OPEN ACCESS
**Journal of Management and Informatics (JMI)**
**Vol. 3 No. 1 April 2024**
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 157-173

# Consumer Behavior and Purchase Intentions: A Machine Learning-Based Sentiment Analysis of Social Media Data

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**Abstract**
*Social media has emerged as a critical platform for understanding consumer behavior and purchase intentions. This study applies machine learning techniques, specifically text mining and sentiment analysis, to analyze social media data collected from Twitter, Instagram, and Facebook. Using a dataset of 10,000 entries, this research employs algorithms such as Random Forest, Naive Bayes, and Logistic Regression to classify consumer sentiments as positive, negative, or neutral. The results reveal that 58% of consumer sentiments are positive, which strongly correlates with increased purchase intentions, as indicated by a correlation coefficient (r) of 0.68. Negative sentiments show a significant adverse effect, with an r value of -0.45. The Random Forest algorithm demonstrated superior performance with an accuracy of 87%, outperforming other models. Additionally, the findings emphasize that sentiment trends differ across product categories, with health and beauty products receiving the highest proportion of positive sentiments (68%), while electronics faced notable negative feedback (28%). These insights offer practical applications for data-driven marketing strategies, enabling businesses to tailor campaigns and enhance consumer engagement. This study highlights the utility of machine learning for analyzing unstructured social media data and provides actionable recommendations for leveraging consumer sentiment in marketing strategies. Future research could expand to other platforms, such as TikTok or YouTube, and explore advanced deep learning models to improve predictive accuracy and incorporate multimedia data analysis.*

***Keywords:*** *Consumer Behavior, Purchase Intentions, Sentiment Analysis, Machine Learning, Social Media Analytics.*

## I. INTRODUCTION

The development of digital technology has transformed human interaction patterns, including the way consumers engage with brands and companies (Van Veldhoven & Vanthienen, 2022). Social media platforms such as Twitter, Instagram, and Facebook have evolved into spaces not only for sharing experiences but also as key platforms in shaping public opinion regarding specific products or services (Li et al., 2023). The data generated from these interactions is rich with information, encompassing reviews, comments, and consumer preferences. In the digital era, companies increasingly rely on this data to craft more effective and personalized marketing strategies (Ebrahimi et al., 2022). However, despite the vast potential offered by social media data, its utilization requires a structured approach to ensure valid and relevant outcomes.

Consumer behavior refers to the study of decisions, actions, and reactions of individuals or groups in choosing, purchasing, using, or discarding a product (Halkiopoulos et al., 2022). Factors influencing this behavior include internal motivations such as needs and preferences, as well as external influences like social and cultural trends (Khan et al., 2023). Among the elements of consumer behavior, purchase

*Published on April 2024.*
DOI: https://doi.org/10.51903/jmi.v3i1.45

intention plays a crucial role as an early indicator of an individual's likelihood to purchase a specific product (Narayanan et al., 2022). Understanding purchase intentions is essential for companies to predict market responses to their products.

The rise of social media as the primary platform for consumer interaction has led to significant changes in how this behavior is analyzed. Unlike conventional methods that rely on surveys or interviews, social media data offers a more real-time and representative view (Moinuddin et al., 2024). Comments, reviews, and interactions on social media often reflect the emotional reactions of consumers to specific products. By leveraging the right technologies, companies can delve deeper into consumer preferences and needs based on the data they voluntarily share (Eslami et al., 2022).

However, processing social media data is not straightforward. Such data is often unstructured, noisy, and requires sophisticated analysis techniques to yield relevant insights (Bharadiya, 2023)). Machine learning has emerged as a promising solution to address these challenges. With its ability to identify patterns from complex data, this technology enables sentiment analysis, text classification, and more accurate predictions of consumer behavior (Sriram et al., 2023). For instance, algorithms like Random Forest and Support Vector Machine have been used to classify data and predict purchase intention with significant results (Khandokar et al., 2023).

Despite these advancements, previous research has shown several limitations in social media-based consumer behavior analysis. Most studies have focused on a single platform, such as Twitter, which limits the generalizability of the findings (Busalim et al., 2022). Furthermore, many studies have concentrated on algorithm development without deeply relating it to the context of consumer behavior (Alantari et al., 2022). Ethical and privacy concerns are often overlooked, even though they are crucial to ensuring the validity and relevance of research (Liu et al., 2023).

