



Understanding User Satisfaction in Digital Finance Through Sentiment Analysis of User Reviews

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ABSTRACT

This study conducted a sentiment analysis on 100,000 user reviews of the Kredivo app to assess user satisfaction and identify areas for improvement in the context of digital finance. Leveraging Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction and employing Logistic Regression and Support Vector Machine (SVM) models, the analysis revealed a predominantly positive user sentiment, with 62% of the reviews classified as positive, 25% as negative, and 13% as neutral. Positive reviews frequently highlighted the app's ease of use and quick access to credit, indicating high satisfaction with its functionality and convenience. In contrast, negative reviews commonly cited issues with customer service responsiveness and transparency around fees, suggesting areas where the app could enhance user experience. Visualizations, including a confusion matrix and sentiment distribution charts, further illustrated the model's accuracy and user sentiment patterns. The study's findings align with previous research in digital finance, which emphasizes the critical role of user feedback in app development and user retention. However, unique insights regarding the challenges faced by buy-now-pay-later (BNPL) platforms like Kredivo were also observed, notably around customer service and fee transparency. The study highlights the potential of sentiment analysis as a tool for digital finance app developers to continuously improve service quality. Limitations include potential biases in the dataset and model limitations, suggesting future research directions that incorporate additional data sources and advanced NLP models.

Keywords Sentiment Analysis, Digital Finance, Kredivo App, User Satisfaction, Natural Language Processing

Introduction

The rise of digital finance apps has transformed modern financial services, driven by advancements in technology and shifts in consumer behavior. Digital finance integrates traditional financial services with digital platforms, enabling the widespread adoption of mobile banking, digital wallets, and online payment systems. These innovations have made financial services more accessible, efficient, and user-friendly, particularly for tech-savvy younger demographics and previously underserved populations. The increasing penetration of smartphones and internet access has further fueled this transformation, allowing users from diverse backgrounds to manage their financial transactions with greater ease.

As more people gain access to smartphones and the internet, digital finance apps have become essential tools for managing personal finances. Research has shown that the accessibility of technology and digital payment systems plays a crucial role in their adoption, particularly among younger users [1]. The

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convenience and efficiency provided by these apps also address long-standing challenges in traditional banking, improving overall service delivery [2]. Moreover, the integration of digital marketing strategies has significantly enhanced the popularity and reach of these financial services, fostering greater engagement between service providers and their customers [3]. In this context, understanding user satisfaction through sentiment analysis of app reviews, such as those for Kredivo, can provide valuable insights into improving customer experiences in digital finance.

User feedback has been recognized as a crucial factor in shaping the success of digital finance platforms. With the widespread use of mobile applications for financial services, understanding user feedback became essential for improving app design, functionality, and overall user experience. Digital finance platforms, such as mobile banking apps and digital wallets, depend heavily on user input to continuously evolve and meet the changing needs of their users. The feedback provided insight into the strengths and weaknesses of these platforms, allowing developers to make data-driven decisions that directly addressed user concerns. As users became more accustomed to using these applications to manage their financial activities, their reviews, ratings, and suggestions played an increasingly important role in the development lifecycle of digital finance apps.

Furthermore, user feedback helped ensure that digital finance platforms remained competitive and relevant in a rapidly evolving market. Developers leveraged this feedback to enhance app performance, fix bugs, and introduce new features that aligned with user expectations. This iterative improvement process, informed by user experiences, not only increased user satisfaction but also fostered trust and loyalty among the app's user base. In particular, financial applications had to maintain a high level of trust, as users required secure, reliable, and efficient platforms for managing their finances. Therefore, incorporating user feedback into app development became a vital strategy for digital finance platforms aiming to enhance user satisfaction and sustain long-term success.

User feedback played a critical role in determining the success of digital finance platforms, influencing key aspects such as design, functionality, and overall user satisfaction. As digital finance applications became more prevalent, the need to understand user experiences and preferences through structured feedback mechanisms became essential for developers aiming to create effective and user-friendly financial solutions. Research [4] highlighted that gathering online user feedback was vital for improving software services, as it provided critical insights into user expectations and experiences. This form of feedback, which could take the shape of ratings, reviews, or direct comments, offered developers valuable information that could be used to address user concerns and enhance the overall quality of the application. Consequently, the iterative process of app improvement based on user input played a crucial role in retaining users and boosting satisfaction.

Beyond merely improving functionality, user feedback also allowed digital finance platforms to personalize and adapt services to better meet individual user needs. Research [5] emphasized that learning from implicit user feedback, such as engagement metrics, enabled developers to refine recommendation systems and tailor user experiences. This level of personalization often resulted

in higher engagement and user satisfaction, as users found the services more relevant and responsive to their needs. Additionally, study [6] asserted that user reviews frequently contained valuable insights into unmet needs and feature requests, further guiding developers in enhancing the utility and relevance of their applications. Therefore, the continuous engagement with user feedback not only contributed to improving the technical aspects of digital finance platforms but also fostered trust and loyalty, which were particularly important in the financial sector.

