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Recommending E-Commerce Platforms for MSMEs: A Sentiment Analysis Approach

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ABSTRACT

The rapid growth of e-commerce in Indonesia presents significant opportunities for micro, small, and medium enterprises (MSMEs), yet the diversity of marketplace platforms complicates the selection of an optimal sales channel. This study addressed this challenge by developing a data-driven recommendation system based on sentiment analysis of user reviews. Utilizing a dataset of 80,000 reviews scraped from four major platforms on the Google Play Store (Shopee, Tokopedia, Lazada, and Blibli), two classification approaches were implemented and compared: support vector machine (SVM) and long short-term memory (LSTM). Both models demonstrated a competitive performance, enabling effective sentiment categorization. Furthermore, multinomial logistic regression was employed to analyze the influence of key variables rating, number of likes, and marketplace brand on sentiment outcomes. The analysis revealed that Shopee yielded the highest probability of receiving positive reviews (97.82%) and showed no significant association with negative sentiment. Consequently, this study recommends Shopee as the primary platform for MSMEs to enhance their digital presence and sales performance. The primary contribution lies in integrating machine learning-based sentiment analysis with statistical modelling to generate actionable, evidence-based marketplace recommendations for MSMEs.

1. Introduction

The digitalization era has fundamentally transformed Indonesia’s economic landscape, with digital transformation emerging as a key driver in enhancing national economic competitiveness. The UMKM Level Up program, prioritized by both central and regional governments, represents a strategic response to the challenges of global market competition through the digital transformation of micro, small, and medium enterprises (MSMEs). With more than 65 million MSMEs in Indonesia, according to data from the Ministry of Cooperatives and MSMEs in 2024, the potential for developing the digital economy is enormous and requires an appropriate approach to optimize its utilization [1].

The growth of internet users in Indonesia, which reached 221.56 million at the beginning of 2024 according to the Indonesian Internet Service Providers Association (APJII), reflects a significant acceleration over the past five years in the adoption of digital technologies by Indonesian society [2]. This momentum is reinforced by data from Bank Indonesia, which recorded e-commerce transactions in July 2025 amounting to IDR44.4 trillion [3], reflecting the high level of interest and online shopping behavior among Indonesians. The future outlook for the market remains highly promising. Forecasts suggest the gross merchandise value (GMV) of e-commerce in Indonesia will approach 150 billion U.S. dollars by 2030, underscoring its vast economic potential. Concurrently, the number of e-commerce users is anticipated to rise to around 99 million by 2029, serving as a primary engine for this expansion [4]. The combination of a vast number of MSME*s*, massive internet penetration, and increasing e-commerce transactions creates a digital ecosystem that strongly supports technology-driven economic growth.

E-commerce, defined as commercial transactions conducted through digital networks, has been proven to provide significant benefits for MSMEs, including expanding market reach, enhancing promotional efficiency, and increasing product exposure, which ultimately contribute to economic growth [5]. Among the various e-commerce models, marketplaces with their market creator business model stand out as a strategic option since they provide platforms and services that connect sellers and buyers online through digital applications. These platforms enable MSMEs actors to easily access digital markets via applications available on the Google Play Store, thereby opening vast opportunities to optimize product sales.

Nevertheless, the diversity of available marketplace options requires MSMEs to carefully select the most suitable platform to optimize their sales strategies. An inappropriate choice of platform may negatively impact sales effectiveness and customer satisfaction, thereby necessitating a systematic approach to evaluating the quality and reputation of various marketplace platforms. In this context, understanding customer opinions and experiences becomes crucial in assessing e-commerce service quality, where sentiment analysis can serve as an effective tool to categorize consumer perceptions as positive, neutral, or negative [6].

Advancements in machine learning and deep learning technologies have created new opportunities for more accurate and comprehensive sentiment analysis [7]. Conventional methods such as support vector machine (SVM) remain relevant, as they demonstrate superior performance in handling large and structured text data. On the other hand, deep learning methods such as long short-term memory (LSTM) offer greater capability in capturing linguistic context and sequential patterns in consumer reviews, as they are specifically designed to process text as sequences of words [8].