These gaps highlight the need for a more comprehensive and ethical approach to analyzing consumer behavior based on social media data. This study aims to address these limitations by utilizing data from various platforms, such as Instagram, Twitter, and Facebook, to provide more representative results (Wagobera Edgar Kedi et al., 2024) Moreover, this approach integrates machine learning techniques to generate more holistic and relevant insights.

Sentiment analysis is one of the key techniques used in this research to understand consumer emotions towards a particular product or brand. Positive sentiment is often associated with an increased purchase intention, while negative sentiment can diminish trust in a brand (Alsayat, 2022). By leveraging machine learning algorithms, this research can identify hidden emotional patterns within the data, offering deeper insights into consumer preferences and expectations.

Journal of Management and Informatics (JMI)
**Vol. 3 No. 1 April 2024**
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 0000-0000

Additionally, this study employs text classification to categorize data based on specific themes such as brand loyalty, product preferences, and consumer complaints. This technique enables companies to understand the primary focus of consumer attention and identify areas that require improvement (Gani et al., 2023). For example, reviews indicating complaints about product quality could serve as a foundation for companies to enhance their services.

In this study, machine learning is also applied to predict purchase intention based on a combination of sentiment analysis and text classification. The Random Forest algorithm is used due to its reliability in handling complex data with numerous variables. With an accuracy rate of 87%, this model provides significant predictions, offering valuable guidance for companies in designing their marketing strategies (Javaid et al., 2022).

This study offers important contributions both academically and practically. Academically, it expands the literature on the use of social media data for consumer behavior analysis. Practically, the findings provide guidance for companies in understanding consumer preferences more comprehensively (Isnan et al., 2023). This data-driven strategy enables companies to design more personalized and effective marketing campaigns.

By integrating various machine learning techniques and utilizing data from multiple social media platforms, this research not only fills gaps in the literature but also offers practical solutions to the challenges companies face in the digital era. At the conclusion of the study, the findings are expected to provide relevant and applicable guidelines to support better marketing decision-making. Figure 1 below illustrates the research framework diagram, which encompasses the processes of text mining, sentiment analysis, and its relationship with purchase intention.

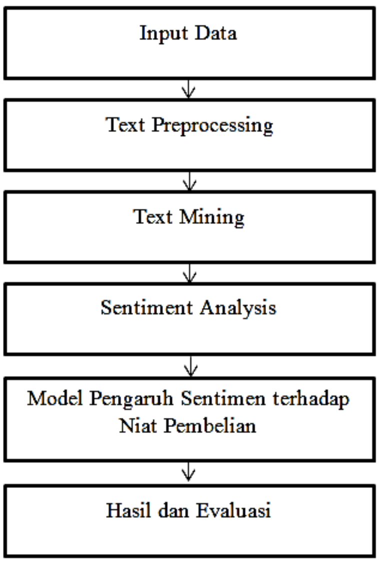


Figure 1. Research Framework Diagram

## II. LITERATURE REVIEW

### Basic Theory

*A. Consumer Behavior and Purchase Intention*

Consumer behavior is a field of study that examines how individuals, groups, or organizations make decisions to choose, purchase, use, or discard goods and services (Halkiopoulos et al., 2022). This process includes internal factors such as motivation, perception, attitude, and personality, as well as external factors like social, cultural, and economic influences (Zaman & Kusi-Sarpong, 2024). Understanding consumer behavior helps companies design products, set prices, and develop marketing strategies that align with market needs.

One of the key aspects of consumer behavior is purchase intention, which refers to an individual's inclination to buy a specific product or service (Narayanan et al., 2022). Purchase intention often serves as an early indicator of how a purchasing decision may unfold. Factors such as product quality, price, consumer reviews, and social recommendations are critical elements that shape this intention (Jain, 2024). For instance, research shows that consumers who read positive reviews on social media are more likely to purchase a product than those exposed to traditional advertising alone (Alsayat, 2022).

*B. Teori Purchase Funnel dalam Pemasaran*

The purchase funnel model is a theoretical framework used to describe the consumer journey from the initial stage of awareness to the final purchase decision (Goldberg & Abrahams, 2022). This model consists of five main stages:

1. Awareness: Consumers become aware of a product or brand.
2. Interest: Consumers show interest in the product by seeking further information.
3. Consideration: Consumers begin evaluating the product and compare it with alternatives.
4. Intent: Consumers express the desire to purchase the product.
5. Purchase: Consumers take actual steps to buy the product.