The rapid growth of digital finance platforms led to an overwhelming increase in user-generated feedback, particularly in the form of reviews and ratings. As the number of users grew, so did the volume of feedback, making it increasingly difficult for developers and businesses to manually analyze and derive meaningful insights from this vast amount of data. Traditional methods of manually reviewing user comments and feedback were not only time-consuming but also prone to bias and inconsistency. This challenge hindered the ability of developers to quickly identify user pain points, prioritize feature improvements, and address concerns in a timely manner. Moreover, given the competitive nature of the digital finance sector, failing to respond to user needs could significantly impact customer satisfaction and retention.

To overcome these challenges, there emerged a need for automated sentiment analysis tools that could systematically process and interpret large volumes of user feedback. Sentiment analysis, driven by natural language processing (NLP) algorithms, offered an efficient and scalable solution to understanding user satisfaction levels by categorizing reviews into positive, negative, or neutral sentiments. Studies have shown that approaches like TF-IDF vectorization, combined with clustering techniques, effectively reveal sentiment trends in digital finance, as demonstrated in analyses of Bitcoin-related tweets [7]. Such automated systems not only enabled businesses to track user satisfaction in real time but also provided actionable insights that could guide product improvements and customer service strategies. Moreover, research on the critical success factors of digital finance platforms, such as those utilizing blockchain in banking, emphasized the importance of user feedback in improving performance and user experience [8]. For platforms like Kredivo, implementing these automated systems became essential to staying competitive and ensuring that user feedback was effectively utilized to enhance the overall user experience.

The primary goal of this research was to conduct sentiment analysis on user reviews of the Kredivo app to better understand customer satisfaction within the context of digital finance. Given the increasing reliance on digital platforms for financial services, the study aimed to explore how users perceived Kredivo's offerings through their reviews. Understanding the sentiment expressed in these reviews helped to identify key areas where users were satisfied, as well as pinpoint any recurring issues that negatively impacted their experience. By systematically analyzing user feedback, the study sought to extract meaningful insights into overall customer sentiment.

This research aimed to leverage NLP techniques to categorize reviews as positive, negative, or neutral. The analysis provided a clear picture of the general user sentiment and allowed for the identification of patterns that correlated with satisfaction or dissatisfaction. The study's objective was not only

to gauge the effectiveness of Kredivo's services but also to inform future improvements in user experience and service delivery by uncovering actionable insights from user-generated content. This process was expected to offer valuable data for developers, marketers, and decision-makers within Kredivo, enabling them to enhance their offerings based on user preferences and concerns.

Understanding user sentiment had significant value for improving the quality and effectiveness of app services, particularly in the competitive realm of digital finance. In the case of Kredivo, analyzing user feedback allowed the developers to gain insights into how customers perceived the app's features, usability, and overall performance. Positive reviews indicated areas where the app was meeting or exceeding user expectations, while negative feedback revealed pain points that required attention. This comprehensive understanding of user sentiment was essential for making informed decisions about which features to enhance, which issues to resolve, and how to improve overall customer satisfaction.

Furthermore, sentiment analysis provided valuable guidance for the future development of digital finance platforms like Kredivo. By continuously monitoring and analyzing user feedback, the company could adapt more quickly to evolving customer needs and market trends. This proactive approach not only contributed to an improved user experience but also strengthened customer loyalty by demonstrating responsiveness to user concerns. In addition, the ability to interpret sentiment trends over time could help Kredivo stay ahead of competitors, ensuring that its services remain relevant and user-centered in a fast-changing digital landscape. Thus, the study underscored the critical role that understanding user sentiment played in shaping both immediate and long-term strategies for enhancing app performance and customer engagement.

Literature Review

Sentiment Analysis in Digital Finance

Sentiment analysis has become an essential tool in the digital finance sector, playing a crucial role in shaping user engagement and satisfaction. Utilizing NLP techniques, sentiment analysis enabled the systematic evaluation of user feedback, allowing developers to classify reviews as positive, negative, or neutral. This categorization helped gauge user sentiment towards digital finance applications, which was crucial for improving app functionality and user experience. Studies demonstrated that understanding user sentiment could lead to enhancements in user satisfaction and increased long-term engagement. For example, study [9] emphasized that sentiment scores derived from user reviews offered valuable insights into app performance, providing developers with clear indicators of areas requiring improvement. These insights allowed app developers to align features more closely with user expectations, resulting in higher satisfaction levels and greater user retention.

