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PUBLIC PERCEPTION OF MSME DIGITAL TRANSFORMATION IN INDONESIA: EVIDENCE FROM YOUTUBE COMMENT SENTIMENT ANALYSIS

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ABSTRACT

Digital transformation has become a strategic requirement for micro, small, and medium enterprises (MSMEs) in Indonesia, particularly in the adoption of marketplaces, QRIS-based payments, digital promotion, and platform-based business operations. This study analyzes public perception of MSME digital transformation using 5,751 YouTube comments collected from January to May 2026 through selected keywords related to MSME digitalization, including marketplace adoption, Shopee UMKM, Tokopedia UMKM, QRIS, and online business practices. The research applies a machine learning-based sentiment analysis pipeline consisting of text preprocessing, TF-IDF feature extraction, classification using Logistic Regression, Support Vector Machine, and Random Forest, and performance comparison with and without SMOTE. The evaluation uses accuracy, macro F1-score, confusion matrix, monthly distribution, keyword frequency, and word cloud visualization. The findings indicate that public discussion is dominated by neutral comments, while positive expressions highlight usefulness, ease, and marketplace opportunities. Negative comments are mainly associated with technical problems, application errors, costs, and platform difficulties. Random Forest without SMOTE achieved the highest accuracy of 98.94%, while SVM with SMOTE obtained the best macro F1-score of 83.77%, showing a better balance in recognizing minority sentiment classes. The study concludes that YouTube comments can function as a useful source of digital social sensing to understand public perception and to support evidence-based MSME digital transformation strategies.

Keywords: MSME digital transformation, YouTube comments, sentiment analysis, TF-IDF, SMOTE, machine learning.

INTRODUCTION

The digital transformation of micro, small, and medium enterprises (MSMEs) has become one of the most important economic adaptation processes in Indonesia. MSMEs are encouraged to use digital platforms to expand market access, improve transaction efficiency, strengthen customer relationships, and increase competitiveness. The transition from traditional selling practices to platform-based operations, such as marketplace selling, QRIS payments, social media marketing, and digital logistics, has created new opportunities and new challenges for business owners (Prihandono et al. 2024).

Public perception is an important indicator in evaluating whether digital transformation is accepted, understood, or resisted by the community. In the context of MSMEs, public comments on YouTube often contain direct expressions about digital platforms, online selling experiences, marketplace competition, system errors, digital payment barriers, and perceived benefits. These comments are valuable because they reflect spontaneous responses from users, sellers, buyers, and general observers (Suhartono et al. 2026).

Sentiment analysis provides a computational approach to transforming unstructured text into measurable information. By classifying comments into positive, neutral, and negative classes, researchers can evaluate the dominant tone of public discussion. In addition, word clouds, keyword frequency charts, and confusion matrices can reveal not only the distribution of sentiment but also the issues that shape public opinion. Therefore, sentiment analysis is relevant for supporting evidence-based policy and organizational decision-making related to MSME digitalization (Purnomo, Nurmalitasari, and Nurchim 2024).

Although many sentiment analysis studies in Indonesia use Twitter or application reviews as data sources, YouTube comments remain highly relevant because YouTube is widely used for public discussion, tutorials, government socialization, product promotion, and business education. This research contributes by focusing on public perception of MSME digital transformation through YouTube comments and by comparing machine learning models with and without SMOTE to understand the effect of data balancing on imbalanced sentiment classes (Sulistianingsih and Switrayana 2024).

The objective of this study is to analyze public perception of MSME digital transformation using YouTube comments, identify dominant discussion themes based on keywords and word clouds, compare machine learning models using accuracy and macro F1-score, and evaluate the contribution of SMOTE in improving model performance on minority sentiment classes (Henderi et al. 2025).

LITERATURE REVIEW

MSME Digital Transformation

MSME digital transformation refers to the use of digital technology to improve business processes, customer engagement, marketing channels, payment systems, and decision-making. In the Indonesian context, digital transformation is closely related to marketplace adoption, e-commerce participation, QRIS transactions, social media marketing, and digital literacy. For MSMEs, digital transformation is not merely the adoption of technology but also a change in business mindset, operating routines, and customer interaction patterns (Ustadus Sholihin and Imam Mukhlis 2023).