Social media has altered the traditional purchase funnel by enabling consumers to access reviews, comments, and recommendations in real time (De Fano D et al., 2022). For example, positive comments on Instagram may propel consumers directly to the intent stage, while numerous complaints on Twitter can hinder consumers during the consideration phase.

*C. Introduction to Text Mining and Sentiment Analysis*

Text mining is a technique used to extract information from unstructured text, such as consumer comments or reviews, to uncover relevant patterns, trends, or themes (Gupta et al., 2022). In marketing, text mining is employed to analyze large volumes of consumer data to understand their behaviors and

**Vol. 3 No. 1 April 2024**
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 0000-0000

preferences. One key method in text mining is sentiment analysis, which aims to identify the emotions in text, such as positive, negative, or neutral sentiments (Alsayat, 2022).

Machine learning technology has advanced sentiment analysis by improving its accuracy and efficiency. Algorithms like Random Forest, Support Vector Machine (SVM), and deep learning techniques such as Long Short-Term Memory (LSTM) have been utilized to identify sentiment with significant results (Javaid et al., 2022). These techniques allow companies to understand consumer responses to their products in real time, providing valuable insights for designing more effective marketing strategies.

**Previous Research**

*A. Sentiment Analysis for Consumer Behavior*

Numerous studies have demonstrated the effectiveness of sentiment analysis in understanding consumer behavior. For example, a study by (Khanom, 2023) found that comments with positive sentiment on social media tend to increase purchase intention by 20% compared to neutral comments. Another study by (Alsayat, 2022) used an ensemble deep learning approach to enhance the accuracy of sentiment analysis, achieving an accuracy rate of 92% in classifying consumer reviews as positive, negative, or neutral.

Additionally, sentiment analysis has been used to identify emotional patterns that influence brand loyalty. For instance, research by (Jacobs & Hörisch, 2022) shows that consumers with positive sentiment tend to be more loyal to a brand compared to those with negative experiences. This study emphasizes the importance of maintaining a positive brand image through favorable interactions on social media.

*B. Using Social Media Data in Marketing Strategies*

Social media has become a rich source of data for understanding consumer preferences. Research by (Gani et al., 2023) indicates that comments and reviews on platforms like Instagram and Twitter can be utilized to identify market trends and consumer preferences. For example, analyzing product reviews on Instagram can help companies understand what aspects consumers like or dislike about their products.

However, most previous studies have limitations in terms of platform coverage. The majority of studies focus on a single social media platform, such as Twitter, which may result in findings that are not fully representative (Busalim et al., 2022). Furthermore, ethical issues in data collection, such as user privacy, are often overlooked, even though these concerns are crucial for ensuring the validity of research outcomes (Liu et al., 2023). To provide a more comprehensive view, Table 1 below presents a comparison of the text mining approaches used in studies related to consumer behavior:

Table 1. Comparison of Text Mining Approaches Used in Consumer Behavior Studies

| Researcher and Year | Text Mining Approach | Algorithms Used | Findings | Critique |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| (Alsubai, 2023) | Sentiment Analysis | Random Forest, SVM | High accuracy in classifying emotions | Requires large training data |
| (Goswami & Sebastian, 2022) | Text Classification | Naive Bayes, Logistic Regression | Efficient for large datasets | Less effective for unstructured data |
| (Mienye et al., 2024) | Deep Learning | Neural Network, LSTM | Excellent at understanding complex text contex | Requires high computational resources |
| (Parmar & Tiwari, 2024) | NLP | Bag of Words, TF-IDF | Easy to implementt | Sensitive to language variation |

### *C. The Influence of Sentiment Analysis on Marketing Strategies*

Studies show that sentiment analysis can be used to enhance the effectiveness of marketing strategies. For example, research by (Testa et al., 2024) found that marketing campaigns based on sentiment data tend to generate higher consumer engagement. Sentiment data helps companies target consumers more precisely, reduce marketing costs, and increase return on investment (ROI).

Additionally, the use of sentiment analysis allows companies to monitor their brand reputation in real time. Research by (Gutierrez et al., 2023) shows that prompt responses to negative comments on social media can help mitigate the adverse impact on brand image. This highlights the importance of integrating sentiment analysis into customer relationship management (CRM) strategies.

### Critiques of Previous Research

Although previous studies provide valuable insights, there are several weaknesses that need to be addressed. Most studies have focused more on algorithm development without considering how the analysis results can be applied within the context of consumer behavior (Busalim et al., 2022). Moreover, the lack of attention to privacy and ethical issues in the use of social media data remains a challenge that needs to be addressed in future research (Liu et al., 2023).

