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SENTIMENT ANALYSIS OF PLAYSTORE REVIEWS FOR THE 'X' APPLICATION: EXAMINING THE IMPACT OF ELON MUSK'S TAKEOVER ON USER SENTIMENT

BEMM466 - Business Project

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# 1. Introduction

Elon Musk's takeover of Twitter, now known as X, in late 2022 was a watershed event for one of the world's most powerful social media sites (Wikipedia contributors, 2024). Musk's aim for the platform to become a hub for free expression, innovation, and less moderation has provoked substantial debate among its global users (Proferes, 2023). These changes have had a substantial impact on user experience and sentiment, making it critical to investigate how such leadership transfers affect user engagement and overall happiness (Garcia-Pueyo et al., 2023). In the fast-changing social media ecosystem, where platforms like X impact public conversation and consumer behavior, this understanding is especially important for app developers and business strategists.

This research will assess user opinion on the X application from October 2022 to July 2024, a period marked by significant changes under Musk's leadership, including the major rebranding of Twitter to X in July 2023. This study aims to uncover key trends in user sentiment and provide actionable insights for app developers by focusing on approximately 200,000 user reviews filtered from a combined dataset that originally included two million entries from Kaggle and additional reviews scraped from November 2023 to July 2024. The primary goal is to recognize fluctuations in user sentiment over time, particularly in reaction to large platform changes, and to provide recommendations that may improve user happiness and engagement.

The approach used in this study includes a number of complex data processing and analytical tools. The preprocessing process involves cleaning up the text data by eliminating URLs, email addresses, special characters, and numerals, translating popular slang phrases, and filtering out foul language. English-language reviews are then normalized, tokenized, and lemmatized to establish a uniform analytical foundation. The VADER sentiment analysis tool is then used to identify reviews as positive, negative, or neutral based on their compound sentiment scores (Zhang, 2023).

The processed text data is then vectorized using the TF-IDF approach, and dimensionality is reduced using Truncated SVD to prepare the data for machine learning models. Several models, including Multinomial Naive Bayes, Support Vector Machines (SVM), Logistic Regression, Random Forest, and XGBoost, are trained and assessed using metrics like accuracy, precision, recall, and F1 score. These models not only identify sentiment, but they also give insights into user input on different app characteristics such as the user interface, ads, performance, and security.

A primary emphasis of this research is the reported reduction in user sentiment in July 2023, which coincided with Twitter's rebranding to X. By linking these sentiment patterns to external events and internal platform modifications, the study provides a full knowledge of the elements driving user sentiment throughout this important era (Proferes, 2023).

This report is arranged as follows: The following section gives the study's context and background, highlighting the research's relevance and significance in the contemporary situation. Following this, the research questions that will lead the inquiry are presented. The literature study then delves into previous studies on sentiment analysis, the effect of leadership changes on technological platforms, and the function of social media in affecting public opinion (Proferes, 2023). The methodology section describes the research strategy, data gathering procedures, analytical approaches, and machine learning models (Zhang, 2023). The results and analysis section summarizes the important findings, with a particular emphasis on the influence of rebranding to X (Garcia-Pueyo et al., 2023). The discussion section evaluates the findings in light of the larger research concerns and considers their business relevance. Finally, the paper makes suggestions for app creators, offers strategic guidance for boosting user sentiment, and discusses future research.

# 2. Context and Background

Elon Musk's acquisition of Twitter in October 2022 and subsequent rebranding as X marks a dramatic change in social media (Wikipedia authors, 2024). Renowned for his transforming leadership at companies like Tesla and SpaceX, Musk carried with him a vision of Twitter being a platform with less content restrictions, an emphasis on free expression, and creative technical integration. The changes Musk has made affected not only how users engage with the platform but also the larger digital ecosystem, so it is a topic of great scholarly and commercial interest (Krishna & Prashanth, 2023). As seen in Figure 1, Twitter's rebranding to X marks the change in platform identity under Musk's direction.



Figure 1. Rebranding the twitter logo to X. Acquired from Drenik (2023).

As one of the most powerful platforms globally, Twitter/X plays a key role in molding public conversation, influencing political narratives, and driving commercial choices (Liao & Huang, 2022). Multiple stakeholders, including app developers, business strategists, marketers, and politicians, must understand the impact Musk's leadership has had on user opinion. For app developers, data from this study can influence the improvement of user experience and advise decisions on feature expansions or revisions (Krishna & Prashanth, 2023). Business strategists and marketers may exploit the insights to forecast industry developments and change their plans appropriately (Wang et al., 2023). Policymakers may also find the data helpful in comprehending the larger social consequences of changes in key digital platforms, especially addressing concerns like disinformation, privacy, and content moderation (Guldemond et al., 2022).

The specific problem this study tackles is the considerable shift in user attitude following Elon Musk’s acquisition and the subsequent rebranding to X. While leadership changes in big firms typically lead to modifications in organizational culture and strategic direction, the direct influence on user opinion and engagement remains underexplored in the context of social media platforms. This research tries to address that vacuum by evaluating how consumers have responded to these big changes. The study will assess if the rebranding to X have favorably or negatively affected user impressions. By doing so, it will give actionable insights for boosting user happiness and engagement, which are crucial for the long-term viability of the platform (Miyazaki et al., 2022). Ultimately, our research hopes to add to the greater knowledge of how leadership transitions in digital businesses effect user behavior and attitude, giving significant lessons for the industry at large (Saepudin et al., 2023).

# 3. Research Questions

The dynamic fluctuations in user attitude on the X platform following Elon Musk’s purchase offer a complicated subject that demands research. To address this issue, the study is directed by a set of research questions aimed to uncover the intricacies of user attitude throughout this transitional moment.

The first study question tries to determine how user attitude on the X platform has developed from October 2022 to July 2024, particularly in reaction to Elon Musk's leadership and the renaming of Twitter to X. This topic is essential to the inquiry since it tries to identify critical times of sentiment shift, with a special focus on the large dip in sentiment reported in July 2023. Existing studies suggest that the takeover and rebranding have greatly influenced user attitudes, with an increase in unfavorable emotions notably visible throughout major milestones in the transition (Schmidt et al., 2023). By evaluating sentiment patterns throughout this timeframe, the research will analyze the long-term ramifications of the rebranding and other strategic adjustments adopted by Musk. This analysis is critical for determining if the transitions in leadership and platform identity have favorably or adversely affected user impressions over time.

Another crucial study topic investigates whether individual elements of the X application have most substantially affected user sentiment and how these attitudes have differed across other parts of the platform, such as the user interface, ads, performance, and security. Research reveals that Musk’s adjustments to content filtering and the platform's user interface have contributed to increasing division and unhappiness among specific user groups (Barrie, 2022). By studying sentiment distribution across various aspects, the study tries to find areas that may require attention from app developers.

Additionally, the study investigates the prominent themes or subjects present in negative and neutral user evaluations and how these themes link with general sentiment patterns on the site. Through topic modeling and word cloud analysis, the research will discover reoccurring difficulties that may not be readily obvious from sentiment scores alone. Previous assessments have shown recurring difficulties including as security concerns and the impact of less content filtering on user experience, which have contributed to unfavorable emotions on the site (Hickey et al., 2023). Understanding these topics will provide deeper insights into the precise factors causing user displeasure or neutrality, delivering a more nuanced perspective on user sentiment.

# 4. Literature Review

## 4.1 Sentiment Analysis in Businesses

It acts as a decision support tool, enabling organizations to monitor customer sentiment in real-time, forecast consumer trends, and measure the impact of marketing activities. Sentiment analysis, for example, has been successfully utilized to anticipate financial market movements by assessing the sentiment of news articles and social media postings, emphasizing its use in situations where consumer sentiment directly impacts market dynamics (Yenkikar & Babu, 2023).

In brand management, sentiment analysis helps organizations to evaluate public perception about their products and services. This is particularly crucial in today’s linked world, as bad opinion may travel swiftly across social media channels, potentially hurting a brand's reputation. By evaluating client feedback, organizations may foresee growing difficulties and respond promptly, thereby preserving a favorable brand image.