The benefits of digitalization include wider market reach, faster communication, lower promotional costs, improved transaction transparency, and better access to digital business ecosystems. However, MSMEs may also face barriers such as limited digital literacy, application errors, platform fees, competition with larger sellers, and lack of consistent mentoring. These barriers are frequently reflected in public comments on social media platforms.

Sentiment Analysis on Social Media

Sentiment analysis is a branch of natural language processing that identifies opinion polarity in text. In this study, sentiment is categorized into three classes: positive, neutral, and negative. Positive comments indicate support, satisfaction, or perceived usefulness. Negative comments indicate complaints, resistance, disappointment, or technical barriers. Neutral comments generally contain information, questions, or topic-related statements without clear emotional polarity.

YouTube comments have a unique character because they often include informal language, abbreviations, slang, repeated words, and mixed topics. Therefore, preprocessing is necessary before classification. Common preprocessing stages include case folding, cleaning symbols and URLs, tokenization, stopword removal, normalization, and stemming.

TF-IDF, Machine Learning, and SMOTE

TF-IDF is commonly used to transform text into numerical features by considering term frequency and inverse document frequency. This representation is effective for traditional machine learning models because it captures the relative importance of words across documents. In this research, TF-IDF is used as the feature extraction method before classification (Amrullah et al. 2024).

Logistic Regression, Support Vector Machine, and Random Forest are used as comparative classifiers. Logistic Regression is a strong baseline for text classification, SVM is effective for high-dimensional sparse data, and Random Forest is an ensemble method that combines multiple decision trees. However, sentiment datasets from social media are often imbalanced, where neutral comments dominate while negative comments are limited. SMOTE is applied to generate synthetic minority samples in the training data to reduce bias toward the majority class (Nurhaliza Agustina et al. 2024).

RESEARCH METHODS

This research uses a quantitative computational approach based on sentiment analysis and machine learning. The object of analysis is public comments on YouTube related to MSME digital transformation. The research design follows a data analytics pipeline consisting of data collection, data understanding, preprocessing, feature extraction, model training, model evaluation, visualization, and interpretation.

Table 1. Research Design

Stage	Activity	Output
Data collection	Collect YouTube comments using selected MSME digitalization keywords	Raw comment dataset
Preprocessing	Case folding, cleaning, tokenization, normalization, stopword removal, stemming	Cleaned text
Feature extraction	Transform text using TF-IDF	Numerical feature matrix
Modeling	Train LR, SVM, and RF with No SMOTE and SMOTE scenarios	Classification models
Evaluation	Use confusion matrix, accuracy, and macro F1-score	Performance comparison
Visualization	Generate charts, word clouds, and keyword frequency	Interpretive figures

The dataset consists of 5,751 YouTube comments collected from January to May 2026. The keywords were designed to capture public discussions about MSME digital transformation, including marketplace participation, Shopee UMKM, Tokopedia UMKM, QRIS, digital assistance, online selling, and digital training. The sentiment labels are grouped into positive, neutral, and negative categories.

Table 2. Dataset Summary

Item	Description
Data source	YouTube comments
Total comments	5,751
Period	January-May 2026
Sentiment classes	Positive, Neutral, Negative
Feature extraction	TF-IDF
Algorithms	Logistic Regression, SVM, Random Forest
Balancing scenario	No SMOTE and SMOTE

Table 3. Example of Text Preprocessing

Original Comment	Preprocessing Step	Output
Aplikasi marketplace untuk UMKM bagus dan mudah digunakan!	Cleaning and case folding	aplikasi marketplace umkm bagus mudah digunakan
QRIS sering error saat transaksi, jadi pelanggan kecewa.	Cleaning, stopword removal, stemming	qris error transaksi pelanggan kecewa
Shopee UMKM membantu usaha kecil masuk pasar online.	Tokenization and stemming	shopee umkm bantu usaha kecil pasar online

RESULTS AND DISCUSSION

Comment Distribution by Month

The monthly distribution shows that public discussion increased from January to March 2026 and then slightly decreased in April and May. March 2026 recorded the highest number of comments with 1,755 comments, or 30.52% of the total dataset. This indicates that public attention toward MSME digital transformation was strongest in March, possibly due to increased public discussion around marketplace participation, QRIS adoption, or digital business programs.

