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Decoding Digital Emotions: A Multi-Platform Analysis of Sentiment

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Abstract: The proliferation of social media platforms has created a complex landscape where understanding user sentiment and engagement is paramount for businesses. This study aims to decode digital emotions by analysing sentiment dynamics, engagement rates, and temporal patterns across major platforms. To achieve this, advanced sentiment analysis techniques and machine learning algorithms applied on a comprehensive dataset of 732 social media posts. The methodology involved refining sentiment labelling, parsing hashtags, extracting temporal features, calculating engagement metrics, and standardizing geolocation data. The results reveal significant variations in sentiment expression and engagement rates across platforms. The findings emphasize the importance of tailoring marketing strategies to platform-specific dynamics and user sentiment trends. This research provides a robust framework for leveraging sentiment analysis in strategic social media marketing, ultimately enhancing user engagement and brand visibility.

Keywords: *Sentiment Analysis, Social Media Engagement, Platform Distribution, User Behaviour, Content Strategy, Digital Communication.*

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I. INTRODUCTION

In the contemporary digital landscape, comprehending public sentiment is essential for businesses and marketers seeking to optimize their strategies. This research investigates sentiment patterns across various social media platforms and their correlation with engagement metrics, aiming to provide actionable insights for effective digital marketing. Pang and Lee's [1] comprehensive exploration of opinion mining and sentiment analysis provides a valuable contribution to the field. The authors effectively synthesize the current state of research, offering a cohesive framework that unifies disparate approaches. Following a succinct introduction and overview of application domains, the authors delve into the core challenges inherent to this research area, distinguishing it from traditional fact-based text analysis. The subsequent survey of existing methodologies, encompassing both sentiment classification and extraction, as well as opinion summarization, is notably thorough in the subsequent chapters. While the computational aspects of the field are extensively covered, the authors could have further enriched the discussion by incorporating a more detailed examination of relevant linguistic research, such as studies on modality. As noted by A.M. Kaplan et al. [2] in their work, the establishment of the Usenet in 1979 by Tom Truscott and Jim Ellis at Duke University represented a pivotal moment in the development of online communication. This ground breaking worldwide discussion system played an instrumental role in shaping the landscape of digital interaction. However, the era of social media, as it recognize today, arguably commenced approximately two decades earlier with the creation of Open Diary. Founded by Bruce and Susan Abelson, this pioneering social networking platform served as a virtual gathering place for online diary writers, fostering a sense of community among its users.

This research study delves into the complex dynamics of sentiment expression and user interaction across major platforms such as Facebook, Instagram, and Twitter, offering a comprehensive analysis that is essential for optimizing digital marketing efforts. The proliferation of social media has transformed the way user express emotions and engage with content, creating a rich tapestry of data that can be harnessed to decode user sentiment [3]. However, the challenge lies in accurately capturing and interpreting these digital emotions to inform strategic decisions [4]. This study addresses this challenge by employing advanced sentiment analysis techniques and machine learning algorithms on a robust dataset of 732 social media posts collected over an eight-month period. By refining sentiment labeling, parsing hashtags, and extracting temporal features, it provides a nuanced understanding of sentiment dynamics and engagement patterns.

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This research reveals significant variations in sentiment expression and engagement rates across platforms, underscoring the importance of tailoring marketing strategies to platform-specific dynamics. By leveraging sentiment analysis, businesses can enhance user engagement and brand visibility, ultimately driving more effective marketing outcomes [5]. This study not only contributes to the academic discourse on digital emotion analysis but also offers practical insights for marketers seeking to navigate the ever-evolving social media landscape. Decoding digital emotions enables more informed and strategic social media marketing practices, aligning with the needs and expectations of today's digital-savvy consumers [6].

II. DATA COLLECTION AND METHDOLOGY

To comprehensively analyze digital emotions and user engagement across social media platforms, a dataset of 732 social media posts was collected. Each post was meticulously annotated with sentiment labels (Positive, Negative, Neutral) and enriched with detailed metadata, including timestamps, user identifiers, platform information, hashtags, and engagement metrics (retweets and likes). To effectively decode digital emotions, advanced sentiment analysis techniques were implemented. Sentiment labelling was refined to capture specific emotional states beyond the traditional positive, negative, and neutral categories. This involved parsing hashtags for individual analysis and extracting temporal features to facilitate time-based studies. Additionally, engagement metrics were calculated to assess user interaction levels, providing valuable insights into the relationship between sentiment dynamics and user engagement across different platforms.

