

Sentiment Analysis : Using Different Models for Monitoring and Analyzing Customer Reviews

Chandra Prakash Gupta¹

V. V. Ravi Kumar²

Abstract

Purpose : Social media platforms offer a variety of useful information to people, resulting in the generation of enormous amounts of data, including images, videos, music, text, etc. Many methods have been developed to extract insights from this data. Accurate polarity identification of customer reviews remains a persistent and fascinating issue. This study explored the efficacy of various sentiment analysis models in monitoring and analyzing customer reviews, focusing on their ability to provide actionable insights for businesses.

Design/Methodology/Approach : The research employed a comparative analysis of different sentiment analysis techniques. Sentiment analysis uses lexicon-based approaches, machine learning, and deep learning models for evaluating data. A dataset of customer reviews collected via Google Forms was utilized to test these models. The study involved data pre-processing and evaluation to determine the accuracy and precision of the customer reviews.

Findings : The study revealed how sentiment analysis can shed light on consumer sentiment and reveal shifting tendencies. This can enable marketers to make better decisions and improve their marketing, product development, and customer service efforts. One important finding of the study is the usage of SA for deriving real-time actionable insights for companies.

Practical Implications : The findings suggested that businesses can enhance their customer experience management by adopting sentiment analysis, particularly in scenarios with diverse datasets.

Originality/Value : This research contributed to the growing field of sentiment analysis, offering valuable insights for both academic researchers and industry practitioners and aimed at improving customer sentiment monitoring practices.

Keywords : social media, sentiment analysis, polarity, customer reviews, customer experience

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Unpredictable customer behavior has become a significant difficulty for organizations today, requiring solutions to address this critical challenge. Consumer behavior has significantly changed when looking for information about goods and services; e-word-of-mouth, online reviews on social media, and other websites have become essential in framing an opinion about the purchase. Customers today look for online reviews before purchasing (Yang et al., 2015). The dynamic and ongoing process of sharing information among future, present, or past clients about a specific product/service is called eWOM (Dwivedi et al., 2021).

¹ Assistant Professor (Corresponding Author), Symbiosis Institute of Business Management, Pune, Symbiosis International (Deemed University), Gram: Lavale, Tal: Mulshi, Pune - 412 115, Maharashtra. (Email : chandragupta@sibmpune.edu.in) ; ORCID iD : <https://orcid.org/0000-0001-7022-1878>

² Professor, Symbiosis Institute of Business Management, Pune, Symbiosis International (Deemed University), Gram: Lavale, Tal: Mulshi, Pune - 412 115, Maharashtra. (Email : vvkumar@sibmpune.edu.in) ; ORCID iD : <https://orcid.org/0000-0002-3492-4469>

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Traditionally, when a business wants to know the public's or customers' opinions, it uses surveys, polls, and focus groups. However, with technological developments now, different automated tools are available. Sentiment analysis (SA) is one such tool for businesses with which they can perform this task automatically. SA involves collecting and comprehending consumer opinions about a brand, service, or product. Keeping track of online conversations enables businesses to identify and address possible problems proactively. The SA objective is to analyze user and client behaviors that help businesses in future development (Tanna et al., 2020). The words in an SA are categorized according to their semantic orientation (SO), which refers to the words' weight, polarity, and strength. Analyzing consumer behavior is the most significant use of SA in business.

This study highlights the role of SA in understanding consumer attitudes through their online reviews. This study seeks to answer the following question: How can SA help better understand consumer sentiments via online reviews to make better business decisions? In terms of SA techniques such as lexicon-based methods, machine learning (ML) algorithms, and deep learning (DL) models, the research work aims to provide valuable findings for businesses, which will help them improve their marketing strategies and boost customer engagement (Srinivas et al., 2021; Vyas & Uma, 2018). The present study contributes to the present body of literature by connecting online consumer behavior with SA methodologies. This research offers practical business implications by demonstrating how SA can be harnessed to draw insights into consumer attitudes, desires, and market trends. Adopting advanced analytical tools will help businesses better grasp customer attitudes and sentiments, propelling strategic decisions and planning (Atmaja & Sasou, 2022).

The importance of SA in comprehending consumer behavior has increased in the past few years; however, advanced SA techniques, such as DL and ML models, are still not entirely integrated into business decision-making processes. Most studies focus on conducting SA as a mere tool for extracting consumer opinions without deeply investigating its predictive ability to impact strategic marketing decisions. To what extent eWOM and online reviews impact consumers' purchasing decisions is acknowledged; however, few studies have dealt with how businesses can systematically use SA to derive insights for actionable real-time decision-making. Therefore, this study hopes to fill the gap by comparing how different SA methods can perceive the subtlety of consumer sentiments and how these can affect business strategies.

Literature Review

Social media has created a new creative opportunity for businesses and brands to engage customers (Menon, 2021). Today, many reviews are being written and uploaded online; tangible and intangible items fall under this. These consumer-generated reviews significantly influence consumers' buying choices (Chen et al., 2017). Consumers review publicly accessible content on the Internet or online comments on social media or other sites before purchasing the goods or services (Baek & Lee, 2021). Looking at this, many organizations have made online reviews an integral part of their online presence since it has emerged as an efficient approach to influencing customers and engaging them directly (Maslowska et al., 2017). Prasad and Amruta (2023) concluded that social media can easily influence the cognitive balance a customer might achieve just before making a purchase; thus, the growing use of social media to check products prior to purchases makes it all the more important for businesses to monitor it closely.

Purchase decisions made by potential customers are significantly influenced by online product reviews (Chen et al., 2018). A favorable impact was measured on online purchase intent by social media usage (Siji, 2021). A brand must prove itself in terms of quality and quantity; otherwise, it would have no time to react before the negative message about the brand reaches a customer (Sharma et al., 2023). A deeper understanding of online reviews can help businesses sell products to improve consumer buying intentions and loyalty (Ismagilova et al., 2021). Businesses can benefit from having a good rating and favorable evaluations of consumer experiences

on social platforms to boost their reputation and eventually improve sales (Banerjee et al., 2017). Businesses must depend on consumer reviews to determine what the users feel since they all may want to buy products or services. Based on the sentiments, a customer might choose the product (Alamanda, 2020). Managers must observe and study consumers' online behavior to follow their opinions and build a strong relationship with them. The importance of eWoM must be appreciated and included in the comprehensive marketing plan, which will increase the business's social media presence (Sharma et al., 2024).

