

## SHORT PAPER

# Sentiment Analysis of Google Play Reviews of Online Lending Platforms in Indonesia

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## ABSTRACT

Sentiment analysis is often useful for grouping sentiments and understanding the general perspective toward a particular topic. There are several models developed for online lending platforms. However, they do not focus on Indonesia, which might have unique characteristics compared to other countries. This paper presents a sentiment analysis model focusing on Indonesian online lending platforms. It features either multinomial naïve bayes, logistic regression, and support vector machine (SVM). Based on our evaluation of 10,000 reviews, our sentiment analysis model achieves approximately 85% precision and 90% recall. The model is highly effective. Our analysis of the reviews shows that while many borrowers appreciate the time efficiency and accessibility, some perceive the platforms as predatory, using aggressive and unethical debt-collection tactics.

## KEYWORDS

sentiment analysis, machine learning, online lending, Google Play, classification

## 1 INTRODUCTION

In the era of digitalization, people can easily get funds online through online lending platforms [1]. This makes things more practical as they do not need to go to the banks in person with a lot of paperwork. Online lending platforms are growing in many countries in continents, including Asia [2] and Europe [3]. However, the public might have difficulty choosing the most appropriate online lending platforms [4]. Even though online reviews are available, reading them one by one might be tedious and time-consuming.

Automated sentiment analysis can be useful for grouping reviews and provides a glimpse into online lending platforms' credibility. It is a machine-learning classification task focused on differentiating content by sentiment [5]. It works by converting content into word features via natural language processing (NLP), weighing each feature for each sentiment, and using the weights to identify the sentiment of new content entries. Sentiment analysis has been employed in many studies to understand public perception of a particular topic.

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In education, sentiment analysis was employed when unprecedented issues or emerging technologies arrived. In the era of the COVID-19 pandemic, for instance, several sentiment analysis models [6] analysed public views on online learning and found that stress, internet connectivity, and technical issues were the three predominant concerns. Another case was the introduction of GenAI, which substantially affected education, particularly in assessments [7]. Simple and conventional assessments could be easily solved by GenAI. One study focused on academic integrity and on how public perceptions changed in the era of GenAI [8]. They highlighted the need for clear and consistent regulations regarding GenAI to ensure students still had the best learning experience. Another study focused on the impact on education [9] and suggested that adaptive peer tutors might be personally developed to assist students in learning. Another study examined educators' perspectives [10] and found that while perceptions were generally positive, they remained cautious, especially regarding ethical considerations.

In finance, sentiment analysis was employed for cryptocurrencies, which, unlike conventional currencies, were backed by blockchain infrastructure [11]. Most of the responses were positive, though they should consider uncertainties. The findings were partly supported by another sentiment analysis study [12], which found that while many people were happy with the introduction of cryptocurrencies, some were afraid of the unexpected turns these currencies might take. Blockchain-based assets such as NFT were also observed through sentiment analysis [13]. Excitement grew over the potential use of the assets, while some people were concerned about scams, price volatility, regulatory uncertainty, and a lack of trust. Sentiment analysis was also employed in the metaverse marketplace [14], a decentralised platform for trading virtual assets. The users were cautious but interested, particularly in investment and passive income opportunities.

Several sentiment analysis models discussed the impact of lending platforms. One sentiment analysis model [15] compared five online lending platforms in India and found that some received more positive responses than others. Another sentiment analysis model [16] focused on comments on a Chinese social media platform about online lending platforms. Lenders were concerned with three aspects: security, return rate, and compliance. Another model focused on online lending platforms in both China and the USA [17]. They found that in the USA, online lending platforms were perceived as more negative.

Indonesia is a developing country with a growing number of online lending platforms. Nevertheless, there is no sentiment analysis focusing on the country. The analysis and model might help policymakers and the public better understand the trends in online lending platforms in Indonesia.

In response to the aforementioned gap, this paper presents a sentiment analysis model of Google Play reviews of online lending platforms in Indonesia. There are 10,000 Google Play reviews compiled, analysed, and discussed. While the findings are specific to Indonesia, we believe they can also be useful to other developing countries and to countries with similar characteristics.