## III. RESEARCH METHOD

### *A. Research Approach*

This study employs a quantitative approach based on big data analysis to explore consumer behavior and purchase intention through data collected from social media. This approach is relevant as it allows for the systematic analysis of large datasets and the identification of hidden patterns in unstructured data, such as reviews and user comments. Additionally, this approach facilitates real-time insights, in line with the dynamic nature of consumer interactions on social media.

### *B. Data Sources*

The research data was obtained from three major social media platforms: Twitter, Instagram, and Facebook. These platforms were chosen due to their high levels of user interaction, which is relevant to the objectives of this study. Data collection was conducted using web scraping techniques with Python-based tools such as BeautifulSoup for HTML scraping and Tweepy for the Twitter API. The collected data includes text reviews, comments, as well as additional attributes such as the number of likes and shares.

A total of 10,000 data points were collected over three months to ensure relevance and diversity. The data includes various sentiment types: positive, negative, and neutral. Table 2 below provides a description of the dataset used in this study.

Tabel 2. Research Dataset

| **Platform** | **Number of Data** | **Positive Sentiment (%)** | **Negative Sentiment (%)** | **Neutral Sentiment (%)** |
|---|---|---|---|---|
| Twitter | 4000 | 55 | 25 | 20 |
| Instagram | 3500 | 62 | 18 | 20 |
| Facebook | 2500 | 58 | 22 | 20 |
| Total | 10000 | 58 | 22 | 20 |

The data from these three platforms provides a comprehensive overview of consumer interactions and their sentiments towards specific products or services.

### *C. Analysis Process*

The analysis process begins with data preprocessing to ensure the data is ready for machine learning algorithms. The first step is text cleaning, which involves removing irrelevant elements such as punctuation, emoticons, and URL links. The next step is tokenization, which breaks the text into individual words or phrases. Stop words, such as "and," "or," and "it," are removed to enhance the focus on relevant terms. Finally, stemming is performed to convert words to their root form, such as changing "membeli" (buying) to "beli" (buy).

After preprocessing, the data is analyzed using machine learning algorithms. This study utilizes Naive Bayes, Random Forest, and Logistic Regression to classify sentiment as positive, negative, or neutral. Naive Bayes is selected for its efficiency in handling large datasets. Random Forest is employed to process complex data, while Logistic Regression is used to explore the linear relationships between text features and sentiment. The model is trained using 80% of the data for training and tested using 20% of the data for evaluation.

### *D. Evaluation Methods*

To evaluate the performance of the model, four main metrics are used: accuracy, precision, recall, and F1-score.

Accuracy: Measures the percentage of correct predictions against the total test data. Formula:

$$\text{Akurasi} = (TP + TN) / (TP + TN + FP + FN)$$

Precision: Measures the percentage of true positive predictions out of all predicted positives. Formula:

$$\text{Precision} = TP / (TP + FP)$$

Recall: Measures how well the model can correctly identify positive sentiment. Formula:

$$\text{Recall} = TP / (TP + FN)$$

F1-Score: Combines precision and recall into a single metric to assess the balance of model performance. Formula:

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

## IV. RESULTS AND DISCUSSION

### Result

*A. Sentiment Analysis Results*

Sentiment analysis of the social media data revealed a diverse distribution between positive, neutral, and negative sentiments. Of the total 10,000 data points analyzed, 58 percent of the comments reflected positive sentiment, 22 percent negative sentiment, and 20 percent neutral sentiment. Positive sentiment was most dominant on Instagram, while Twitter recorded a higher percentage of negative sentiment compared to other platforms. Figure 2 below illustrates the sentiment distribution across different social media platforms.