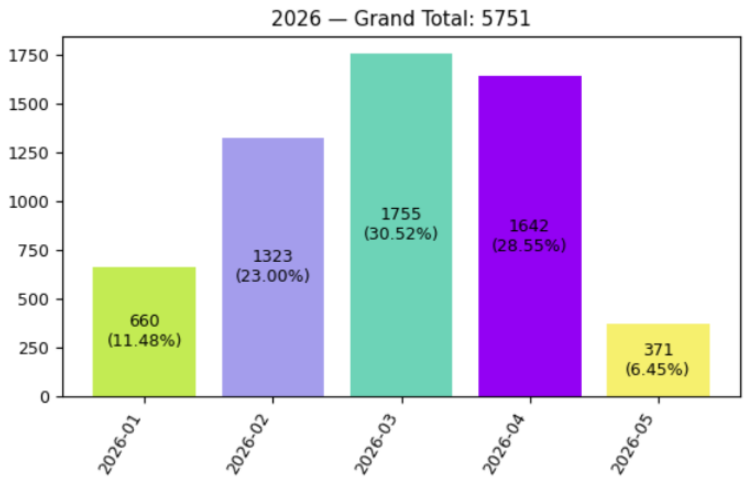

Figure 1. Monthly Distribution of YouTube Comments in 2026

Keyword Frequency Analysis

The keyword frequency chart indicates that the most dominant discussions are related to marketplace entry and specific digital platforms. The keyword "UMKM masuk marketplace" produced the highest number of comments, followed by "Shopee UMKM," "UMKM jualan online," "Tokopedia UMKM," and "bantuan digital UMKM." This distribution confirms that marketplace adoption is the central issue in public discussion about MSME digital transformation.

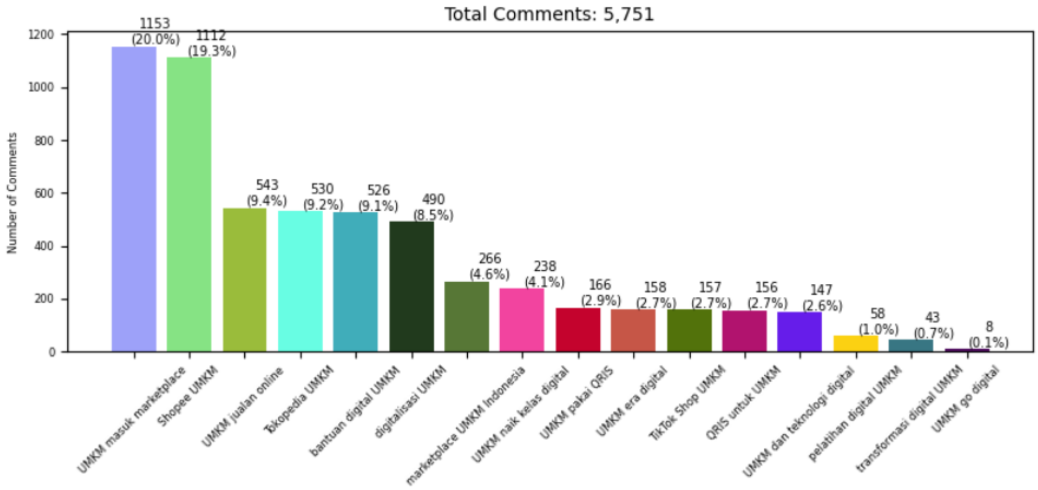

Figure 2. Keyword Frequency Distribution of MSME Digital Transformation Comments

Word Cloud and Top Issue Analysis

The word cloud visualization reveals different semantic patterns in each sentiment class. Positive comments are dominated by words such as "bagus," "mantap," "usaha," "UMKM," and "mudah," indicating support for digital platforms and perceived usefulness. Negative comments contain terms such as "error," "jelek," "buruk," "aplikasi," and "mahal," which reflect complaints about system problems, usability barriers, and cost concerns. Neutral comments are dominated by topic-related terms such as "UMKM," "usaha," "bisnis," "Shopee," and "QRIS," showing that much of the public discussion is informational rather than emotional.

