IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 1, February 2025, pp. 447~456
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i1.pp447-456

User sentiment dynamics in social media: a comparative analysis of X and Threads

Rezki Khairunnas, Jeri Apriansyah Pagua, Ghina Fitriya, Yova Ruldeviyani
Department of Information Technology, Faculty of Computer Science, University of Indonesia, Jakarta, Indonesia

Article Info

Article history:

Received Feb 17, 2024
Revised Oct 12, 2024
Accepted Oct 18, 2024

Keywords:

Correlation
Sentiment analysis
Social media
Support vector machine
Threads
X (Twitter)

ABSTRACT

This research examines the dynamics of user sentiment and its correlation with the usage factors of applications in the context of the competition between X (formerly Twitter) and Threads, a social media application under the umbrella of Meta. Through sentiment analysis of user reviews on the Google Play Store and App Store, the study aims to identify the key factors contributing to a significant decline in user engagement with Threads and the return of users to X. The method employed in this research is the support vector machine (SVM) for sentiment classification of reviews. The study then correlates the classified sentiments with application usage factors: usability, features, design, and support. The research findings indicate user sentiment influences user engagement, especially in features and design. The research concludes with insights regarding implications for application developers and suggests directions for future research.

Corresponding Author:

Rezki Khairunnas
Department of Information Technology, Faculty of Computer Science, University of Indonesia
Kenari 2 St. No.4, RW.5, Jakarta Pusat, DKI Jakarta, Indonesia
Email: rezki.khairunnas@ui.ac.id

1. INTRODUCTION

The digital age has seen numerous social media platforms rise and fall, each vying for a share of the global user base. On July 5, 2023, the social media landscape witnessed the launch of Threads, a new platform developed by Meta aimed at challenging the dominance of X (formerly Twitter). X, which Elon Musk acquired in October 2022, had long been a critical player in online public discourse [1]. The introduction of Threads was seen as a strategic move by Meta CEO Mark Zuckerberg to capitalize on the perceived vulnerabilities of X and to fulfil the ambition of creating a platform that could host public conversations on a scale exceeding a billion users.

Threads made an impressive debut, reaching unprecedented milestones in user acquisition. Within four hours of its release, the application had been downloaded five million times, and by July 10, 2023, it had amassed 100 million users [2]. This explosive growth surpassed record holders like TikTok and ChatGPT, marking Threads as history's fastest-growing social media platform. The rapid adoption of Threads was further fueled by discontent among X users, who were disenchanted with Elon Musk's controversial policies [2], including limitations on tweet visibility, the introduction of paid verification, and frequent application glitches.

Despite its initial success, Threads experienced a steep decline in user engagement. Reports indicated that the daily active user count halved within just two weeks of its peak, and by August 7, 2023, the average daily usage time had plummeted to a mere three minutes per user [3]. In stark contrast, X demonstrated resilience, maintaining a steady base of 100 million daily active users with an average usage time of 25 minutes.

This research seeks to unravel the complex dynamics of user sentiment in the face of the competition between X and Threads. It aims to identify the factors contributing to the dramatic fluctuations in user engagement observed with Threads and to understand why users return to X. This study will analyze user reviews from the Google Play Store and App Store using support vector machine (SVM) for sentiment classification, correlating the classified sentiments with various application usage factors, including usability, features, design, and support.

The motivation for this research stems from the need to comprehend the shifting landscape of social media user engagement. Previous social media sentiment analysis research has primarily focused on user satisfaction and platform growth. However, there is a gap in understanding the rapid changes in user engagement and the role of sentiment in competitive dynamics between platforms. By delving into user sentiment, this study aims to shed light on the competition dynamics between X and Threads, offering insights into the elements that drive user preferences and behaviours. The findings are expected to provide valuable guidance for social media application developers, enabling them to enhance product quality and user experience, thereby fostering a deeper understanding of the factors influencing user engagement in the social media domain.

2. LITERATURE STUDIES

This literature review provides a comprehensive overview of sentiment analysis and text mining, specifically focusing on their application in identifying factors influencing the decline in usage of the Threads social media application. Through an understanding of these critical concepts, this research aims to provide in-depth insights into the latest trends and challenges in sentiment analysis in the continuously evolving era of social media. Furthermore, previous studies discussing SVM and Naive Bayes methods will be briefly explained to establish a foundational understanding for this research.