Previous studies have shown that factors such as e-commerce platforms, price competitiveness, logistics speed, user reviews, and personalized recommendations significantly influence consumer purchase decisions in both traditional commerce and e-commerce platforms [9]. In addition, factors of online customer reviews and online customer ratings play an important role in purchasing decisions on Shopee [10]. Furthermore, information quality, system quality, and trust have also been proven to be key drivers of customer satisfaction in e-commerce, highlighting the multidimensional nature of factors affecting consumer behavior [11]. Research [12] concluded that marketplaces play a strategic role in expanding MSME market access. However, the study was qualitative in nature and limited to describing benefits and challenges without offering recommendations on the most suitable platform for MSMEs. Similarly, research [13] revealed methodological limitations, indicating the need for more complex and diverse analytical methods to yield comprehensive findings. Likewise, research [14] was constrained by limited data and insufficient exploration of consumer perceptions, thus failing to provide an in-depth understanding of consumer preferences across different marketplace platforms. Overall, prior studies have largely focused on analyzing individual factors without integrating a comprehensive sentiment analysis approach to provide platform-specific recommendations for MSMEs.

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Addressing these limitations, this study integrates two machine learning approaches, SVM and LSTM, which have both demonstrated competitive classification performance with accuracy rates exceeding 90%. Furthermore, the study utilized a large dataset of 80,000 reviews collected from the Google Play Store and applied machine learning-based methods to gain more detailed insights into consumer perceptions and generate more accurate sentiment predictions. This approach is expected to fill existing research gaps by providing stronger, empirically grounded recommendations for MSMEs in selecting the optimal marketplace platform.

Based on this background, the objective of this study is to provide recommendations for MSMEs in choosing marketplace platforms using sentiment analysis of user reviews on four major platforms available on the Google Play Store, namely Shopee, Tokopedia, Lazada, and Blibli. In this study, LSTM and SVM were applied, specifically to analyze and measure the level of public interest in the e-commerce platforms under review. This interest is measured indirectly by identifying and quantifying the dominant positive sentiment in user reviews. To strengthen the descriptive analysis of e-commerce platforms selection based on the highest number of positive reviews, multinomial regression was used to show that factors such as application ratings, number of likes, marketplace brands, and review time categories influence consumer sentiment. This is in line with the results of [15], stating that online customer reviews are significantly related to consumer perceptions, purchasing decisions, and brand reputation in the digital market.

By employing a dataset of 80,000 reviews scraped from the Google Play Store over the past three months, this research is expected to provide MSMEs factors with valuable insights in selecting the most optimal marketplace platform based on consumer perspectives and experiences. In doing so, the study contributes to supporting the sustainable digital transformation of MSMEs and enhancing national economic competitiveness. The main contribution of this study is to provide e-commerce platforms recommendations to MSMEs based on the identification of platforms with the most positive reviews. These recommendations are reinforced by an analysis of electronic word-of-mouth (e-WOM), which reveals the key factors that influence consumer sentiment in marketplace selection.

2. Method

2.1. Data Collection

Data for this study were collected via web scraping using the google-play-scraper library from the Google Play Store. Four major e-commerce applications (Tokopedia, Shopee, Lazada, and Blibli) were selected based on popularity and download volume. The scraping process collected not only review texts but also important metadata, including star ratings, the number of likes or thumbs up, and review dates, which were later used for extended analysis. All collected data were merged into a comprehensive dataset and subsequently annotated by experts to ensure consistency of sentiment labels before the modeling stage.

2.2. Data Preprocessing

The annotated dataset then underwent several preprocessing stages to improve the quality of the textual data and prepare it for machine learning models. Case folding was applied to standardize all text into lowercase letters, followed by stopword removal to eliminate common words that did not carry significant semantic meaning, such as "*yang*," "*dan*," or "*di*." Emoticons were mapped into their equivalent textual representation to capture emotional context, for example, "😊" was transformed into the word "*senang*." In addition, URLs and non-alphanumeric characters were removed to ensure readability, and whitespace normalization was carried out to eliminate redundant spacing. These steps were essential to ensure that the dataset was clean, consistent, and suitable for subsequent modeling.