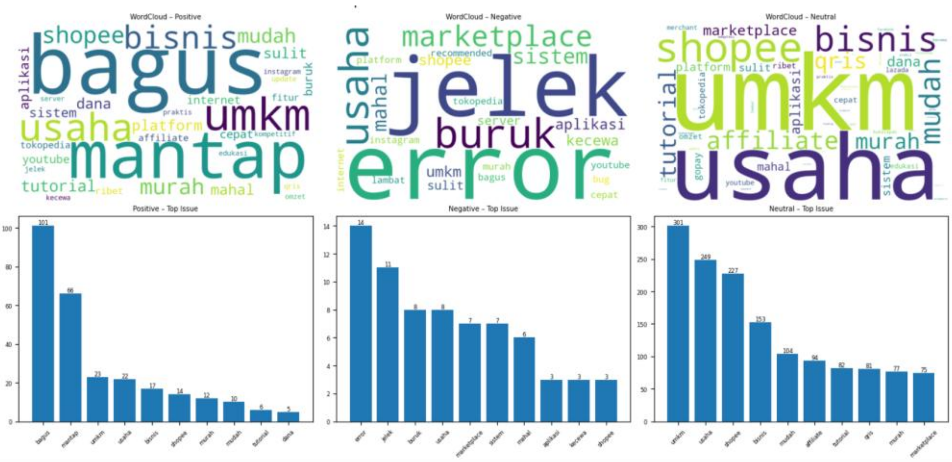

Figure 3. WordCloud and Top Issue Analysis by Sentiment Class

Confusion Matrix Analysis: No SMOTE

In the No SMOTE scenario, Logistic Regression achieved high overall accuracy but showed weak recognition of minority classes, especially negative sentiment. The percentage matrix indicates that many negative comments were predicted as neutral. This pattern demonstrates the effect of class imbalance: the model tends to prioritize the dominant neutral class (Wahyuni Kalumbang n.d.).

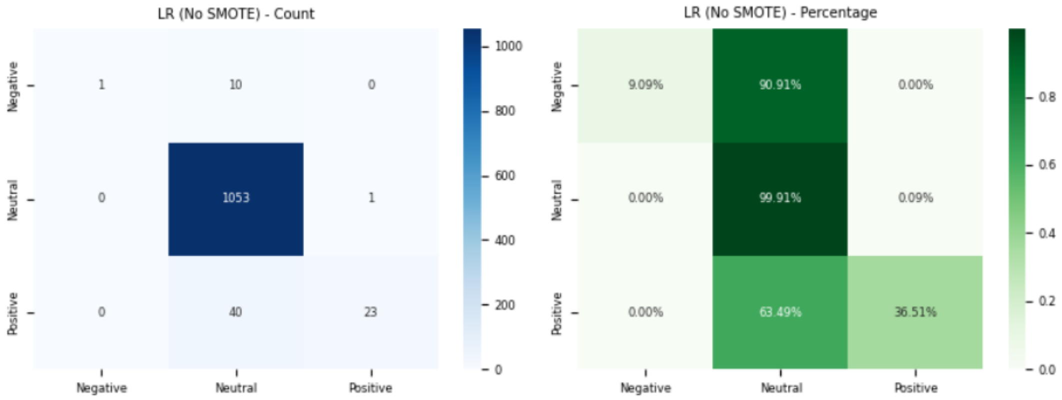

Figure 4. Logistic Regression Confusion Matrix without SMOTE

SVM without SMOTE shows better performance than Logistic Regression in recognizing negative and positive classes. The model identified 27.27% of negative comments and 71.43% of positive comments correctly, while maintaining very high recognition of neutral comments. This confirms that SVM is suitable for sparse TF-IDF features (Hutapea and Maharani 2023).