2.1. Sentiment analysis

Sentiment analysis, alternatively referred to as opinion mining, constitutes a domain of research focusing on examining individuals' viewpoints, evaluations, appraisals, judgments, perspectives, and emotional responses concerning various entities, including but not limited to products, services, organizations, individuals, issues, events, topics, and their respective characteristics. The field of sentiment analysis encompasses a diverse array of concerns. Moreover, numerous terms exist alongside slightly varied objectives, encompassing sentiment analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, and review mining [4]. Sentiment analysis has become crucial in gaining insights from social networks [5]. Machine learning-driven sentiment analysis techniques, like SVM classification, have demonstrated their efficacy. Feature selection strategies have been employed to bolster model effectiveness and streamline operations, among which the chi-square method stands out as a frequently utilized approach [6].

2.2. Text mining

Text mining involves uncovering patterns or extracting information from large-scale text data, encompassing unstructured or semi-structured formats. It represents a prevalent application of data mining, often utilized for tasks such as text clustering, categorization analysis, and sentiment evaluation. The text mining workflow typically encompasses multiple stages, including feature selection, text representation, and the utilization of various text mining methodologies [4]. According to Mussalimun *et al.* [7], the steps in performing classification-based sentiment analysis on text data or text mining data are as i) initial stage: dataset collection; ii) preprocessing: stages including tokenization, stop-word removal, and stemming; iii) transformation: stage where text data is weighed; iv) feature selection: stage of reducing unnecessary data; v) classification: the text classification stage usually uses algorithms such as naive Bayes, K-nearest neighbor (KNN), and SVM; and vi) evaluation: the evaluation stage is conducted to calculate accuracy and area under the curve values.

2.3. Support vector machine

The supervised machine learning method, like SVM, applies to classification and regression tasks [8]. SVM is a classification method that does not rely on probabilities and requires substantial training data. This algorithm utilizes the concept of a decision boundary to establish limits between different classes on each object. The decision boundary is a separator between objects' membership in other classes [9]. For instance, consider a dataset containing pairs m $\{(xi, yi)\}$, where each xi represents the characteristics of a data point, and yi indicates its class label [10]. The SVM classification algorithm assumes that a hyperplane exists, or more generally, a d−1 surface, capable of separating the two classes within the feature space. This hyperplane is delineated by a linear decision function f(x), characterized by parameters w ∈ Rd, referred to as the weight, and b ∈ R, termed the bias, as depicted in (1) and (2).

$$f(x) = w^T x + \mathrm{b}, \tag{1}$$

$$\text{s.t.}\begin{cases} f(x_i) > 0 \text{ if } y_i = +1, \\ f(x_i) < 0 \text{ if } y_i = -1. \end{cases} \tag{2}$$

The primary objective of the SVM algorithm is to identify a hyperplane represented by parameters (w, b) that maximize the margin 1/||w|| (where ||·|| denotes the Euclidean norm) between the hyperplane and the nearest data points belonging to each class [11]. Bhalla and Jasy, in their research, explained that SVM exhibits a high level of accuracy compared to naïve Bayes and KNN [12], [13].

2.4. Correlation

In statistical analysis, correlation or dependence denotes any statistical connection, whether causative or not, between two random variables. While "correlation" can encompass various forms of association in a general context, statistical discourse commonly refers to the degree to which a pair of variables exhibit a linear relationship [14]. The Pearson correlation coefficient is the most widely used measure of correlation, and it detects explicitly the linear relationship between two variables. It's worth noting that this correlation measure can capture linear associations even in cases where one variable is a nonlinear function of the other. Correlation is a fundamental aspect of descriptive and exploratory research and functions as an effect measure, aiding in the interpretation and comparison of findings across various studies [15]. The formula for Pearson correlation is as (3) [16].

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{[\sum_{i=1}^{n}(x_i-\bar{x})^2][\sum_{i=1}^{n}(y_i-\bar{y})^2]}} \tag{3}$$

Regarding the strength of the relationship, correlation coefficient values range from +1 to -1. A value of ±1 denotes a perfect degree of relationship between the variables. For example, as the correlation coefficient approaches 0, the relationship between the variables weakens. The sign of the coefficient indicates the direction of the relationship: a "+" sign signifies a positive relationship, whereas a "-" sign signifies a negative relationship [17].

2.5. Previous researches

A review of four previous studies was conducted to determine the most suitable machine learning method for sentiment classification in this study. The analysis focused on comparing the performance of various algorithms, including SVM, naive Bayes, KNN, and decision tree, in different sentiment analysis contexts. Sukma *et al.* [9] explored sentiment analysis of the Indonesian government's policy (Omnibus Law) on Twitter. They compared naive Bayes, SVM, and decision tree algorithms, finding that SVM achieved the highest accuracy rate at 91.80%, followed by naive Bayes at 89.75% and decision tree at 73.60%. Similarly, Jasy *et al.* [13] evaluated sentiment classification using SVM, KNN, and naive Bayes on the Sentiment140 dataset, with SVM again demonstrating superior accuracy at 92%, compared to KNN at 88% and naive Bayes at 85%. In another study, Bhalla [12] performed a comparative analysis of text classification using SVM, naive Bayes, and KNN, though the specific research object or data source was not mentioned. Rahat *et al*. [18] focused on comparing naive Bayes and SVM using a dataset of airline reviews on Twitter, with SVM achieving an accuracy of 82.48% and naive Bayes trailing at 76.56%.