Moreover, by measuring changes in sentiment over time, organizations may modify their offers to better match consumer expectations, ultimately boosting customer happiness and loyalty. For example, sentiment analysis has been utilized in the tourist industry to leverage on big data, enabling firms to adapt their offerings depending on consumer feedback and market needs (Alaei et al., 2017).

## 4.2 Impact of Leadership Changes on Technology Platforms

When a high-profile individual such as Elon Musk assumes leadership of a firm, the impact is typically compounded, given the power such executives carry in the IT industry. The literature on leadership transitions in technology platforms highlights numerous critical topics, including adjustments in business strategy, changes in organizational culture, and the influence on stakeholder perceptions. Chiu and Walls (2019) underline that changes in strategic leadership may dramatically affect company social performance and stakeholder involvement, particularly when new leaders prioritize shareholder interests above other stakeholders during moments of financial difficulty. This underlines the essential role that leadership plays in setting the strategic direction and general culture of a technological organization.

Twitter's operations and policies have changed significantly under his aggressive decision-making and challenge to the status quo attitude to leadership. Among these developments have been significant layoffs, modifications to the content management rules on the site, and the addition of fresh tools meant to increase user interaction. While some of these developments have been hailed for encouraging creativity, others have generated debate and drawn closer examination of Musk's leadership approach (Dey et al., 2020).

In the case of Twitter, Musk's promotion of free speech and his choice to eliminate content regulation have been received with differing reactions, with some users praising the changes and others raising distress about the possibility for greater disinformation and dangerous content (Barrie, 2022).

The influence of leadership changes on technology platforms is directly connected to the larger company culture. However, such transitions may also result in pushback from staff used to the prior leadership's attitude. In the case of Twitter, the quick changes under Musk’s leadership apparently led to higher staff turnover and worries about job security, showing the possible drawbacks of such transitions. According to Al-Ali et al. (2017), change-oriented leadership has a substantial effect on organizational culture, which in turn determines the success of change management inside companies.

## 4.3 Case studies and relevant theories

One famous example is the leadership change at Apple following Steve Jobs' resignation and eventual demise. Tim Cook's rise to CEO brought about a transition in Apple's leadership style, with a stronger emphasis on operational efficiency and gradual innovation. While Cook's leadership has been lauded with sustaining Apple's profitability and increasing its product line, it has also been critiqued for losing the visionary approach that typified Jobs' tenure (Liu, 2021).

Another interesting case study is Microsoft's transition under Satya Nadella, who succeeded Steve Ballmer as CEO in 2014. Nadella's leadership has been defined by a strategic focus on cloud computing, artificial intelligence, and open-source technologies, which have created tremendous development for the corporation. Nadella's emphasis on empathy and a growth mentality has also led to a favourable transition in Microsoft's organizational culture, making it a more inclusive and inventive firm (Prakash et al., 2021).

These case studies illustrate the role of leadership in defining the direction and success of technology enterprises. They also emphasise the possible issues involved with leadership transitions, particularly when the new leader's vision varies from that of their predecessor. In the case of Twitter, Musk's leadership signals a striking break from the company's prior management, raising doubts about the long-term repercussions for the platform's users and stakeholders. This circumstance coincides with results from research that indicates how transformational digital leadership plays a significant role in generating organizational innovation and influencing strategic direction during digital transitions (Pepe & Pavone, 2021).

According to transformational leadership theory, good leaders inspire and encourage their subordinates by developing a vision for the future and supporting innovation and change. Elon Musk's leadership style fits this hypothesis very nicely as he is renowned for his imaginative approach and readiness to take chances in search of audacious objectives (Chen et al., 2019). Conversely, contingency theory contends that the context in which a leader operates determines their effectiveness, so stressing the need of situational elements in determining the success of leadership transitions, especially in dynamic and fast-paced sectors like technology (Kim & Shin, 2019).

## 4.4 The Role of Social Media in Brand Perception

Social media has a vital role in moulding public impressions of brands, particularly in the technology industry. Platforms like Twitter, Facebook, and Instagram give firms with a direct avenue to engage with customers, post information, and respond to comments. However, these platforms also expose firms to public scrutiny, since consumers can quickly share their ideas and experiences with a broad audience. Schivinski and Dabrowski (2016) underline that in this dynamic context, user-generated material frequently has a beneficial impact on both brand equity and brand attitude, while firm-created content predominantly impacts brand attitude.

Research suggests that social media can amplify both good and negative attitudes, making it a strong tool for brand management. Positive social media interactions may boost a brand's reputation, promote client loyalty, and drive sales. Conversely, bad encounters can swiftly snowball into public relations catastrophes, possibly hurting the brand's image and undermining consumer trust (Gupta & Sandhane, 2022).

Within Twitter, the platform's influence on brand perception has especially been noteworthy. Twitter is a great source of consumer comments as it is a real-time public arena where individuals may quickly express their ideas and opinions. Negative sentiment, then, may likewise travel quickly and possibly affect the impressions of other people. Research examining user sentiment towards different businesses and brands on Twitter, for instance, indicated that sentiment towards brands greatly influences brand perception and loyalty, particularly in cases when unfavourable comments are spread rapidly and broadly on the site (Hu et al., 2017).

Social proof, which holds that people are more likely to adopt the ideas and behaviours of others when they see them being expressed publicly, directly relates to the function of social media in brand perception. Good interactions on social media can create a virtuous cycle whereby people are likely to regard the brand more favourably depending on the positive experiences shared by others. bad interactions, on the other hand, might cause a downward spiral whereby bad attitude spreads and compromises brand image even more. On sites like Twitter, where the public and conversational character magnifies the influence of user interactions, this phenomena is especially noticeable (Barhorst et al., 2020).

Moreover, social media sites like Twitter can act as crucial conduits for brand communication amid emergencies. The speed at which information spreads on social media implies that corporations must be proactive in controlling their online presence and responding to unfavourable feedback. A well-handled crisis may lessen the harm to a brand's reputation, while a badly managed reaction might compound the problem. Studies have indicated that organisations who actively communicate with their audience on social media during a crisis are more likely to sustain consumer trust and loyalty, as opposed to those that remain mute or unresponsive (Palomino & Aider, 2022).

Public perception about businesses is greatly shaped by influencers, who frequently have sizable following on sites such Twitter, Instagram, and YouTube. Particularly among younger customers who are more inclined to be swayed by social media celebrities, their praises or critiques can significantly affect the impression of a business. This emphasises the significance of businesses closely controlling their connections with influencers and making sure their brand is shown favourably on several social media platforms.

Elon Musk's prominence on Twitter, especially after the platform's renaming to X, and strong leadership have magnified its impact on brand impression. Mixed responses have greeted the rebranding; some people welcome the changes while others voice doubt or fear. Companies seeking to negotiate the changing terrain of brand image in the digital era must first understand how these emotions are communicated and spread on social media. Musk's purchase of Twitter had a clear effect on the social media activity of entrepreneurs, according to Zinoviev et al. (2023), therefore highlighting how greatly user behaviour and public opinion may be influenced by changes in platform leadership.

## 4.5 Gaps in the Literature

The present study on sentiment analysis, leadership transitions, and the influence of social media in brand perception gives significant insights, but there are noteworthy gaps that this study tries to solve. One notable gap is the scant study on the particular influence of leadership changes on user sentiment inside technological platforms. While studies have explored the impact of leadership transitions on company strategy and performance, there is a dearth of empirical study on how these changes influence user sentiment, particularly in the context of social media platforms like Twitter/X. For instance, it has been proven that leadership styles and decisions strongly effect user interactions and feelings, as evidenced in digital transformations driven by leadership inside firms (Sow & Aborbie, 2018).