Businesses can determine areas where they must focus their efforts by identifying the important elements affecting the customer experience (Zhou et al., 2014). SA provides a broader view, leading to improved decision-making (Küçükali & Erdoğan, 2024). Businesses can grasp the pulse of the consumers' market with its help, leading to the design of an astounding strategy. Since SA is essential in comprehending consumer opinions and reactions, it is widely employed in different industries (Patel & Goswami, 2024). SA enables businesses to understand consumers' perceptions about the products/services and helps prospects collect details about their product/service from other users' experiences. SA is an information extraction technique that collects and classifies feelings or attitudes toward a particular subject or entity (Wankhade et al., 2022). The lexicon-based method, hybrid methodology, and ML- and DL-based methods are the most commonly used techniques for performing SA. Lexicon-based techniques use pre-made dictionaries of words and phrases associated with positive or negative emotions. Lexicon-based SA algorithms are considered modest since the sequential integration of words is not considered. Implementation requires more work because lexicon-based systems must be tuned and maintained frequently. Natural Language ToolKit (NLTK), TextBlob, Valence-Aware Dictionary, and Segment Reasoner (VADER) are the few lexicon-based SA tools. Though adopted generally by analysts, the lexicon-based approaches tend to have restricted accuracy because of their inability to address most of the nuances and complexities of language. The guidelines cover natural language processing (NLP) methods, including lexicons, tokenization, stemming, and part-of-speech tagging. By eliminating blank spaces, commas, and other symbols, etc., tokenization breaks up a text string into tokens. Stop phrase words (such as “a, an, the, of, and for”) are removed (Kaushik et al., 2015).

Formal concept analysis (FCA) is a revolutionary method in SA (Ojeda-Hernández et al., 2023), where it builds classification dictionaries. Unlike the other methods that depend on pre-defined lexicons, Ojeda-Hernández et al. (2023) allowed the development of data-centered and needs-specific dictionaries. In their study, Kumar et al. (2025) reviewed many techniques and identified which techniques are suitable for different kinds of data, opening a much wider and well-informed view of SA than was hitherto available.

A massive pile of sagacious data concerning consumer sentiment is available on the online platform, which helps in understanding how consumers provide feedback and how ML techniques can be employed for prediction in the recommendations using that feedback (Jain et al., 2022). In an ML-based method of SA, a model is trained to look for patterns associated with positive, negative, or neutral sentiment using an extensive collection of labeled data. Training and testing datasets were separated by the authors Kaur and Sharma (2023); they used the training dataset to teach the model how to connect a specific input text to a conforming output during training. Generally speaking, supervised or unsupervised ML methods can analyze sentiment. In a supervised approach, a collection of labeled training data is used to create a classification model, which is then used to categorize additional data for which labels are missing. There is no need for training data for unsupervised methods (Grljevic & Bosnjak, 2018). Naïve Bayes classifier, support vector machine (SVM), Kernel trick, KNN (K-Nearest Neighbor), etc., are well-known methods for SA through ML to detect positive, negative, or neutral sentiments. Dey et al. (2016) used three evaluation metrics using ML algorithms K-NN and Naïve Bayes in their study. They found that the Naïve Bayes classifier gave better output than the K-NN classifier. Huq et al. (2017) used two approaches on a sentiment classification model. In the first approach, the K-NN classifier was utilized in the sentiment classification algorithm, and the second used the SVM algorithm. Based on actual tweets, the classification algorithm's efficacy

was verified. The outcomes demonstrated that, for experimental validation, the sentiment classification algorithm produced more accurate results than the SVM algorithm. Using a novel combination of the DL approach convolution neural network (CNN) and the unsupervised learning method K-means, a comparative study was conducted on movie reviews, which provided a more accurate evaluation of the sentiments compared to other methods. Several ML and NLP-based approaches were used to analyze these ideas. A subfield of AI called NLP reads and comprehends much material people create, including social media comments, and turns it into structured data for study (Patel & Patel, 2021).

This processing and analysis of text via NLP provides users with the answers they are searching for (Khurana et al., 2023). Although ML algorithms are quicker, their accuracy is debatable. It was found that for textual sentiment classification, DL techniques outperform ML techniques (Gulati et al., 2022). SA was performed by Ferdous et al. (2024) on a Bengali dataset by utilizing the term frequency-inverse document frequency (TF-IDF) method for feature extraction and the extra tree classifier method for feature selection. The authors trained their ML model, resulting in 92% accuracy. In recent years, numerous DL models have been used successfully for various NLP applications. DL trains computers to learn from experiences similarly to people.

DL extracts and transforms features through many layers of non-linear processing units. While lower layers near the data input learn simpler features, higher layers acquire more sophisticated characteristics derived from lower-layer features. According to the study by Zhang et al. (2018), DL employs multiple-layered artificial neural networks to carry out learning tasks. It can utilize a far more significant portion of neural networks' learning (representation) capabilities, which were previously believed to be only helpful with a few layers (1 or 2) and a small amount of data (Chen & Manning, 2014). In their study, Sun et al. (2021) presented a throughput DL model for anticipating demand to help catering businesses operate more efficiently with less waste. They trained and verified the proposed model using extensive data from a company's online booking system. They monitored seasonal trends and regional or global events that significantly impacted sales. When compared to the best-performing forecast methods, Xgboost and the autoregressive moving average model (ARMA), the results showed that the method suggested by Sun et al. (2021) brought a considerable improvement in the demand forecasting accuracy for dishes along with a reduction in related costs and labor allocation. Talaat (2023) presented four DL models based on combinations of BERT (a powerful NLP) with bidirectional long short-term memory (BiLSTM) and bidirectional gated recurrent units (BiGRU) algorithms.

Thakur et al. (2022) studied the traveler's motivation to provide online reviews and concluded that a positive trip experience will motivate people to write online reviews. eWoM has a direct and significant relationship with the purchase intentions of online travelers, so marketing professionals should consider this when employing them to influence online customer purchase intention (Gupta & Savita, 2024). Jaiswal et al. (2024) revealed that social welfare tweets could increasingly serve the purposes of brand marketing and loyalty and have established the importance of social media in business marketing strategies. Afify et al. (2020) checked the genuineness of the Facebook account. A two-level approach was used to establish credibility. A binary classification was applied to ascertain whether the account was fake or genuine. After that, a genuine class credibility score was calculated using an analytical hierarchical process. The score determined the account's credibility. For this purpose, Afify et al. (2020) used scikit-learn (ML technique) and Keras with TensorFlow (DL technique). Hao et al. (2020) used a distinctive approach called CrossWord to address the problem of cross-domain sentiment encoding with stochastic word embeddings. SentiVec was suggested by Zhu et al. (2021) as a kernel optimization method for sentiment word embedding. Deng and Liu (2025) conducted research on SA of online public opinion by using the RoBERTa (Robustly Optimized BERT Pretraining Approach)–BiLSTM model. Cai et al. (2025) contemplated a model founded on the basic principle of multi-layer feature extraction and multi-task learning methodologies. Ahamad and Mishra (2025) suggested investigating sentiment insights in handwritten and E-text through advanced machine learning (ESIHE_AML) algorithms that found sentiment polarity and emotion types of handwritten texts and E-texts.

Research Methodology

Descriptive research was conducted using the following sampling frame:

Sampling Frame Design

- ✎ **Target Population** : Fast-moving consumer goods (FMCG) product users.
- ✎ **Sampling Unit** : Individual users of FMCG products who participated in the survey.
- ✎ **Sampling Method** : Convenience sampling was used in the study. Google Forms were circulated online, and responses were collected from those who voluntarily participated.
- ✎ **Sample Size** :
 - Total Distributed Surveys: 250
 - Total Usable Responses: 105
 - Response Rate: 42%
- ✎ **Data Collection Instrument** : An online Google Form containing questions on:
 - Demographic (age group, gender, occupation).
 - General Consumer Behavior Questions (Two, measured using a Likert scale with a Cronbach's alpha value of 0.836).
 - Opinion Statements (Five, asking respondents' opinions about the nature of the statement).
- ✎ **Data Processing & Analysis** : SA was performed using MonkeyLearn's and text2data online tools.
- ✎ **Period of Study** : From May 2023 to December 2023.

