



Comparative Sentiment Analysis of TheoTown Reviews on Steam and Google Play Store Using Support Vector Machine

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Received Mar 03rd 2026; Revised Apr 13th 2026; Accepted Apr 23th 2026; Available Online Apr 28th 2026

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Abstract

The rapid expansion of the digital gaming industry has led to a substantial increase in player-generated textual reviews across major distribution platforms such as the Google Play Store and Steam. These reviews offer valuable insights into user experiences and perceived game quality; however, their large volume renders manual analysis inefficient. This study explores cross-platform sentiment patterns of TheoTown using a Support Vector Machine (SVM) classification approach. A dataset comprising 24,754 Google Play Store reviews and 1,452 Steam reviews, collected between January 2021 and December 2025, was processed using a structured pipeline that included text cleaning, normalization, tokenization, stopword removal, and stemming, followed by TF-IDF feature extraction. The findings indicate that a linear SVM model delivers consistently strong performance across both platforms, achieving F1 Scores exceeding 97%. Nevertheless, differences appear in probabilistic evaluation, where the Google Play Store dataset attains a higher AUC (0.8501) than Steam (0.6114). Both datasets are highly dominated by positive sentiment (above 94%), yet the Steam model fails to detect negative instances, highlighting the effects of severe class imbalance and limited data. These results emphasize that platform ecosystems influence both sentiment expression and model performance, underscoring the importance of cross-platform analysis.

Keywords: Google Play Store, Sentiment Analysis, Steam, Support Vector Machine, User Reviews

1. INTRODUCTION

The way consumers evaluate and engage with video games has fundamentally changed as the digital entertainment sector continues to grow. Today, digital storefronts like Steam and Google Play function as primary venues for gamers to express their opinions via textual feedback. These reviews provide valuable insights into user satisfaction and game quality. However, the sheer volume of such data poses a challenge for manual interpretation, making automated approaches such as sentiment analysis essential for extracting meaningful patterns from large-scale textual data. Sentiment analysis has been widely utilized to examine player responses across various digital games, including Honkai Star Rail [1], Genshin Impact [2], PUBG Mobile [3], and Mobile Legends [4]. These studies demonstrate how user feedback can be systematically analyzed to understand player preferences and improve game development strategies. Despite this, most existing research tends to focus on a single platform, limiting the ability to capture differences in user behavior across distinct ecosystems.

One game that has recently attracted widespread attention in Indonesia is TheoTown, a city-building simulation that lets players design urban environments, manage infrastructure, and simulate governance decisions. Its popularity was further amplified by a unique trend in which Indonesian players recreated chaotic government scenarios in the game, sparking viral discussions on social media. This phenomenon not only increased the game's visibility but also shaped how users perceive and evaluate it. Such conditions raise an important question: do user sentiments differ significantly across platforms with different user characteristics? Although existing research covers games such as Stumble Guys [5], eFootball [6], and Ojol The Game [7] Studies involving PC-based platforms like Steam remain relatively limited. This is important because PC users often represent a more niche and engaged audience, potentially producing more detailed and nuanced reviews compared to mobile users [8]. As a result, analyzing sentiment across both mobile and PC platforms may reveal differences that are not observable in single-platform studies.

Recent advancements in sentiment analysis have demonstrated the effectiveness of machine learning approaches, particularly Support Vector Machine (SVM), in handling classification tasks involving textual

data. SVM has been widely applied in various sentiment analysis contexts, including implicit aspect identification [9], fake review detection [10], and social media analysis [11], where it shows strong performance due to its ability to handle high-dimensional and sparse data representations .

Furthermore, comprehensive studies have highlighted the growing importance of combining machine learning and deep learning techniques for analyzing user-generated content in e-commerce platforms, emphasizing both challenges and future research opportunities [12]. Other approaches using language representation models have also been explored to improve sentiment classification performance in customer feedback analysis [13]. Beyond sentiment analysis, SVM has also demonstrated strong performance across a wide range of domains. It has been successfully applied in environmental prediction [14], transportation forecasting [15], and geotechnical analysis [16], indicating its versatility and reliability as a classification model.

From a methodological standpoint, Support Vector Machine (SVM) remains one of the most reliable algorithms for text classification tasks, particularly in handling high-dimensional data. Previous studies have shown that SVM frequently outperforms methods such as Naive Bayes and Random Forest in various sentiment analysis contexts, including public policy evaluation [17], technology adoption [18], the development of Indonesia’s new capital city (Ibukota Nusantara) [19], and social media analysis [20]. Its performance can be further optimized through kernel selection and hyperparameter tuning, which play a crucial role in improving classification outcomes [21].