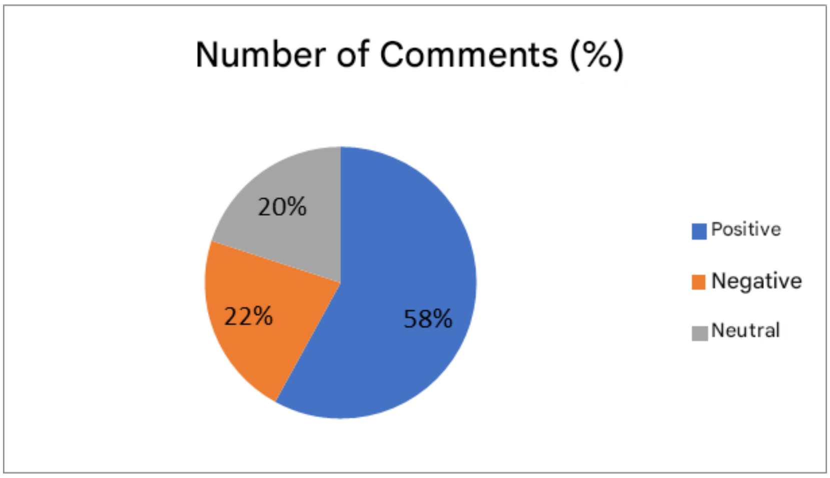


Figure 2. Sentiment Distribution Across Various Social Media Platforms

In addition to the overall sentiment distribution, a further analysis was conducted on specific product categories. Products focusing on health and beauty had the highest proportion of positive sentiment, at 68 percent. In contrast, the electronics category recorded a significant level of negative sentiment, at 28 percent, primarily related to reviews concerning product quality and after-sales service. Figure 3 below

Journal of Management and Informatics (JMI)
**Vol. 3 No. 1 April 2024**
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 0000-0000

presents a word cloud from social media posts for health product categories, highlighting keywords such as "effective," "natural," and "high quality."

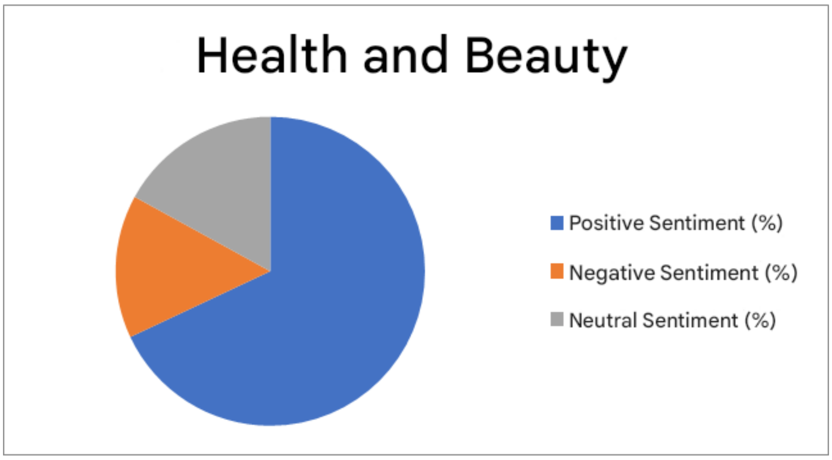


Figure 3. Word Cloud of Social Media Posts for Health Product Categories

Table 3 below summarizes the evaluation results of the sentiment analysis model, showing the accuracy, precision, recall, and F1-score for each algorithm used.

Table 3. Sentiment Analysis Model Evaluation Results

| Algorithm | Akurasi (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Naive Bayes | 84 | 82 | 81 | 81 |
| Random forest | 87 | 85 | 84 | 84 |
| Logistic Regression | 83 | 81 | 80 | 80 |

From the table above, the Random Forest algorithm demonstrated the best performance, with an accuracy of 87 percent, reflecting its reliability in accurately classifying sentiment.

*B. Relationship Between Sentiment and Purchase Intention*

This study also analyzed the relationship between user sentiment on social media and purchase intention using simple linear regression. The analysis results indicated a significant positive correlation between positive sentiment and purchase intention, with a correlation coefficient (r) of 0.68. This suggests that the higher the positive sentiment toward a product, the greater the likelihood that consumers will intend to purchase it. Conversely, negative sentiment exhibited a negative correlation with purchase intention, with an r value of -0.45. Table 4 below presents the results of the analysis of the relationship between sentiment and purchase intention.

Table 4. Analysis Results of the Relationship Between Sentiment and Purchase Intention

| Sentiment | Correlation Coefficient (r) | Significance (T-Value) |
|---|---|---|
| Positif | 0,68 | <0,01 |
| Negatif | -0,45 | <0,05 |
| Netral | 0,12 | 0,07 |

These results indicate that positive sentiment is a strong predictor of purchase intention, while negative sentiment has a significant inhibiting impact.

**Discussion**

The results of this study support marketing theories that posit positive sentiment can enhance purchase intention by building consumer trust in a product or brand. As described in the purchase funnel theory, positive reviews help consumers move from the consideration stage to the intention-to-purchase stage (Gao et al., 2023). In contrast, negative reviews can hinder a consumer's journey through the funnel, as evidenced by the negative correlation between negative sentiment and purchase intention.