Data Analysis and Results

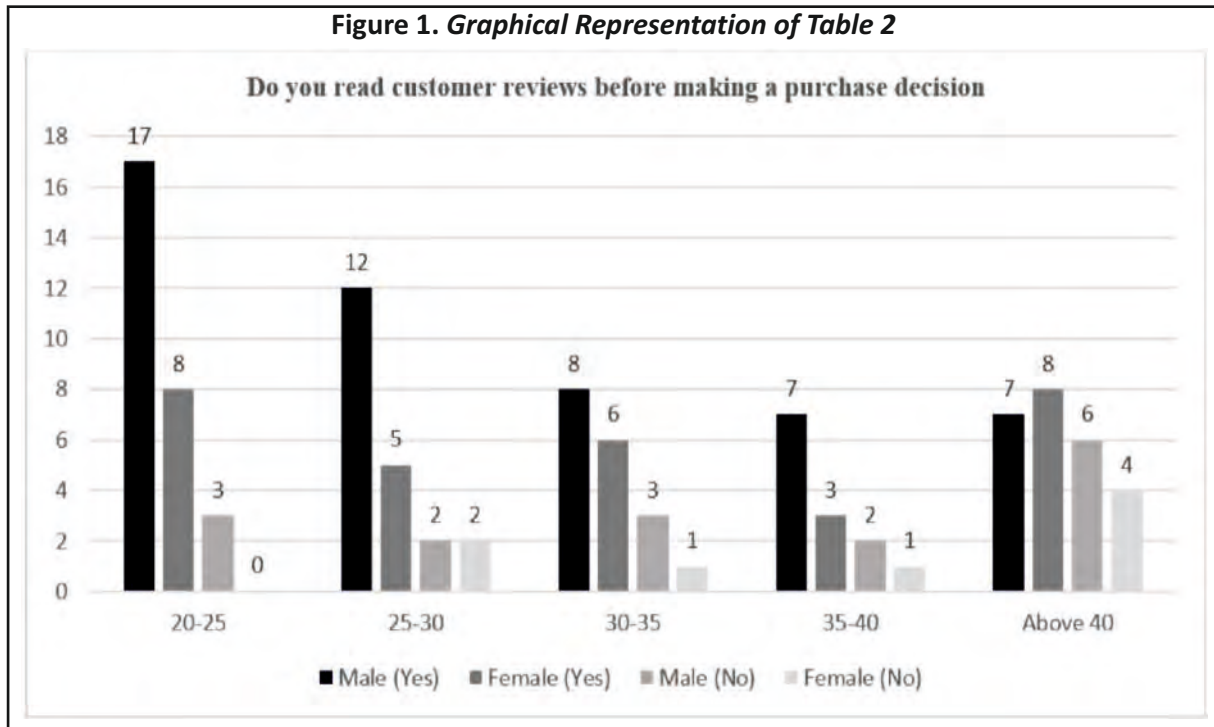
Table 1 depicts the demographic details of the respondents. Table 2 shows if the respondents read reviews before making a purchase decision.

Table 1. Demographic Details of the Respondents

Age Group	Gender		Profession			Total
	M	F	Service	Business	Any Other	
20-25	20	08	04	05	16	28
25-30	14	07	12	04	05	21
30-35	11	07	15	01	02	18
35-40	09	04	07	04	02	13
Above 40	13	12	20	03	05	25
						105

Table 2. Reading Reviews Before Making a Purchase Decision

	20-25	25-30	30-35	35-40	Above 40
Male (Yes)	17	12	08	07	07
Female (Yes)	08	05	06	03	08
Male (No)	03	02	03	02	06
Female (No)	00	02	01	01	04

Figure 1. Graphical Representation of Table 2**Table 3. Posting Reviews After Purchase**

	20-25	25-30	30-35	35-40	Above 40
Male (Yes)	14	12	09	07	07
Female (Yes)	07	04	06	03	08
Male (No)	06	02	02	02	06
Female (No)	01	03	01	01	04

According to data analysis in Table 2 and represented graphically in Figure 1, 77.14% of the respondents considered online reviews when deciding on a purchase. Table 3 data ascertained if the respondents posted reviews after making a purchase.

According to data analysis in Table 3 and represented graphically in Figure 2, 73.33% of the respondents posted their reviews about the product/service once they used it.

The SA on the statements was done using an online tool at the link <https://monkeylearn.com/spirit-analysis-online/>. On a scale, the score is 0 to 1, where zero means negative, and 1 reflects positive customer opinion. The result is shown in Table 5.

Table 5 presents the SA results for different statements about a store's product quality. Every statement is