To address the gap in the literature indicating the need for greater study on the long-term consequences of leadership transitions and rebranding initiatives using sentiment analysis, it is vital to examine how these factors influence user engagement and platform success over time. While sentiment analysis has been widely utilised in numerous fields, most research focus on short-term sentiment swings. However, there is insufficient understanding of how sentiment changes over lengthy periods following big business events. This gap is particularly pertinent in the context of Twitter's rebranding to X, where the long-term ramifications for user engagement and platform performance remain undetermined. Research has demonstrated that rebranding initiatives can have various consequences depending on the nature of the modifications made and the market position of the company (Roy & Sarkar, 2015).

To increase the comprehension of user sentiment, it's vital to connect sentiment analysis with other data sources, such as user demographics and behavioral data. While sentiment research delivers useful insights into user perceptions, it sometimes lacks the contextual information essential to properly appreciate the underlying causes of sentiment. By integrating sentiment analysis with different types of data, researchers may get a more holistic picture of user behavior and preferences, ultimately influencing more successful business initiatives. This integrated method has been proved to increase the accuracy of sentiment categorisation and user behavior predictions, leading to better-informed decision-making processes (Gong & Wang, 2018).

Finally, there is a need for greater study on the usefulness of alternative sentiment analysis methodologies in capturing the subtleties of user sentiment, particularly in the setting of informal and unstructured social media data. While machine learning and natural language processing techniques have evolved tremendously, issues persist in reliably reading the sentiment represented in social media messages, which typically incorporate slang, acronyms, and emojis. Addressing these problems is critical for enhancing the accuracy and reliability of sentiment analysis in commercial applications (Kalaivani & Jayalakshmi, 2021).

In conclusion, while the literature on sentiment analysis, leadership changes, and social media's effect on brand perception is substantial, there are various areas where further research is needed. This study tries to address these gaps by studying the influence of Elon Musk's leadership on user sentiment and brand perception following the rebranding of Twitter to X. By merging sentiment analysis with other data sources and concentrating on the long-term implications of leadership transitions, this research will contribute to a fuller understanding of the dynamics at play in the fast expanding technology industry.

# 5. Methodology

## 5.1 Research Method

This study adopts a mixed-methods research methodology, incorporating both quantitative and qualitative methodologies to examine user sentiment on the X platform following Elon Musk’s purchase and rebranding of Twitter. The quantitative part incorporates sentiment analysis utilising machine learning models such as Naive Bayes, SVM, and Random Forest, which are highly known for their effectiveness in categorising user evaluations into positive, negative, and neutral feelings. These models have been effectively employed in numerous research to categorise social media data, delivering strong accuracy in sentiment categorisation (Bhardwaj, 2020). A dataset of about 200,000 user evaluations was employed, giving a complete quantitative estimate of sentiment trends across time. The qualitative component supports this by employing Latent Dirichlet Allocation (LDA) to detect and examine repeating themes within negative and neutral reviews, offering deeper insights into the causes driving user opinion. LDA has shown useful in identifying significant themes from huge text corpora, delivering actionable insights beyond simple sentiment categorisation (Asgari et al., 2022). This mixed-methods approach offers a detailed and complete investigation of the influence of leadership changes and rebranding activities on user opinion. The picture below offers an overview of the technique utilised in this investigation.

A diagram of a process

Description automatically generated

Figure 2. Overview of the Methodology (Author’s own work)

## 5.2 Data Collection

For this study, two datasets of Google Play Store evaluations pertaining to the X application were gathered and merged. The initial dataset came from the well-known data science and machine learning portal Kaggle. Originally scraped using the Google Play Scraper, this dataset included user evaluations of the X app covering a period from April 30, 2010, to November 14, 2023. This large collection gave a historical perspective of user attitude prior to the momentous event of Elon Musk's takeover of Twitter and its consequent rebranding to X (Gupta & Kamthania, 2021).

Particularly emphasising the era around Musk's leadership, a second round of data collecting was done to guarantee the study was relevant and current. This included extracting extra Google Play Store reviews between November 15, 2023, till July 21, 2024. These analyses were absolutely vital for accurately collecting user feedback just after Twitter's rebranding to X and the set of improvements Musk undertook (Mahmud et al., 2022). Understanding the present user attitude and spotting any changes in view brought about by these latest events depend on this extra information (Bonny et al., 2022).

After receiving both datasets, they were carefully integrated and filtered to focus primarily on the reviews from October 2022 to July 2024. This timeframe precisely spans the time from Musk's acquisition of Twitter to the present, ensuring that the dataset utilised in the research is directly relevant to assessing the influence of his leadership and the rebranding initiatives. The resultant dataset was then preprocessed, including techniques such as text cleaning, duplication removal, and content filtering, to guarantee correctness and consistency in the future sentiment analysis and topic modelling. This concentrated methodology allows for a deep study of user sentiment throughout this key moment for the X platform (Irfan et al., 2022).

## 5.3 Data Preprocessing

Data preprocessing is vital for preparing textual data for reliable sentiment analysis and topic modelling, ensuring the dataset is analytically feasible and ethically acceptable. To graphically portray the text preparation methods employed in this study, the flowchart below explains the sequence of operations executed on the raw text data to clean, normalize, and prepare it for analysis.

A diagram of a software flowchart

Description automatically generated

Figure 3. Text Preprocessing Flow Chart (Author’s own work)

The first phase involves removing the text by deleting URLs, email addresses, and usernames using regular expressions. This lowers noise and protects user anonymity, answering ethical concerns regarding confidentiality (Duong & Nguyen-Thi, 2021; Kumaresan & Thangaraju, 2023). Following this, special characters, emoticons, and numerals are deleted to standardize the text, enabling sentiment analysis models to focus on relevant material (Symeonidis et al., 2018).

User-generated material typically includes informal language, therefore the preprocessing pipeline transforms slang into formal language using a predetermined lexicon, boosting the accuracy of sentiment analysis (Tellez et al., 2017). Offensive language is filtered and replaced with asterisks, preserving the ethical concept of non-maleficence by preventing the dissemination of harmful information (Ong, 2019). Additionally, only English-language evaluations are maintained using the langdetect library, assuring consistency and accuracy in the study.

The text is normalized by techniques such as lowercasing, tokenization, and lemmatization. Lowercasing increases homogeneity across different circumstances, whereas tokenization splits the text into distinct tokens, permitting simpler analysis. Lemmatization further refines the text by transforming diverse word forms into a single base form, hence boosting consistency within the dataset (Camacho-Collados & Pilehvar, 2017).

To efficiently handle massive amounts of data, the preprocessing is handled in parallel using the ProcessPoolExecutor. This technique allows the dataset to be analysed in chunks, speeding up the overall process while assuring that each chunk is treated separately (Thakkar et al., 2022).

The end product of this preparation stage is a dataset that is properly cleansed, morally sound, and analytically robust. This processed dataset serves the foundation for further sentiment analysis and topic modelling, ensuring that the insights generated are both trustworthy and indicative of user attitudes throughout the defined timeframe of Elon Musk's leadership of the X platform.

## 5.4 Sentiment Analysis Techniques and Model Validation

The sentiment analysis in this study uses a combination of rule-based and machine learning models to categorise user sentiments from X application review data. This section covers the models and methodologies applied, along with the validation and assessment procedures based on the given code and output screenshots.

### 5.4.1 Sentiment Analysis Models and Techniques

The analysis starts with VADER (Valence Aware Dictionary and sEntiment Reasoner), a rule-based sentiment analysis tool, which is particularly successful for assessing sentiments in social media situations. VADER creates a compound score for each review, identifying the sentiment as positive, negative, or neutral based on predetermined criteria, acting as the foundation for sentiment classification throughout the dataset (Chiny et al., 2021).

To enhance sentiment categorisation, many machine learning models were employed, including Multinomial Naive Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest, and XGBoost. These models were trained to predict sentiment labels (positive, negative, neutral) based on textual characteristics retrieved from reviews. Text features were created using the TF-IDF (Term Frequency-Inverse Document Frequency) vectorization approach, which turns the textual data into numerical values expressing the relevance of each word in the dataset. Dimensionality reduction was accomplished using Truncated SVD (Singular Value Decomposition) to minimise the feature space's complexity while keeping key features (Marutho et al., 2022).