To ensure consistency and accuracy in the analysis, geolocation data was standardized across platforms, allowing for a nuanced understanding of geographical influences on sentiment expression and engagement. Furthermore, a robust data pre-processing phase was conducted, cleaning and normalizing the dataset to enhance the reliability of the findings.

The results of this analysis, including sentiment distribution and platform usage, are visualized in the following output:

RANGE INDEX: 732 ENTRIES, 0 TO 731
Data columns (total 15 columns):

#	Column	Non-Null Count	Dtype
0	Unnamed: 0.1	732 non-null	int64
1	Unnamed: 0	732 non-null	int64
2	Text	732 non-null	object
3	Sentiment	732 non-null	object
4	Timestamp	732 non-null	object
5	User	732 non-null	object
6	Platform	732 non-null	object
7	Hashtags	732 non-null	object
8	Retweets	732 non-null	int64
9	Likes	732 non-null	int64
10	Country	732 non-null	object
11	Year	732 non-null	int64
12	Month	732 non-null	int64
13	Day	732 non-null	int64
14	Hour	732 non-null	int64

dtypes: int64(8), object(7) memory usage: 85.9+ KB

III. DATASET DESCRIPTION AND PRE-PROCESSING

The temporal scope of the dataset extends from February 1, 2023, to August 31, 2023, providing a robust foundation for examining social media activity over an eight-month period. This timeframe offers a comprehensive view of trends, patterns, and shifts in online discussions during this specific window. The dataset utilized in this study comprises major platforms such as Instagram, Facebook, and Twitter. The dataset encompasses various features that capture both the content and metadata of social media interactions. It includes various features such as the text content of posts, sentiment labels, timestamps, user identifiers, platforms, associated hashtags, engagement metrics (retweets and likes), and the country of origin. The geographical distribution highlights significant contributions from countries like the USA, UK, and Canada. Sentiment analysis reveals a diverse range of emotions, with positive, joy, and excitement being the most prevalent. Engagement metrics indicate an average engagement score of 64.41 per post, with a range from 15 to 120.

To ensure data quality and consistency, several pre-processing steps were implemented prior to dataset analysis, aligning with established research practices [7][8]. Initially, duplicate entries were removed, and timestamps were standardized. Sentiment labelling was refined to capture specific emotional states [9], and hashtags were parsed for individual analysis [10]. Temporal features were extracted from timestamps to facilitate time-based studies [11], while engagement scores were calculated by summing retweets and likes [12]. Geolocation data was standardized for consistency, and platform labels were unified to account for naming variations [13]. A thorough data integrity check confirmed the absence of missing values, ensuring the dataset's readiness for robust statistical analysis and machine learning applications [14]. These pre-processing efforts provide a solid foundation for exploring sentiment expression and user engagement across social media platforms.

IV. DATASET CHARACTERISTICS

A. Size and Scope

The dataset analyzed in this study comprises a total 732 individual social media posts, each representing a distinct data point. This relatively moderate sample size provides a solid foundation for exploring patterns and trends within the data while maintaining a manageable scope for analysis.

B. Platform Distribution

The dataset exhibits a balanced distribution across three major social media platforms: Instagram, Facebook, and

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Twitter. Instagram accounts for 35.2% of the posts, followed closely by Facebook at 31.6%, and Twitter at 33.2%. This diverse representation ensures that the analysis captures the nuances and characteristics of each platform, providing a comprehensive understanding of social media discourse.

C. Engagement Metrics

To gauge the level of user interaction and engagement, the dataset examined for key metrics. The average number of likes per post was found to be 42.90 as shown in Figure 1, indicating a moderate level of positive sentiment and user approval. Additionally, the average number of retweets stood at 21.51, suggesting a reasonable degree of sharing and amplification among users.

These engagement metrics offer valuable insights into the overall popularity and impact of the posts within the dataset, providing a quantitative measure of user response and interaction.