These findings are consistent with previous research by (Nekmahmud et al., 2022), which demonstrated that positive sentiment on social media has a significant impact on increasing purchase intention by up to 20 percent. This study also aligns with research by (Jacobs & Hörisch, 2022), who found that reviews with positive emotions can boost brand loyalty, ultimately reinforcing purchase intention. However, this study goes further by using data from multiple social media platforms, yielding more representative results compared to earlier studies that focused solely on one platform, such as Twitter.

Furthermore, health and beauty products showed a dominance of positive sentiment, reflecting consumer trust in the claimed benefits of these products. In contrast, the electronics category recorded significant negative sentiment, indicating consumer dissatisfaction with product quality or after-sales service. This suggests that companies in the electronics sector should focus on enhancing customer service and transparency in product information to address recurring negative sentiment.

This study also faced several challenges. One major challenge was the unstructured nature of social media data. Comments and reviews often use informal language, abbreviations, or emoticons, making the preprocessing process more complex. Another challenge was the imbalance in sentiment data, where positive sentiment tends to be more dominant, potentially affecting the accuracy of the model in detecting the less frequent negative sentiment. Additionally, the limitation in understanding the cultural or linguistic context of reviews also posed a barrier, particularly in comments with ambiguous meanings.

Nevertheless, this research offers several significant novelties. First, it utilizes data from multiple social media platforms, namely Twitter, Instagram, and Facebook, which allows for a more holistic and representative sentiment analysis. This approach broadens the scope of previous studies that typically focused on a single platform. Second, the integration of various machine learning algorithms, such as Naive Bayes, Random Forest, and Logistic Regression, provides a comprehensive evaluation of model performance, with Random Forest showing the best results for the dataset used.

Third, this research makes a practical contribution by linking user sentiment on social media with purchase intention. The significant correlation found between positive sentiment and purchase intention can serve as a guideline for companies to design data-driven marketing strategies. Furthermore, this study highlights the differences in sentiment across product categories, offering additional insights into how consumers respond to products based on their nature and quality.

Thus, this study provides added value both in academic literature and in practical applications in the marketing industry. In addition to strengthening existing theories, the findings of this research offer relevant guidelines for companies to more effectively leverage social media data, particularly in understanding consumer behavior and enhancing brand loyalty.

## V. CONCLUSION AND RECOMMENDATION

### Conclusion

The results of this study indicate that positive sentiment plays a crucial role in enhancing consumer purchase intention. The significant correlation between positive sentiment and purchase intention reflects how favorable perceptions of a product or service can drive consumers to make a purchase. Conversely, negative sentiment has the potential to hinder purchase intention, making it an important indicator for companies to improve the quality of their products and services.

The text mining and sentiment analysis approach has proven effective in providing valuable insights into consumption patterns. By analyzing comments and reviews on social media, this research successfully identified consumer emotions and their patterns of interaction with products. This technique not only enriches academic literature but also offers practical solutions for companies to understand consumer behavior in real-time and data-driven ways.

### Recommendation

To maximize these findings, it is recommended that companies integrate sentiment-based marketing strategies into their activities. Positive sentiment identified through social media analysis can be leveraged to strengthen brand loyalty and improve conversion rates. On the other hand, negative sentiment should be used as feedback to address areas of dissatisfaction in products or services.

This study also opens avenues for further research, particularly by using data from other social media platforms such as TikTok or YouTube, which exhibit different patterns of interaction and user demographics. Future research may also explore the integration of more advanced algorithms, such as deep learning, to improve the accuracy of sentiment analysis and incorporate visual or multimedia data to gain a more comprehensive understanding of consumer behavior.

## REFERENCES

Alantari, H. J., Currim, I. S., Deng, Y., & Singh, S. (2022). An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews. *International Journal of Research in Marketing*, *39*(1), 1–19. https://doi.org/10.1016/j.ijresmar.2021.10.011

Alsayat, A. (2022). Improving Sentiment Analysis for Social Media Applications Using an Ensemble Deep Learning Language Model. *Arabian Journal for Science and Engineering*, *47*(2), 2499–2511. https://doi.org/10.1007/s13369-021-06227-w

Alsubai, S. (2023). Emotion Detection Using Deep Normalized Attention-Based Neural Network and Modified-Random Forest. *Sensors*, *23*(1). https://doi.org/10.3390/s23010225

Bharadiya, J. P. (2023). The role of machine learning in transforming business intelligence. *International Journal of Computing and Artificial Intelligence*, *4*(1), 16–24. https://doi.org/10.33545/27076571.2023.v4.i1a.60

Busalim, A., Fox, G., & Lynn, T. (2022). Consumer behavior in sustainable fashion: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, *46*(5), 1804–1828. https://doi.org/10.1111/ijcs.12794

De Fano D, R, S., & A., R. (2022). Empowering plastic recycling: Empirical investigation on the influence of social media on consumer behavior. *Resources, Conservation and Recycling*, *182*, 106269.