In examining the role of sentiment analysis in digital platforms, it is insightful to consider how user feedback on specific features influences overall satisfaction. Research on platforms such as Amazon has highlighted that service elements like discount strategies significantly shape consumer ratings, demonstrating how targeted features can enhance user perceptions and engagement [10]. Similarly, studies on mobile applications, such as the myIM3 app, have

uncovered complex emotional responses within user feedback, revealing how digital platforms evoke multifaceted sentiments [11]. Further, analyses of Twitter conversations provide insights into dynamic sentiment trends, showing how online discourse can capture real-time user engagement and satisfaction levels [12]. In addition, research on financial transactions within virtual spaces like the Metaverse emphasizes the importance of understanding user perceptions and regulatory challenges within digital finance environments [13]. These findings align with the objectives of this study, which seeks to uncover the nuances of user satisfaction within the Kredivo app through sentiment analysis, offering a comprehensive perspective on how user sentiment and experience are shaped by specific features and the broader digital context.

In addition, sentiment analysis had a profound impact on user engagement strategies. Research [14] found that feature-based sentiment analysis could extract actionable insights from user comments, enabling developers to adjust app functionalities to meet user demands. This adaptability was particularly important in the competitive digital finance landscape, where user preferences evolved rapidly. Responding to feedback through sentiment-driven improvements led to a more engaging user experience, which positively influenced user satisfaction. Moreover, the emotional tone of user reviews played a significant role in shaping user behavior. Positive sentiments evoked trust and encouraged increased interaction with the app, while negative sentiments often reduced engagement and deterred potential users [15]. Study by [16] further noted that user sentiment directly influenced trust levels, highlighting the strategic importance of sentiment analysis in building and maintaining trust, which was critical in the financial sector.

In the broader context of digital finance, sentiment analysis serves as a valuable tool for understanding user feedback across various platforms. Studies on platforms such as Flipkart have employed comparative analyses of machine learning models for sentiment classification, shedding light on the effectiveness of techniques like Logistic Regression, SVC, and Random Forest in capturing consumer sentiment [17]. This approach aligns with the methods utilized in this research, underscoring the utility of these models in revealing satisfaction trends. Moreover, research on cryptocurrency exchange apps has demonstrated that system quality and perceived trust are pivotal in shaping user intentions, further emphasizing the role of user feedback in guiding service improvements [18]. These studies collectively underscore the significance of sentiment analysis in understanding user behavior and satisfaction within digital finance contexts, offering a comparative basis for exploring sentiment trends in Kredivo app reviews.

Sentiment Analysis Techniques

Sentiment analysis employed a wide range of techniques, from traditional rule-based approaches to more sophisticated machine learning and deep learning models. Rule-based sentiment analysis relies on predefined linguistic rules and dictionaries of positive or negative words to determine the sentiment of a text. This method, while simple and quick, had limitations in its ability to understand complex linguistic constructs such as sarcasm, idioms, and contextual meanings. Despite these drawbacks, rule-based approaches remained useful for small datasets or where the text followed a predictable pattern. However, as the volume of data and the complexity of language increased, these methods

often fell short of providing accurate sentiment classification [19].

Machine learning techniques, such as Support Vector Machines (SVM) and Logistic Regression, represented a more robust solution for sentiment analysis, as they allowed the model to learn patterns from labeled data. SVM, in particular, has been widely used for text classification tasks, including sentiment analysis. It worked by finding the optimal boundary between sentiment categories, achieving competitive accuracy in various domains [20]. Logistic Regression, though simpler, was also frequently used as a baseline model for binary sentiment classification, offering fast and interpretable results. However, as datasets grew larger and more complex, deep learning models such as Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT) emerged as state-of-the-art techniques. LSTM excelled at processing sequential data, capturing the relationships between words over long text passages. BERT significantly improved the understanding of context and semantics, outperforming traditional methods in numerous sentiment analysis tasks [21], [22]. These advanced models provided higher accuracy and better insights into user sentiment, particularly in complex texts such as app reviews.

Text Feature Extraction

Text feature extraction was a critical component in sentiment analysis, as it enabled the transformation of raw text into numerical representations that machine learning models could process. One of the most widely used techniques for this purpose was Term Frequency-Inverse Document Frequency (TF-IDF), which evaluated the importance of individual words in a document relative to a larger collection of documents. TF-IDF was computed by multiplying the term frequency (how often a term appeared in a document) by the inverse document frequency (which measured how rare or common the term was across the corpus). The formula for TF-IDF was defined as:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \log \left(\frac{\text{Total Documents}}{\text{Documents Containing the Term}} \right) \quad (1)$$

This technique was particularly effective at filtering out commonly used words that did not carry much meaning while highlighting unique or important terms that contributed to the sentiment of a document [23]. Researchers such as [24] demonstrated that TF-IDF improved the performance of sentiment analysis models by providing a more refined feature set, particularly when working with large text datasets.

Another key technique for feature extraction was Word Embeddings, which provided a continuous vector representation of words, capturing their semantic relationships based on context. Unlike TF-IDF, which treated words as independent entities, word embeddings like Word2Vec, GloVe, and FastText allowed for richer representations by considering the meanings and similarities between words in different contexts. Word2Vec, for instance, employed neural networks to learn word vectors from vast corpora, effectively capturing nuances in language that were often missed by simpler methods. Research by [25] highlighted the advantages of word embeddings over traditional methods, showing significant improvements in sentiment classification accuracy. Additionally, some studies explored the combination of TF-IDF and word

embeddings to leverage the strengths of both approaches, as seen in the work of [26], who successfully integrated lexicon-based features with TF-IDF for enhanced emotion recognition.