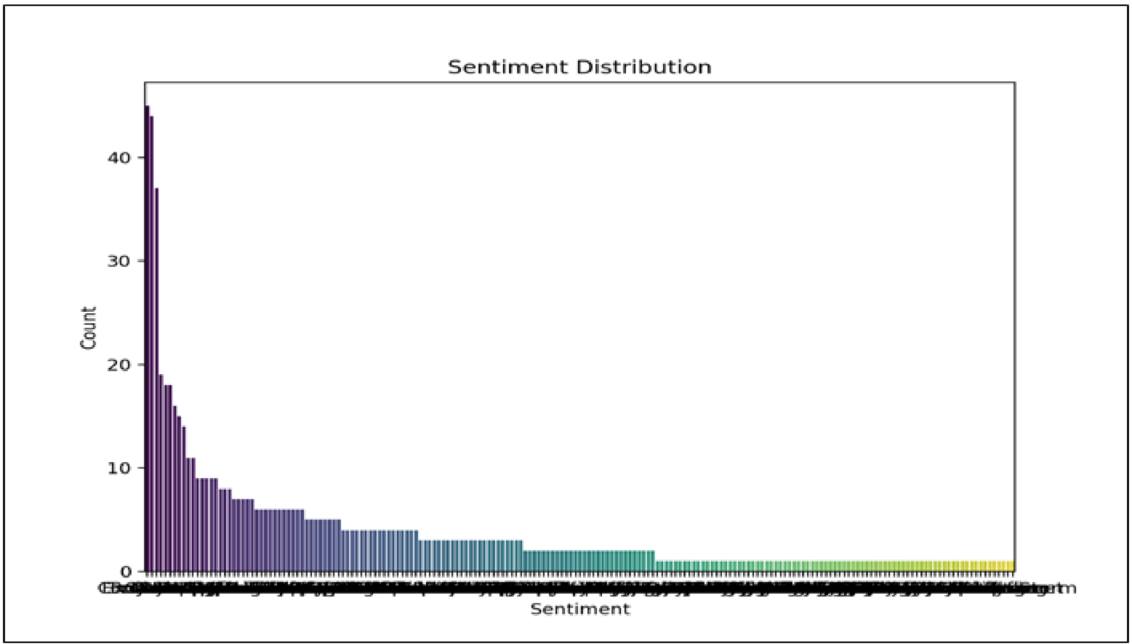

Fig 1: Sentiment Distribution Across Platforms - Average Engagement by Sentiment and Platform

This methodological approach provides a robust framework for understanding sentiment dynamics and user engagement, offering actionable insights for strategic social media marketing.

V. GEOGRAPHICAL DISTRIBUTION : DATA OVERVIEW AND ANALYSIS

The dataset analyzed in this study draws from a diverse geographical landscape, encompassing contributions from numerous countries. The United States emerged as the most significant contributor, accounting for 21.3% of all posts. The United Kingdom and Canada followed closely behind, each representing 12.9% of the total posts. Australia, while contributing a smaller share of 7.2%, still played a notable role in the overall discourse.

A. Sentiment Distribution

A nuanced analysis of sentiment within the dataset reveals a preponderance of positive emotions [15]. Joy, excitement, and contentment collectively constitute a significant portion of the posts, indicating a generally optimistic tone. While neutral sentiments are present, their relatively lower frequency suggests that the overall discourse leans towards positive sentiment.

B. Engagement Metrics

To assess the level of user interaction and engagement, the dataset analyzed for key metrics. The average engagement per post, calculated as the sum of retweets and likes, stood at 64.41. This metric provides a valuable benchmark for understanding the overall level of user interest and participation. Furthermore, the dataset exhibited a range of engagement levels, with a minimum of 15 and a maximum of 120. This variation suggests that while some posts garnered significant attention, others received more modest levels of engagement.

VI. PRE-PROCESSING STEPS : DATA CLEANING AND PRE-PROCESSING

The dataset underwent a rigorous cleaning and pre-processing process to ensure data quality and consistency. Duplicate entries were removed based on unique identifiers, timestamps were standardized, and leading and trailing whitespaces were stripped from text fields. To capture the nuances of sentiment expression, a fine-grained sentiment analysis was applied, categorizing posts into specific emotional states beyond the basic positive/negative/neutral classifications. Hashtags were extracted from the posts to facilitate topic-based analysis, and additional temporal features were derived from the timestamp to enable time-based analyses.