Even though extensive research exists on sentiment analysis, comparative studies that directly evaluate user sentiment across multiple platforms for the same game remain scarce. Most prior works, including those by (Firmansyah et al.) and (Bisono & Zulherry), focus exclusively on a single platform. Therefore, this study aims to address this gap by comparing cross-platform sentiment in TheoTown reviews on Steam and the Google Play Store using the SVM approach. By doing so, this research provides empirical insights into how platform differences influence user sentiment patterns and contribute to a more comprehensive understanding of digital game perception across diverse user ecosystems [1], [2].

2. MATERIALS AND METHOD

A quantitative approach combining machine learning algorithms and text mining was employed in this research to analyze and compare sentiment patterns from two distinct platforms. Rather than relying on manual inspection, the approach emphasizes automated pattern extraction from large-scale textual data, enabling systematic comparisons of sentiment characteristics across ecosystems. The research flow diagram is shown in Figure 1.

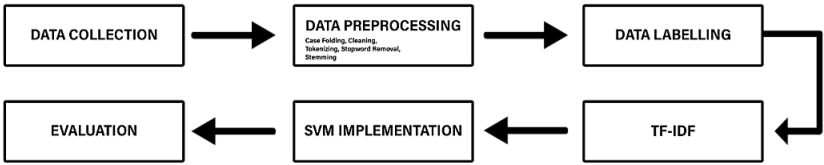


Figure 1. Research Flow Diagram

2.1. Data Collection

The analysis is based on secondary data consisting of publicly accessible user reviews collected from the official TheoTown pages on both platforms. We utilized the Google Play Scraper tool and the official Steam Web API as the primary extraction mechanisms to automatically gather user feedback from both storefronts. To maintain temporal consistency, only reviews published between January 2021 and December 2025 were included. After removing duplicate entries and filtering out irrelevant content, the final dataset comprised 24,754 reviews from the Google Play Store and 1,452 reviews from Steam. Neutral reviews (rating score of 3) were intentionally excluded to ensure a clear binary classification setup. This decision allows the model to focus on more definitive sentiment signals, although it reduces the representation of moderate opinions.

2.2. Data Preprocessing

To transform raw textual data into a structured format suitable for machine learning, a sequence of preprocessing steps was applied. The initial phase of data refinement involved eliminating extraneous characters, including web links, emojis, and special symbols. Following this, the remaining text underwent case folding to ensure uniform lowercase formatting. Subsequently, tokenization was conducted to segment sentences into individual lexical units. To reduce redundancy, common words with minimal semantic contribution were eliminated using a combination of Indonesian and English stopwords dictionaries. The final stage involved stemming, where words were reduced to their base forms using the Sastrawi library, enabling

better generalization across variations of similar terms. These steps collectively improve feature consistency and reduce dimensional noise, which is essential for effective text classification.

2.3. Sentiment Labeling

The dataset was dichotomized based on user ratings: scores of four to five constituted the positive class, whereas scores of one and two formed the negative class. This labeling approach follows the practices commonly adopted in prior sentiment analysis studies. The resulting datasets exhibit a strong imbalance in class distribution, with positive sentiment dominating both platforms. While this reflects real-world user behavior, it also poses challenges for the classification model, particularly in learning patterns of the minority class. This labeling strategy aligns with methodologies commonly adopted in previous sentiment analysis research on digital platforms [4], [22].

2.4. Feature Extraction Using TF-IDF

The TF-IDF algorithm was applied to transform the raw text into a numerical format. This statistical measure evaluates how relevant a specific word is to a document within the entire collection of reviews. In this study, we kept only the top 5,000 words to ensure the system ran quickly without losing important details. TF-IDF was selected for its proven effectiveness with sparse, high-dimensional text data, making it well-suited for sentiment classification. This approach was chosen due to its capability to efficiently manage high-dimensional textual data and its proven effectiveness in various sentiment analysis studies [23], [24], [25].

2.5. Classification Using SVM

This study used the Support Vector Machine (SVM) algorithm to classify reviews into positive and negative sentiments. SVM is highly effective for text analysis because it finds the best mathematical boundary to separate different categories of data [8], [21]. The SVM algorithm was chosen to classify the reviews. We divided the data 80:20 for training and testing, ensuring the ratio of positive to negative reviews remained the same in both sets. Finally, we used GridSearchCV and cross-validation to test different configurations like kernel types and C values to find the most accurate model for each platform.