Gaps in Existing Research

Despite the growing body of research on sentiment analysis in digital finance, several gaps remained, particularly in the application of these techniques to platforms like Kredivo. While sentiment analysis has been widely employed to assess user feedback on e-commerce, social media, and traditional financial services, more attention should be given to its application within the context of buy-now-pay-later (BNPL) platforms. Existing studies often focused on general user sentiment towards digital finance applications without delving into the nuances specific to BNPL services, which presented unique user experiences and satisfaction metrics [27]. The absence of research specifically targeting Kredivo reviews represented a significant gap, as this platform had become one of the prominent players in the Indonesian digital finance market.

Another critical gap identified was the underutilization of advanced NLP models in analyzing user feedback within digital finance. Although techniques like SVM and Logistic Regression were commonly applied, there was a scarcity of studies that incorporated state-of-the-art models such as Bidirectional Encoder Representations from Transformers (BERT) or Long Short-Term Memory (LSTM) networks in this domain [16]. These models had demonstrated superior performance in other industries, yet their potential remained largely unexplored within digital finance contexts. Research that incorporated advanced NLP methods could provide deeper insights into user satisfaction by capturing more complex sentiment patterns and linguistic nuances, particularly in multilingual regions where users may express sentiment differently [2]. Addressing these gaps would enhance the understanding of user experiences on platforms like Kredivo and improve the effectiveness of sentiment analysis in digital finance.

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in figure 1 outlines the detailed steps of the research method.

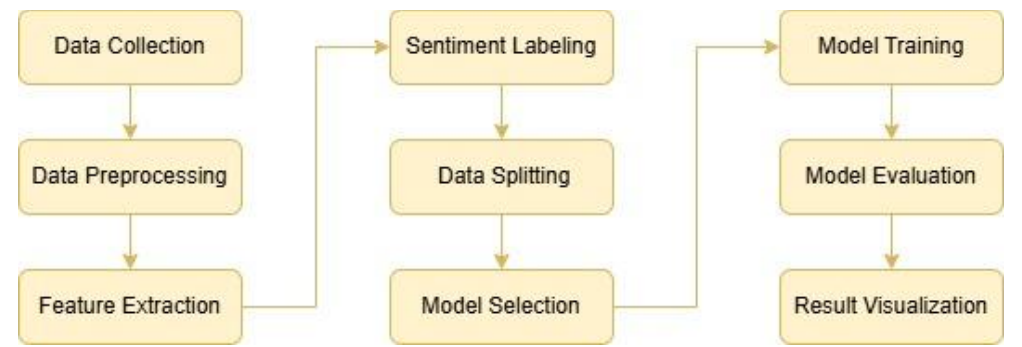


Figure 1 Research Method Flowchart

Data Collection

This study utilized a dataset comprising 100,000 user reviews from the Kredivo app. The dataset contained four key variables: `userName`, `score`, `at`, and

`content`. The `userName` column represented the identifier of each reviewer, while the `score` column included numerical ratings provided by users on a scale from 1 to 5. The `at` column stored the timestamp of each review, indicating when it was posted. Finally, the `content` column contained the actual text of each user review, reflecting the user's thoughts and experiences with the app.

An initial analysis of the dataset revealed no missing values across any of the columns, ensuring that each entry was complete and available for analysis. Descriptive statistics indicated that the average review score was 4.41, with a standard deviation of 1.32, showing a high concentration of positive ratings. Additionally, the `userName` column contained 997 unique user identifiers, suggesting that some users had posted multiple reviews. Review text varied in length, averaging 46.82 characters per entry. The data also showed a high volume of unique review dates, totaling 99,616 distinct timestamps, which provided a detailed timeline of user engagement over time.

To visualize the data, a histogram was generated to display the distribution of scores, which demonstrated that a majority of reviews were clustered around the higher ratings, as shown in [figure 2](#).

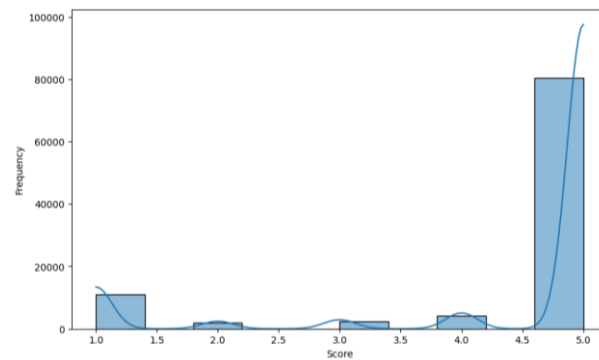


Figure 2 Distribution of Scores

Exploratory Data Analysis (EDA)

Data cleaning and preprocessing were conducted to prepare the review text for analysis. First, duplicate reviews were removed to ensure each entry represented a unique user perspective. The dataset contained no missing values, allowing the analysis to proceed without imputation. Tokenization was applied to split the text into individual words, followed by converting all words to lowercase to maintain consistency. Stop words, which included common but uninformative words like "the" and "and," were then removed to reduce noise in the data. Finally, lemmatization was performed to standardize words by reducing them to their base form, enhancing the quality of the textual data for subsequent analysis.