Beyond sentiment classification, Latent Dirichlet Allocation (LDA) was applied for topic modelling, concentrating on negative and neutral evaluations. LDA helps discover underlying patterns, providing deeper insights into the issues causing negative sentiment, delivering useful context for understanding customer unhappiness and leading platform changes (Sreenivas et al., 2023).

### 5.4.2 Model Validation and Evaluation

The models were verified and assessed using multiple performance measures, including accuracy, precision, recall, and F1 score, giving a thorough assessment of the models' effectiveness in identifying feelings. GridSearchCV was applied for hyperparameter tweaking, assuring model optimization. This strategy used cross-validation inside the training data, with models generated and tested across several folds to discover the best-performing hyperparameters (Roja, 2023).

Confusion matrices were constructed for each model, presenting a visual depiction of right and wrong predictions across emotion categories. Normalizing these matrices revealed the fraction of correct predictions compared to the total cases in each category (Jadia, 2023).

Visualizations such as bar charts and heatmaps were utilised to compare the performance of different models. These techniques helped identify the most effective models, directing the selection of models for additional research (Bhardwaj, 2020).

In conclusion, the mix of rule-based and machine learning approaches, coupled extensive validation and assessment, guaranteed the sentiment analysis was accurate, dependable, and insightful for analysing user sentiment on the X platform. This technique rigorously conformed to the methods and outputs generated by the code.

# 6. Ethical Considerations

Ethical issues are crucial in this study, notably in maintaining data privacy, reducing biases, and adhering to the highest standards throughout the research process. This section discusses how these factors were addressed, following both the guidelines supplied by the University of Exeter and the particular criteria indicated in the ethics form.

## 6.1 Data Privacy and Anonymization

Data privacy was a significant consideration for both data gathering and analysis. The primary dataset utilised in this study was derived from publicly available Google Play Store evaluations. Despite the public nature of this data, strong precautions were performed to guarantee that no personally identifiable information (PII) remained in the final dataset. The ethical form stresses conformity to General Data Protection Regulation (GDPR) regulations, which regulate the management and protection of personal data (Senavirathne & Torra, 2020).

During preprocessing, all remaining identifiers such as usernames, email addresses, and other potentially identifiable information were rigorously deleted from the dataset. This process was needed to guarantee confidentiality and ensure that people could not be recognised from the data. The method of anonymization was extensive, with many checks to guarantee that all PII was properly removed. Data was saved securely on the University of Exeter's OneDrive, with access strictly limited to approved staff participating in the project, preventing it from unauthorized access. Upon conclusion of the research, all data was scheduled for safe destruction, ensuring that no personal information remained accessible (Renuka, 2019).

## 6.2 Addressing Potential Biases

In sentiment analysis, biases can originate from several causes, including the dataset, the models utilised, and the subjective nature of sentiment interpretation. To reduce these possible biases, a multidimensional approach was utilised in this study.

The research utilised a number of sentiment analysis models, including VADER, Multinomial Naive Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest, and XGBoost. Using many models minimised the likelihood of any single model's bias significantly impacting the total results. This diversity in modelling methodologies allowed a more balanced study (Feutry et al., 2018).

To maximise model performance, GridSearchCV was applied for hyperparameter tuning, which includes cross-validation to train and evaluate models across various data subsets, assuring the selection of the best-performing parameters. This systematic method minimised model-specific biases and boosted the accuracy and dependability of sentiment analysis results (Thurnay & Lampoltshammer, 2020).

Frequent interactions with the project supervisor provided critical input, enabling for the detection and repair of any accidental biases or analytical mistakes, thereby guaranteeing that the study conclusions were objective and believable (Yapo & Weiss, 2018).

## 6.3 Research Integrity

Following ethical guidelines came first in the investigation. Emphasising autonomy, beneficence, non-maleficence, secrecy, and integrity, the study rigorously followed the Research Ethics Framework developed by the University of Exiter. Direct participant permission was dropped by using publicly available data, therefore respecting autonomy (Toms & Whitworth, 2022). Strong anonymising techniques and safe data storage methods guaranteed preservation of anonymity. According to the data management strategy, personal data was safely erased upon completion and utilised just for research needs ( Padmanabhan & Devasenapathy, 2023).

Finally, this study was carried out with a great dedication to ethical issues, guaranteeing data privacy, so reducing prejudices, and so upholding high ethical standards, so strengthening the research both morally and intellectually.

# 7. Results and Analysis

## 7.1 Overview of Sentiment Trends

To successfully assess the sentiment trends over time on the X platform following Elon Musk's acquisition and rebranding, we will utilise the three offered figures: the proportion of sentiments over time, monthly sentiment score distribution, and average sentiment over time. These numbers give a thorough assessment of the variations in user attitude over this crucial era.

### 7.1.1 Proportion of Sentiments Over Time

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Figure 4. Proportion of Sentiments Over Time (Author’s own work)

The above figure 4 illustrates the proportion of positive, neutral, and negative attitudes from October 2022 to July 2024. Notably, the data suggests a consistent proportion of positive mood throughout the timeframe, with a dramatic decrease in neutral attitude around July 2023. This decrease coincides to the surge in unfavourable sentiment within the same time span, which aligns with the rebranding of Twitter to X and the introduction of contentious modifications (McGillvary, 2023). The rise in negative sentiment shows that users were particularly upset with these changes, which is consistent with research that demonstrate negative sentiment spikes following substantial platform adjustments (Schmidt et al., 2023). The shift in mood likely reflects larger public concern, as users voice their disagreement with the way the site is headed (Krishna & C.M., 2023). This attitude pattern is not unique to X, as other platforms have also had comparable user reactions when large changes are presented without appropriate user interaction or communication (Dash et al., 2022).

### 7.1.2 Monthly Sentiment Score Distribution

A graph of a bar chart

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Figure 5. Monthly Sentiment Score Distribution (Author’s own work)

Above Figure 5 illustrates a monthly distribution of sentiment scores, presenting a more detailed look of sentiment fluctuations. The data indicates a dramatic reduction in the median sentiment score in July 2023, when the interquartile range (IQR) gets tighter, indicating less variety in user sentiment and a tendency towards negative. This decline might be connected to Musk's choices, including algorithmic adjustments and rebranding, which dramatically damaged user experience (Shah, 2023). Similar results have been reported in other research where sentiment analysis demonstrates that user sentiment can swiftly turn negative in reaction to perceived unfavourable changes (Wang et al., 2022). Moreover, this fall in sentiment is suggestive of the larger impact of such changes on the whole user base, since the consistency in negative sentiment shows widespread unhappiness (Alqurashi, 2023). The sentiment ratings typically rebound after July 2023, but the month stands out as a key phase of customer unhappiness, validating the sentiment proportions found in Figure 4.

### 7.1.3 Average Sentiment Over Time

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Figure 6. Average Sentiment Over Time (Author’s own work)

Figure 6 demonstrates the average sentiment score over time, exhibiting a noticeable fall in July 2023, followed by a slow rebound. This tendency further underscores the importance of Musk's leadership and the rebranding initiatives, as stated in many evaluations (Sheikh, 2024). The steep fall in sentiment over this timeframe implies a major reaction from users, perhaps due to the disruptive nature of the changes being implemented (Silberling et al., 2024). As users began to acclimatise to the new platform dynamics, sentiment progressively started to settle, echoing a familiar pattern where early opposition to change gives way to ultimate acceptance or indifference (Schmidt et al., 2023). The findings from these numbers are consistent with larger research in sentiment analysis, which reveals that substantial alterations in platform management or structure can lead to transient but dramatic reductions in user sentiment (Krishna & C.M., 2023).