2.3. Variables

This study employed two categories of variables. The dependent variable was marketplace customer sentiment, which was classified into three categories: negative, neutral, and positive. These categories were derived from the annotated user reviews, reflecting customer experiences with each marketplace platform. The independent variables consisted of four components. The first was the application rating, representing numerical evaluations of the marketplace applications. The second was the number of likes or thumbs up received by each review, indicating the degree of resonance or agreement from other users. The third was the marketplace brand, which identified whether the review was associated with Shopee, Tokopedia, Lazada, or Blibli. The fourth was the review time category, which captured the temporal aspect of when the review was posted, allowing for analysis of potential contextual influences on consumer sentiment. Together, these independent variables represent key dimensions of customer experience that may shape consumer perceptions and sentiment toward marketplace platforms.

2.4. Machine Learning Models

Two modeling approaches were employed to classify consumer sentiment, namely SVM and LSTM. The SVM model was combined with feature representation using the term frequency–inverse document frequency (TF-IDF). TF-IDF was applied to calculate the importance of words within the corpus and to transform text into numerical vectors that could be processed by the SVM algorithm [16]. Based on this representation, SVM constructed an optimal hyperplane to separate sentiment classes, while in nonlinear cases, the kernel trick was applied to map the data into higher-dimensional spaces, enabling non-linear separation [17]. In contrast, LSTM, a deep learning model specifically designed to handle sequential data, was utilized to capture linguistic context and long-term dependencies within consumer reviews. Its ability to process text as a sequence of words made LSTM particularly effective in identifying sentiment patterns that extend beyond individual word frequencies, offering deeper insights into consumer perceptions. Fig. 1 illustrates the LSTM architecture.

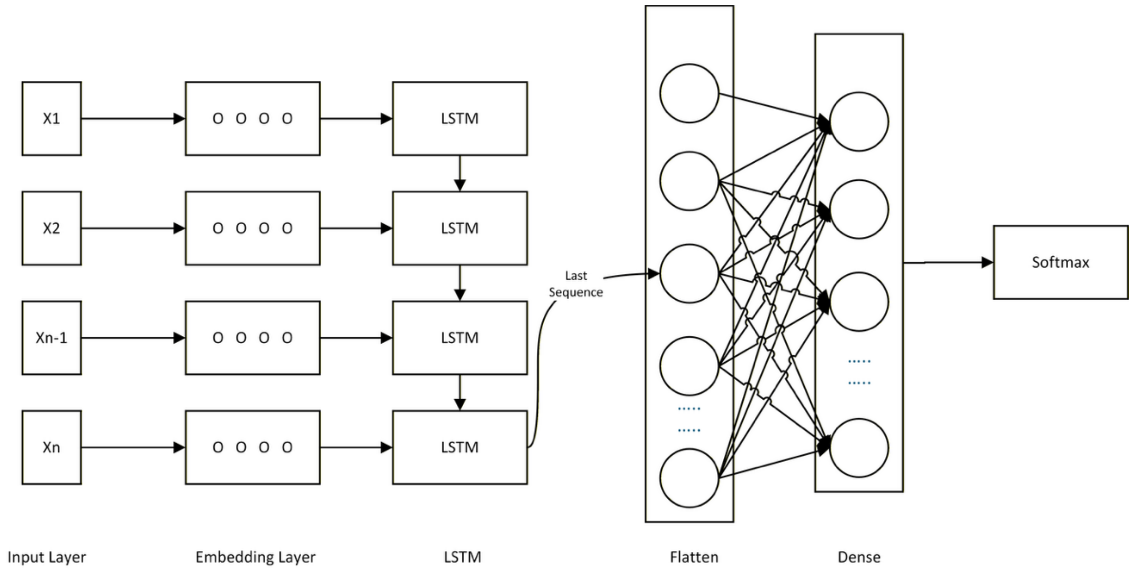

Fig 1. Illustration of the LSTM architecture.