2.6. Model Evaluation

To evaluate the model, we used several metrics: AUC, a Confusion Matrix, Precision, Recall, F1-Score, and Accuracy. Because our data was imbalanced, we focused primarily on F1-Score and AUC, as they are more robust to imbalanced data. The evaluation results from both platforms were then compared to identify differences in model behavior and sentiment distribution patterns, enabling a deeper understanding of how platform characteristics influence analytical outcomes.

2.7. Literature Review

2.7.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm widely used for classification tasks. Particularly in high-dimensional data such as text. The fundamental objective of SVM is to find the optimal hyperplane that maximizes the margin between two classes. The decision function of SVM can be formulated as as Equation 1.

$$f(x)=w \cdot x+b \quad (1)$$

where w represents the weight vector and b is the bias. The optimal hyperplane is determined by maximizing the margin while minimizing classification error, and can be viewed as Equations 2 and 3.

$$\min 1/2 \|w\|^2 \quad (2)$$

subject to:

$$y_i (w \cdot x_i + b) \geq 1 \quad (3)$$

SVMs are particularly effective for sentiment analysis because textual data is typically high-dimensional and sparse. Previous international studies have shown that SVMs often outperform traditional classifiers, such as Naïve Bayes, in text classification tasks.

Several previous studies have demonstrated the effectiveness of SVM in sentiment analysis tasks. For instance, SVM has been successfully used for implicit aspect identification in sentiment classification [9], as well as for detecting fake reviews in e-commerce platforms [10]. In the context of social media, SVM combined with lexicon-based approaches such as VADER has shown promising results in analyzing user

sentiment on platforms like TikTok [11]. In addition, systematic literature reviews indicate that machine learning and deep learning methods, including SVM, remain dominant approaches in analyzing product reviews and customer feedback due to their adaptability and strong performance [12]. Language representation-based approaches have also been proposed to enhance sentiment classification accuracy by capturing contextual information more effectively [13].

Despite its strong performance, several studies highlight limitations of SVM, particularly in handling highly imbalanced datasets and complex contextual semantics in textual data. In such cases, hybrid models or deep learning approaches are often explored to improve classification performance [12], [13]. This indicates that while SVM remains effective, its performance may vary depending on data characteristics and preprocessing techniques.

2.7.2 Confusion Matrix

A confusion matrix is used to evaluate classification performance by comparing the predicted labels to the actual labels. It consists of four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Evaluation metrics derived from the confusion matrix are presented in Equations 4-7.

1. Accuracy:

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \quad (4)$$

2. Precision:

$$Precision = TP/(TP+FP) \quad (5)$$

3. Recall:

$$Recall = TP/(TP+FN) \quad (6)$$

4. F1-Score:

$$F1 = 2 \cdot (Precision \cdot Recall) / (Precision + Recall) \quad (7)$$

2.7.3 Receiver Operating Characteristic (ROC) Curve

The ROC curve is a graphical representation used to evaluate the performance of a classification model by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR). Can view Equation 8.

$$TPR = TP/(TP+FN), FPR = FP/(FP+TN) \quad (8)$$

The Area Under the Curve (AUC) quantifies the model's ability to distinguish between classes. A higher AUC value indicates better classification performance.

3. RESULTS AND DISCUSSION

3.1. Google Play Store Dataset Overview

After applying the filtering process to data collected between 2021 and 2025, a total of 24,754 valid reviews from the Google Play Store were obtained. The subsequent sentiment labeling, based on user ratings, yielded a dataset characterized by pronounced class imbalance, as illustrated in Figure 2.

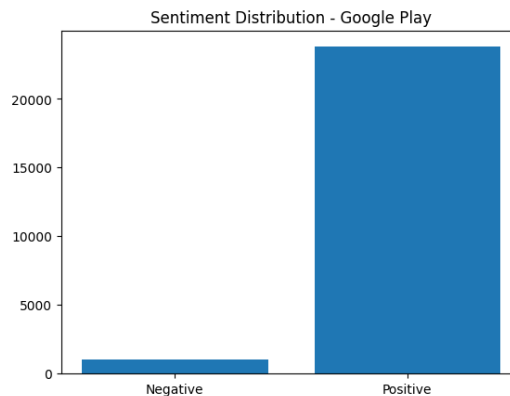


Figure 2. Sentiment Distribution Google Play Store

Figure 2 shows that the dataset from the Google Play Store is overwhelmingly positive, with 23,724 positive reviews (95.8%) and only 1,030 negative reviews (4.2%). This imbalance suggests that most TheoTown users on the mobile platform have a generally positive perception of the game. Such a trend aligns with previous studies on mobile game sentiment, which commonly report a higher proportion of positive feedback on app store platforms [4], [5], [6].