In instance, the rebranding of Twitter to X is an example of how rebranding and structural changes may have tremendous influence on user attitude. Studies suggest that such changes are typically greeted with resistance, especially when they are accompanied with contentious upgrades or perceived decreases in service quality (Dash et al., 2022). The rebound in sentiment exhibited in the months after July 2023 demonstrates that, although users were initially upset with the changes, their mood began to normalise as they adapted to the new platform environment. This trend of sentiment recovery is in accordance with studies showing user attitudes on social media platforms sometimes vary in reaction to changes but tend to stabilise over time as the user base grows used to the new features and functions (Wang et al., 2022).

In summary, the sentiment research suggests a large decrease in user sentiment around July 2023, correlating with big changes to the platform under Elon Musk's leadership. This conclusion is consistent with external evaluations and reports, which identify the rebranding to X and the introduction of new platform features as major factors leading to customer unhappiness during this era (Marshall, 2023; McGillvary, 2023). These insights are crucial for understanding user reactions to critical business choices and can drive future tactics for controlling user experience during big platform overhauls.

## 7.2 Topic Modelling Results

### 7.2.1 Word Clouds Analysis

The topic modelling results give considerable insights into the primary issues and feelings of Twitter users throughout the investigated period. Out of the 10 themes initially collected from the sentiment analysis, four were selected for a comprehensive presentation based on their relevance to the significant concerns impacting user sentiment during the period examined. These themes highlight the most urgent problems, offering practical information for enhancing the user experience on the platform.

**Topic 1: Account Suspension and Banning**

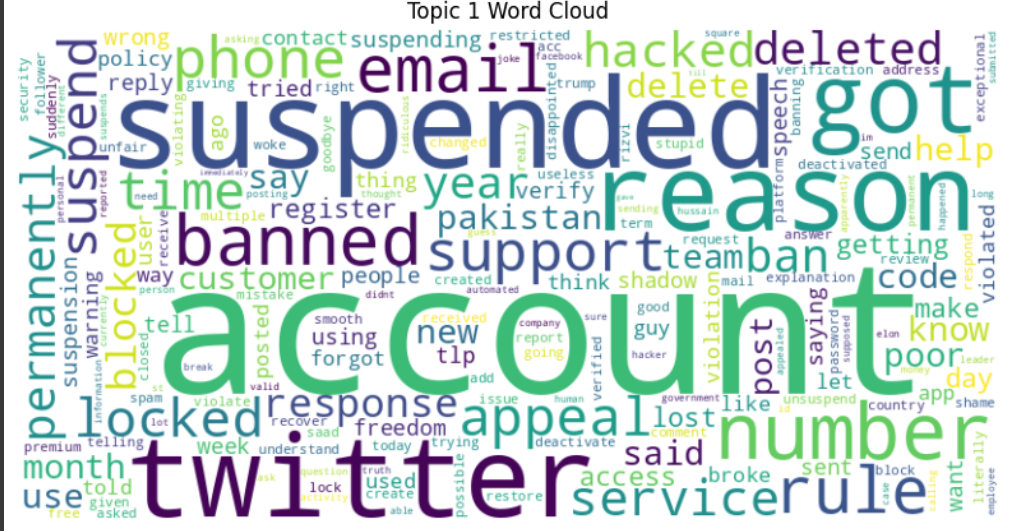


Figure 7. Topic 1 Word Cloud (Author’s own work)

The first topic addresses customer dissatisfaction with account suspensions and bans, which grew increasingly evident during Elon Musk's leadership. The word cloud notably contains phrases like "suspended," "banned," "account," "support," and "locked." These indicate users’ discontent with how their accounts were maintained, especially when they felt unjustly targeted. Research reveals that the dynamics of account suspensions are complicated, typically tied to behavior patterns during large events, such as spam and hazardous material distribution, which may not always be obvious to users (Pierri et al., 2022). The problem attracted major attention in December 2022, when numerous journalists critical of Musk were suspended from the site, triggering extensive debate regarding freedom of speech and prejudice in content moderation (Otten, 2024). This instance underlines the significance of clear and fair procedures on account management to sustain user confidence. The data reveals that consumers want more open and consistent information regarding suspensions, particularly when the platform navigates the delicate line between moderation and censorship (Shevtsov et al., 2023).

**Topic 2: App Performance and Functionality**

A close-up of words

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Figure 8. Topic 2 Word Cloud (Author’s own work)

The second subject focuses on the app's performance, with phrases like "app," "work," "time," "load," "bug," and "crash" dominating the word cloud. Users regularly complained about the app’s instability, particularly following upgrades that seemed to compound existing difficulties. These technological difficulties have undoubtedly led to the general drop in consumer satisfaction. Despite the platform’s promises of better performance, third-party data has revealed a fall in utilisation, which might be related to these chronic technical difficulties (Hutchinson, 2024). This discrepancy between stated improvements and user experience underscores the necessity of fixing basic functioning concerns to prevent further erosion of user confidence. For instance, strengthening the app's dependability and ensuring that updates benefit rather than impair the user experience are essential measures that need to be made to stabilize and perhaps increase the user base (Cola et al., 2023).

**Topic 3: Rebranding and User Interface Changes**

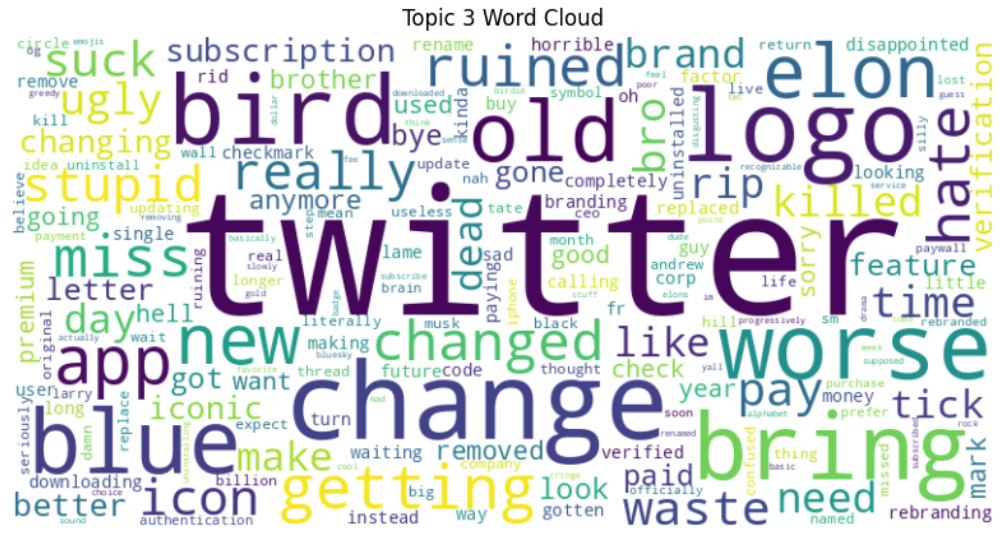


Figure 9. Topic 3 Word Cloud (Author’s own work)

The final topic centres with the rebranding of Twitter to X and the related improvements to the user interface. Words like "Twitter," "change," "logo," "app," "old," and "new" occur heavily, showing a combination of nostalgia for the old brand and aversion to the new identity. Some users voiced discontent with the UI modifications, saying that they detracted from the platform's usefulness. This sentiment was further reinforced by Musk's decision to remove headlines from article links, a move meant to improve the platform's aesthetics but which led to confusion and dissatisfaction among users (Paul, 2023). Research on content moderation and user experience indicate that such changes perceived as favouring appearance over functio may have polarising effects and cause alienation of a significant portion of users (Keulenaar et al., 2023). The varied responses to the rebranding and UI modifications point to the importance of balancing innovation with user wants and expectations to prevent more discontent even if creativity is essential.