Figure 2. Graphical Representation of Table 3

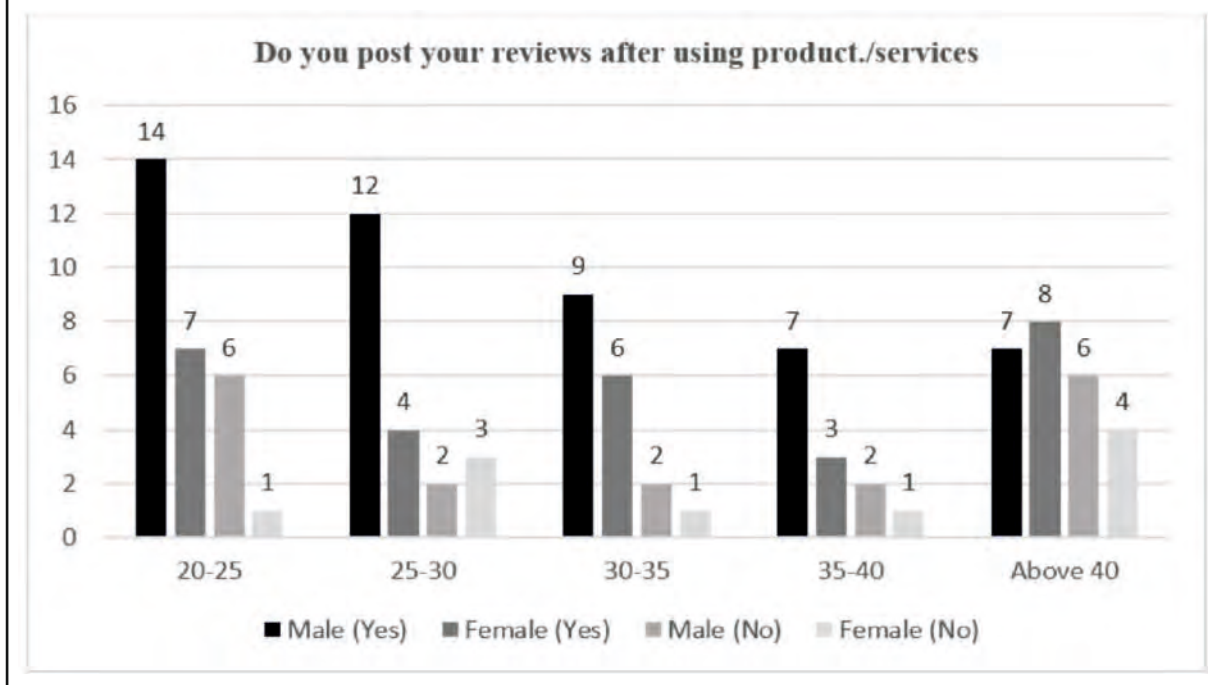


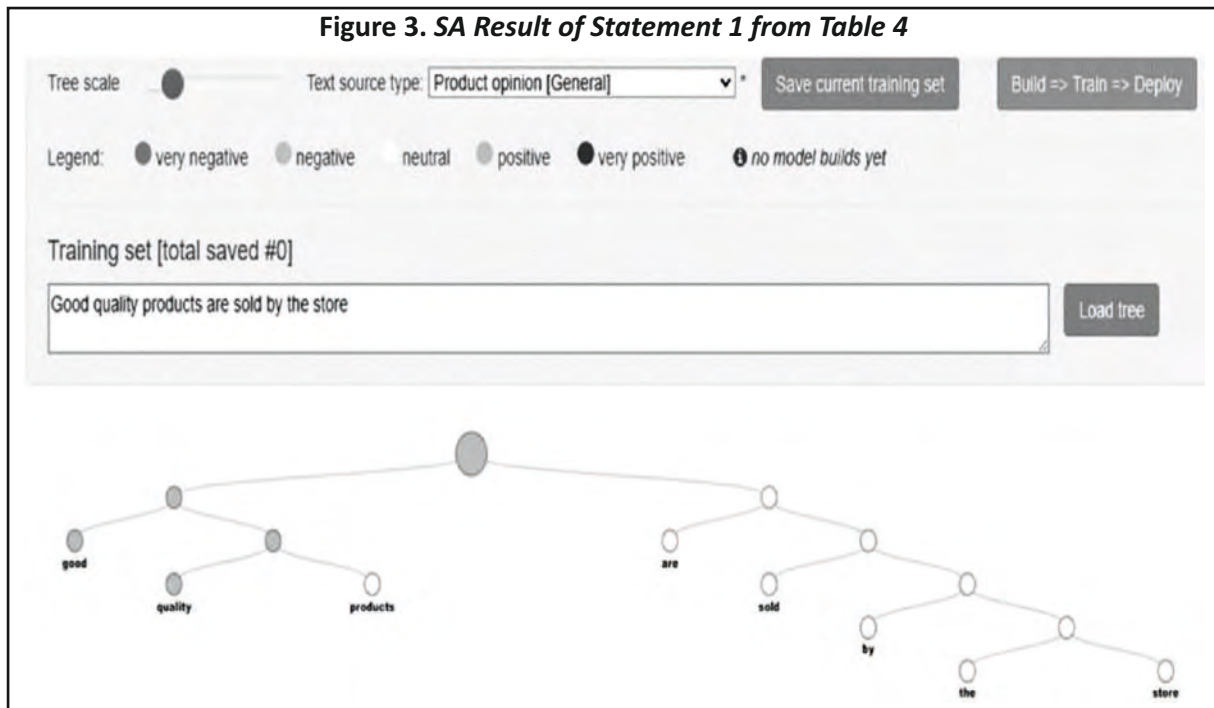
Table 4. Respondents' Opinion About the Nature of the Statement

Statement	Positive	Negative	Neutral	Cannot Say
1. The store sells good quality products.	105	0	0	0
2. The store does not sell good-quality products.	0	91	0	14
3. The quality of the products sold at the store is pathetic.	0	105	0	0
4. I cannot comment on the quality of the products sold at the store.	0	67	31	07
5. The quality of the products sold at the store seems fine.	12	0	78	15

Table 5. Output of SA

Statement	Tag	Confidence	Confidence	Neutral	Score
1. The store sells good quality products.	+Ve	87.7%			0.877
2. The store does not sell good-quality products.	-Ve		82.4%		0.176
3. The quality of the products sold at the store is pathetic.	-Ve		89.7%		0.103
4. I cannot comment on the quality of the products sold at the store.	-Ve		58.7%		0.413
5. The quality of the products sold at the store seems fine.	Neutral			67.6%	0.676

classified into a positive, negative, or neutral polarity, along with confidence scores indicating the certainty of classification. The first statement, "The store sells good quality products," shows positive polarity with a confidence of 87.7% and a score of 0.877 out of 1. The statement expresses a clear positive sentiment about product quality, and the confidence score is high, indicating substantial certainty in classification. The second statement, "The store does not sell good-quality products," shows a negative polarity with a confidence of 82.4% and a score of 0.176 out of 1. The presence of "does not" negates the quality aspect, making this a negative sentiment about product quality. High confidence indicates substantial certainty in classification. The third



statement, “Quality of the products sold at the store is pathetic,” shows a negative polarity with a high confidence of 89.7% and a score of 0.103 out of 1. The word pathetic comes with strong condemnation and almost a full negative bias toward the given product with high confidence. The fourth statement, “I cannot comment about the quality of the products sold at the store,” shows a negative polarity with a low confidence of 58.7% and a score of 0.413 out of 1. While this statement does not explicitly express a positive or negative opinion, it was classified as negative due to uncertainty or lack of endorsement. The lower confidence of 58.7% suggests weaker certainty in classification. The statement “The quality of the products sold at the store seems fine” has a neutral polarity with a confidence of 67.6% and a score of 0.676 out of 1. The phrase “seems fine” indicates a neutral stance rather than strong approval or disapproval. The confidence score of 67.6% reflects moderate certainty in this classification.

The SMTT method was applied to corroborate the findings presented in Table 4. It is another online tool that can be reached at <https://text2data.com/Sentiment-Model-Training>. The biggest circle on the graph reflects the overall sentiments. The actual figures generated by the tool show negative polarity as a big pink circle, neutral as a big white circle, and positive polarity as a big green circle. However, as per the requirements, the figures were converted into grayscale with a big dark gray circle in Figure 3 representing positive polarity, a big light gray circle in Figures 4, 5, and 6 representing negative polarity, and a big white circle in Figure 7 representing neutral polarity. The results are as follows.

➤ **Statement 1 :** Good quality products are sold by the store.

The output of Figure 3 for the first statement is in sync with the results in Table 5 (positive: the biggest circle depicted by dark gray color).

➤ **Statement 2 :** The store does not sell good quality products.

The output of Figure 4 for the second statement is in sync with the results in Table 5 (negative: the biggest circle depicted by a light gray color).