Although the dataset exhibits a significant class imbalance, this study intentionally does not apply the Synthetic Minority Oversampling Technique (SMOTE). This decision is based on several considerations. First, in textual data, synthetic sampling methods such as SMOTE may introduce semantic noise, as generated samples do not always preserve the contextual meaning of natural language. Second, the imbalance observed in this study reflects the real-world distribution of user sentiment, where positive reviews naturally dominate. Furthermore, SVM is known to perform relatively well in high-dimensional feature spaces, even under imbalanced conditions. To mitigate potential bias, this study employs stratified data splitting and cross-validation techniques, ensuring that class proportions are preserved during training and testing.

Regarding overfitting, the model demonstrates stable performance across folds during cross-validation, with consistent F1-scores. This indicates that the model generalizes well and is not significantly overfit. However, it is acknowledged that class imbalance contributes to the model's limitations in detecting minority-class instances, particularly in the Steam dataset.

3.2. Google Play Store Classification Results

The optimal tuning parameters for the Google Play dataset, specifically a linear kernel, $C=1$, and scale gamma, were discovered through a 5-fold cross-validation approach using GridSearchCV. The cross-validation results yielded an average F1-Score of 0.9801, with individual fold scores consistently ranging from 0.979 to 0.982, indicating strong stability and good generalization across different data splits. The performance evaluation of the SVM model on the Google Play Store dataset is illustrated in Figure 3.

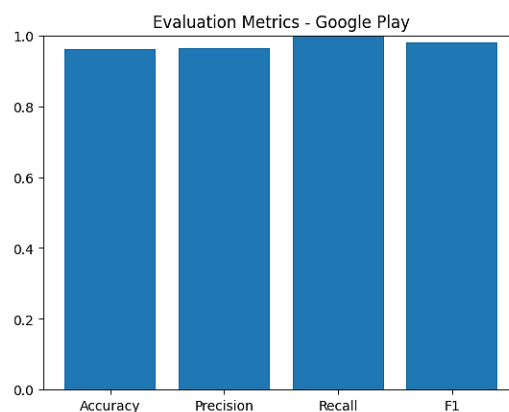


Figure 3. Evaluation Metrics Google Play Store

Based on the data presented in Figure 3, the SVM model delivered an Accuracy of 96.17%, along with Precision, Recall, and F1-Score values of 96.44%, 99.68%, and 98.03%, respectively. The exceptionally high Recall of 99.68% suggests that the model is very capable of capturing positive sentiment instances, with only a minimal number being overlooked. Meanwhile, the F1-Score of 98.03% indicates a strong balance between precision and recall, which is especially important given the dataset's imbalanced nature. A more detailed overview of the prediction results is presented through the Confusion Matrix shown in Figure 4.

The confusion matrix in Figure 4 indicates that the model successfully identified 4,744 instances as true positives, while 175 negative cases were incorrectly predicted as positive (False Positives). The occurrence of these False Positives highlights the difficulty in accurately recognizing the minority negative class, particularly when the dataset is highly imbalanced. The ROC curve and AUC value for the Google Play Store model are depicted in Figure 5.

As shown in Figure 5, the model achieved an AUC score of 0.8501, indicating a strong ability to differentiate between positive and negative sentiment classes in the Google Play Store dataset. This finding aligns with the results reported by Parameswari et al., which show that SVM with a linear kernel provides dependable performance in separating classes probabilistically when applied to high-dimensional textual data [25].