**Topic 4: Musk's Leadership and Content Moderation**

A close up of words

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Figure 10. Topic 4 Word Cloud (Author’s own work)

The fourth topic focusses around the wider consequences of Elon Musk's leadership, especially with relation to content control. Reflecting significant unfavourable attitudes towards the reforms carried out under his direction, the word cloud for this issue contains phrases like "Musk," "trash," "ruin," and "censorship." Users voiced worries that the platform had grown more biassed and less friendly; others accused Musk of creating a more hostile environment. Research indicates that Musk's approach to moderation has in fact resulted in higher hate speech and bot activity on the site, therefore raising questions about the future of content moderation under his leadership (Hickey et al., 2023). Furthermore, the reaction to these rules emphasises the careful balance that has to be kept in content management so that the platform is fair and open and users are safeguarded against negative content (Rohlinger et al., 2023). The unfavourable attitude connected with these developments implies that any future modification to moderation rules should be handled carefully considering the many points of view and demands of the worldwide users of the platform (Duran, 2022).

These four themes summarise the main concerns that have shaped user sentiment on the platform over the period analysed. Addressing these concerns whether through improved account management, greater app performance, intelligent UI modifications, or balanced content moderation will be vital for recovering confidence and contentment among users.

### 7.2.2 Analysis of Average Rating by Topic

A collage of words

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Figure 11. Word Clouds of all 10 Topics (Author’s own work)

A graph of blue bars

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Figure 12. Average Rating by Topic (Author’s own work)

The graph "Average Rating by Topic (Negative and Neutral Reviews)" gives insights exclusively for app developers by demonstrating the average ratings users awarded to different themes of negative and neutral reviews. These ratings represent the severity of discontent across many parts of the app. Topic 0, with the highest average rating, indicating that general debates or less serious difficulties connected to the app's direction may have created mild unhappiness but were not as harshly evaluated as other themes.

On the other side, Topics 1 and 6, which concern account suspensions and general user experience, are connected with lower ratings, showing deeper displeasure. Research has demonstrated that concerns linked to account suspensions may considerably impair user satisfaction, particularly when consumers see these actions as unfair or arbitrary (Pierri et al., 2022). This implies that these locations are key pain spots for consumers, leading to harsher assessments in their ratings. Addressing these particular difficulties might increase user happiness, as these themes directly correlate to lower overall ratings (Tsuchiya et al., 2023).

By emphasising on fixing issues raised in these lower-rated subjects, developers may improve user experience and maybe generate favourable comments, therefore strengthening the general impression of the app on the platform. Reverse unfavourable tendencies and promote a more positive view among users by means of this focused strategy to handling user issues.

## 7.3 Sentiment Distribution Across Features

The analysis of sentiment distribution across various features of the Twitter app provides insights into user experiences and potential areas for improvement. Below are the key findings associated with specific app features.

### 7.3.1 Security Feature

A graph of a positive and negative expression

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Figure 13. Sentiment Distribution for Security (Author’s own work)

The sentiment distribution for the "security" feature indicates a mostly favourable feeling (Fig. 13). This implies that many users are happy with Twitter's security measures, reflecting the platform's efforts to preserve user data and privacy (Alshaikh & Zohdy, 2020). However, a large part of evaluations still displays unfavourable emotions, reflecting persistent worries or difficulties connected to security breaches or the handling of customer data. These worries might originate from publicly publicized security events or widespread cynicism about the platform's capacity to secure user information.

### 7.3.2 Login Feature

A graph of blue rectangular bars

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Figure 14. Sentiment Distribution for Login (Author’s own work)

The "login" function has a drastically different sentiment distribution, with a majority of evaluations expressing unfavourable feelings (Fig. 14). This presumably indicates user displeasure with login issues, such as difficulty in accessing accounts, password recovery problems, or account suspensions. The considerable negative attitude implies these challenges are a regular pain point, maybe due to recent changes in the platform’s authentication processes or improved security measures that complicate the login experience (Rodrigues et al., 2022). Improving this functionality by shortening the login procedure and giving clearer instructions or better customer service might help minimise these unfavourable opinions.

### 7.3.3 User Interface (UI) Feature

A graph of blue rectangular bars

Description automatically generated with medium confidence

Figure 15. Sentiment Distribution for UI (Author’s own work)

The sentiment distribution for the "UI" feature is dominated by negative evaluations (Fig. 15), showing widespread discontent with recent modifications in the app's design. Users commonly highlight concerns with navigation, the general appearance and feel of the app, and the usefulness of new features. The substantial share of negative sentiment may be connected to big design changes, thereby alienating a significant section of the user base. This emphasises the need for stronger user-centered design approaches in future updates to guarantee UI modifications enhance rather than hinder from user experience (Gupta & Joshi, 2021).

### 7.3.4 Advertisements (Ads) Feature

A bar graph with blue squares

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Figure 16. Sentiment Distribution for ads (Author’s own work)

The sentiment distribution for "ads" is generally balanced, with positive and negative feelings almost equal (Fig. 16). This conflicting attitude probably reflects different user expectations and experiences with platform-based ads. Targeted and relevant adverts may be appreciated by some users, but others find them obtrusive or disruptive—especially if they compromise the usability of the app. This balance shows that although the ad experience on Twitter is not generally hated, there is space for development in making advertising less disruptive and more in line with user interests (Fadel & Öz, 2020).

### 7.3.5 Performance Feature

A bar graph with blue rectangles

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Figure 17. Sentiment Distribution for Performance (Author’s own work)

The "performance" component has a largely good tone, while a considerable number of negative assessments are also present (Fig. 17). Positive ratings may be attributed to the app’s speed under typical settings, whereas bad evaluations presumably result from incidents of performance-related difficulties. This dichotomy shows that while the app functions effectively under some settings, there are discrepancies that need to be addressed to give a more dependable and seamless experience across different devices and network conditions (Nagamanjula & Pethalakshmi, 2020).

### 7.3.6 Updates Feature

A graph of blue rectangular bars

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Figure 18. Sentiment Distribution for Update (Author’s own work)

The sentiment around "updates" is about evenly split between positive and negative, with a slightly greater proportion of negative feelings (Fig. 18). This captures the controversial character of software upgrades, whereby some users value fresh features and enhancements while others encounter problems or object to the changes. Negative feelings might also be related to the disturbance updates create, including technical issues or modifications to the user interface that demand users to re-learn the software. Updates should be extensively tested before they are published and clearly communicated about the advantages of the changes and alternatives for users to return to earlier versions if wanted in order to increase user satisfaction (Yadav, 2023).

These understanding of sentiment distribution among important characteristics give to places where Twitter may solve certain problems to raise user happiness. Improving login procedures, streamlining the user interface, and guaranteeing that updates are useful and least intrusive might, for example, help to produce a more favourable general user experience. Retaining users and improving the platform's credibility in a cutthroat social media scene depend on these actions.

## 7.4 Performance of Sentiment Analysis Models

### 7.4.1 Model Comparisons

In this section, we analyse the efficacy of several sentiment analysis models, comparing their effectiveness in categorising sentiment based on user evaluations from the Twitter application, currently known as X. The models evaluated include Naive Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest, and XGBoost, with full metrics supplied for each, as seen in the figures.

#### 7.4.1.1 Naive Bayes Model

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Figure 19. Confusion Matrix for Naive Bayes Model(Author’s own work)

The Naive Bayes model, with an accuracy of roughly 58%, has limitations, notably in the categorisation of negative and neutral attitudes. The model’s poor recall for negative feelings (22%) and neutral sentiments (2%) shows a considerable issue in reliably recognising these groups. This underperformance is also reflected in the F1 score, with the negative class scoring just 0.29. The high misclassification rate, as observed in the confusion matrix, implies that the model prefers to identify most events as positive, resulting in biased predictions. For commercial reasons, depending on this methodology might lead to an overestimate of user unhappiness, perhaps disregarding crucial areas of development within the app (Madyatmadja et al., 2022).