## 2 METHOD

Our method consists of three parts, starting from data collection and sentiment analysis model building, to sentiment classification. Data collection is performed on Google Play reviews, focusing on five popular online lending platforms in Indonesia: AdaKami, Akulaku, EasyCash, Indodana and Kredivo. For each platform, 2,000 reviews are collected using RapidMiner [18] and then labelled as “positive”,

“neutral”, or “negative”. All reviews with a rating of four or more out of five are considered “positive”. Those with a rating of three are considered “neutral”. Others are considered “negative”. The sentiment label of each review is then manually checked by the authors. The sentiment distribution of the collected reviews is illustrated in Figure 1. Most sentiments are either positive or negative.

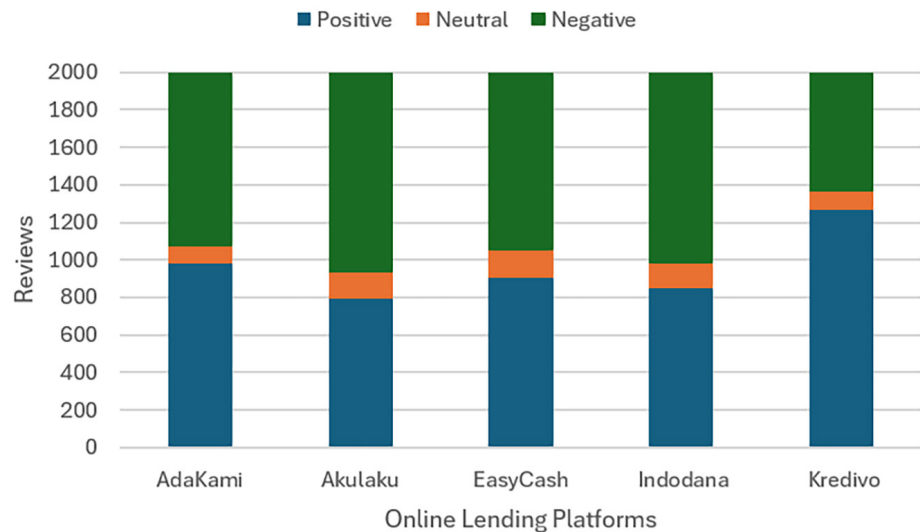


Fig. 1. Sentiment proportion of collected reviews

Sentiment analysis model building takes the datasets as input and generates the model as output. Each input entry is represented as a tuple containing text and a single sentiment label. The text is then preprocessed into features in the following steps [19]:

1. Cleansing: removing all non-alphanumeric characters, links, emoji, and punctuation. They are either challenging to process or have little correlation to the sentiment label.
2. Case folding: lowercasing all characters to not consider trivial capitalization differences.
3. Tokenizing: splitting the entry into words, which will be considered as features.
4. Stopword removal: removing all Indonesian common words which have little meaning to the sentiment label.
5. Stemming: converting each word to its base form through the Indonesian stemmer

Each word will be considered as a feature in the sentiment analysis model. To proportionally weigh the occurrence, Term-Frequency Inverse-Document-Frequency weighting is applied [19]. It prioritizes words that occur frequently in a few documents.

After the input dataset is converted to weighted feature matrices, it will be fed into a classification model. There are three models available for this study: multinomial naïve bayes, logistic regression, and support vector machine (SVM) [20].

The built sentiment analysis model is then used as the basis for sentiment classification. Given a piece of text, it will identify the sentiment, either “positive,” “neutral,” or “negative.”

### 3 RESULTS AND DISCUSSION

Using the dataset, we compared the three models in our sentiment analysis module through 5-fold cross-validation [19]. Two evaluation metrics were

considered: precision and recall. Precision measured the proportion of reviews assigned to a specific sentiment class (such as “neutral”) that actually belong to that class. Recall measured how many of the actual reviews belonging to a specific class were successfully caught by the model.

We were also interested in identifying the theme of each sentiment to capture a general overview of the online lending platform. We manually investigated the sentiments and drew a qualitative analysis towards the dataset.

### 3.1 Precision

Figure 2 showed that all models share a close performance in terms of their precision. Both multinomial naïve bayes and logistic regression achieved the highest scores, with 85% precision. This suggests that, in the context of sentiment analysis, these two models were equally effective at achieving high accuracy without incurring many false positives.