The consistent superior performance of SVM in these studies highlights its practicality as a machine learning technique for sentiment classification. Despite variations in research subjects, such as sentiment towards government policies or product reviews, SVM has consistently demonstrated higher accuracy than naive Bayes and other techniques. Therefore, SVM has been chosen as the sentiment analysis model for this research based on its demonstrated superiority in terms of accuracy.

3. METHODOLOGY

This study systematically collects, processes, and analyses user reviews of the Threads and X applications from the Google Play and App Store. The methodology is designed to examine the impact of application usage factors on user sentiment and engagement. The research procedure is inspired by the work of Amrie *et al.* [19], with modifications to suit the specific context of this study. The stages of the research methodology are illustrated in Figure 1.

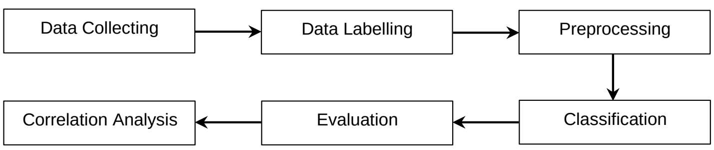

Figure 1. Research methodology

3.1. Data collecting

The first step in the methodology is the collection of user reviews. Using web scraping techniques, we extracted reviews for the Threads and X applications from the Google Play Store and App Store. The tools google-play-scraper and app-store-scraper are utilized for this purpose. The collected reviews are then categorized based on the respective application and platform. This categorization helps investigate whether the platform used contributes to the observed changes in daily active users for Threads and X. The reviews, which are in English, are merged into a single dataset using the pandas library in Python.

3.2. Data labelling

Once the data is collected, the next step is labelling the reviews based on sentiment. The sentiment of each review is determined using the rating provided by the user:

– Positive: reviews with a rating above three (>3).
– Neutral: reviews with a rating of three.
– Negative: reviews with a rating below three (<3).

This labelling process is automated using a Python script that utilizes the pandas library.

3.3. Preprocessing

Before entering the classification or sentiment analysis stage for user reviews of applications X and Threads, essential steps in the text mining process must be applied to prepare the data correctly. These steps help ensure the accuracy and efficiency of sentiment analysis and allow the smooth execution of natural language processing (NLP) algorithms and tools. The tools used for this preprocessing are natural language toolkit NLTK and demoji. The text mining process consists of several steps that need to be performed to prepare review data, both from application X and Threads, before sentiment analysis is conducted. These steps include as follows.

3.3.1. Tokenization

According to Kumar *et al*. [20], after the data is cleaned, the first step is tokenization to enhance the efficiency of NLP algorithm execution. Tokenization involves breaking down reviews into tokens, where each word in a sentence is considered a token. During this process, the frequency of each word is measured and stored for further reference. In the tokenization stage, periods and punctuation marks are removed, and all words initially in uppercase are converted to lowercase to achieve uniformity in the system. This step is considered very useful in preparing data for sentiment analysis.

3.3.2. Removal of stop words

Kumar *et al*. [20] explain that stop words, such as is, an, and the, which do not play a significant role in determining the sentiment of a word, are eliminated from the dataset. These words often only fill space and do not contribute meaningfully to sentiment analysis. The process of removing stop words aims to improve the efficiency of algorithms, as these words can cause performance degradation by consuming resources without providing valuable information. Depending on the language and script used, each country may have a different list of stop words, and this removal helps ensure a focus on words that have a more significant impact on sentiment analysis.

3.3.3. Stemming

Stemming is a technique used to strip away affixes (such as suffixes, prefixes, infixes, and circumfixes) from a word or phrase to derive a root form. For instance, transforming the words "amazing" or "amazed" into "amaze" aims to extract a more fundamental representation of the term. Stemming aims to eliminate inflected forms and various types related to a term into a specific base form. This process reduces the overall number of words and improves processing efficiency [9].

Feature extraction involves extracting relevant characteristics from a dataset, including formats like text and images, and converting them into a format compatible with machine learning (ML) algorithms. This study employs the term frequency-inverse document frequency (TF-IDF) technique using the scikit-learn library. TF-IDF is utilized for weighting to assess the significance of a word or term within a document or corpus [21].