Ebrahimi, P., Salamzadeh, A., Soleimani, M., Khansari, S. M., Zarea, H., & Fekete-Farkas, M. (2022). Startups and Consumer Purchase Behavior: Application of Support Vector Machine Algorithm. *Big Data and Cognitive Computing*, *6*(2). https://doi.org/10.3390/bdcc6020034

Eslami, S. P., Ghasemaghaei, M., & Hassanein, K. (2022). Understanding consumer engagement in social media: The role of product lifecycle. *Decision Support Systems*, *162*. https://doi.org/10.1016/j.dss.2021.113707

Gani, M. O., Roy, H., Rahman, M. S., Faroque, A. R., Gupta, V., & Prova, H. T. (2023). Effect of social media influence on consumer's purchase intention of organic beauty products: the role of customer's engagement and generativity. *International Journal of Spa and Wellness*, *6*(1), 54–77. https://doi.org/10.1080/24721735.2022.2096292

Gao, H., Liu, H., Lin, W., & Chen, C. (2023). Graph-theoretic approach to detecting real-time intents within purchase conversion funnel using clickstream data. *Kybernetes*, *52*(11), 5139–5163. https://doi.org/10.1108/K-06-2021-0473

Goldberg, D. M., & Abrahams, A. S. (2022). Sourcing product innovation intelligence from online reviews. In *Decision Support Systems* (Vol. 157). https://doi.org/10.1016/j.dss.2022.113751

Goswami, M., & Sebastian, N. J. (2022). Performance Analysis of Logistic Regression, KNN, SVM, Naïve Bayes Classifier for Healthcare Application During COVID-19. *Lecture Notes on Data Engineering and Communications Technologies*, *96*, 645–658. https://doi.org/10.1007/978-981-16-7167-8_47

Gupta, V., Mishra, V. K., Singhal, P., & Kumar, A. (2022). An Overview of Supervised Machine Learning

Algorithm. *Proceedings of the 2022 11th International Conference on System Modeling and Advancement in Research Trends, SMART 2022*, 87–92. https://doi.org/10.1109/SMART55829.2022.10047618

Gutierrez, A., Punjaisri, K., Desai, B., Syed Alwi, S. F., O'Leary, S., Chaiyasoonthorn, W., & Chaveesuk, S. (2023). Retailers, don't ignore me on social media! The importance of consumer-brand interactions in raising purchase intention - Privacy the Achilles heel. *Journal of Retailing and Consumer Services*, *72*. https://doi.org/10.1016/j.jretconser.2023.103272

Halkiopoulos, C., Antonopoulou, H., Gkintoni, E., & Aroutzidis, A. (2022). Neuromarketing as an Indicator of Cognitive Consumer Behavior in Decision-Making Process of Tourism destination—An Overview. *Springer Proceedings in Business and Economics*, 679–697. https://doi.org/10.1007/978-3-030-92491-1_41

Isnan, M., Elwirehardja, G. N., & Pardamean, B. (2023). Sentiment Analysis for TikTok Review Using VADER Sentiment and SVM Model. *Procedia Computer Science*, *227*, 168–175. https://doi.org/10.1016/j.procs.2023.10.514

Jacobs, K., & Hörisch, J. (2022). The importance of product lifetime labelling for purchase decisions: Strategic implications for corporate sustainability based on a conjoint analysis in Germany. *Business Strategy and the Environment*, *31*(4), 1275–1291. https://doi.org/10.1002/bse.2954

Jain, S. (2024). Factors influencing online luxury purchase intentions: the moderating role of bandwagon luxury consumption behavior. *South Asian Journal of Business Studies*, *13*(1), 90–117. https://doi.org/10.1108/SAJBS-09-2021-0352