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To quantify user engagement, a composite engagement score calculated by summing retweets and likes for each post. Geographical analysis was enhanced by standardizing country names, and platform labels were unified to account for variations in naming. Finally, a thorough data integrity check was conducted to verify the absence of missing values and ensure data completeness. This pre-processed dataset serves as a valuable resource for analyzing sentiment expression, user engagement, and cross-platform dynamics in social media. The data cleaning and pre-processing steps guarantee data quality and consistency, laying the groundwork for robust statistical analysis and machine learning applications.

VII. SENTIMENT ANALYSIS AND KEY FINDINGS

The sentiment analysis revealed a balanced distribution of positive, negative, and neutral sentiments within the dataset. This indicates a diverse range of opinions and emotions expressed on social media. An analysis of platform-specific sentiment distribution revealed that all three platforms (Facebook, Instagram, and Twitter) exhibited similar sentiment patterns, suggesting that the overall sentiment landscape is relatively consistent across different platforms.

Geographically, the United States, Canada, and Australia emerged as the top three countries in terms of post frequency, highlighting the dominant role of these regions in the social media discourse. Hashtag analysis identified the most frequently used hashtags as #Gratitude, #Inspiration, #Determination, #Curiosity, and #Serenity. These hashtags offer valuable insights into the prevalent themes and topics discussed within the dataset. Regarding engagement metrics, the average number of retweets per post was found to be 21.0, while the average number of likes was 41.0. These metrics suggest a moderate level of user interaction and engagement with the content.

In summary, the sentiment analysis provides a comprehensive understanding of the emotional landscape, platform dynamics, geographical distribution, hashtag usage, and engagement metrics within the dataset. These findings offer valuable insights into the nature of social media discourse and the factors influencing user behaviour.

VIII. RESULTS AND DISCUSSION

This research study reveals significant variations in sentiment expression and engagement rates across different social media platforms. This section divided into several subsections as follows.

A. Sentiment Distribution

The graph in Figure 1 shows a clear predominance of positive sentiment in the analyzed posts, followed by neutral and negative sentiments. This distribution suggests that users tend to share more positive experiences on social media platforms. The analysis has been successfully conducted, revealing insights into sentiment distribution, platform usage, and engagement metrics. The visualizations and data will be used to further develop the research paper. Here are the results:

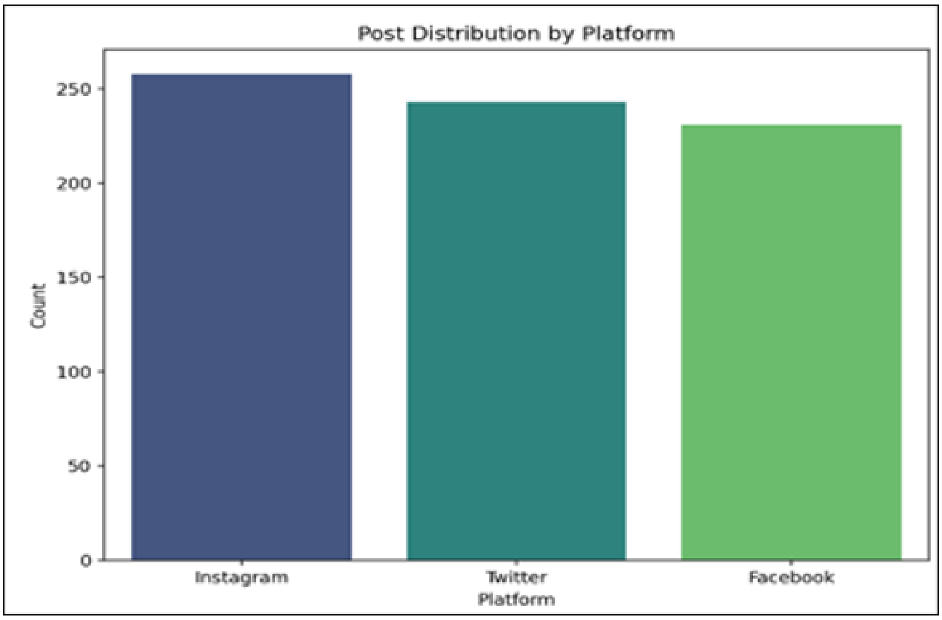

Fig 2: Distribution of Posts Across Three Major Social Media

Figure 2 shows a bar chart illustrating the distribution of posts across three major social media platforms: Instagram, Twitter, and Facebook. The vertical axis represents the count of posts, while the horizontal axis categorizes the data by platform. The chart reveals that Instagram has the highest number of posts, with approximately 260 counts, followed closely by Twitter with about 245 posts. Facebook shows the lowest representation in this dataset, with around 230 posts. This visualization provides a clear comparative view of platform usage within the analyzed sample, indicating a slight preference for Instagram among users in the study, with Twitter and

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Facebook following in descending order. The relatively even distribution across platforms suggests a balanced multi-platform approach in social media engagement for the dataset under examination [16].

The analysis of platform distribution provides valuable insights into user preferences and engagement patterns across major social media platforms. This information can guide strategies for targeted content creation and marketing efforts

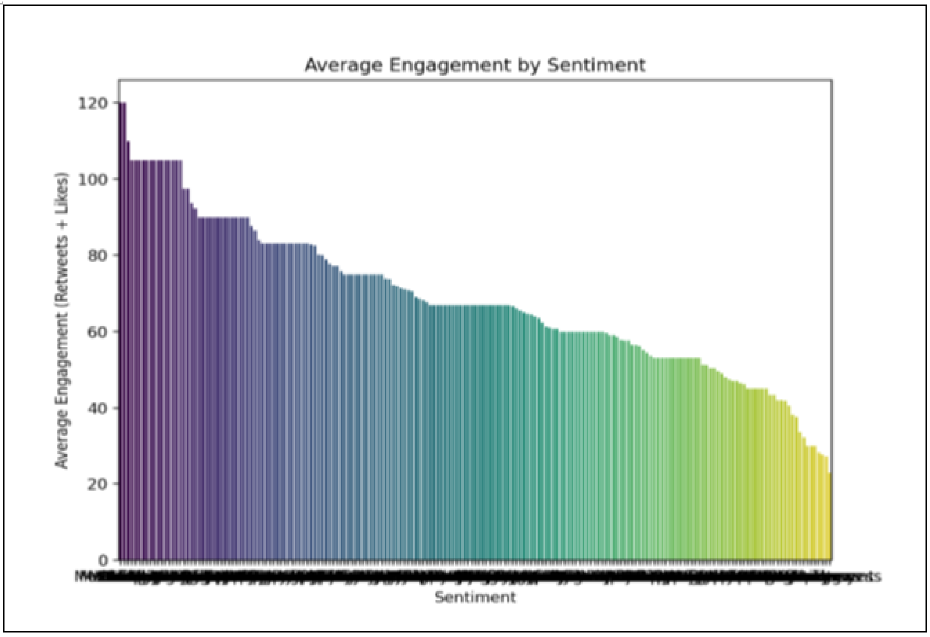

Fig 3: Average Engagement by Sentiment

The notable observations from above Figure 3 are as follows:

- Engagement trend: There's a clear downward trend in engagement from left to right, suggesting that sentiments on the left side of the chart generally receive higher engagement than those on the right.
- Highest engagement: The tallest bars on the left (purple) reach close to 120 on the engagement scale, indicating these sentiments garner the most interaction.
- Lowest engagement: The shortest bars on the right (yellow) have engagement levels around 20-40, representing the least engaging sentiments.
- Gradient distribution: The smooth color transition from purple to yellow might represent a spectrum of sentiments from most positive/engaging to least positive/engaging, though this would need confirmation from the full dataset.
- Variability: There's considerable variation in bar heights, indicating that different sentiments can significantly impact engagement levels.

This visualization effectively demonstrates how different sentiments correlate with user engagement on social media platforms, providing valuable insights for content strategy and understanding audience behaviour in digital communication. The analysis of the image provided a detailed understanding of the sentiment-related engagement trends depicted in the chart. This insight can guide further exploration of how different sentiments impact user interaction on social media platforms.