3.4. Classification

In performing the classification, the approach used in this research is the SVM approach. SVM is a binary linear classification that is not probabilistic. The primary objective of SVM is to partition the dataset into distinct groups to attain the maximum marginal hyperplane (MMH). SVM employs the kernel trick strategy, wherein the kernel transforms a low-dimensional input space into a higher-dimensional space. In other words, by adding more dimensions, the kernel resolves problems that cannot be separated into separable issues. SVM classification has excellent precision and functions efficiently in high-dimensional spaces [21].

3.5. Evaluation

Evaluation is conducted to measure the performance of the implemented classification model. This evaluation process includes accuracy, precision, recall, and F1-score metrics. Accuracy reflects how well the model can classify correctly, while precision measures the model's accuracy in identifying a particular class. Recall indicates how well the model can rediscover instances of a class, and the F1 score provides a balance between precision and recall. The implementation of the SVM model in this research is evaluated using the scikit-learn library.

3.6. Correlation analysis

After completing the sentiment analysis process on the testing data of X and Threads application reviews, the next step is to correlate the sentiment analysis results with application usage factors. The application usage factors in this research are divided into four main categories: usability, features, design, and support, with each category having a list of keywords representing those aspects. Usability, encompassing ease of use and application efficiency, is crucial in early user experiences [22]. Application features can enhance user engagement and encourage repeated usage [23]. The application design also plays a vital role, where an attractive and intuitive design can improve user satisfaction [24]. Furthermore, customer support significantly impacts building trust and user loyalty. Effective support factors can help resolve user issues quickly and efficiently [25]. These four factors interact to form the overall user experiences. Table 1 contains keyword lists for each category utilizing the NLTK corpus lemmas and synsets library.

Each review will be examined to determine whether it contains keywords from one of the categories of usage factors (usability, features, design, support) by utilizing the NLTK corpus lemmas and synsets library to obtain hypernyms, hyponyms, meronyms, and holonyms for these four factors. If a correspondence is found, the review will be categorized as positive, negative, or neutral based on the sentiment detected. The correlation results will then be interpreted to conclude the influence of user sentiment on each application usage factor. The implications of these findings are expected to guide application developers in enhancing specific aspects that impact user preferences.

The Pearson method from the pandas library will be used in the correlation analysis stage. Correlation visualization will be generated using the matplotlib library. The entire correlation analysis process will be implemented using a Python script. All these steps will be executed through Python scripts, utilizing the mentioned functions and ensuring accuracy, clarity, and ease of interpretation of the correlation analysis results.

Table 1. List of keywords for application usage factors

Factors	Keywords	Subcategories
Usability	function, application, utility, enjoy, useful, usability, and usable	positive, neutral, negative
Features	features, feed, product, profile, and trending	positive, neutral, negative
Design	design, interface, interaction, navigation, and experience	positive, neutral, negative

4. RESULTS AND DISCUSSION

In this section, an analysis will be conducted on the research results based on the previously explained methodology. The main focus of this analysis is to identify the factors that have led to a significant decrease in the usage of the social media application Threads in a relatively short period. Additionally, it aims to understand why users return to using Twitter or X after leaving Threads.

4.1. Data collecting

Reviews for the social media applications X and Threads were collected through scraping from the Google Play Store and App Store. Following the collection, reviews were grouped by application and merged to form a comprehensive dataset for each platform. Subsequent data engineering steps included cleaning the data to remove noise and irrelevant information and performing text mining processes like tokenization, stop-word removal, emoticon/emoji removal, stemming, and weighting. These processes utilized the NLTK and demoji libraries to prepare the data for analysis. The results of the collected data can be seen in Table 2.

Table 2. Data collecting result

Application	Dataset	Number of rows
X/Twitter	Raw data	179.622
	Raw data starting from July 5, 2023 (Threads release date)	35.642
	Training dataset (80% of the dataset)	28.513
	Testing dataset (20% of the dataset)	7.129
Threads	Raw data	39.316
	Training dataset (80% of the dataset)	31.452
	Testing dataset (20% of the dataset)	7.864

4.2. Data labelling

The training data collected from the user reviews of both X and Threads applications was labelled according to the ratings provided by users on the Google Play Store and App Store. Reviews were categorized into positive (>3), neutral (3), and negative (<3) sentiments. The distribution of these labels is summarized in Table 3, which highlights the sentiment trends across both platforms.

The data shows that X has more negative reviews than positive and neutral ones, indicating general user dissatisfaction. In contrast, Threads has a more balanced distribution with a significant number of positive reviews, which suggests a more favourable reception among its users. This sentiment distribution provides a foundation for analyzing user behaviour towards each application and understanding the factors that may influence shifts in user engagement. Insights derived from this labelling process are critical for subsequent analyses focusing on the decline in user engagement with Threads and the factors contributing to users returning to X after initially leaving.

