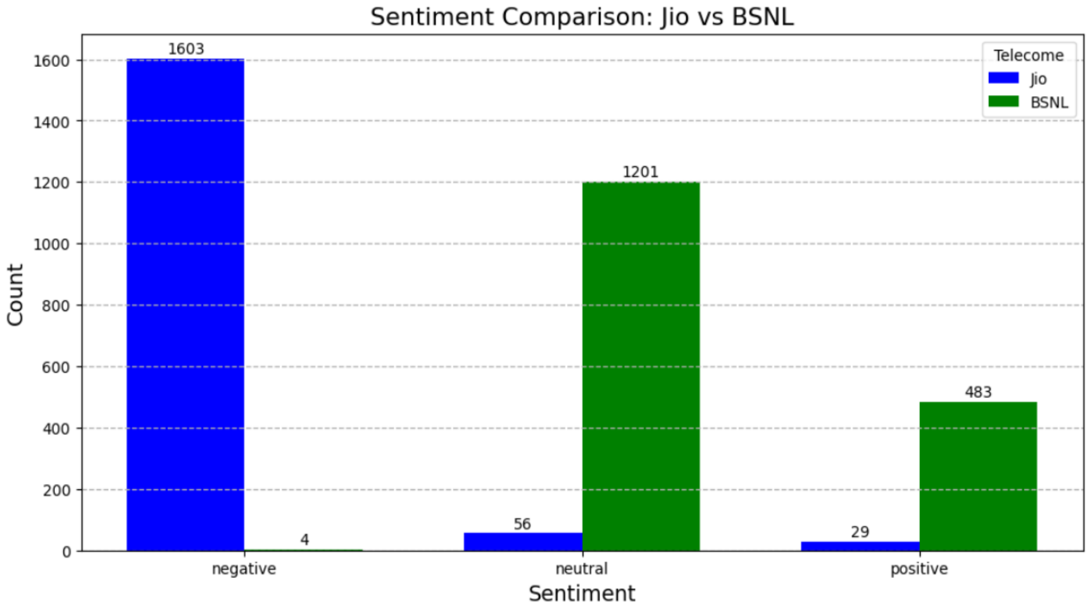

Fig.6 Comparative Sentiment Analysis of Reliance Jio and BSNL

Fig.6 presents the comparative analysis of consumer sentiments for both companies, which clearly states that the impact of the action taken by the Reliance Jio company was huge. It caused negativity and hate among its customers, which they expressed through their negative comments on social media platforms. It further influenced them to take action against the company by switching to the rival brand BSNL.

After this, the model was trained using various machine-learning algorithms. Four popular algorithms used in this paper for the classification are mentioned below:

- LOGISTICS REGRESSION: It is a type of multivariate statistical methodology used to identify the relationships and predict the outcomes (Healy, 2006).
- NAÏVE BAYES: Naive Bayes is a classifier that uses its feature vector to estimate the most likely class of an example. It has shown efficacy in predictive applications such as text categorization, medical diagnosis, and system performance monitoring etc. (Rish, 2001).
- SUPPORT VECTOR MACHINE: It is a learning model used for binary classification. It is effective for both classification and regression analysis (Boswell, 2002).
- K-NEAREST NEIGHBORS: It is one of the most basic and simple classification techniques, which usually entails dividing samples into training and testing groups (Peterson, 2009).

RESULTS

The model based on the above four classifications was further analyzed using four different parameters: Accuracy, Precision, Recall, and F-1 Score, to evaluate the performance of each parameter and the best suitable model.

1. Measurement

In line with previous studies, the most commonly utilized measures, ‘Accuracy’, ‘Precision’, ‘Recall’, and ‘F1_Score’, were used in the present study to evaluate models. These measures help evaluate the quality of classification models in machine learning. Table 4 depicts the formula to calculate the value of these measures along with the definitions given by different researchers (Kaur & Sharma, 2020; Powers, 2020).