The SVM model performed similarly but slightly lower, at 83% precision. It might have a little difficulty classifying sentiments, especially neutral ones. Regardless, the overall performance of all three models remains relatively high and clustered closely together. They were quite effective at classifying sentiments, with only a limited number of incorrect classifications.

### 3.2 Recall

Based on Figure 3, all three models showed high sensitivity, consistently detecting many relevant sentiments across the dataset. The logistic regression and SVM achieved high performance, with 90% recall. These models were reliable for identifying nearly all instances of a target sentiment.

The multinomial naïve bayes model was just one percentage point lower at 89% recall, which still showed good performance. There were specific words that identified the correct sentiments in the dataset.

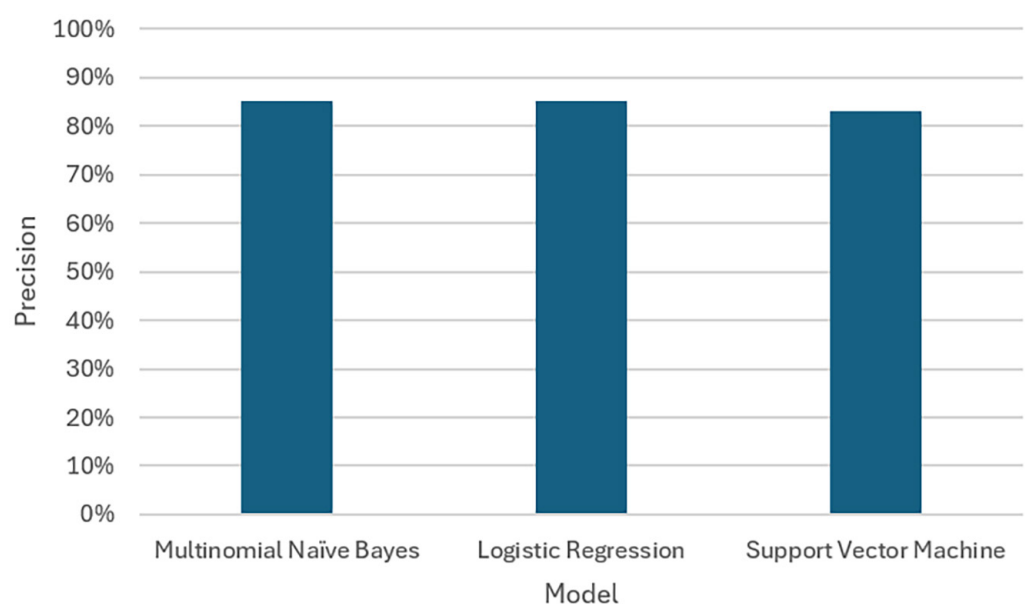


Fig. 2. Precision of the selected models

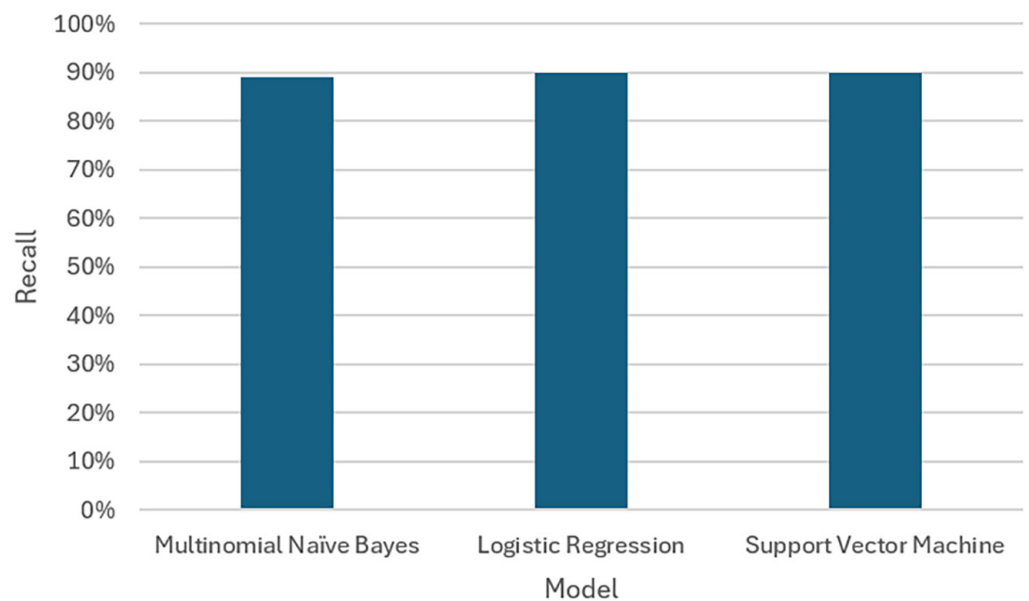


Fig. 3. Recall of the selected models

### 3.3 Reasons for the sentiments

**Positive reviews.** Based on our analysis, many positive reviews highlight the fast processing of online lending platforms, bypassing traditional banking hurdles and long waiting lines. The entire process, starting from application to approval, often took just a few minutes. This was really useful in catering to the urgent need for cash.

Another major benefit was the accessibility of the online lending platforms. Borrowers could secure cash simply by fulfilling basic requirements, such as uploading a selfie with their ID card. Online loans also served as reliable financial support during emergencies, especially for small businesses that might occasionally need a swift cash injection to sustain operations.

Finally, positive reviews expressed strong appreciation for clear financial transparency, manageable interest rates, and flexible monthly instalment options. Some reviews stated that users trusted online lending platforms because responsible borrowing habits were rewarded. Borrowers who consistently paid their dues on time were quickly granted higher credit limits and exclusive promotional discounts.

**Neutral reviews.** For the neutral reviews, many focused on the balanced benefits and drawbacks of the technical operations of the lending platforms, specifically repayment channels and account maintenance. Borrowers frequently requested more diverse payment options, such as the integration of specific bank virtual accounts. Some reviews raised questions about routine account management, such as navigating login issues after changing a phone number or email and requesting data deletion or account closure after fully paying off a loan.

Many borrowers express mixed views about automated credit-scoring and limit-adjustment systems. It was common practice for borrowers to leave a baseline star rating as a placeholder, explicitly stating that they would upgrade their review only after their pending application was approved or their verification was completed.