Table 3. Distribution of sentiment labelling for training data

Application	Sentiment	Number of data
X/Twitter	Positive	10.199
	Neutral	1.172
	Negative	17.142
Threads	Positive	16.720
	Neutral	2.397
	Negative	12.335

4.3. Sentiment analysis

The sentiment analysis employs the SVM classification method, categorizing user reviews into positive, neutral, or negative sentiments. The SVM's performance was assessed using precision, recall, F1-score, and accuracy metrics, with key results summarized in Table 4. Based on Table 4, the method shows strong results in identifying positive and negative sentiments for X, with respective F1-scores of 81 and 88%, indicating a robust ability to classify these sentiments correctly. However, it fails to identify neutral sentiments, reflected in a 0% score across precision, recall, and F1-score. It suggests that the SVM could not discern any neutral reviews, likely due to their under representation or ambiguous linguistic features in the training data.

For Threads, while the SVM also demonstrates a high recall of 93% for positive sentiments, suggesting it captures the majority of positive reviews, the precision is lower at 76%, indicating some non-positive sentiments are mistakenly labelled as positive. Like X, Threads reviews show poor SVM performance on neutral sentiments, with a very low recall of 3%, emphasizing the model's consistent struggle with neutral classifications across platforms. Though relatively effective, negative sentiment detection in Threads reviews is weaker than in X, which might be attributed to less distinctive linguistic cues in expressing dissatisfaction on Threads. These findings underscore a significant class imbalance and the necessity for better training data balance or enhanced feature extraction to improve classification accuracy, especially for neutral sentiments.

Based on Table 5, the results for X indicate a predominance of negative sentiments consistent with training data performance. In contrast, Threads displayed a majority of positive sentiments in the testing phase despite some neutral and negative feedback. This variation underscores the platforms' differing user experiences and potential areas for improvement, particularly in enhancing sentiment detection algorithms.

Table 4. Classification performance

Application	Class	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
X/Twitter	Positive	84	78	81	83.57
	Neutral	0	0	0	
	Negative	84	92	88	
Threads	Positive	76	93	84	78.00
	Neutral	42	3	6	
	Negative	82	72	76	

Table 5. Sentiment analysis results

Application	Sentiment	Number of data
X/Twitter	Positive	2.249
	Neutral	0
	Negative	4.880
Threads	Positive	5.245
	Neutral	53
	Negative	2.566

4.4. Correlation between X and Threads

Following the sentiment analysis, the study correlated these results with application usage factors categorized into usability, features, design, and support. The analysis examined whether the reviews contained keywords related to these usage factors and classified them into positive, negative, or neutral sentiments based on their content. The mapping results are summarized in Table 6. Table 6 presents the distribution of user sentiments across usability, features, design, and support for the applications X and Threads. It's important to note that one review may address multiple usage factors, reflecting complex user experiences that do not easily categorize into unique categories.

X exhibits a predominance of negative sentiments across all factors, with exceptionally high discontent noted in support (3518 negative reviews) and usability (2391 negative reviews). Despite receiving many positive reviews, the high volume of negative feedback highlights critical areas for improvement in user experience. Threads show a more even distribution between positive and negative sentiments across all usage factors. However, even with a balanced feedback profile, negative reviews closely match the positives, especially in features and support, indicating areas where user satisfaction could be enhanced. A small but notable number of neutral reviews suggests that some users remain indifferent or unsatisfied with certain aspects of the application, which could signal a need for targeted improvements.

Figure 2 illustrates the correlation between user sentiments on usability, design, features, and support for applications X and Threads. Correlations range from -1 to 1, with +1 indicating a perfect positive relationship, -1 signifying a perfect negative relationship, and 0 showing no relationship. While correlation does not imply causation, it offers insights into how user sentiments towards one application may relate to sentiments towards another.