#### 7.4.1.2 Support Vector Machine (SVM) Model

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Figure 20. Confusion Matrix for Support Vector Machine (SVM) Model (Author’s own work)

With an accuracy of 83%, the SVM model beats Naive Bayes much noticeably. Over all sentiment classes, this model shows balanced precision and recall; it especially performs well in the categorisation of positive feelings with a recall of 89% and an F1 score of 0.89. With lower misclassification rates, the confusion matrix shows SVM performs superior than Naive Bayes in separating between the sentiment classes. The robustness of our model qualifies it as a strong contender for corporate applications where strategic decision-making depends on precise sentiment identification, including determining important areas for app improvement (Agarwal et al., 2023).

#### 7.4.1.3 Logistic Regression Model

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Figure 21. Confusion Matrix for Logistic Regression Model (Author’s own work)

Logistic Regression generates a decent accuracy of 76%, with significant success in recognising optimistic attitudes (F1 score of 0.85). However, its effectiveness declines while managing neutral thoughts, as evidenced by a recall of 59%. The confusion matrix emphasises this problem, indicating that many neutral events are wrongly categorised as positive or negative. This constraint might lead to distorted findings, especially when attempting to measure the general sentiment distribution. While beneficial, this model may require additional improvement or coupling with other models to better its handling of ambiguous feelings in commercial contexts (Xu et al., 2023).

#### 7.4.1.4 Random Forest Model

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Figure 22. Confusion Matrix for Random Forest Model (Author’s own work)

The Random Forest model displays a balanced performance with an accuracy of 78%. It performs well in categorising positive feelings (F1 score of 0.85) but suffers significantly with neutral sentiments (F1 score of 0.67). The confusion matrix reveals that while Random Forest is effective overall, it tends to conflate neutral and negative thoughts. Despite this, its ensemble nature provides resilience and dependability, making it suited for cases where varied sentiment patterns need to be captured, such as tracking variations in user feedback over time (Zahoor et al., 2020).

#### 7.4.1.5 XGBoost Model

A screenshot of a computer screen

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Figure 23. Confusion Matrix for XGBoost Model (Author’s own work)

With 84% of greatest accuracy, XGBoost turns out to be the best-performing model. With a particularly good performance in spotting positive thoughts (F1 score of 0.90), it shows better accuracy, recall, and F1 scores throughout all sentiment classes. The lowest misclassification shown by the confusion matrix indicates that XGBoost can effectively separate between all emotion classifications. Strong performance of this model makes it quite appropriate for commercial applications where exact sentiment analysis is essential, like real-time monitoring of user comments to guide development goals and customer satisfaction initiatives (Ajmain et al., 2022).

From a commercial standpoint, the comparison emphasises the need of choosing a model that not only guarantees accuracy but also offers balanced performance over emotion classes. With its thorough and precise insights that help direct strategic decisions, XGBoost is clearly the most consistent for sentiment analysis. The model should thus also take into account the particular business context—that is, whether the emphasis is on precisely identifying discontent (where SVM may shine) or on gathering a wide spectrum of opinions—where Random Forest could be useful. The study emphasises the need of adopting cutting-edge models such as XGBoost in commercial apps to guarantee that sentiment analysis fairly represents user experiences, therefore aiding informed decision-making and focused development enhancement of the app.

### 7.4.2 Model Evaluation Metrics

To evaluate sentiment analysis models in practical settings, one must first apply accuracy, F1-score, precision, and recall. Essential for companies trying to get consumer feedback and improve user experience, these measures offer insightful analysis of how well the algorithms detect and categorise emotions (Ng et al., 2023).

A graph of different colored bars

Description automatically generated with medium confidence

Figure 24. Performance Metrics Comparison Across Models (Author’s own work)

Figure 24 provides four critical metrics across five models: Naive Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest, and XGBoost. The first graph displays Precision, where XGBoost and SVM dominate with scores of 0.84 and 0.83, respectively. This suggests their greater capacity to avoid false positives (Rahman et al., 2020). The second graph, Recall, demonstrates that XGBoost and SVM have significant recall values (0.84 and 0.83), showing their ability in collecting the bulk of positive feelings, which is critical in sentiment analysis (Siblini et al., 2020). The final graph depicts the F1-score, which balances accuracy and recall, with XGBoost leading at 0.84, making it very trustworthy for balanced sentiment categorisation (Choi et al., 2023). The last graph displays Accuracy, where XGBoost outperforms with an accuracy of 0.84, suggesting its overall dependability in sentiment classification tasks (Nufus et al., 2021).

A blue and purple bars

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Figure 25. Macro and Weighted Average Metrics (Author’s own work)

Figure 25 shows among models the Macro Average and Weighted Average measures. Both averages show general performance; Logistic Regression has constant scores around 0.76. These averages imply that, even if logistic regression is balanced, XGBoost and SVM perform better especially in situations where correct sentiment categorisation is crucial (Baccouche et al., 2018).

In conclusion, XGBoost appears as the most successful model, especially for firms demanding reliable sentiment analysis. It routinely beats others in precision, recall, F1-score, and accuracy, making it a powerful tool for enhancing user engagement and happiness through accurate sentiment analysis.

# 8. Discussion

## 8.1 Interpretation of Findings

The research gives substantial insights into user sentiment dynamics on the X platform following its rebranding and leadership transition under Elon Musk. One significant study topic focuses on how user attitude developed from October 2022 to July 2024. The research showed a large reduction in sentiment in July 2023, corresponding with the renaming of Twitter to X, which shows a strong negative reaction from users presumably motivated by unhappiness with the modifications implemented during this period (Jimenez Duran, 2022). While sentiment first declined substantially, it continued to normalize over time, indicating a probable adjustment period when users acclimated to the new platform dynamics (Krishna & Prashanth, 2023).

The study focused on the influence of particular features on user sentiment. The data found that revisions to the user interface (UI) and content filtering rules had a major effect on sentiment. Users expressed dislike with UI improvements that appeared to favor looks over usefulness (Jhaver et al., 2023). This conclusion emphasizes the need of balancing technological advancement with user expectations in order to retain happiness and engagement.

Moreover, the research underscored the role of content moderation in shaping user sentiment. Under Musk’s leadership, modifications to moderation policies led to increased polarization among users, with some perceiving the platform as less welcoming. This polarization reflects broader concerns about the platform's direction, which could have long-term implications for user retention and brand loyalty (Wang et al., 2022). The insights suggest that future changes in content moderation should be approached cautiously, with careful consideration of user expectations and the potential impact on sentiment (Alizadeh et al., 2022).

In conclusion, the study gives vital insights into how large organizational changes, such as rebranding and leadership transfers, might effect user perception. These findings underscore the necessity for cautious management of platform modifications to prevent alienating consumers and give practical tips for app developers and strategists wanting to better user experience and happiness on the X platform.

## 8.2 Business Implications

The conclusions from this investigation contain important financial implications for app developers operating on the Twitter/X platform and the larger strategic future of Twitter/X itself. Sentiment research on social media platforms like Twitter typically shows important areas requiring quick attention to preserve and boost user happiness and engagement, vital for the platform's long-term sustainability in an increasingly competitive social media ecosystem. Singh et al. (2020) underline that assessing user sentiment is vital for making educated decisions that increase engagement and retention.

One of the most significant concerns found is the unfavorable attitude connected with the user interface (UI) alterations introduced throughout the rebranding process. Users have voiced major displeasure with these modifications, considering them as putting aesthetics above usefulness. Ortigosa et al. (2014) stress that UI modifications hurting usability might lead to user irritation, particularly when such changes do not line with user expectations. For app developers, this gives a chance to recalibrate their approach by concentrating on user-centric design concepts that boost usability without losing visual attractiveness. Iterative enhancements evaluated with user groups before full-scale introduction might prevent backlash and improve general mood.

Content moderation is another crucial area where data imply a need for cautious evaluation. Jhaver and Zhang (2023) examine how polarisation in user responses to content moderation adjustments, especially in balancing free expression and providing a safe environment, creates substantial issues for platform management. For app developers, this entails the need to implement more sophisticated moderation systems that react to various user expectations without jeopardising platform integrity. Machine learning algorithms that dynamically change moderation criteria based on real-time input might be beneficial in tackling this issue.