Based on Fig. 1, LSTM is a recurrent neural network (RNN) architecture designed to handle long-term dependencies in sequential data by addressing the vanishing or exploding gradient problems commonly found in standard RNNs. LSTM is applied in sentiment analysis by utilizing an embedding layer and an LSTM layer, followed by a dense layer with SoftMax activation to classify reviews. Variants of the LSTM method have been shown to close the gap with transformer-based models on several large-scale benchmarks when properly designed and scaled, and remain relevant in many natural language processing (NLP) tasks, including data-limited language modeling [18] [19]. Both models, LSTM and SVM, were evaluated using accuracy, precision, recall, and F1-score metrics to ensure optimal performance in sentiment classification.

Fig. 2 illustrates the process of data classification through the transformation from an input space to a feature space.

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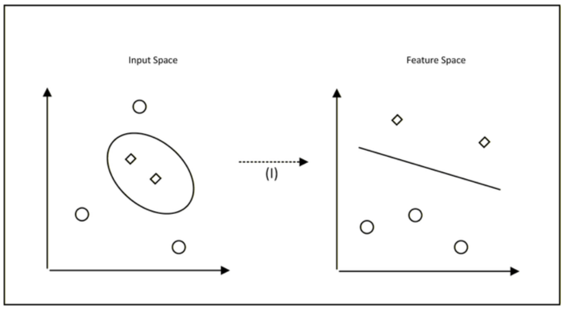

Fig 2. Example of data classification with dividing margin lines.

In the left panel (input space), data points from two classes are intermixed and cannot be separated by a straight line. This nonlinear distribution is then mapped into a higher-dimensional feature space (right panel), where the classes become linearly separable. In the feature space, optimal dividing margin lines are established. The central line represents the decision boundary, while the parallel dashed lines indicate the maximum margin between the two classes. Maximizing this margin enhances the classifier's robustness and generalization, a key principle in methods such as SVMs.

2.5. Statistical Analysis

Multinomial logistic regression is a statistical method used to analyze the influence of independent variables on a dependent variable measured on a nominal scale with more than two categories. This model estimates the log of the odds of each category relative to a reference (baseline) category through a linear combination of predictors. The mathematical formulation of multinomial logistic regression [20] is presented in equations (1) to (3).

$$log\frac{P(Y=j\mid X)}{P(Y=K\mid X)} = \beta_{j0} + \beta_{j1}X_1 + \cdots + \beta_{jp}X_p \text{ , for each category } j = 1, \ldots, K-1 \quad (1)$$

$$P(Y=j\mid X) = \frac{e^{\beta_{j0}+\beta_{j1}X_1+\cdots+\beta_{jp}X_p}}{1+\sum_{r=1}^{K-1} e^{\beta_{r0}+\beta_{r1}X_1+\cdots+\beta_{rp}X_p}} \quad (2)$$

$$P(Y=K\mid X) = \frac{1}{1+\sum_{r=1}^{K-1} e^{\beta_{r0}+\beta_{r1}X_1+\cdots+\beta_{rp}X_p}} \quad (3)$$

3. Results and Discussion

3.1. Dataset Description and Preprocessing

The dataset was collected from four major e-commerce marketplaces in Indonesia, namely Shopee, Tokopedia, Lazada, and Blibli, with 20,000 of the most recent Indonesian language reviews retrieved from each platform. In total, 80,000 reviews were gathered, complemented with additional variables such as rating score, number of likes or thumbs-up, and review date.

To provide an initial overview of the dataset, a word cloud visualization was generated as shown in Fig. 3. The most frequently appearing words were "*bagus*," "*saya*," "*sangat*," "*bisa*," and "*tidak*." The dominance of the word "*bagus*" indicates that, in general, consumer reviews tend to carry a positive sentiment toward marketplace services.

Fig 3. Wordcloud of reviews from four marketplace platforms.