Table 6. Mapping results of reviews with application usage factors

Application	Sentiment	Application usage factors			
		Usability	Features	Design	Support
X/Twitter	Positive	859	586	497	840
	Neutral	0	0	0	0
	Negative	2391	1703	1438	2678
	Total	3250	2289	1935	3518
Threads	Positive	859	785	543	604
	Neutral	35	35	18	27
	Negative	1042	859	478	947
	Total	1936	1679	1039	1578

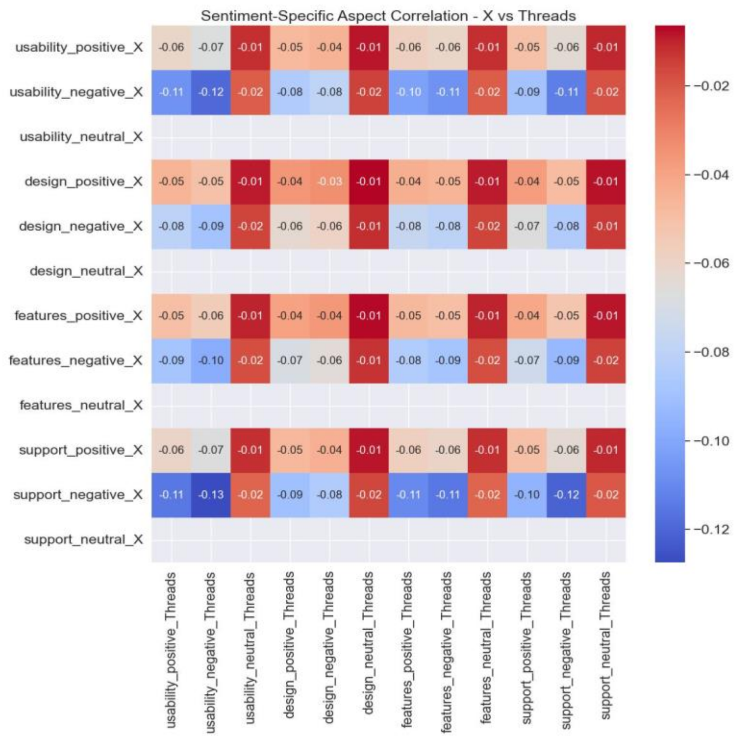

Figure 2. Correlation analysis of sentiment and application usage factors

From the correlation matrix, it is evident that there is a negative correlation between positive sentiments on the usability of application X and negative sentiments on the usability of Threads, suggesting an inverse relationship between user satisfaction across these two applications. Similarly, positive sentiments about the features and support of application X correlate negatively with negative sentiments about the features and support of Threads. This indicates that users who appreciate the features and support of application X tend to view these aspects less favourably in Threads.

5. DISCUSSION AND IMPLICATIONS

In addressing the gaps identified in previous research on user sentiment and engagement in social media, this study provides a nuanced understanding of how user sentiments directly correlate with shifts in platform usage, especially in the competitive dynamics between platforms like X and Threads. While existing literature has often highlighted the volatility of user engagement, our analysis delves deeper into the immediate impacts of user dissatisfaction on one platform benefiting another, albeit temporarily, if the newcomer fails to maintain superior service and continuous innovation. Our findings suggest a complex relationship between platform features, user satisfaction, and engagement dynamics. Initial positive reception towards Threads, driven by negative sentiments towards X, underscores the influence of user perception on platform competition. However, as Threads failed to sustain user engagement, our study illustrates the critical need for platforms to continuously adapt and improve based on user feedback to retain their user base.

The study employed sentiment analysis through ML, primarily focusing on user reviews from the Google Play and App Store. While effective, this method has limitations in fully capturing the nuances of human emotions, such as sarcasm, and may not comprehensively represent the global user base. The methodology, centred on a broad selection of keywords and application usage factors, may not encompass the full spectrum of reasons why users might choose to engage with or abandon a platform. Future research could incorporate diverse data sources to address these limitations, such as direct user surveys and interviews. This approach would allow for a richer and more detailed understanding of user motivations and reactions, potentially offering insights more reflective of different regional contexts and nuanced user experiences.

Conclusively, this research highlights that sustained user engagement in social media platforms requires more than initial user acquisition; it necessitates a relentless focus on enhancing user experience and quickly adapting to their evolving needs. Future studies should explore the long-term effects of platform strategies on user retention and satisfaction, potentially guiding more tailored and effective enhancements in platform development. By broadening the scope of data and incorporating advanced analytical techniques, further research can provide deeper insights into the intricate dynamics of user sentiment and platform success.

6. CONCLUSION

After dominating as Twitter, now rebranded as X, the platform witnessed significant competition from Meta's Threads, which, despite a strong start, saw a quick decline in user engagement. This study reveals a nuanced dynamic between X and Threads, where initial dissatisfaction with X due to controversial changes contributed to early positive sentiments towards Threads. However, as Threads' user engagement waned, X began to recover its user base. Our findings indicate that positive sentiments toward features, usability, design, and support in one platform often correlate with dissatisfaction in these areas on the rival platform, suggesting that enhancements in one app can negatively impact perceptions of the other. Notably, this relationship is underscored by negative correlations such as -0.060775 and -0.049719 between the usability and features of X and Threads, respectively. While these insights are valuable, the study's limitations include a narrow data set that might not fully capture the fluid dynamics of social media trends and user behaviour changes post-analysis. Moreover, the sentiment analysis used may not fully grasp the complexities of human emotion due to the broad keyword selection. To address these gaps, future research should delve deeper into sentiment analysis at more granular levels and consider diverse demographic factors to understand better what drives user preferences and satisfaction across different social media platforms.