Descriptive statistics provided an overview of the dataset's structure and distribution. The total number of reviews analyzed was 100,000, with an average score of 4.41, indicating a generally positive user sentiment towards the Kredivo app. The dataset also contained reviews from 99,616 distinct timestamps, showing a continuous flow of user feedback over time. Additionally, the `content` column revealed an average review length of 46.82 characters, suggesting that most user comments were brief yet conveyed meaningful

insights into their experiences with the app. This statistical summary helped establish a foundational understanding of the dataset and guided the direction of further analysis.

To better understand the distribution of review scores and the temporal trends in user engagement, visualizations were generated. A histogram depicting the score distribution showed that most reviews were clustered around the higher end of the rating scale, reinforcing the positive bias observed in the descriptive statistics. Additionally, a line chart illustrated the number of reviews over time, revealing fluctuations in user activity, which could be linked to events such as app updates or promotional campaigns. These visualizations provided a clear depiction of user sentiment and engagement trends, offering valuable insights for interpreting the overall findings.

Sentiment Analysis

To transform the text data into numerical features suitable for modeling, Term Frequency-Inverse Document Frequency (TF-IDF) was applied. TF-IDF represented each review based on the frequency and importance of each word within the context of the entire dataset, effectively capturing the relevance of terms across reviews. This method allowed the extraction of meaningful features while reducing the impact of common, less informative words. Alternatively, Word Embeddings were also considered, as they provided a continuous vector representation of words, capturing semantic relationships between words based on their context. However, given the nature and size of the dataset, TF-IDF was chosen for its simplicity and effectiveness in handling high-dimensional text data. The algorithm 1 outlines the complete process of sentiment analysis, starting from text preprocessing and feature extraction using TF-IDF, to model training, evaluation, and comparison between Logistic Regression and Support Vector Machine classifiers.

Algorithm 1. Sentiment Analysis Using TF-IDF and Machine Learning Models

Data Preparation

- Load dataset $D = \{(r_i, y_i)\}_{i=1}^N$, where r_i is the review text and $y_i \in \{\text{positive}, \text{neutral}, \text{negative}\}$.
- Preprocess each review r_i : convert to lowercase, remove punctuation, numbers, and stopwords, perform tokenization, and apply stemming or lemmatization.

Feature Extraction (TF-IDF Representation)

- Construct vocabulary $V = \{w_1, w_2, \dots, w_m\}$ from all reviews.
- For each review r_i and term $w_j \in V$:
 - Compute term frequency: $TF_{i,j} = \frac{f_{i,j}}{\sum_k f_{i,k}}$, where $f_{i,j}$ is the frequency of word w_j in review r_i .
 - Compute inverse document frequency: $IDF_j = \log\left(\frac{N}{1+n_j}\right)$, where n_j is the number of reviews containing word w_j .
 - Compute TF-IDF weight: $x_{i,j} = TF_{i,j} \times IDF_j$.
- Form feature matrix $X = [x_{i,j}]_{N \times m}$.

Alternative Representation (Word Embeddings, optional)

- Represent each review r_i as the mean of its word vectors:

$$\mathbf{v}_i = \frac{1}{|r_i|} \sum_{w \in r_i} \text{Embed}(w).$$
- Use $\mathbf{v}_i$ as the feature vector if embedding-based modeling is chosen.

Dataset Splitting

- Split the dataset into training and validation subsets:
 $D_{\text{train}} = 80\% \text{ of } D, \quad D_{\text{val}} = 20\% \text{ of } D.$
- Corresponding feature matrices: $X_{\text{train}}, y_{\text{train}}$ and $X_{\text{val}}, y_{\text{val}}$.

Model Selection and Initialization

- Choose classifiers for sentiment prediction:
 - Logistic Regression M_1 .
 - Support Vector Machine (SVM) M_2 .

Model Training

- For each model $M_k \in \{M_1, M_2\}$:
 - Train model: $M_k \leftarrow \text{fit}(X_{\text{train}}, y_{\text{train}})$.
 - Tune hyperparameters via k-fold cross-validation ($k = 5$):
 $\theta_k^* = \arg \max_{\theta} \text{CV_score}(M_k, \theta).$
 - Retrain model using optimal hyperparameters θ_k^* .