Table 4: Definitions and Formula

SN	Measurement	Definition	Formula
1.	**Recall**	Recall, also known as sensitivity in Psychology, represents the proportion of correctly predicted positive observations to all observations in the actual class. It tells us whether a machine learning model can find all the objects of a target class or not.	Recall= True positive/True positive + False Negative or τπ |(τπ+φν)
2.	**Precision**	Precision, also known as confidence in data mining, is a metric that defines how much a machine learning model correctly predicts the positive class. The number of genuine positives divided by the sum of the true positives and false positives yields this value.	Precision = True positive/True positive + False Positive or τπ |(τπ+φν)
3.	**F1_Score**	It is a harmonic mean of Precision and recall, which provides a balanced measure even when there is an uneven class distribution. Both precision and recall are used to assess a machine learning model's performance.	F1_Score = 2 * ((Precision * Recall) / (Precision + Recall))
4.	**Accuracy**	It is a measurement used to evaluate the classification model to determine how accurately the model performs. It is a metric indicating the proportion of outcomes correctly predicted by a machine learning model. The overall correctness of a classification model is also identified.	Accuracy= Correct predictions/All predictions

Tables no. 5 and 6 depict the performance of each classifier as identified using different machine learning tools and techniques.

Table 5: Performance Result (Reliance Jio)

Algorithms	Accuracy	Precession	Recall	F-1 Score
Logistic Regression	92	87	92	89
Naïve Bayes	83	90	83	86
SVM	92	86	92	89
K-Nearest Neighbor	93	87	93	90

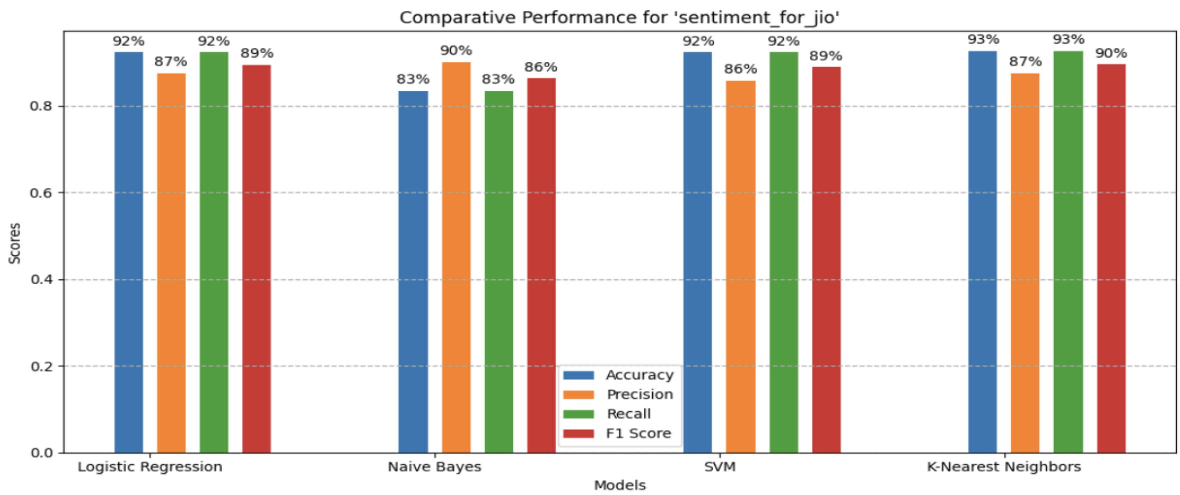

Fig.7 Comparative Performance Analysis of Sentiment for Reliance Jio

Tables 5 and Fig.7 depict the accuracy results of each classifier used for Reliance Jio in the model, which was evaluated by applying various machine-learning tools and techniques. Parameters like Precision, Recall, and F-1 Score were used for evaluation. The accuracy score is higher for K-Nearest Neighbor (93%), whereas precision is higher in Naïve Bayes (90%) than in other classifiers. Among all the classifiers, Recall and F-1 Score are the highest in the case of K-Nearest Neighbor, i.e., (93%) and (90%) respectively. Therefore, as per the result, the performance of K-Nearest Neighbor is the highest among all the classifiers used for Reliance Jio.