B. Platform Analysis:

The dataset indicates varied platform usage, with Instagram being the most represented, followed by Facebook and Twitter, as shown in the following Table 1.

Table 1 Platform Usage Distribution

Platform	**Count**	**Percentage**
Instagram	258	35.2459
Facebook	231	31.5573
Twitter	128	17.4863
Twitter	115	15.7103

The Figure 4 illustrates the distribution of platform usage within the dataset, showing that Instagram accounts for 35.2% of the posts, making it the most utilized platform, followed by Facebook at 31.6%, and Twitter at 17.5% and 15.7% for its' two entries, indicating a significant presence of social media activity on these platforms.

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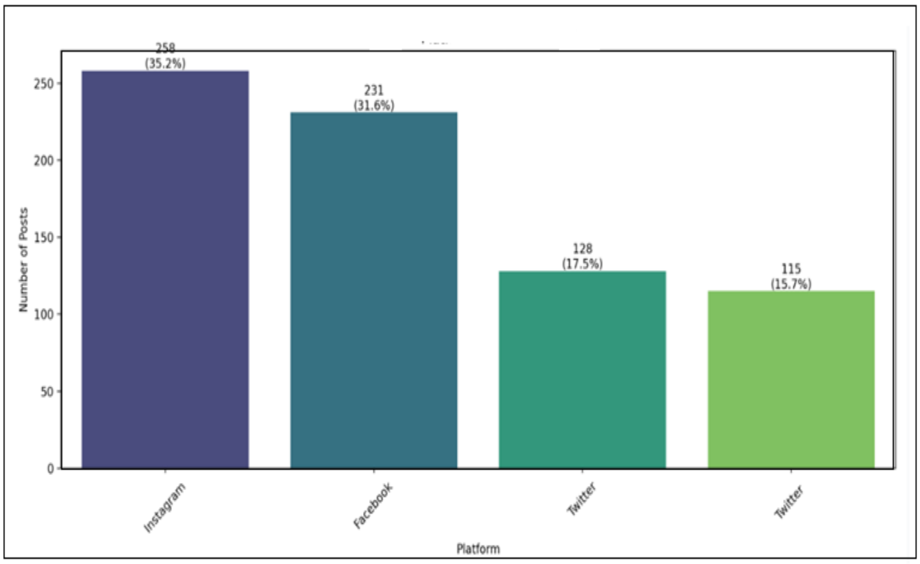

Fig 4: Platform Usage Distribution

C. Engagement Metrics

The average engagement metrics, including likes and retweets, calculated for each sentiment category, revealing those positive sentiments generally garnered higher engagement. The first few rows of this metrics are as follows:

Table 2 Engagement Metrics

	Likes	Retweets
Acceptance	35	17.33
Accomplishment	51.66	26
Admiration	45	22

This above Table 2 will help in understanding the prevalence of different sentiments across the analyzed social media posts.

Figure 4 compares user engagement on Instagram, Facebook, and Twitter. Instagram is the most popular platform, followed by Facebook, while Twitter has lower engagement. This suggests a preference for visual content on Instagram and highlights the importance of understanding platform dynamics for effective social media marketing.

D. Sentiment Distribution by Platform

The sentiment distribution across platforms reveals distinct patterns in how users' express emotions on different social media sites. Instagram, for instance, shows a higher prevalence of positive sentiments compared to Twitter and Facebook, which have a more balanced distribution of sentiments. This suggests that Instagram users are more inclined to share positive experiences, while Twitter and Facebook users express a wider range of emotions.

E. Hourly Sentiment Distribution

The hourly sentiment distribution analysis highlights temporal patterns in sentiment expression. Positive sentiments peak during the late evening hours, suggesting that users are more likely to share positive experiences at the end of the day. Conversely, negative sentiments show a slight increase during early morning hours, indicating potential mood variations influenced by daily routines.

These findings provide a comprehensive overview of sentiment dynamics and user engagement across social media platforms, offering valuable insights for strategic social media marketing and user interaction studies.