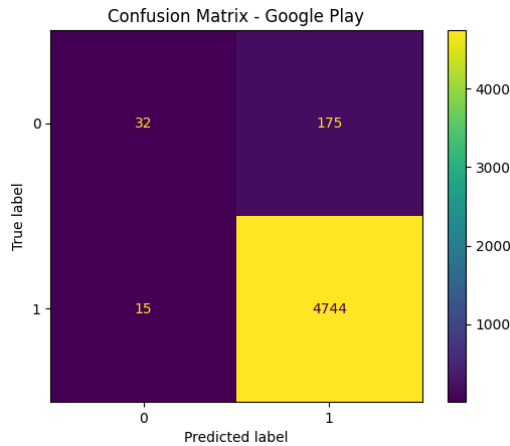


Figure 4. Confusion Matrix Google Play Store

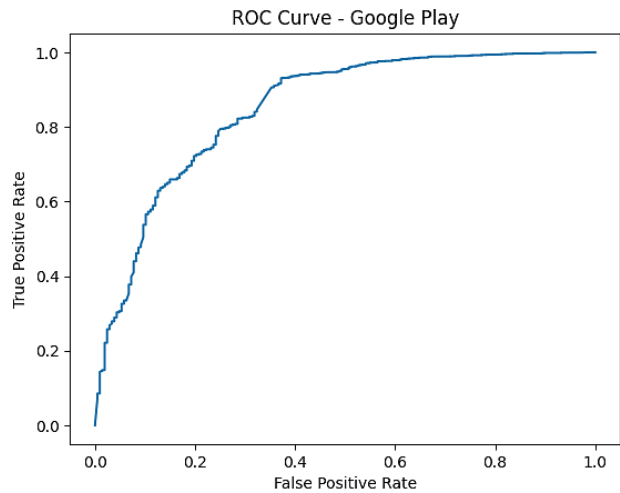


Figure 5. ROC Curve Google Play Store

3.3. Steam Dataset Overview

After applying the same filtering criteria for the 2021–2025 period, a total of 1,452 valid reviews were obtained from the Steam dataset. The distribution of sentiment within this dataset is illustrated in Figure 6.

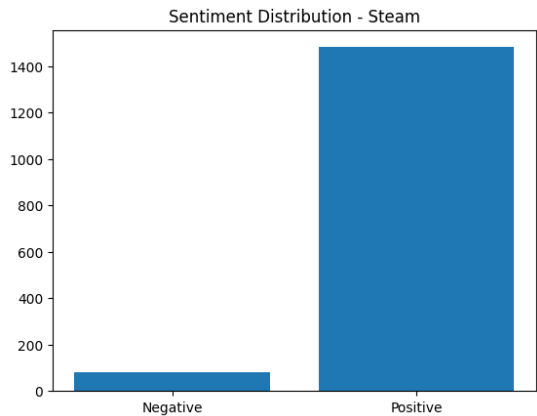


Fig 6. Sentiment Distribution Steam

As illustrated in Figure 6, the Steam dataset, like the Google Play Store, is largely dominated by positive sentiment, with 1,379 positive reviews (94.97%) and 73 negative reviews (5.03%). The noticeably lower number of total reviews compared to the Google Play Store highlights fundamental differences in user demographics, where PC platform users typically represent a more specialized and engaged audience that tends to generate fewer reviews overall [8].

3.4. Steam Classification Results

Based on hyperparameter optimization using GridSearchCV, the best configuration for the Steam model was identified as a linear kernel with $C=0.1$ and gamma set to scale. The cross-validation results produced an average F1-Score of 0.9733, indicating stable and reliable generalization across various data splits, even with the relatively smaller dataset size. The performance metrics of the SVM model on the Steam dataset are illustrated in the Figure 7.

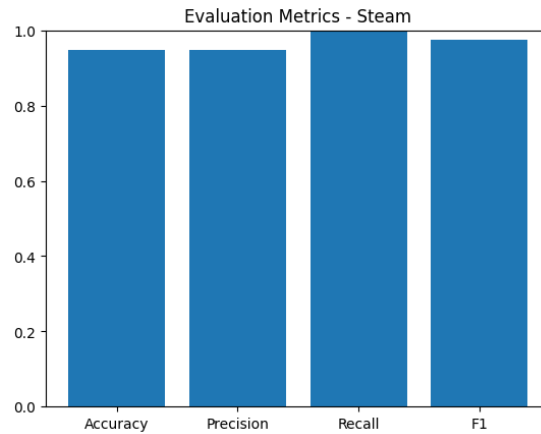


Figure 7. Evaluation Metrics Steam

As illustrated in Figure 7, the model obtained an Accuracy of 94.88% and a precision of 94.88%, along with a Recall value of 1.000 and an F1-Score of 97.37%. The perfect Recall score indicates that all positive sentiment instances in the test dataset were correctly identified, with no occurrences of false negatives. A detailed representation of the classification results for the Steam dataset is provided through the Confusion Matrix in Figure 8.