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Based on manual annotation, the distribution of sentiment labels per application is shown in Fig. 4. Shopee recorded the highest proportion of positive reviews, followed by Blibli and Lazada, while Tokopedia had relatively fewer positive reviews, but a higher proportion of negative reviews compared to the other platforms. Neutral reviews were relatively low across all marketplaces, indicating that customers tend to provide more explicit evaluations, either positive appreciation or direct criticism.

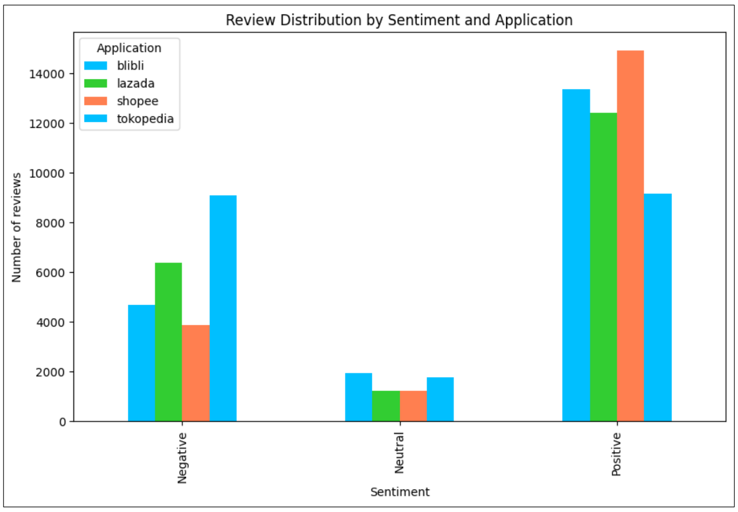

Fig 4. Distribution of reviews by sentiment category and application.

All reviews were then processed through several text preprocessing steps are summarized in Table 1. The preprocessed dataset was subsequently split into 70% training data and 30% testing data.

Table 1. Text Preprocessing Pipeline Before and After

Before Preprocessing	After Preprocessing
Saya sangat suka belanja di tokopedia ini 😊	Sangat suka belanja tokopedia senang
Cek di http://promo.shopee.co.id diskon besar 👍	cek promo diskon besar bagus

The preprocessing steps included case folding to standardize text into lowercase format, URL removal to eliminate irrelevant links, stopword removal to discard non-informative words, emoticon mapping, nonalphanumeric character elimination, and whitespace normalization.

3.2. Machine Learning Classification Result

The SVM model achieved an accuracy of 90%, with the highest performance observed in the positive sentiment class (F1-score = 0.95) and the lowest in the neutral sentiment class (F1-score = 0.55). In comparison, the LSTM model demonstrated slightly higher performance with an accuracy of 91% and balanced evaluation metrics (precision = 0.91, recall = 0.91, F1-score = 0.91). As an additional benchmark, naïve Bayes was tested as a baseline model, producing an accuracy of 88%. Table 2 presents the performance comparison.

Table 2. Evaluation Results of The Classification Model

Model	Precision	Recall	F1-Score	Accuracy
SVM	0.90	0.96	0.95	0.90
LSTM	0.91	0.91	0.91	0.91
Naïve Bayes	0.89	0.88	0.86	0.88

The results presented in Table 2 indicate that both SVM and LSTM models perform with high accuracy. While SVM shows a particularly high recall (0.96) and F1-score for positive sentiment (0.95), LSTM provides more balanced performance across all metrics.

3.3. Multinomial Logistic Regression Analysis

To further investigate the factors influencing customer sentiment, multinomial logistic regression was applied with four independent variables rating, number of likes, brand, and review date. Based on Table 3, the likelihood ratio test indicated that the review date was not statistically significant (p-value 0.253 > alpha 0.05) and therefore was excluded from the final model.