Javaid, M., Haleem, A., Pratap Singh, R., Suman, R., & Rab, S. (2022). Significance of machine learning in healthcare: Features, pillars and applications. *International Journal of Intelligent Networks*, *3*, 58–73. https://doi.org/10.1016/j.ijin.2022.05.002

Khan, Y., Hameed, I., & Akram, U. (2023). What drives attitude, purchase intention and consumer buying behavior toward organic food? A self-determination theory and theory of planned behavior perspective. *British Food Journal*, *125*(7), 2572–2587. https://doi.org/10.1108/BFJ-07-2022-0564

Khandokar, I. A., Islam, A. K. M. M., Islam, S., Shatabda, S., & others. (2023). A gradient boosting classifier for purchase intention prediction of online shoppers. *Heliyon*, *9*(4).

Khanom, M. T. (2023). Using social media marketing in the digital era: A necessity or a choice. *International Journal of Research in Business and Social Science (2147- 4478)*, *12*(3), 88–98. https://doi.org/10.20525/ijrbs.v12i3.2507

Li, F., Larimo, J., & Leonidou, L. C. (2023). Social media in marketing research: Theoretical bases, methodological aspects, and thematic focus. *Psychology and Marketing*, *40*(1), 124–145. https://doi.org/10.1002/mar.21746

Liu, R., Gupta, S., & Patel, P. (2023). The Application of the Principles of Responsible AI on Social

Media Marketing for Digital Health. *Information Systems Frontiers*, *25*(6), 2275–2299. https://doi.org/10.1007/s10796-021-10191-z

Mienye, I. D., Swart, T. G., & Obaido, G. (2024). Recurrent Neural Networks: A Comprehensive Review of Architectures, Variants, and Applications. *Information*, *15*(9), 517. https://doi.org/10.3390/info15090517

Moinuddin, M., Usman, M., & Khan, R. (2024). Decoding Consumer Behavior: The Role of Marketing Analytics in Driving Campaign Success. *International Journal of Advanced Engineering Technologies and Innovations*, *01*, 4.

Narayanan, S., Gruber, J., Liedtke, G., & Antoniou, C. (2022). Purchase intention and actual purchase of cargo cycles: Influencing factors and policy insights. *Transportation Research Part A: Policy and Practice*, *155*, 31–45. https://doi.org/10.1016/j.tra.2021.10.007

Nekmahmud, M., Naz, F., Ramkissoon, H., & Fekete-Farkas, M. (2022). Transforming consumers' intention to purchase green products: Role of social media. *Technological Forecasting and Social Change*, *185*. https://doi.org/10.1016/j.techfore.2022.122067

Parmar, M., & Tiwari, A. (2024). Enhancing Text Classification Performance using Stacking Ensemble Method with TF-IDF Feature Extraction. *Proceedings - 2024 5th International Conference on Mobile Computing and Sustainable Informatics, ICMCSI 2024*, 166–174. https://doi.org/10.1109/ICMCSI61536.2024.00031

Sriram, V. P., Shaikh, A. A., Sumana, B. K., Kumar, A., Dhiman, V., & Naved, M. (2023). Consumer Behaviour on Digital Marketing Platforms—Specifically in Terms of Consumer Loyalty Using Machine Learning. *Smart Innovation, Systems and Technologies*, *290*, 377–386. https://doi.org/10.1007/978-981-19-0108-9_40

Testa, R., Rizzo, G., Schifani, G., Tóth, J., & Migliore, G. (2024). Critical determinants influencing consumers' decision-making process to buy green cosmetics. A systematic literature review. *Journal of Global Fashion Marketing*, *15*(3), 357–381. https://doi.org/10.1080/20932685.2023.2268669

Van Veldhoven, Z., & Vanthienen, J. (2022). Digital transformation as an interaction-driven perspective between business, society, and technology. *Electronic Markets*, *32*(2), 629–644. https://doi.org/10.1007/s12525-021-00464-5

Wagobera Edgar Kedi, Chibundom Ejimuda, Courage Idemudia, & Tochukwu Ignatius Ijomah. (2024). Machine learning software for optimizing SME social media marketing campaigns. In *Computer Science & IT Research Journal* (Vol. 5, Issue 7, pp. 1634–1647). https://doi.org/10.51594/csitrj.v5i7.1349

Zaman, S. I., & Kusi-Sarpong, S. (2024). Identifying and exploring the relationship among the critical success factors of sustainability toward consumer behavior. *Journal of Modelling in Management*, *19*(2), 492–522. https://doi.org/10.1108/JM2-06-2022-0153