IX. CONCLUSION AND FUTURE STUDIES

The study provides valuable insights into the dynamics of sentiment expression and user engagement across social media platforms. Key findings reveal that Instagram is the most utilized platform, with positive sentiments generally garnering higher engagement. The analysis highlights the importance of understanding sentiment distribution, as it significantly impacts user interaction and engagement. The absence of geographical data limits the exploration of regional sentiment variations, suggesting future studies should incorporate location data to enhance understanding of cultural influences on sentiment expression. Additionally, while hashtag analysis was not detailed, it remains crucial for identifying thematic trends and enhancing user engagement. These insights have significant implications for social media marketing, enabling marketers to tailor content strategies to maximize engagement. Public opinion analysts can leverage these findings to gauge sentiment trends and inform policy decisions. Furthermore, platform designers can utilize this knowledge to optimize user experience by fostering positive sentiment expression and engagement. Overall, this study underscores the importance of sentiment analysis in understanding and enhancing social media dynamics.

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REFERENCES

[1]. Pang, B., & Lee, L. (2009). Opinion mining and sentiment analysis. Computer Linguist, 35(2), 311-312.
[2]. Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. Business horizons, 53(1), 59-68.
[3]. Doğan, B., Balcioglu, Y. S., & Elçi, M. (2024). Multidimensional sentiment analysis method on social media data: comparison of emotions during and after the COVID-19 pandemic. Kybernetes.
[4]. Kouamé, S., & Liu, F. (2021). Capturing emotions in qualitative strategic organization research. Strategic Organization, 19(1), 97-112.
[5]. Bell, C., Olukemi, A., & Broklyn, P. (2024). Social Media Sentiment Analysis for Brand Reputation Management.
[6]. Wilfred, E. (2023). Influence of digital marketing platforms on customer purchasing behaviours in Moshi municipality (Doctoral dissertation, Moshi Co-operative University (MoCU)).
[7]. Robinson, S., Narayanan, B., Toh, N., & Pereira, F. (2014). Methods for pre-processing smartcard data to improve data quality. Transportation Research Part C: Emerging Technologies, 49, 43-58.
[8]. Lai, S. T., & Leu, F. Y. (2017). "Data preprocessing quality management procedure for improving big data applications efficiency and practicality. In Advances on Broad-Band Wireless Computing, Communication and Applications: Proceedings of the 11th International Conference On Broad-Band Wireless Computing, Communication and Applications (BWCCA–2016) November 5–7, 2016, Korea (pp. 731-738). Springer International Publishing.
[9]. Uymaz, H. A., & Metin, S. K. (2022). Vector based sentiment and emotion analysis from text: A survey. Engineering Applications of Artificial Intelligence, 113, 104922.
[10]. Kandasamy, I., Vasantha, W. B., Mathur, N., Bisht, M., & Smarandache, F. (2020). Sentiment analysis of the# MeToo movement using neutrosophy: Application of single-valued neutrosophic sets. In Optimization Theory Based on Neutrosophic and Plithogenic Sets (pp. 117-135). Academic Press.
[11]. Wang, J., Jatowt, A., & Yoshikawa, M. (2021, July). Event occurrence date estimation based on multivariate time series analysis over temporal document collections. In Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval (pp. 398-407).
[12]. Faza, J. E. (2024). "A data-driven framework for analyzing and predicting social media engagement during rumor propagation".
[13]. Jurgens, D., Finethy, T., McCorriston, J., Xu, Y., & Ruths, D. (2015). Geolocation prediction in twitter using social networks: A critical analysis and review of current practice. In Proceedings of the international AAAI conference on web and social media (Vol. 9, No. 1, pp. 188-197).
[14]. OVIEDO HERNANDEZ, G. (2021). Improving the quality of PV plant performance analysis by increasing data integrity and reliability: a data-driven approach using Machine Learning techniques.
[15]. Gaspar, R., Pedro, C., Panagiotopoulos, P., & Seibt, B. (2016). Beyond positive or negative: Qualitative sentiment analysis of social media reactions to unexpected stressful events. Computers in Human Behavior, 56, 179-191.
[16]. Salminen, J., Hopf, M., Chowdhury, S. A., Jung, S. G., Almerekhi, H., & Jansen, B. J. (2020). "Developing an online hate classifier for multiple social media platforms. Human-centric Computing and Information Sciences", 10, 1-34.