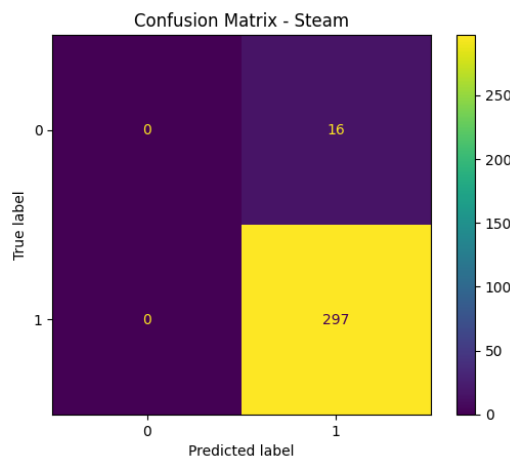


Figure 8. Confusion Matrix Steam

As shown in Figure 8, an important observation can be made from the Confusion Matrix: the model assigned all 297 test samples to the positive class, resulting in 297 True Positives and 16 False Positives, with no True Negatives recorded. This indicates that the model was unable to identify any negative sentiment instances within the Steam dataset. Such behavior is primarily due to the extreme class imbalance, where negative reviews account for only 5.03% of the data, making it challenging for the model to effectively learn and generalize from the minority class. The ROC curve and corresponding AUC value for the Steam model are displayed in Figure 9.

As illustrated in Figure 9, the Steam model achieved an AUC of 0.6114, which is notably lower than the 0.8501 obtained from the Google Play Store dataset. Based on standard AUC interpretation, a score of 0.6114 is categorized within the “fair” to “poor” range, suggesting that the model’s ability to distinguish between positive and negative sentiment on Steam is only slightly better than random prediction. This limitation can largely be attributed to the relatively small dataset size combined with a severe class

imbalance, both of which hinder the model’s capacity to learn a robust decision boundary for the minority (negative) class.

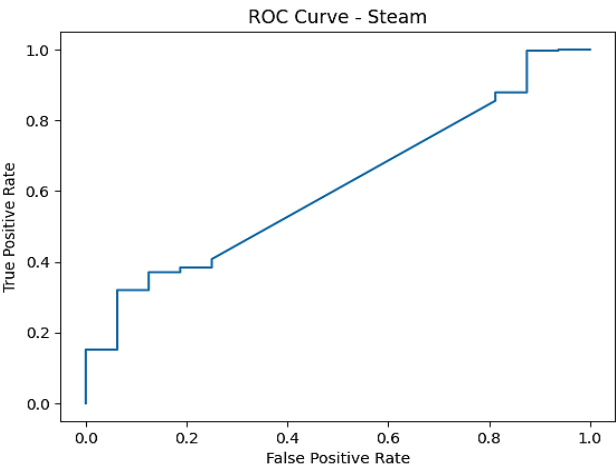


Fig 9. ROC Curve Steam

3.5. Cross-Platform Comparison

A comprehensive comparison of model performance metrics across both platforms is presented in Table 1. The cross-platform analysis highlights several important insights. First, both platforms exhibit a strong dominance of positive sentiment with nearly identical proportions (95.8% vs 94.97%), suggesting that TheoTown receives a favorable reception from users in both mobile and PC environments. Second, the Google Play Store model demonstrates more consistent and reliable performance, as indicated by its higher AUC score (0.8501 compared to 0.6114). This can largely be explained by the significantly larger dataset, which provides more comprehensive and varied training data for the model [25], [26]. Third, although there is a noticeable gap in AUC values, both platforms achieved high F1-Scores exceeding 97%, reinforcing the effectiveness of linear SVM for sentiment classification in high-dimensional text data [21], [24].