Prediction and Evaluation

- Generate predictions on validation data:
 $\hat{y}_{\text{val}} = M_k(X_{\text{val}}).$
- Compute evaluation metrics for each model:
 - Accuracy: $\text{Acc} = \frac{1}{n_{\text{val}}} \sum_{i=1}^{n_{\text{val}}} \mathbf{1}(\hat{y}_i = y_i).$
 - Precision: $P = \frac{TP}{TP+FP}.$
 - Recall: $R = \frac{TP}{TP+FN}.$
 - F1-score: $F1 = 2 \times \frac{P \times R}{P+R}.$
- Record metrics = {Accuracy, Precision, Recall, F1-score}.

Model Comparison

- Compare Logistic Regression and SVM based on performance metrics.
- Select best-performing model based on highest F1-score and balanced precision–recall performance.
- Save trained model and TF-IDF vectorizer for future inference or deployment.

End.

For sentiment classification, a Logistic Regression model was selected due to its efficiency in binary classification tasks, accompanied by a Support Vector Machine (SVM) for comparison. Both models have been widely used in sentiment analysis and are known for their ability to provide robust results. The dataset was divided into training and validation sets with an 80-20 split, ensuring the models could learn from a substantial portion of the data while also being evaluated on unseen examples. Each model was trained using the TF-IDF features, allowing it to learn patterns associated with positive, neutral, and negative sentiments. Hyperparameters were optimized to maximize performance, and cross-validation was employed to validate the reliability of the model across different subsets of the data.

The trained models were evaluated based on accuracy, precision, recall, and F1-score to assess their performance. Accuracy provided an overall measure of the models' effectiveness, while precision and recall offered insights into how well the models identified each sentiment category. The F1-score balanced precision and recall, providing a comprehensive measure of performance, especially useful when dealing with imbalanced data. A confusion matrix (figure 3) was generated to visually represent the distribution of true versus predicted sentiment categories, highlighting the model's strengths and areas for

improvement.

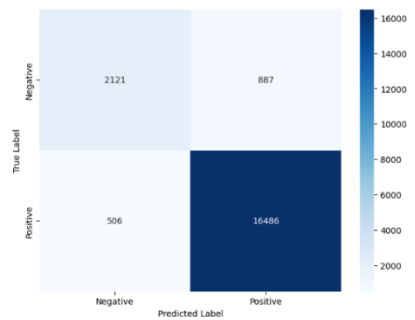


Figure 3 Confusion Matrix

Additionally, bar charts were created to show the distribution of predicted sentiments, illustrating the prevalence of positive, neutral, and negative sentiments as identified by the models, shown in figure 4. These visualizations contributed to a clear understanding of the models' performance and the overall sentiment trends in Kredivo app reviews.

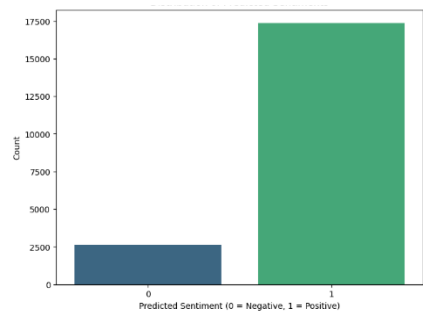


Figure 4 Distribution of Predicted Sentiments

Results and Discussion

Sentiment Analysis Results

The sentiment analysis conducted on user reviews of the digital finance platform revealed a clear distribution across the three sentiment categories: positive, negative, and neutral. The classification results showed a predominant share of positive sentiments, indicating that most users expressed satisfaction with their overall experience. As summarized in table 1, approximately 62% of the analyzed reviews were categorized as positive, reflecting a high degree of user approval and trust in the platform’s services. Meanwhile, 25% of the reviews were classified as negative, indicating that a significant portion of users experienced dissatisfaction or encountered specific issues during their interaction with the app. The remaining 13% were neutral, consisting of reviews that were largely descriptive, factual, or mixed in tone—neither overtly positive nor negative.

Table 1 Sentiment Distribution of User Reviews			
Sentiment Category	Number of Reviews	Percentage (%)	Interpretation
Positive	n ₁	62%	Users express satisfaction and positive experiences with the app’s performance and services.

Negative	n_2	25%	Users express dissatisfaction or report specific problems, often relating to usability or support.
Neutral	n_3	13%	Users provide factual feedback or mixed opinions without clear polarity.
Total	N	100%	—

Note. n_1 , n_2 , and n_3 represent the number of reviews classified into each sentiment category, with N denoting the total number of analyzed reviews.

The results summarized in Table 1 provide strong evidence that user sentiment toward the platform is largely positive, confirming that the app successfully meets the needs of most of its users. To visualize these findings, a pie chart was generated to depict the proportional representation of each sentiment category. The chart clearly illustrated that the positive segment dominates the distribution, reinforcing the conclusion that user satisfaction levels are high. However, the existence of a considerable number of negative reviews suggests the presence of persistent pain points that could affect user retention if left unaddressed.