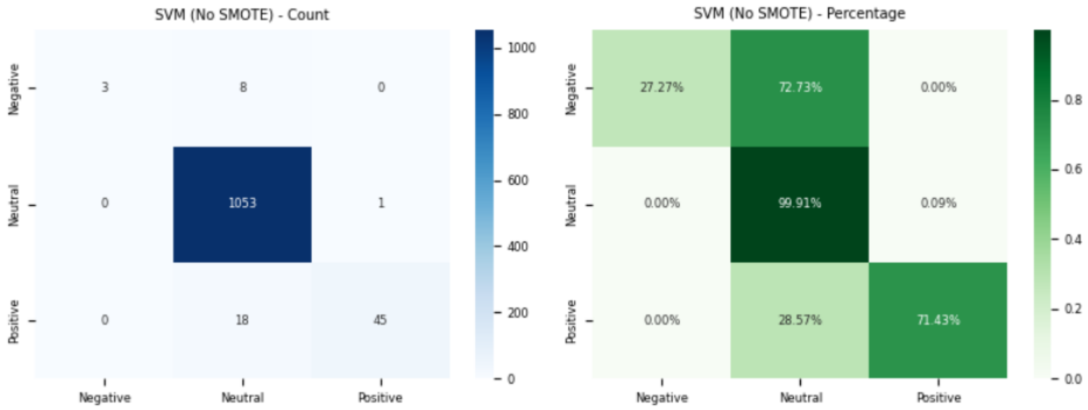

Figure 5. SVM Confusion Matrix without SMOTE

Random Forest without SMOTE obtained the strongest performance among the No SMOTE scenarios. It recognized 36.36% of negative comments and 93.65% of positive comments while retaining 99.91% accuracy for neutral comments. This result shows that Random Forest can capture non-linear patterns in the TF-IDF feature space, although the negative class remains difficult due to limited samples (Jakarta, Lestari, and Hutagalung 2025).

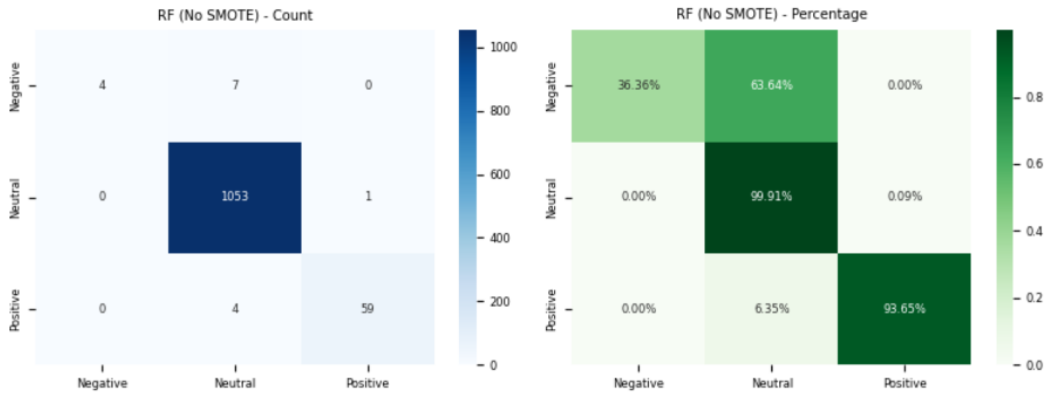

Figure 6. Random Forest Confusion Matrix without SMOTE

Confusion Matrix Analysis: SMOTE

After applying SMOTE, Logistic Regression improved substantially in recognizing minority classes. Negative recall increased to 45.45%, and positive recall increased to 71.43%. This suggests that synthetic minority oversampling helped Logistic Regression reduce majority-class bias.

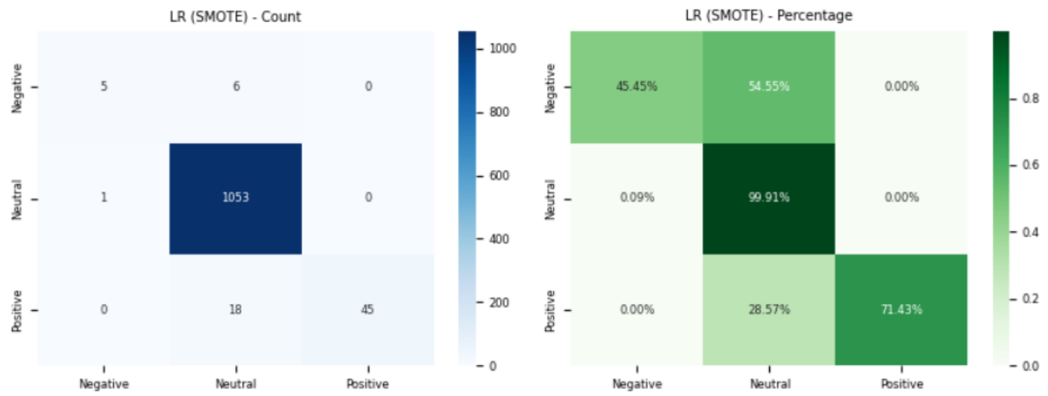

Figure 7. Logistic Regression Confusion Matrix with SMOTE

SVM with SMOTE produced the most balanced macro performance. Negative recall reached 45.45%, positive recall reached 82.54%, and neutral recall remained 99.91%. This shows that SVM benefits from SMOTE while retaining strong performance in the dominant class.