Table 1. Cross-Platform Performance Comparison

Metric	Google Play Store	Steam
Total Data	24,754	1,452
Positive Sentiment	23,724 (95.8%)	1,379 (94.97%)
Negative Sentiment	1,030 (4.2%)	73 (5.03%)
Best Kernel	Linear	Linear
Best C	1	0.1
CV F1-Score (mean)	0.9801	0.9733
Accuracy	96.17%	94.88%
Precision	96.44%	94.88%
Recall	99.68%	100%
F1-Score	98.03%	97.37%
AUC	0.8501	0.6114

The comparatively lower AUC observed on the Steam dataset implies that separating sentiment classes on the PC platform is more complex. This difficulty is influenced by several factors, including the smaller dataset size, a more pronounced class imbalance, and the possibility that PC users tend to write more detailed and nuanced reviews. In contrast, mobile users on the Google Play Store often provide shorter and more polarized feedback. This suggests that mobile reviews are generally more direct, whereas Steam reviews tend to be more elaborate and critical, aligning with established patterns of platform-specific user behavior [8], [27], [28].

Furthermore, these results both support and expand upon prior studies. For instance, Wardhana & Kesumawati [8], focused solely on Steam reviews for local games without incorporating cross-platform comparisons, while research by Firmansyah et al. and Bisono & Zulherry examined sentiment exclusively within mobile platforms [1], [2]. By conducting a direct comparison between two distinct ecosystems for the same game, this study provides empirical evidence that platform characteristics and interface differences contribute to variations in sentiment patterns as well as model performance [29], [30].

The extremely high recall values observed in both datasets indicate that the model is strongly biased toward predicting the majority class (positive sentiment). While this results in high overall performance metrics, it also suggests a limitation in detecting minority class instances. This phenomenon is particularly

evident in the Steam dataset, where the model failed to identify any negative samples. This behavior highlights a common issue in imbalanced classification, where the model prioritizes the dominant class to minimize overall error. Additionally, the discrepancy between F1-Score and AUC values suggests that relying solely on accuracy-based metrics may lead to misleading conclusions. While the F1-Score indicates strong performance, the relatively low AUC on the Steam dataset reveals limited discriminative capability.

The results obtained in this study are consistent with previous research, indicating that SVM performs effectively in sentiment classification tasks across different domains. Prior studies have demonstrated that SVM is capable of achieving high accuracy in detecting user sentiment, including fake reviews and social media opinions [10], [11]. This confirms that SVM remains a reliable baseline model for text classification tasks. The robustness of SVM observed in this study is also supported by its successful application in various non-text domains, such as environmental prediction and engineering analysis [14], [15], [16]. This further reinforces the generalization capability of SVM across different types of datasets.

The findings of this study are aligned with previous research, indicating that SVM performs effectively in sentiment classification tasks [10],[11]. However, unlike some studies that incorporate hybrid or deep learning approaches [12], this study focuses on a classical SVM model, which may explain certain limitations observed in handling minority class instances.

Limitations of the Study: Nevertheless, this study has several limitations. Removing neutral reviews limits the analysis to a binary classification framework, potentially excluding nuanced user opinions. In addition, the severe class imbalance across both datasets negatively impacts the model's ability to accurately learn the minority (negative) class, as reflected by the absence of True Negative predictions in the Steam results. Future work could address these issues by incorporating techniques such as SMOTE or class-weighted SVM to balance the dataset, utilizing deep learning approaches like IndoBERT for improved semantic representation [31], [32], or expanding the scope to include multilingual text processing, especially considering the mixture of Indonesian and English reviews present in the Steam dataset [33].

4. CONCLUSION

This research successfully conducted an analysis and comparison of user sentiment in TheoTown reviews from Steam and the Google Play Store using the Support Vector Machine approach. The linear SVM model demonstrated strong performance, achieving F1 Scores exceeding 97% on both platforms, confirming its suitability for sentiment classification in high-dimensional textual data. The Google Play Store dataset consisted of 24,754 reviews and demonstrated more stable probabilistic performance, reflected by an AUC value of 0.8501, whereas the Steam dataset, with 1,452 reviews, produced a lower AUC of 0.6114. Both platforms showed clear dominance of positive sentiment, accounting for 95.8% on the Google Play Store and 94.97% on Steam, indicating that TheoTown is generally well-received across both mobile and PC platforms.

An important observation from the Steam Confusion Matrix is that the model failed to identify any negative class instances (True Negative = 0), underscoring the substantial impact of class imbalance on detecting minority classes. Furthermore, the variation in AUC scores and overall model behavior suggests notable differences in user characteristics between the two platforms. Mobile users tend to give more extreme positive ratings, while Steam users often provide more detailed and nuanced feedback. Overall, these findings underscore the importance of cross-platform comparative analysis for a more comprehensive understanding of user perceptions in the digital game market and offer developers valuable insights for interpreting user feedback across different platform ecosystems.

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