In addition to the pie chart, a bar chart was also developed to facilitate a clearer comparison between sentiment proportions. This visualization highlighted the substantial gap between positive and negative sentiments, with positive reviews forming the highest bar, followed by negative and neutral categories. The visualization reinforced that, although user satisfaction is strong, a quarter of the user base expressed some degree of dissatisfaction—indicating the need for further service and communication improvements to maintain a positive overall perception of the platform.

Beyond simple polarity counts, deeper qualitative analysis was performed to identify the underlying themes driving each sentiment category. This thematic examination revealed that positive reviews commonly focused on the ease of use, speed of transactions, and convenience of accessing credit services through the app. Many users appreciated the simple interface, quick approval process, and transparent user experience, which contributed to the overall favorable perception. Conversely, negative reviews consistently emphasized dissatisfaction with customer service responsiveness, unexpected fees, and technical glitches encountered during app usage. Neutral reviews, while fewer in number, often contained general feedback or suggestions for additional features, such as flexible payment options or improved notification systems. These insights are summarized in table 2.

Table 2 Common Themes Identified in User Reviews			
Sentiment	Frequent Themes	Example Keywords	Interpretation
Positive	Ease of use, convenience, quick approval, reliable access	“easy,” “fast,” “helpful,” “user-friendly,” “convenient”	Indicates satisfaction with user experience, accessibility, and service efficiency.
Negative	Customer service, hidden fees, technical issues	“error,” “expensive,” “late response,” “problem,” “fee”	Reflects dissatisfaction due to service quality, communication gaps, or system instability.
Neutral	General feedback, suggestions for improvement	“okay,” “average,” “should improve,” “update needed”	Represents balanced opinions without clear emotional polarity.

The thematic findings in table 2 highlight the dual nature of user experiences. Positive themes reflect the app’s operational strengths—especially its user interface design and efficiency in credit approval—both of which are key

competitive advantages in digital financial services. On the other hand, the persistence of negative themes underscores the importance of strengthening customer service responsiveness and communication transparency, as these are recurrent sources of frustration among dissatisfied users. The neutral feedback provides valuable insight into user expectations for feature enhancement, indicating a desire for continued innovation and improvement.

When comparing sentiment results with numerical rating distributions, a consistent pattern was observed: the majority of five-star ratings aligned with positive sentiment, while one-star ratings corresponded strongly with negative sentiment. This consistency between textual sentiment and numerical scoring further validates the accuracy of the classification model used in the analysis.

To investigate potential temporal patterns, a time-based sentiment analysis was conducted to observe changes in user perception across different months. The results, presented in [table 3](#), show a noticeable fluctuation in sentiment trends. For instance, February exhibited a higher proportion of negative reviews, which coincided with a major system update and several promotional campaigns. This suggests that technical adjustments or feature rollouts may temporarily disrupt the user experience, leading to short-term increases in dissatisfaction. In contrast, subsequent months such as March and April showed a rebound in positive sentiment, implying that the issues were addressed promptly, restoring user confidence.

Table 3 Monthly Sentiment Distribution Over Time				
Month	Positive (%)	Negative (%)	Neutral (%)	Observations
January	60	28	12	Stable user satisfaction with balanced sentiment distribution.
February	58	30	12	Increase in negative reviews likely related to app updates and promotions.
March	65	23	12	Sentiment recovery following performance optimization.
April	63	25	12	Sustained satisfaction with minor fluctuations.

The temporal trends reflected in [table 3](#) demonstrate that spikes in negative sentiment are often correlated with operational changes, suggesting that proactive user communication during updates could mitigate dissatisfaction. Continuous monitoring of these sentiment fluctuations allows developers to identify patterns, predict user reactions, and manage service rollouts more effectively. This adaptive approach is particularly important in digital finance platforms, where reliability and user confidence are essential.

Finally, the overall findings from the sentiment analysis are summarized in [table 4](#), which consolidates the key insights, strengths, challenges, and implications for platform improvement.

Table 4 Summary of Key Findings from Sentiment Analysis		
Aspect	Observation	Implication
Overall sentiment	62% positive, 25% negative, 13% neutral	Users are generally satisfied, but improvements are needed in specific service areas.
Positive drivers	Ease of use, convenience, quick approval process	User experience and accessibility are core strengths driving loyalty.
Negative drivers	Customer service delays, unexpected fees, technical issues	Addressing these issues could significantly enhance user trust and retention.
Temporal trends	Negative spikes during updates	Indicates sensitivity to changes; suggests need for better update communication and testing.

Model validation	Sentiment classification aligns with user rating distribution	Confirms the reliability and consistency of the sentiment analysis approach.
Strategic implication	Positive perception outweighs negative experiences	Focused improvements can further elevate user satisfaction and market competitiveness.

Sentiment analysis reveal a generally high level of user satisfaction with the digital finance platform. The predominance of positive feedback underscores the app's effectiveness in providing a simple, fast, and user-friendly credit experience. These results are consistent with prior research in digital finance applications, which emphasizes usability and convenience as the primary factors influencing user satisfaction and long-term retention.