Table 3. Likelihood Ratio Test Results

Effect	Model Fitting Criteria			Likelihood Ratio Test		
	AIC of Reduced Model	*BIC of Reduced Model*	*-2 Log Likelihood of Reduced Model*	*Chi-Square*	*df*	*Sig.*
Intercept	6650.309	6873.261	6602.309	.000	0	.
Total Sentimen Likes	675.983	6956.355	6707.983	105.674	2	<,001
Marketplace Ratingf	58589.330	58737.964	58557.330	51955.021	8	.000
Time Review Applications	6646.112	6813.326	6610.112	7.803	6	.253
Brand Marketplace	7297.470	7464.684	7261.470	659.161	6	<,001

The multinomial logistic regression test for the model without the marketplace application review time variable show that both the overall and partial model tests yielded significant values in estimating the influence of the three remaining independent variables on customer sentiment at a 95% confidence level. This model produced an R square value of 0.621, indicating that the variables application rating, number of likes, and marketplace brand explain 62.1% of the variation in customer sentiment categories, while the remaining variance is accounted for by other factors not included in the model. The mathematical equation derived from the regression model test results, based on the parameter estimation in Table 4, are presented in (4) and (5).

$$log\frac{P(Y=3)}{P(Y=1)} = \frac{Positive\ Sentiment}{Neutral\ Sentiment}$$

$$= \beta_0 + \beta_1 X_1 + \beta_2 X_{2(1)} + \beta_3 X_{2(2)} + \beta_4 X_{2(3)} + \beta_5 X_{2(4)} + \beta_6 X_{3(1)} + \beta_7 X_{3(2)} + \beta_8 X_{3(3)} \quad (4)$$

$$= 2{,}569 - 0.004X_1 - 3{,}363X_{2(1)} - 3{,}152X_{2(2)} - 2{,}567X_{2(3)} - 1.304X_{2(4)} + 0.081X_{3(1)} + 0.511X_{3(2)} + 0.411X_{3(3)}$$

$$log\frac{P(Y=2)}{P(Y=1)} = \frac{Negative\ Sentiment}{Neutral\ Sentiment}$$

$$= \beta_0 + \beta_1 X_1 + \beta_2 X_{2(1)} + \beta_3 X_{2(2)} + \beta_4 X_{2(3)} + \beta_5 X_{2(4)} + \beta_6 X_{3(1)} + \beta_7 X_{3(2)} \quad (5)$$

$$= 0.144 + 0.001X_1 + 2{,}210X_{2(1)} + 1{,}654X_{2(2)} + 1{,}075X_{2(3)} + 0.498X_{2(4)} - 0.634X_{3(1)} + 0.172X_{3(2)}$$

The model adopted the neutral sentiment category as the reference outcome. To further examine the extent to which marketplace brands influence customer sentiment categories, the odds ratio was employed as an interpretive tool. Based on the results of the multinomial logistic regression analysis shown in Table 4, the odds ratio values for each marketplace brand demonstrate differences in the likelihood of customer sentiment reviews compared to the reference brand, Tokopedia.

For the marketplace brand Blibli, the odds ratio for negative sentiment was 0.53, indicating that Blibli is 0.53 times more likely to receive negative sentiment reviews compared to Tokopedia. Conversely, in the positive sentiment category, Blibli showed an odds ratio of 1,085, meaning that the likelihood of receiving positive reviews is 1,085 times higher compared to Tokopedia. The marketplace brand Lazada exhibited a different pattern. Its odds ratio for negative sentiment was 1,187, suggesting that it is 1,187 times more likely to receive negative reviews than Tokopedia. For positive sentiment, Lazada displayed an even greater effect, with an odds ratio of 1.668, indicating that it is 1,668 times more likely to receive positive reviews relative to Tokopedia. Meanwhile, the

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Shopee demonstrated significance only in the positive sentiment category. The analysis showed that Shopee was 1,509 times more likely to receive positive reviews compared to Tokopedia, as indicated by its odds ratio value. However, Shopee's variable in the negative sentiment category did not demonstrate a statistically significant effect on the regression model therefore, its odds ratio cannot be reliably interpreted within this analysis.