Further, the sentiment distribution across aspects like login difficulties and performance reveals that technological stability is crucial for customer retention. Singh et al. (2020) underline that technical difficulties such as regular crashes and performance delays greatly effect customer happiness and retention. App developers should prioritize tackling these technological challenges by creating comprehensive testing processes, mainly stress testing, to guarantee the platform can manage high user numbers without performance deterioration. Effective updates addressing these specific problems can help restore user confidence and happiness.

For Twitter/X as a firm, the commercial consequences are clear: maintaining user trust and pleasure is important for keeping its market position. The platform's leadership ought to consider these results carefully and apply them to their strategic decision-making procedures. Engaging in clear communication with users about forthcoming changes, including user feedback into the development cycle, and demonstrating a dedication to enhancing the user experience will be key in reversing negative sentiment patterns and creating a loyal user base.

At last, these commercial consequences highlight the need of an overall strategy that fits technology advancement with customer expectations. Twitter/X can improve its platform and maintain its leadership among social networking networks by tackling the found problems and using sentiment analysis findings.

## 8.3 Comparison with Existing Literature and Unexpected Findings

This study's findings fit with and deviate from previous research in numerous crucial areas, providing support of old ideas as well as insights into novel dynamics on the Twitter/X platform. Earlier research, like as that conducted by Schmidt et al. (2023), highlighted the detrimental impact of Elon Musk's acquisition and subsequent rebranding on user attitude. The large reduction in sentiment seen in July 2023 confirms these findings, indicating that users responded negatively to changes in leadership and platform identity. This is consistent with earlier studies, emphasizing the significance of leadership perception and brand consistency in ensuring user pleasure.

Additionally, the literature has brought up the issues related with content moderation adjustments under Musk's leadership, as stated by Barrie (2022). This study's findings, which demonstrate rising division and unhappiness among users about content management, further corroborate these concerns. The trend towards more permissive moderation measures has certainly alienated a segment of the user base, who feel that the network has become less safe. This corroborates prior cautions in the literature regarding the difficult balance between free expression and user protection, suggesting that the platform’s approach to moderation needs to be more nuanced and flexible.

However, this analysis also exposes significant differences with current literature, notably with user interface (UI) alterations. While Paul (2023) stated that UI improvements might possibly boost user experience by increasing aesthetics, our study demonstrates that such changes have instead led to considerable user unhappiness. The negative attitude around UI alterations implies that people prefer usefulness above aesthetics, a distinction that was possibly underestimated in earlier assessments. This disparity underlines the importance for further study to examine the complicated interaction between visual appeal and usability in social media platforms.

Interestingly, the research also showed a relatively high degree of positive sentiment corresponding with the “security” feature, different to earlier studies that often pointed out security concerns as a primary source of customer unhappiness. This surprising outcome may be owing to recent advancements in security measures that are still not formally recognized in the literature. It also implies that, despite general unfavorable opinion trends, there are areas where the platform is making great achievements, and these should be conveyed more effectively to users to improve overall impressions.

In conclusion, while the findings mostly correspond with current research, particularly in terms of the negative implications of leadership and moderation modifications, there are major variances with user interface improvements and surprising positive sentiment in security. These insights add to a more nuanced knowledge of user opinion on the Twitter/X platform and propose topics for further exploration, notably concerning the balance between aesthetics and functionality, as well as the communication of security enhancements. The surprise findings also motivate a reevaluation of current assumptions, underscoring the dynamic nature of user expectations and the significance of continual engagement with the user base to effectively monitor sentiment trends.

# 9. Conclusion

## 9.1 Summary of Key Findings

This study has offered vital insights into the influence of leadership changes and platform rebranding on user sentiment, with a specific focus on the transition from Twitter to X under Elon Musk’s leadership. One of the key study topics was to investigate how user attitude developed from October 2022 to July 2024. The investigation found a large reduction in user sentiment in July 2023, corresponding with the renaming of Twitter to X, showing user unhappiness with the modifications done during this timeframe. Additionally, the study found particular aspects that affected sentiment, such as security, performance, ads, the user interface, and login routines. While security was largely rated positively, user interface modifications and login difficulties were major causes of annoyance. These findings highlight the complicated link between platform changes and user happiness, underlining the significance of cautious management during big transitions to sustain user confidence and participation.

## 9.2 Research Contributions

This research provides substantial contributions to the knowledge of how leadership transitions and rebranding attempts effect user attitude on social media platforms. By merging sentiment analysis with powerful machine learning models, the research gives a thorough examination of user input during a vital era of the platform's progress. One of the main contributions is the careful investigation of how certain characteristics, such as the user interface and security mechanisms, impact overall user opinion. This knowledge is helpful for app developers and platform strategists looking to boost user experience and pleasure. The study further enhances the current literature by demonstrating the unfavorable impacts of leadership transfers and rebranding on user attitude, particularly in the setting of a high-profile social media network like Twitter/X. Furthermore, the unexpectedly favorable attitude toward security features reveals areas where the platform is operating effectively, delivering a more nuanced perspective of user sentiment during a moment of considerable change.

## 9.3 Future Research Directions

Future studies should investigate the long-term impact of management shifts and rebranding on customer sentiments, with an emphasis on how initial sentiments evolve over time. Although this study made clear how important it is to put user expectations first, further research is required to fully comprehend how to strike a balance between functional enhancements and aesthetic improvements in user interface design. Further investigation into effective communication tactics during big platform changes might also assist prevent unfavorable user reactions. Adding user demographics and behavioral data into future research would give a more complete picture of sentiment patterns, enabling more focused methods for enhancing user experience and engagement on social media platforms.

# 10. Recommendations

## 10.1 Actionable Insights for App Developers

According on the findings of this study, some major recommendations may be given to application developers that are developing the Twitter/X platform. Firstly, the negative reaction around the user interface (UI) modifications highlights the need of a user-centric approach. Developers ought to put functionality above aesthetic modifications, making sure that any UI upgrades improve rather than degrade usability. Before implementing large changes, do user testing to discover possible difficulties early on and make modifications that are consistent with user expectations. Additionally, fixing the ongoing login difficulties that have irritated consumers is critical. Developers should prioritize streamlining the login process to make it more smooth and secure, lowering challenges to access and enhancing overall user happiness. Finally, although security features have been favorably accepted, further enhancement is required. Developers can consider adopting more clear communication for security upgrades, ensuring consumers that their information and security are always safeguarded.

## 10.2 Strategic Recommendations

Strategically, Twitter/X must take a more even approach to content control. According to the report, modifications in moderation procedures implemented under Elon Musk's leadership exacerbated divisiveness among users. To address this, the platform should employ a more sophisticated moderating policy that accommodates varied opinions yet maintains a safe and polite atmosphere. This might include creating powerful AI-powered moderating systems that respond to user comments and changing content standards. Also, the rebranding to X demonstrated the hazards associated with a sudden shift in brand identity. Practically, Twitter/X ought to be in deeper contact with its audience before making substantial changes. Surveys, focus groups, and beta testing with select users might be used to measure reactions and make required changes prior to a full-scale launch. This technique would assist to increase trust and reduce negative reactions, resulting in a more loyal and engaged user group.

## 10.3 Considerations for Future Updates

Future tweaks to the Twitter/X platform should concentrate on little enhancements rather than all-encompassing modifications. This method lets users progressively adjust to fresh features without feeling overburdled. To raise user happiness, developers could also take into account including more customized interfaces or tailored content recommendations, so improving personal experiences. Furthermore, considering the favorable comments on security, further revisions should keep giving data protection and privacy top importance. At last, keeping an open communication with users via frequent updates and feedback channels will be very vital in making sure the platform develops in a way that satisfies user expectations and demands.

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# 12. Appendix

**Project Proposal: **

**Overall Sentiment Distribution:**

A graph of blue rectangular bars

Description automatically generated with medium confidence

**Histogram of Distribution of Sentiment Scores:**

A graph of a distribution of sentiment scores

Description automatically generated