Table 6: Performance Result (BSNL)

Algorithms	Accuracy	Precession	Recall	F-1 Score
Logistic Regression	86	86	86	85
Naïve Bayes	86	87	86	85
SVM	86	86	86	85
K-Nearest Neighbor	86	86	86	85

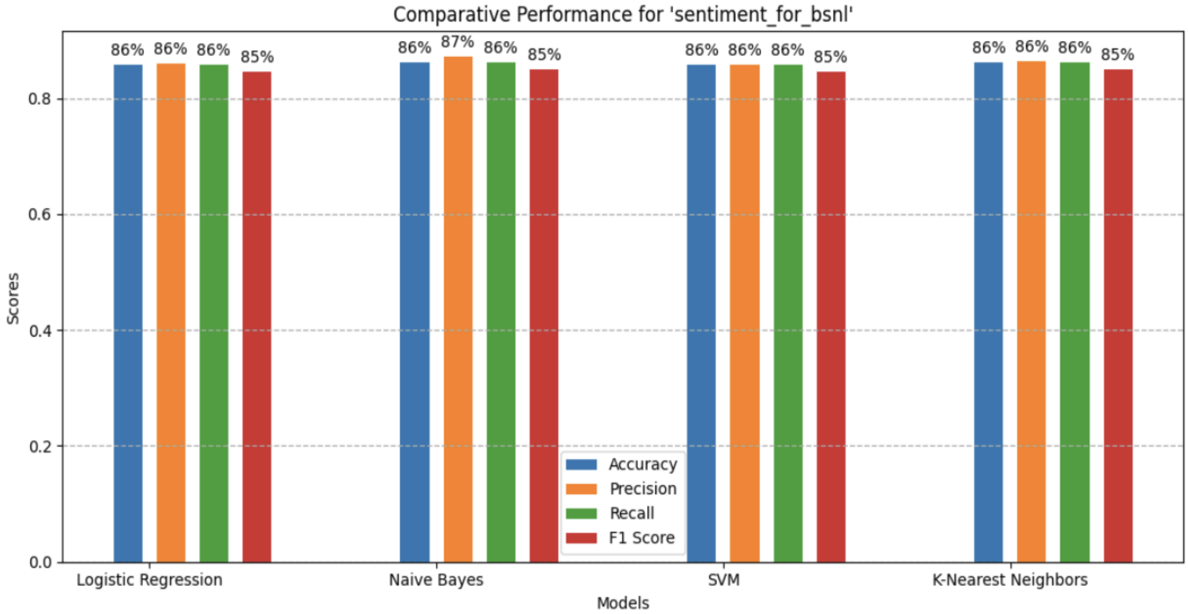

Fig.8 Comparative Performance Analysis of Sentiment for BSNL

Tables 6 and Fig.8 illustrate the accuracy results for each classifier used in the model built for BSNL that was evaluated by applying various machine-learning tools and techniques. Parameters like Precision, Recall, and F-1 Score were used for evaluation. The accuracy score (86%) is constant for all the classifiers, whereas precision is higher in Naïve Bayes (87%) than in other classifiers. Recall and F-1 Score are also constant at (86%) and (85%), respectively, among all the classifiers.

DISCUSSION

As the aim of the study was to identify the hidden sentiments embedded in the customers' comments, it used four prominent classification models for the given set of data and analyzed it on four different parameters, namely accuracy, precision, recall, and F1 score. The results of the study show that the K-nearest neighbor is the best model for the data set for Reliance JIO, as the performance for this classifier is higher than all other classifiers in the given dataset. However, in the case of BSNL, all the classifiers show the same level of accuracy, which means the results generated by all the models are equally good.

Overall, the findings of the study show that an unfavorable price hike action of the company influenced the customers to express their animosity towards the company on the social media platform. They used offensive language and negative words to express their aggression in comments that fluctuate over the period. Through analysis, it was identified that amongst 1688 consumer comments, 95% of comments reveal the negative emotions of customers for Reliance JIO. These customers further expressed their intention to switch to another service provider. Moreover, among these 1688 comments, 29% of the comments solely depict their positive attitude toward BSNL, which brings future growth possibilities for the company. The results of the study are also validated by all four classifiers used, which ensures that the outcomes produced are accurate and precise.