Table 4. Parameter Estimation for Multinomial Logistic Regression

	Sentiment Category	B	Std. Error	Wald	Df	Sig.	95% Confidence Interval for Exp (B)		
							Exp(B)	*Lower Bound*	*Upper Bound*
Negative	intercept	.144	.037	14,865	1	<,001			
	Total Sentiment Likes	.001	.000	5,602	1	.018	1,001	1,000	1,002
	[Marketplace rating=1,00]	2,210	.000	5,602	1	.000	9,114	8,457	9,823
	[Marketplace rating=2,00]	1,654	.059	772.973	1	<,001	5,227	4,652	5,873
	[Marketplace rating=3,00]	1,075	.053	410.631	1	<,001	2.931	2,641	3,252
	[Marketplace rating=4,00]	.498	.055	81,773	1	<,001	1.646	1,478	1,834
	[Marketplace rating=5,00]	0	.	.	0	.	.	.	.
	[brand marketplace=1,00]	.634	.040	251.863	1	<,001	.530	.491	.574
	[brand marketplace=2,00]	.172	.043	16,022	1	<,001	1.187	1,092	1,291
	[brand marketplace=3,00]	.013	.045	.086	1	.770	.987	.903	1.078
	[brand marketplace=4,00]	0	.	.	0	.	.	.	.
Positive	intercept	2,569	.033	6116.950	1	.000	.		
	Total Sentimen Likes	.004	.001	39,551	1	<,001	.996	.995	.997
	[Marketplace rating=1,00]	-3,363	.046	5352.217	1	.000	.035	.032	.038
	[Marketplace rating=2,00]	-3,152	.078	1623.219	1	.000	.043	.037	.050
	[Marketplace rating=3,00]	-2,567	.056	2075.609	1	.000	.077	.069	.086
	[Marketplace rating=4,00]	1,304	.046	786.928	1	<,001	.271	.248	.297
	[Marketplace rating=5,00]	0	.	.	0	.	.	.	.
	[brand marketplace=1,00]	.081	.039	4.305	1	.038	1,085	1,005	1,171
	[brand marketplace=2,00]	.511	.043	141,457	1	<,001	1,668	1,533	1,814
	[brand marketplace=3,00]	.411	.043	93,168	1	<,001	1,509	1,388	1,640
	[brand marketplace=4,00]	0	.	.	0	.	.	.	.

a. The reference category is: Netral.

b. This parameter is set to zero because it is redundant.

Table 4 above shows that the marketplace brand Lazada has the highest likelihood of receiving positive sentiment reviews compared to the brands Blibli and Shopee, with Tokopedia serving as the baseline brand. However, the marketplace brand Lazada also has the highest likelihood of receiving negative sentiment reviews compared to Blibli and Shopee, with Tokopedia as the baseline brand. Therefore, this study suggests that MSMEs optimize their product sales through the Shopee marketplace platform, as it demonstrates a relatively strong reputation and higher potential for positive reviews, while showing minimal negative reviews (with insignificant test results) from the perspective of Play Store customers.

The model selection technique in regression analysis, used to balance model fit with its complexity, was carried out by comparing the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) values across several models. The results of the multinomial logistic

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regression analysis in this study indicate that the interaction of four or three independent variables collectively shows that the variable of review time does not have a significant effect on customer sentiment categories. Therefore, it is recommended to select the three-variable interaction model without including the review time variable. The best model is the one with the smallest error, as indicated by the lowest AIC and BIC values. Table 5 shows that the model including the review time variable has the smallest AIC and BIC values; however, since this study focused on recommending marketplace brand selection for MSMEs, the interaction model between the independent variable of brand and the dependent variable of customer sentiment category was preferred to determine the likelihood of sentiment categories occurring for a specific brand. The following section presents the probability calculation of a marketplace customer providing a positive sentiment review when the marketplace brand is Shopee.

$$P(Y = 3 \mid X_3 = 3) = \frac{e^{2.569+0.411(3)}}{1 + e^{2.569+0.411(3)}} = 0.97817 = 97.82\%$$