The remaining neutral reviews covered mixed application experiences, standard customer support interactions, and promotional mechanics. While users recognize that the initial sign-up and approval processes could be fast, they had a frustrating

time dealing with technical issues. Furthermore, in-app features such as lucky draws, referral point systems, and promotional vouchers were viewed with mild skepticism due to their complex mechanics.

**Negative reviews.** Many of the negative reviews described online lending platforms as predatory financial structures, with hidden fees and deceptive marketing. Many borrowers expressed outrage over high interest rates and inflated service charges that completely contradict the marketing. Some borrowers reported that vouchers were unavailable once their loans were approved.

Another issue with the online lending platform was its aggressive and unethical debt-collection tactics. Borrowers complained that missing a deadline by just a few hours or a single day triggered non-stop phone calls, which could easily escalate into psychological harassment, threats, and privacy violations. Some debt collectors easily leaked personal information, hacked contacts, and humiliated borrowers.

Finally, borrowers highlighted technical glitches and anxieties regarding data security. A recurring frustration was the platform's lack of consistency. Loyal borrowers who responsibly paid off their debts were then rejected for new loans. Technical bugs further ruined the experience, including broken login systems, faulty verification procedures, and errors in the disbursement of funds.

## 4 CONCLUSIONS AND FUTURE WORK

This paper presents a sentiment analysis model of Google Play Reviews of online lending platforms in Indonesia. The model is built based on 10,000 reviews from five online lending platforms. Further, it employs one of three machine learning models: multinomial naïve bayes, logistic regression, and SVM. Based on our evaluation, the model is highly effective, with around 85% precision and 90% recall. It can accurately identify certain sentiments from the reviews. Further observations from the reviews show that many borrowers appreciate the time efficiency, accessibility, and transparency of the platforms. However, some borrowers perceived the platforms as predatory with aggressive and unethical debt-collection tactics. Neutral reviews are dominated by general inquiries.

For future work, we plan to employ more data with deeper machine learning models. We are also interested in evaluating the sentiment analysis model with more metrics to strengthen our findings.

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