Figure 4. SA Result of Statement 2 from Table 4

Tree scale: Text source type: Product opinion [General] Save current training set Build => Train => Deploy

Legend: very negative negative neutral positive very positive no model builds yet

Training set [total saved #0]

The store does not sell good-quality products Load tree

Sentiment tree structure:

- Root: very negative
 - the: neutral
 - store: neutral
 - does: neutral
 - not: very negative
 - sell: positive
 - good: positive
 - quality: positive
 - products: neutral

Figure 5. SA Result of Statement 3 from Table 4

Tree scale: Text source type: Save current training set Build => Train => Deploy

Legend: ☒ very negative ☐ negative ☐ neutral ☐ positive ☒ very positive ☐ no model builds yet

Training set [total saved #0]

Quality of the products sold at the store is pathetic

Load tree

```
graph TD; Root(( )) --- L1L(( )); Root --- L1R(( )); L1L --- L2L1((quality)); L1L --- L2L2(( )); L1R --- L2R1((is)); L1R --- L2R2((pathetic)); L2L1 --- L3L1(( )); L2L1 --- L3L2(( )); L2L2 --- L3L3(( )); L2L3 --- L3L4(( )); L3L1 --- L4L1((the)); L3L1 --- L4L2((products)); L3L2 --- L4L3(( )); L3L3 --- L4L4(( )); L3L4 --- L4L5(( )); L4L3 --- L5L3((at)); L4L3 --- L5L4(( )); L5L3 --- L6L3((the)); L5L4 --- L6L4((store));
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Figure 6. SA Result of Statement 4 from Table 4

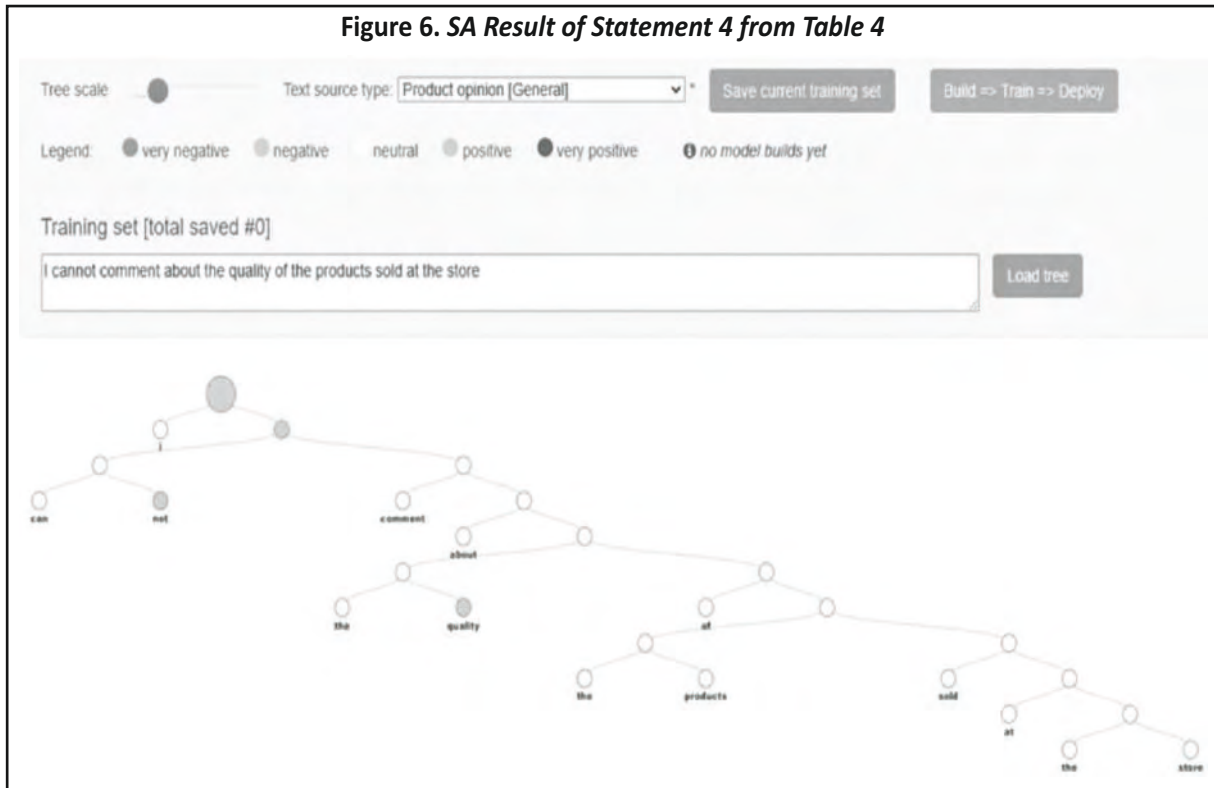
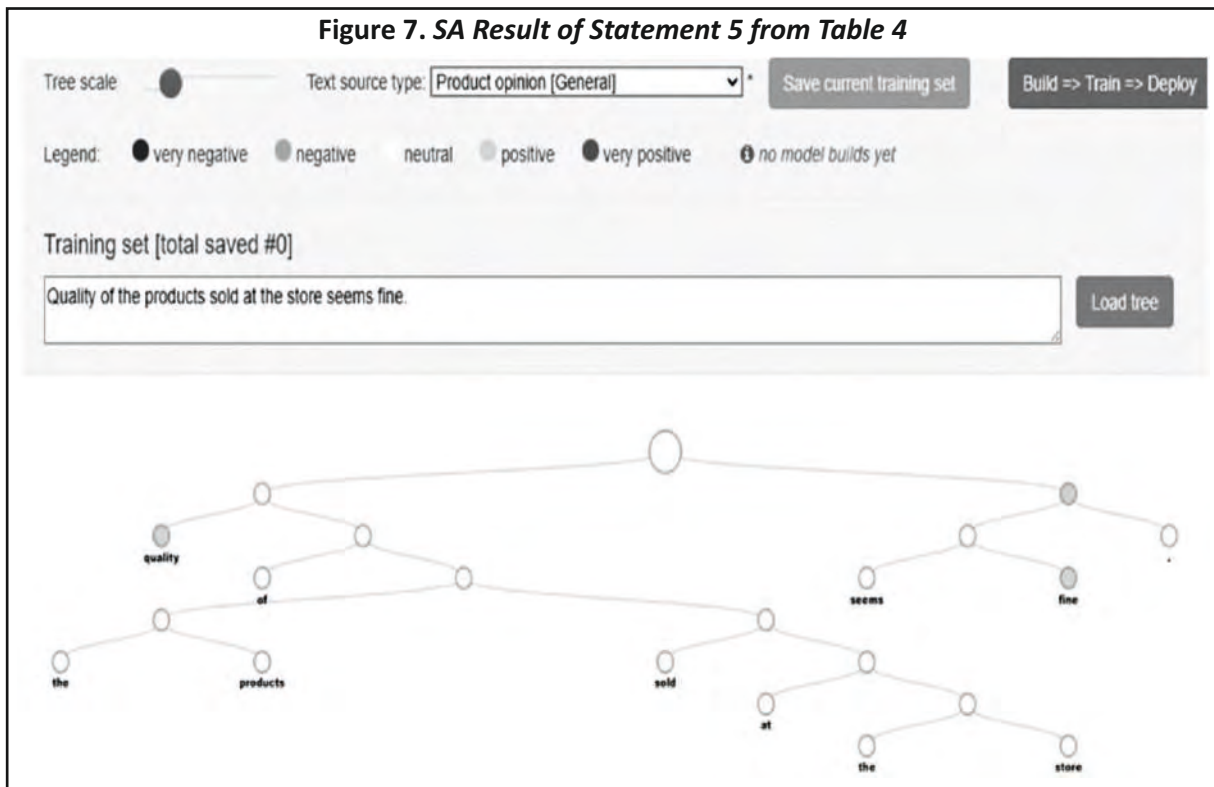


Figure 7. SA Result of Statement 5 from Table 4



⇒ **Statement 3 :** The quality of the products sold at the store is pathetic.

The output of Figure 5 for the third statement is in sync with the results in Table 5 (negative: the biggest circle depicted by light gray).

⇒ **Statement 4 :** I cannot comment on the quality of the products sold at the store.

The output of Figure 6 for the fourth statement is in sync with the results in Table 5 (negative: biggest circle depicted by light gray).

⇒ **Statement 5 :** The quality of the products sold at the store seems fine.

The output of Figure 7 for the fifth statement is in sync with the results in Table 5 (Neutral: Biggest circle depicted by white color).

Discussion

The study's literature evaluation makes it abundantly evident that consumers today rely less on corporate advertisements and more on social media reviews and posts when deciding to purchase a product or service. Fortunately, a variety of tools are available for performing SA that can provide precise analysis of the customer sentiments available on their social media. It provides businesses with intuition about the swing in favor of or against their products or services in the market. SA is essential for business organizations to measure consumer sentiment and image about a product, service, or brand. Although frequently practiced, surveys and focus-group studies are often less effective in terms of speed and scalability. Automated SA tools, in contrast, analyze vast volumes of text data in real-time to generate business insights. According to the survey results, 77.14% of respondents first visited social media websites to read other users' reviews, and 73.33% posted their views about the product or service for others. Table 4 data represents the respondents' opinions of the polarity of the statement asked. The statements in Table 4 are tested by the online tools MonkeyLearn and text2 data to verify polarity. Table 5 shows the output generated by MonkeyLearn, which validates the findings outlined in Table 4. The same statements were then subjected to polarity evaluation by another tool, text2data. The results provided by this tool are represented in Figures 3, 4, 5, 6, and 7. The results again validated the findings of Table 4 and the previous tool used, MonkeyLearn. This is unmistakably a strong indication for businesses that they must examine what other users post on social media, as it provides many insights. Two separate tools were used to analyze the same sentences, and the outcome was the same.

Employing SA will be a predictive measure in decision-making, which will help businesses forecast possible trends in the market and consumers' actions. The literature has revealed an important gap: the lack of application of SA in real-time business decisions. While existing studies discuss the influence of eWOM and online reviews on consumer behavior, relatively few studies consider how businesses can systematically use SA for strategic insights. This study bridges this gap by comparing SA techniques and assessing their effectiveness in capturing consumer sentiment. The study results show that SA tools can capture the essence of consumer perceptions; however, some challenges also arise from complex responses. SA has thus become a pillar of business strategy today, giving life to a data-driven approach to understanding consumer sentiment. The infusions of new-age techniques such as ML and DL models provide greater accuracy and predictive capacity to the functioning of SA. Indeed, businesses that embrace SA for strategic purposes can easily outdistance competitors by aligning their offerings with consumer preferences and thus enhancing customer experience.

Implications

Managerial Implications

Businesses can leverage SA technology to track and evaluate customer reviews in real-time, which will aid in better decision-making on product development, service quality, customer satisfaction, engagement, and general strategy development. Businesses need to take control of their online reputations by providing excellent service because SA can tell these businesses how other people feel about them. Businesses can use SA to respond to negative brand image trends and alter them before they become too challenging to manage. The SA enables businesses to improve target marketing campaigns by providing data-driven insights. It helps businesses prepare more successful promotion strategies, targeted advertisements, and customized material based on customers' requirements and needs. SA will help businesses develop a competitive advantage by better understanding market trends, customers' requirements, and knowledge of industry dynamics. Businesses can compare their performance against the competition and adapt their strategies to stay ahead. SA enables businesses to correctly identify customers' pain points and areas to improve their products or services. By integrating SA in product development and innovation processes, businesses can increase the satisfaction and loyalty of customers. Businesses can use SA to track customers' grievances and proactively resolve them, resulting in better brand management and customer trust.