Table 5. Accuracy of the Regression Model

No	Independent Variables	AIC	BIC
1	Number of likes sentiment (X1), Application rating (X2), Marketplace brand (X3), and Review time sentiment (X4)	6650,309	6873,261
2	Number of likes sentiment (X1), Application rating (X2), and Marketplace brand (X3)	4469,760	4636,973
3.	Number of likes sentiment (X1), Marketplace brand (X3), and Review time sentiment (X4)	10658,791	10807,425
4.	Number of likes sentiment (X1), Application rating (X2), and Review time sentiment (X4)	4231,129	4398,343
5.	Application rating (X2), Marketplace brand (X3), and Review time sentiment (X4)	1165,703	1370,075
6.	Number of likes sentiment (X1) and Review time sentiment (X4)	9895,513	9988,409
7.	Number of likes sentiment (X1) and Marketplace brand (X3)	9139,410	9232,306
8.	Number of likes sentiment (X1) and Application rating (X2)	2968,103	3079,579
9.	Application rating (X2) and Marketplace brand (X3)	453,996	602,631
10.	Application rating (X2) and Review time sentiment (X4)	329,712	478,346
11.	Marketplace brand (X3) and Review time sentiment (X4)	378,880	508,935
12.	Number of likes sentiment (X1)	8994,342	9031,501
13.	Application rating (X2)	105,475	198,371
14.	Marketplace brand (X3)	92,595	166,912
15.	Review time sentiment (X4)	91,735	166,052

Table 5 presents the AIC and BIC values for 15 different regression models, each comprising a distinct combination of the four independent variables. Lower values for both AIC and BIC indicate a better model, balancing goodness of fit with model parsimony. The results reveal a clear pattern: models with fewer predictors, particularly those containing only application rating (X2), marketplace brand (X3), or review time sentiment (X4), consistently yield the lowest AIC and BIC scores.

Specifically, the single-predictor models (13, 14, 15) and the two-predictor model combining the application rating (X2) and review time sentiment (X4) (model 10) demonstrate the most favorable information criteria. This suggests that these variables alone provide a highly efficient explanation of the dependent variable, with minimal unnecessary complexity. In contrast, models incorporating Number of likes sentiment (X1), especially in combination with multiple other variables, result in significantly higher AIC and BIC values, indicating a poorer trade-off between fit and parsimony and suggesting that this variable may contribute less unique explanatory power in the presence of the others.

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3.2. Marketplace Recommendation for MSME

Fig 5. Word cloud of reviews from Shopee platform.

Based on Fig. 5, marketplace customers who reviewed applications on the Play Store mostly associated the Shopee brand with words such as "very," "good," "application," "great," "shopping," "satisfied," "shipping cost," and "okay." These words indicate positive sentiment from customers toward the Shopee marketplace brand. This study identifies Shopee as the most positively reviewed platform among the four major Indonesian marketplaces. These findings are particularly relevant given Indonesia's expanding digital marketplace, which is expected to grow to 150 billion U.S. dollars GMV by 2030 [4]. In this expanding digital marketplace, MSMEs that strategically align with platforms exhibiting strong positive sentiment such as Shopee with its 97.82% probability of positive reviews are better positioned to capture market share and build sustainable online presence.

4. Conclusion

This study successfully developed a data-driven recommendation system for MSME*s* by integrating machine learning-based sentiment analysis with statistical modeling. Through the analysis of 80,000 user reviews from four major Indonesian marketplaces (Shopee, Tokopedia, Lazada, and Blibli), both SVM and LSTM models demonstrated high accuracy (90% and 91%, respectively) in classifying customer sentiment.

The multinomial logistic regression analysis identified application rating, number of likes, and marketplace brand as significant factors influencing sentiment. Shopee emerged as the most recommended platform, characterized by the highest probability of receiving positive reviews (97.82%) and no significant association with negative sentiment. Therefore, based on comprehensive evidence from consumer perceptions, this study concludes by recommending Shopee as the optimal primary marketplace platform for MSMEs to enhance their digital sales strategy and market presence.

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