ACKNOWLEDGEMENTS

The authors sincerely thank the Ministry of Communication and Information Technology, Indonesia (KOMINFO), for providing the scholarship and financial support that made this study and research possible. This assistance has been instrumental in facilitating the pursuit of academic endeavours and contributing to completing this paper. The authors sincerely appreciate the opportunities and resources provided by Kominfo, which have contributed significantly to the advancement of knowledge and the successful completion of this paper.

REFERENCES

[1] M. A. Habib and M. A. H. Anik, "Impacts of covid-19 on transport modes and mobility behavior: analysis of public discourse in twitter," *Transportation Research Record*, vol. 2677, no. 4, pp. 65–78, 2023, doi: 10.1177/03611981211029926.

[2] L. Pophal, "Should you add threads to your social media strategy?," *Information Today*, vol. 40, no. 7, pp. 39–40, 2023.

[3] D. F. Carr, "Threads app usage down 79% after a month," *Similar Web*. Accessed: Feb. 12, 2024. [Online]. Available: https://www.similarweb.com/blog/insights/social-media-news/threads-first-month/

[4] B. Liu, *Sentiment analysis and opinion mining*. Morgan & Claypool Publishers, 2012.

[5] C. A. Iglesias and A. Moreno, "Sentiment analysis for social media," *Applied Sciences*, vol. 9, no. 23, Nov. 2019, doi: 10.3390/app9235037.

[6] M. C. Rahmadan, A. N. Hidayanto, D. S. Ekasari, B. Purwandari, and Theresiawati, "Sentiment analysis and topic modelling using the lda method related to the flood disaster in jakarta on twitter," in *2020 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)*, IEEE, Nov. 2020, pp. 126–130, doi: 10.1109/ICIMCIS51567.2020.9354320.

[7] Mussalimun, E. H. Khasby, G. I. Dzikrillah, and Muljono, "Comparison of k-nearest neighbor (K-NN) and naïve bayes algorithm for sentiment analysis on google play store textual reviews," in *2021 8th International Conference on Information Technology, Computer and Electrical Engineering (ICITACEE)*, IEEE, Sep. 2021, pp. 180–184, doi: 10.1109/ICITACEE53184.2021.9617217.

[8] B. R. S, S. L. G. Moses, G. Chinnadurai, J. V. Anand, V. Janakiraman, and P. Anand, "Support vector machine for image classification," *Journal of the Asiatic Society of Mumbai*, vol. 97, no. 4, 2023.

[9] E. A. Sukma, A. N. Hidayanto, A. I. Pandesenda, A. N. Yahya, P. Widharto, and U. Rahardja, "Sentiment analysis of the new indonesian government policy (omnibus law) on social media twitter," in *2020 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)*, Nov. 2020, pp. 153–158, doi: 10.1109/ICIMCIS51567.2020.9354287.

[10] C. Sanavio, E. Tignone, and E. Ercolessi, "Entanglement classification via witness operators generated by support vector machine," *The European Physical Journal Plus*, vol. 138, no. 10, Oct. 2023, doi: 10.1140/epjp/s13360-023-04546-5.

[11] A. Acín, D. Bruß, M. Lewenstein, and A. Sanpera, "Classification of mixed three-qubit states," *Physical Review Letters*, vol. 87, no. 4, p. 040401, Jul. 2001, doi: 10.1103/PhysRevLett.87.040401.

[12] A. Bhalla, "Comparative analysis of text classification using svm, naïve bayes, and knn models," in *2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Aug. 2023, pp. 878–883, doi: 10.1109/ICIRCA57980.2023.10220728.

[13] M. D. H. Jasy, S. Al Hasan, M. I. K. Sagor, A. Noman, and J. M. Ji, "A performance evaluation of sentiment classification applying svm, knn, and naive bayes," in *2021 International Conference on Computing, Networking, Telecommunications & Engineering Sciences Applications (CoNTESA)*, IEEE, Dec. 2021, pp. 56–60, doi: 10.1109/CoNTESA52813.2021.9657115.

[14] M. S. Shaqiri, T. Iljazi, L. Kamberi, and R. Ramani-Halili, "Differences between the correlation coefficients pearson, kendall and spearman," in *5th International Conference of Natural Science and Mathematics*, Tetovo, 2023, pp. 392-397.