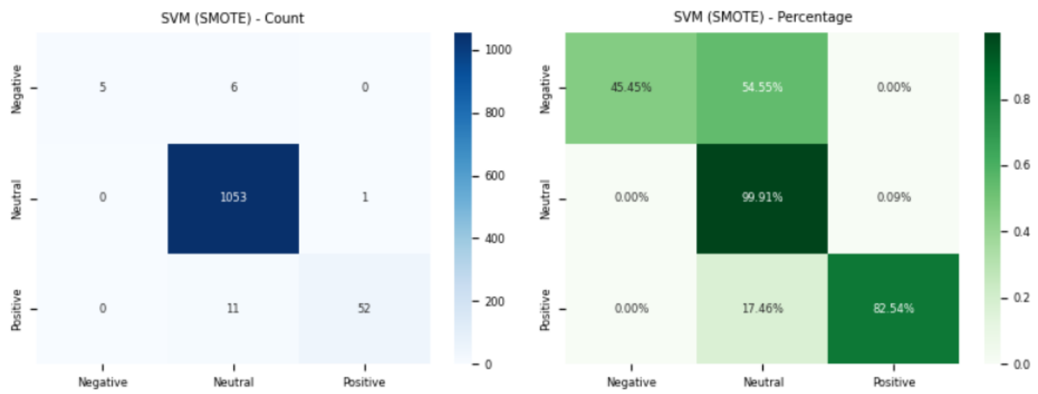

Figure 8. SVM Confusion Matrix with SMOTE

Random Forest with SMOTE produced lower macro F1-score compared with Random Forest without SMOTE. Although positive recall remained strong at 82.54%, negative recall dropped to 9.09%. This result indicates that SMOTE does not always improve ensemble tree models and may introduce synthetic noise in sparse text features.

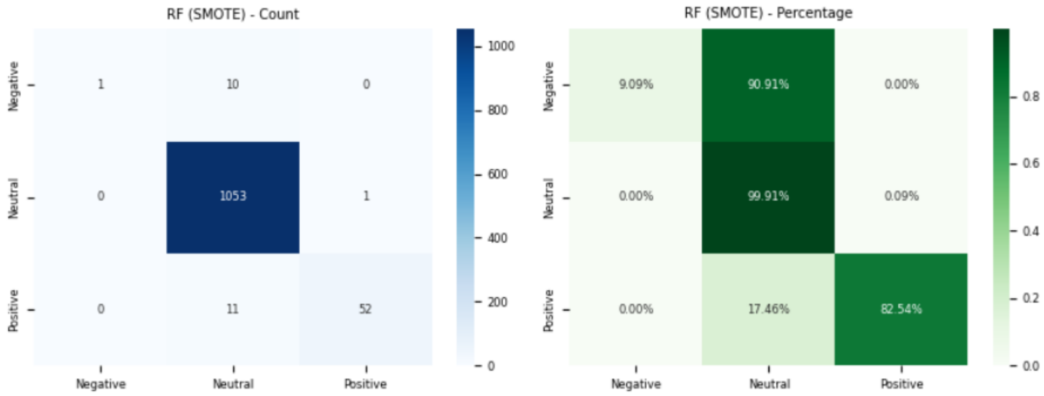

Figure 9. Random Forest Confusion Matrix with SMOTE

Model Comparison svm

The final comparison table shows that Random Forest without SMOTE achieved the highest accuracy at 98.94%, while SVM with SMOTE achieved the highest macro F1-score at 83.77%. Accuracy alone may be misleading because the dataset is dominated by neutral comments. Therefore, macro F1-score is important because it evaluates the model across all sentiment classes equally (Sulistianingsih and Switrayana 2024),(Ustadus Sholihin and Imam Mukhlis 2023), (Asro and Solihin 2026).