Theoretical Implications

This study seeks to augment the existing literature by proving that SA is vital in understanding consumer behavior. It is positioned between conventional methods of gauging consumer insight and the new digital world, wherein online reviews have emerged as potent determinants of consumer purchasing decisions. In conjunction with applying SA, lexicon-based, ML, and DL methods, the research adopts a coherent strategy to analyze consumer sentiments and their implications on business strategies. Unlike previous studies, the present one recognizes the role of SA in consumer research and critically appraises its predictive ability with respect to strategic marketing decision-making. Much of the previous literature has primarily discussed using SA as an opinion extraction mechanism. The present study provides a critical view of using SA to derive real-time actionable business insights.

The comparative evaluation of techniques for SA adds even more methodological rigor, thereby providing businesses with a refined way of interpreting consumer sentiment. Thus, the existing SA models are capitalized and improved to apply them better in business decision-making. The study's findings concur with and enhance the work of their predecessors by providing a holistic perspective for the systematic application of SA in consumer research to equip scholars about the various types of SA while advocating for real-time sentiment analytics to be incorporated into business intelligence systems for better agility in handling consumer trends. Theoretical perspectives and practical applications are synthesized in this study to highlight the changing focus of SA in contemporary marketing and consumer research. It calls upon practitioners and researchers to embrace a more integrated sentiment-predictive analysis approach to inform decision-making processes.

Conclusion

SA has proved to be an important tool for analyzing online user reviews and helping identify the review's polarity, thereby assisting the organization in understanding consumer behavior. This immensely helps businesses modify their market offerings as per their preferences. The present study strengthens the case for considering SA as an

important variable for research into consumer behavior and business decision-making. Moreover, it validates the transition from traditional consumer opinion-gathering methods toward advanced SA techniques, which increasingly need businesses to understand technology through market sentiment. The study illustrates businesses' need to actively grasp consumer opinions and systematically integrate such sentiment insights into real-time decision-making processes. The comparative study of different SA techniques makes a case for businesses to incorporate sophisticated analytical tools that advance beyond simple hindsight measures to support foresight strategic planning.

The literature review establishes the fact that SA has found its role in different areas: Zhou et al. (2014) conducted a study on the hotel industry; Huq et al. (2017) applied the SA techniques to analyze Twitter data; Sun et al. (2021) developed a DL model to forecast dish sales volume, which may help caterers be highly efficient and avoid wastage. Afify et al. (2020) studied Facebook profile credibility using ML and DL techniques. Wankhade et al. (2022) and Patel and Goswami (2024) employed various techniques, including lexicon-based methods, ML, and DL, to classify and extract insights from consumer feedback. The study proves that SA is a valuable tool for analyzing customer behavior and gives businesses helpful information about the opinions and preferences of their customers. In summary, SA represents the connection between consumer insights and business strategy. As digital communication continues to influence consumer behavior, businesses must rely on complex models for SA. Future studies must emphasize the design of more sophisticated and flexible frameworks of SA in real time, where SA as a fluid tool will enable businesses to cement customer relationships, bolster brand equity, and ensure growth in business in the digital marketplace.

Limitations of the Study and Scope for Further Research

Valuable insights are provided by the study into the role of SA in understanding consumer behavior; it is subject to some limitations. The study is based on the reactions of 105 participants; a large dataset can provide more realistic results. The sentiments expressed online can change rapidly due to external factors such as time, trends, social movements, or brand crises. Different SA models vary in accuracy, and their output effectiveness depends on factors such as effective pre-processing of data and an appropriate algorithm selection.

The scope for future research in this area is immense; future studies may include a large, more diverse sample in various demographics, industries, and geographical locations to increase generality. A deep assessment of lexicon-based, ML, and DL approaches can help determine the most effective model for SA in various business contexts. It will provide a comprehensive understanding of consumer behavior if this study is tested across different languages. Future research can focus on real-time tracking of sentiments over an extended period, allowing businesses to predict trends and continuously respond. Traditional market research techniques, such as focus groups, surveys, and a combination of SA, can provide a more overall understanding of consumer behavior. By addressing these areas, future research can further enhance the effectiveness of SA in consumer behavior studies and business strategy formulation.