CONCLUSION

To conclude, brand hate has become a matter of serious concern. Previous studies urge researchers to conduct more studies related to the issue of hate among customers for further exploration of the concept. Their findings draw the attention of the researchers to the opportunity of researching brand hate concepts across different industries, particularly in the context of products and services. The Indian telecommunication sector, which has emerged as one of the largest telecom markets in the world, has recently witnessed this critical issue of brand hate. A recent price hike action of the company Reliance JIO brought a major revolution in the market. People influenced by this action started expressing their negative emotions on various social media platforms. Targeting this incident, this study analyzed the sentiments of the customers of Reliance Jio. For this purpose, data was collected from the company's official Facebook page and analyzed using different machine-learning tools and techniques in Python. After initial cleaning, preprocessing, and model building from the data, four different machine learning algorithms, namely 'Logistic Regression', 'Naïve Bayes', 'K-nearest neighbor', and 'Support Vector Machine', were used to analyze the data. Parameters, namely recall, precision, F1-score, and accuracy, were used to predict the sentiments of the customers, hidden in the text, accurately and precisely. The study's results reveal that brand hate caused by an unfavorable pricing action of the company influenced customers to express their negative sentiments on social media. A majority of customers (i.e., 95%) expressed their aggression toward Reliance Jio. The word cloud above illustrates how they expressed their negative feelings using negative terms. Those who expressed their hate further expressed their intention to switch to BSNL. However, their rate was quite low (i.e., 29%) as this paper considers the comments depicting their intention to switch to BSNL only. While the customer's intention to switch to another telecom operator was not considered, it was also substantial. Therefore, it is recommended to cover this gap in further studies, as growing hate among customers for the brands has become a critical issue for businesses and must be addressed thoroughly.

Implications

The study of the brand hate concept presented in this paper makes two major contributions. First, it contributes to the academic literature by providing actual data obtained by analyzing a real-life instance of consumer brand hatred, particularly connected to the telecommunications sector. It offers a comprehensive analysis of consumers' animosity towards a telecom service provider brand, which stems from the company's negative behavior, and also examines the switching intentions of hateful consumers. This analysis can also serve as a base for future brand hate research related to the telecommunications sector. Moreover, the insights related to consumers' emotions and behavioral response can help management and policymakers develop coping mechanisms to prevent and deal with their customers' hostility, as it highlights how an unfavorable action of the brand causes animosity and negative feelings in consumers and prompts them to switch to a rival brand. It will assist the management in maintaining cordial relationships with their customers by formulating policies to enhance and improve their customers' purchase experience by fulfilling their unmet needs and transforming their negative feelings into positive emotions.

Limitations and Suggestions

Research, based on negative consumer brand interactions, is still in its development stage. Various issues related to negative consumer-brand relationships have been discussed in previous studies. However, several issues still need to be discussed. Some of them are mentioned here as limitations of this research work and could be used as a base for future studies. Firstly, the current study particularly targeted the Indian telecommunication sector and aims to identify the customers' sentiments for Reliance JIO and BSNL only. However, there are some other market players in the telecommunications industry. Customers' sentiments for them can also be analyzed in future research. Secondly, future studies can identify the change in the performance of these companies after this incident. A comparative analysis depicting the pre- and post-incident performance of these companies could also serve as a base for future research. Moreover, the data collection in the present study is limited to one source, i.e., Facebook. However, several other social media platforms are used by the general public to share their opinion and thoughts, which could be targeted for collecting data for analyzing the sentiments. Moreover, time was also a major constraint in this current study. The duration of the study could be extended for future research works, considering the different industries. At last, as modern problems require cutting-edge technologies to support data-driven decision making, hence, other emerging tools and techniques could be used to analyze more current instances of brand hate occurring in various industries.

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