Table 4. Final Model Performance Comparison

Model	SMOTE	Accuracy	F1-Macro
Logistic Regression	No	95.48%	55.73%
SVM	No	97.61%	74.72%
Random Forest	No	98.94%	82.90%
Logistic Regression	Yes	97.78%	80.33%
SVM	Yes	98.40%	83.77%
Random Forest	Yes	98.05%	68.43%

The visualization of accuracy and macro F1-score confirms that the best model depends on the evaluation priority. If the objective is to maximize overall correctness, Random Forest without SMOTE is the strongest option. However, if the objective is to obtain balanced classification across positive, neutral, and negative comments, SVM with SMOTE is more appropriate. This finding is important because public perception studies should not ignore minority sentiment, especially negative comments that may contain complaints, barriers, or policy-relevant issues (Chaidir and Friadi 2025),(Asro 2024).

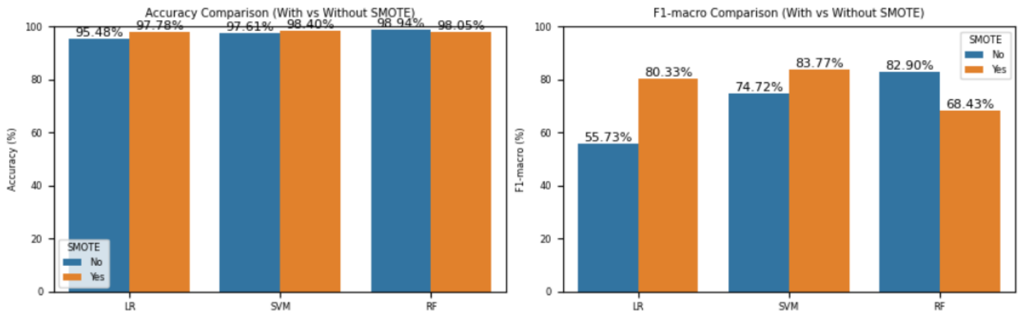

Figure 11. Accuracy and F1-Macro Comparison with and without SMOTE

Discussion

The results demonstrate that MSME digital transformation receives broad public attention on YouTube. The dominance of neutral comments suggests that many users discuss digitalization as information, tutorial content, policy news, or marketplace-related explanation rather than direct emotional evaluation. However, positive sentiment shows that many users perceive digital platforms as useful for improving business opportunities and market access (Bina and Informatika 2022).

Negative comments, although smaller in quantity, are analytically important. Words such as "error," "jelek," "buruk," "mahal," and "aplikasi" indicate that technical reliability, transaction smoothness, and cost remain key barriers. These issues should be considered by policymakers, platform providers, and MSME facilitators because negative perceptions may reduce adoption willingness among small business owners.

The comparison between SMOTE and No SMOTE indicates that data balancing should be applied carefully. SMOTE improved Logistic Regression and SVM significantly in terms of macro F1-score, but reduced Random Forest performance. This confirms that there is no single universal method for all models. The best strategy depends on the algorithm, feature representation, and distribution of sentiment classes (Nurkholis, Alita, and Munandar 2022).

From a methodological perspective, this study supports the use of YouTube comments as a source of digital social sensing. Public comments can be analyzed to detect emerging issues, evaluate digital literacy needs, and identify friction points in digital transformation. The approach can be expanded into a dashboard system for real-time monitoring of MSME digitalization discourse.

CONCLUSION

This study analyzed public perception of MSME digital transformation using 5,751 YouTube comments collected from January to May 2026. The analysis shows that marketplace adoption is the dominant topic, with keywords related to UMKM entering marketplaces, Shopee UMKM, Tokopedia UMKM, QRIS, and online selling. The word cloud analysis indicates that positive comments emphasize usefulness, ease, and business benefits, while negative comments focus on system errors, poor application experience, high costs, and practical barriers.

The machine learning evaluation shows that Random Forest without SMOTE achieved the highest accuracy of 98.94%, while SVM with SMOTE achieved the best macro F1-score of 83.77%. These results suggest that accuracy is not sufficient for evaluating imbalanced sentiment datasets. Macro F1-score provides a more balanced perspective because it considers minority classes such as negative and positive sentiment (Homepage et al. 2026).

The study concludes that YouTube comment sentiment analysis can provide meaningful insights into public perception of MSME digital transformation. The findings can support policymakers, digital platform providers, and MSME assistance programs in identifying public concerns, improving platform reliability, strengthening digital literacy, and designing more inclusive digital transformation strategies.

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