Authors' Contribution

Chandra Prakash Gupta and V. V. Ravi Kumar shared their expertise equally in the conduction of the study. Chandra Prakash Gupta oversaw the process of data collection, identifying the research gaps, and conducting the online analysis part using the tools available at MonkeyLearn and text2data. Dr. V. V. Ravi Kumar did the data analysis and interpretation. Both authors contributed to the revision part of the paper, giving it its present structure.

Conflict of Interest

The authors certify that they have no affiliation or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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References

- Afify, E. A., Eldin, A. S., & Khedr, A. E. (2020). Facebook profile credibility detection using machine and deep learning techniques based on users' sentiment response on status messages. *International Journal of Advanced Computer Science and Applications*, 11(12), 622–637. <https://doi.org/10.14569/IJACSA.2020.0111273>
- Ahamad, R., & Mishra, K. N. (2025). Exploring sentiment analysis in handwritten and e-text documents using advanced machine learning techniques: A novel approach. *Journal of Big Data*, 12, Article no. 11. <https://doi.org/10.1186/s40537-025-01064-2>
- Alamanda, M. S. (2020). Aspect-based sentiment analysis search engine for social media data. *CSI Transactions on ICT*, 8, 193–197. <https://doi.org/10.1007/s40012-020-00295-3>
- Atmaja, B. T., & Sasou, A. (2022). Sentiment analysis and emotion recognition from speech using universal speech representations. *Sensors*, 22(17), Article no. 6369. <https://doi.org/10.3390/s22176369>
- Baek, J., & Lee, J. (2021). A conceptual framework on reconceptualizing customer share of wallet (SOW): A perspective of dynamic process in the hospitality consumption context. *Sustainability*, 13(30029), Article no. 1423. <https://doi.org/10.3390/su13031423>
- Banerjee, S., Bhattacharyya, S., & Bose, I. (2017). Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on the business. *Decision Support Systems*, 96, 17–26. <https://doi.org/10.1016/j.dss.2017.01.006>
- Cai, Y., Li, X., Zhang, Y., Li, J., Zhu, F., & Rao, L. (2025). Multimodal sentiment analysis based on multi-layer feature fusion and multi-task learning. *Scientific Reports*, 15(1), Article no. 2126. <https://doi.org/10.1038/s41598-025-85859-6>
- Chen, A., Lu, Y., & Wang, B. (2017). Customers' purchase decision-making process in social commerce: A social learning perspective. *International Journal of Information Management*, 37(6), 627–638. <https://doi.org/10.1016/j.ijinfomgt.2017.05.001>
- Chen, D., & Manning, C. (2014). A fast and accurate dependency parser using neural networks. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* (pp. 740–750). Association for Computational Linguistics. <https://doi.org/10.3115/v1/D14-1082>
- Chen, J., Kou, G., & Peng, Y. (2018). The dynamic effects of online product reviews on purchase decisions. *Technological and Economic Development of Economy*, 24(5), 2045–2064. <https://doi.org/10.3846/tede.2018.4545>

- Deng, J., & Liu, Y. (2025). Research on sentiment analysis of online public opinion based on RoBERTa–BiLSTM–attention model. *Applied Sciences*, 15(4), Article no. 2148. <https://doi.org/10.3390/app15042148>
- Dey, L., Chakraborty, S., Biswas, A., Bose, B., & Tiwari, S. (2016). Sentiment analysis of review datasets using Naïve Bayes and K-NN classifier. *International Journal of Information Engineering and Electronic Business*, 8(4), 54–62. <https://doi.org/10.5815/ijieeb.2016.04.07>
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, 59, Article ID 102168. <https://doi.org/10.1016/j.ijinfomgt.2020.102168>
- Ferdous, S. M., Newaz, S. N., Mugdha, S. B., & Uddin, M. (2024). Sentiment analysis in the transformative era of machine learning: A comprehensive review. *Statistics, Optimization & Information Computing*, 13(1), 331–346. <https://doi.org/10.19139/soic-2310-5070-2113>
- Grljevic, O., & Bosnjak, Z. (2018). Sentiment analysis of customer data. *Strategic Management*, 23(3), 38–49. <https://doi.org/10.5937/StraMan1803038G>
- Gulati, K., Kumar, S. S., Boddu, R. S., Sarvakar, K., Sharma, D. K., & Nomani, M. Z. (2022). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. *Materials Today Proceedings*, 51(1), 38–41. <https://doi.org/10.1016/j.matpr.2021.04.364>
- Gupta, A., & Savita, U. (2024). Do eWOM and brand image drive purchase intention of online travel shoppers: A case study of Delhi - NCR. *Indian Journal of Marketing*, 54(3), 44–60. <https://doi.org/10.17010/ijom/2024/v54/i3/173567>
- Hao, Y., Mu, T., Hong, R., Wang, M., Liu, X., & Goulermas, J. Y. (2020). Cross-domain sentiment encoding through stochastic word embedding. *IEEE Transactions on Knowledge and Data Engineering*, 32(10), 1909–1922. <https://doi.org/10.1109/TKDE.2019.2913379>
- Huq, M. R., Ali, A., & Rahman, A. (2017). Sentiment analysis on Twitter data using KNN and SVM. *International Journal of Advanced Computer Science and Applications*, 8(6). <https://doi.org/10.14569/IJACSA.2017.080603>
- Ismagilova, E., Rana, N. P., Slade, E. L., & Dwivedi, Y. K. (2021). A meta-analysis of the factors affecting eWOM providing behavior. *European Journal of Marketing*, 55(4), 1067–1102. <https://doi.org/10.1108/EJM-07-2018-0472>
- Jain, P. K., Pamula, R., & Yekun, E. A. (2022). A multi-label ensemble predicting model to service recommendation from social media contents. *Journal of Supercomputing*, 78, 5203–5220. <https://doi.org/10.1007/s11227-021-04087-7>
- Jaiswal, A., Mishra, V., Bhatnagar, S., & Bandyopadhyay, N. (2024). Sentiment analysis of social welfare tweets for supervised learning about brand loyalty. *Indian Journal of Marketing*, 54(2), 8–26. <https://doi.org/10.17010/ijom/2024/v54/i2/173473>

- Kaur, G., & Sharma, A. (2023). A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. *Journal of Big Data*, 10, Article no. 5. <https://doi.org/10.1186/s40537-022-00680-6>
- Kaushik, A., Kaushik, A., & Naithani, A. (2015). A study on sentiment analysis: Methods and tools. *International Journal of Science and Research*, 4(12), 287–292.
- Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: State of the art, current trends, and challenges. *Multimedia Tools and Applications*, 82(3), 3713–3744. <https://doi.org/10.1007/s11042-022-13428-4>
- Küçükali, H., & Erdoğan, M. S. (2024). AI for Tobacco control: Identifying Tobacco-promoting social media content using large language models. *Nicotine & Tobacco Research*, ntae276. <https://doi.org/10.1093/ntr/ntae276>
- Kumar, M., Khan, L., & Chang, H.-T. (2025). Evolving techniques in sentiment analysis: A comprehensive review. *PeerJ Computer Science*, 11, Article ID e2592. <https://doi.org/10.7717/peerj-cs.2592>
- Maslowska, E., Malthouse, E. C., & Viswanathan, V. (2017). Do customer reviews drive purchase decisions? The moderating roles of review exposure and price. *Decision Support Systems*, 98, 1–9. <https://doi.org/10.1016/j.dss.2017.03.010>
- Menon, P. B. (2021). Influence of social media marketing efforts on brand equity and consumer response to branded shoes in India. *Indian Journal of Marketing*, 51(9), 24–40. <https://doi.org/10.17010/ijom/2021/v51/i9/166162>
- Ojeda-Hernández, M., López-Rodríguez, D., & Mora, A. (2023). Lexicon-based sentiment analysis in texts using formal concept analysis. *International Journal of Approximate Reasoning*, 155, 104–112. <https://doi.org/10.1016/j.ijar.2023.02.001>
- Patel, R., & Patel, S. (2021). Deep learning for natural language processing. In M. S. Kaiser, J. Xie, & V. S. Rathore (eds.), *Information and communication technology for competitive strategies (ICTCS 2020)* (Vol. 190, pp. 523–533). Springer. https://doi.org/10.1007/978-981-16-0882-7_45
- Patel, S. J., & Goswami, S. A. (2024). A comparative study of supervised and unsupervised classification techniques for sentiment analysis in IMDB. *Journal of Scholastic Engineering Science and Management*. <https://doi.org/10.5281/zenodo.11044986>
- Prasad, S. S., & Amruta, Y. K. (2023). Influence of social media on post-purchase dissonance: An empirical study. *Indian Journal of Marketing*, 53(6), 28–46. <https://doi.org/10.17010/ijom/2023/v53/i6/172766>
- Sharma, J., Agarwal, B., & Malati, N. (2024). Examining the factors influencing eWOM through social networking sites and the effect of eWOM on consumers' purchase intention. *Indian Journal of Marketing*, 54(6), 65–82. <https://doi.org/10.17010/ijom/2024/v54/i6/173947>
- Sharma, P. B., Pathak, R., & Ahuja, D. (2023). Effect of negative customer experience and negative confirmation on electronic - word of mouth: A case of food delivery apps in India. *Indian Journal of Marketing*, 53(11), 23–40. <https://doi.org/10.17010/ijom/2023/v53/i11/170523>
- Siji, S. (2021). Social commerce of Indian customers: Role of social media usage. *Indian Journal of Marketing*, 51(8), 26–38. <https://doi.org/10.17010/ijom/2021/v51/i8/165760>

- Srinivas, A. C., Satyanarayana, C., Divakar, C., & Sirisha, K. P. (2021). Sentiment analysis using neural network and LSTM. *IOP Conference Series: Materials Science and Engineering*, 1074(1), Article ID 012007. <https://doi.org/10.1088/1757-899X/1074/1/012007>
- Sun, Q., Feng, X., Zhao, S., Cao, H., Li, S., & Yao, Y. (2021). Deep learning based customer preferences analysis in industry 4.0 environment. *Mobile Networks and Applications*, 26(6), 2329–2340. <https://doi.org/10.1007/s11036-021-01830-5>
- Talaat, A. S. (2023). Sentiment analysis classification system using hybrid BERT models. *Journal of Big Data*, 10, Article no. 110. <https://doi.org/10.1186/s40537-023-00781-w>
- Tanna, D., Dudhane, M., Sardar, A., Deshpande, K., & Deshmukh, N. (2020). Sentiment analysis on social media for emotion classification. In *Proceedings of the 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 911–915). IEEE. <https://doi.org/10.1109/ICICCS48265.2020.9121057>
- Thakur, C. K., Vijay, T. S., & Chatterjee, T. K. (2022). A study on travelers' motivation to provide online reviews. *Indian Journal of Marketing*, 52(2), 8–22. <https://doi.org/10.17010/ijom/2022/v52/i2/164156>
- Vyas, V., & Uma, V. (2018). An extensive study of sentiment analysis tools and binary classification of tweets using Rapid Miner. *Procedia Computer Science*, 125, 329–335. <https://doi.org/10.1016/j.procs.2017.12.044>
- Wankhade, M., Rao, A. C., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review*, 55, 5731–5780. <https://doi.org/10.1007/s10462-022-10144-1>
- Yang, C.-S., Chen, C.-H., & Chang, P.-C. (2015). Harnessing consumer reviews for marketing intelligence: A domain-adapted sentiment classification approach. *Information Systems and E-Business Management*, 13(3), 403–419. <https://doi.org/10.1007/s10257-014-0266-z>
- Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. *WIREs: Data Mining and Knowledge Discovery*, 8(4), Article ID e1253. <https://doi.org/10.1002/widm.1253>
- Zhou, L., Ye, S., Pearce, P. L., & Wu, M.-Y. (2014). Refreshing hotel satisfaction studies by reconfiguring customer review data. *International Journal of Hospitality Management*, 38, 1–10. <https://doi.org/10.1016/j.ijhm.2013.12.004>
- Zhu, L., Li, W., Shi, Y., & Guo, K. (2021). SentiVec: Learning sentiment-context vector via Kernel optimization function for sentiment analysis. *IEEE Transactions on Neural Networks and Learning Systems*, 32(6), 2561–2572. <https://doi.org/10.1109/TNNLS.2020.3006531>

About the Authors

Dr. Chandra Prakash Gupta is an Assistant Professor at Symbiosis Institute of Business Management, Pune, Symbiosis International (Deemed University), Pune. He holds a Ph.D. in management and has over 33 years of experience spanning the corporate and academic sectors. He has published many papers indexed in Scopus in the field of technology in management and has also presented many papers at national and international conferences.

Dr. V. V. Ravi Kumar is a Professor at Symbiosis Institute of Business Management, Pune, Symbiosis International (Deemed University), Pune. He holds a Ph.D. in management from Birla Institute of Technology, Mesra, India, and has over 25 years of experience spanning the academic and corporate sectors. He has published many research papers in the field of services, indexed in Scopus and ABDC, and presented papers at several conferences.