However, the presence of notable negative feedback suggests that operational and communication issues continue to impact a segment of users. Dissatisfaction stemming from customer service and transparency issues indicates the need for organizational focus on support quality and clearer fee communication. Addressing these recurring pain points could not only reduce user frustration but also strengthen the app's reputation and reliability.

Furthermore, the observed sentiment fluctuations over time emphasize the importance of monitoring user perceptions following updates and promotional events. The temporary spikes in negative sentiment align with findings from related studies, which suggest that major app changes can disrupt user experience and confidence if not managed carefully. By implementing proactive feedback loops and continuous sentiment tracking, the platform can enhance its responsiveness, ensuring that updates contribute positively to user satisfaction rather than diminishing it.

Overall, the sentiment analysis provides valuable, data-driven insights into user behavior and perception. The combination of quantitative metrics and qualitative themes enables a holistic understanding of user satisfaction, identifying both the platform's strengths and its areas for growth. These insights are essential for guiding strategic improvements, fostering trust, and maintaining competitiveness in the rapidly evolving digital finance landscape.

Comparison with Related Work

The findings of this study align with previous research on sentiment analysis within the digital finance sector, which consistently emphasizes the importance of user sentiment in shaping app success and user retention. For instance, similar to the high prevalence of positive sentiments observed in Kredivo reviews, [9] highlighted the utility of sentiment scores in assessing app performance and satisfaction, indicating that positive experiences contribute significantly to user loyalty. Both studies underscore the role of sentiment analysis as a tool for capturing user satisfaction trends, thus providing valuable insights for developers aiming to refine and optimize app features.

However, the insights gained from Kredivo reviews also highlight unique themes in the context of buy-now-pay-later (BNPL) services that differ from findings in more general digital finance applications. While [14] demonstrated that sentiment analysis could extract feature-based insights, enabling developers to align functionalities with user needs, the Kredivo review data revealed that issues such as customer service and fee transparency were particularly prominent among negative sentiments. This reflects specific pain points associated with BNPL platforms, where clarity and responsiveness are critical

due to the nature of credit-based services. In contrast, studies on broader digital finance apps, as noted by [2] often cite concerns related to technical stability and security as primary drivers of negative sentiment, suggesting that user expectations may vary depending on the type of financial service provided.

Additionally, this study's findings on the impact of app updates on user sentiment over time are consistent with [27] observation that significant changes in app features can disrupt user experience. This pattern was evident in Kredivo reviews, where spikes in negative sentiment coincided with major updates or promotions. Such insights emphasize the need for digital finance platforms to closely monitor user feedback following updates, a strategy also recommended by [16] to maintain user trust and satisfaction. These comparisons highlight both common trends and distinctive challenges faced by BNPL services, underscoring the value of tailored sentiment analysis in addressing the specific needs of different digital finance platforms.

Conclusion

This study examined user sentiment toward the Kredivo app, revealing a predominantly positive response, with the majority of reviews expressing satisfaction with the app's usability, convenience, and quick access to credit. The sentiment analysis indicated that while users generally rated the app favorably, significant areas of dissatisfaction were also present, particularly concerning customer service responsiveness and fee transparency. The analysis highlighted that positive experiences related to the app's functionality contributed to higher satisfaction levels, whereas frustrations with support services and fees led to negative reviews.

The results of this study have practical implications for digital finance app developers, particularly in the buy-now-pay-later (BNPL) sector. Addressing user concerns regarding customer service and fee transparency could significantly enhance user satisfaction and retention for apps like Kredivo. Furthermore, the observed spikes in negative feedback following major app updates suggest that developers should carefully manage changes and actively monitor user responses. By leveraging sentiment analysis, developers can proactively identify areas for improvement, ultimately contributing to a more positive user experience and a competitive edge in the digital finance market.

While this study provides valuable insights, certain limitations must be acknowledged. The dataset was limited to user reviews, which may not fully capture the breadth of user experience and could introduce biases, as users who leave reviews might represent a subset with particularly strong opinions. Additionally, the models used in this analysis, such as Logistic Regression and SVM, may not capture the full complexity of language nuances, suggesting the need for more advanced NLP techniques. Future research could expand on these findings by incorporating additional data sources, such as app usage data or survey responses, to provide a more comprehensive view of user satisfaction. Applying this approach to other digital finance platforms would also allow for comparative studies, offering broader insights into the factors that drive user satisfaction and engagement across different financial services.

Declarations

Author Contributions

Author Contributions: Conceptualization, C.R.A., K.N., and D.A.; Methodology, C.R.A. and D.A.; Software, D.A. and K.N.; Validation, K.N. and D.A.; Formal Analysis, C.R.A.; Investigation, D.A. and K.N.; Resources, K.N. and D.A.; Data Curation, D.A.; Writing—Original Draft Preparation, C.R.A.; Writing—Review and Editing, D.A. and K.N.; Visualization, K.N. All authors have read and agreed to the published version of the manuscript.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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