[15] T. Gnambs, "A brief note on the standard error of the pearson correlation," *Collabra: Psychology*, vol. 9, no. 1, Sep. 2023, doi: 10.1525/collabra.87615.

[16] H. Al-Oklah, T. M. Said, and T. Alodat, *Introduction to Statistics Made Easy*, Riyadh, Saudi Arabia: King Saud University Press, 2014.

[17] K. Hameli, *Teknikat statistikore me shumë ndryshore me aplikim në spss*. Open Source, 2015.

[18] A. M. Rahat, A. Kahir, and A. K. M. Masum, "Comparison of naive bayes and svm algorithm based on sentiment analysis using review dataset," in *2019 8th International Conference System Modeling and Advancement in Research Trends (SMART)*, 2019, pp. 266–270, doi: 10.1109/SMART46866.2019.9117512.

[19] S. Amrie, S. Kurniawan, J. H. Windiatmaja, and Y. Ruldeviyani, "Analysis of google play store's sentiment review on indonesia's p2p fintech platform," in *2022 IEEE Delhi Section Conference (DELCON)*, Feb. 2022, pp. 1–5, doi: 10.1109/DELCON54057.2022.9753108.

[20] S. Kumar, N. A. Jailani, A. R. Singh, and S. Panchal, "Sentiment analysis on online reviews using machine learning and nltk," in *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*, IEEE, Apr. 2022, pp. 1183–1189, doi: 10.1109/ICOEI53556.2022.9776850.

[21] A. P. Pimpalkar and R. J. R. Raj, "Influence of pre-processing strategies on the performance of ml classifiers exploiting tf-idf and bow features," *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, vol. 9, no. 2, pp. 49–68, Jun. 2020, doi: 10.14201/ADCAIJ2020924968.

[22] Z. Huang and M. Benyoucef, "A systematic literature review of mobile application usability: addressing the design perspective," *Universal Access in the Information Society*, vol. 22, no. 3, pp. 715–735, Aug. 2023, doi: 10.1007/s10209-022-00903-w.

[23] D. Anandya, Indarini, and A. T. Septiani, "The formation of customer satisfaction in social media, the role of frequency, and duration of use," in *The 17 th International Symposium on Management (INSYMA 2020)*, Paris, Atlantis Press, 2020, doi: 10.2991/aebmr.k.200127.018.

[24] B. M. Martinez and L. E. McAndrews, "The influence of mobile application design features on users' stickiness intentions as mediated by emotional response," *International Journal of Retail & Distribution Management*, vol. 49, no. 11, pp. 1497–1511, Oct. 2021, doi: 10.1108/IJRDM-06-2020-0232.

[25] N. L. Rane, A. Achari, and S. P. Choudhary, "Enhancing customer loyalty through quality of service: effective strategies to improve customer satisfaction, experience, relationship, and engagement," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 5, no. 5, May 2023, doi: 10.56726/IRJMETS38104.

BIOGRAPHIES OF AUTHORS

Rezki Khairunnas is pursuing a master's in information technology at the University of Indonesia (UI). He obtained his bachelor's degree in information systems and technology from the Bandung Institute of Technology (ITB) in 2018. He has since been actively engaged as an IT Consultant, leveraging his expertise to tackle complex challenges in the industry. He can be contacted at email: rezki.khairunnas@ui.ac.id.

Jeri Apriansyah Pagua is a seasoned banking professional with a bachelor's degree in Informatic Technology from the University of Bengkulu and is currently pursuing a Master of Information Technology at the University of Indonesia. Beyond his professional endeavours, he is deeply immersed in research, focusing on information retrieval, IT adoption, knowledge management, data management, and project management. He can be contacted at email: jeri.apriansyah@ui.ac.id.

Ghina Fitriya holds a bachelor's degree in applied computer science from the State Polytechnic of Cyber and Crypto with a major in cybersecurity in 2020. She is pursuing a master's degree at the University of Indonesia's Faculty of Computer Science. With experience in cybersecurity and cyber incident handling, she is pursuing research in network security, computer forensics, knowledge management, and incident response. She can be contacted at email: ghina.fitriya@ui.ac.id.

Yova Ruldeviyani holds bachelor's and master's degrees in computer science from the University of Indonesia and currently serves as an associate professor at the same institution. Her research interests encompass Database systems, business intelligence, enterprise resource planning, e-government, and software development. With expertise in IS/IT management & governance, software engineering, and data science & analytics. She has made significant academic contributions through numerous publications and research projects. Her dedication to advancing knowledge and innovation in areas such as E-government and software engineering establishes her as a prominent figure in computer science. She can be contacted at email: yova@cs.ui.ac.id.