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Analyzing Public Perceptions of MSME Digitalization Through TikTok Comments Using IndoBERT

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Abstract. *The digitalization of MSMEs is one of the important efforts to increase business competitiveness and sustainability in the digital economy era. Various information related to the digitization of MSMEs circulating on social media has generated various responses from the public, especially on the TikTok platform. This study aims to analyze the sentiment of TikTok users' comments on the digitization of MSMEs using the IndoBERT model. The research data was obtained through the TikTok* comment scraping *process using Apify in the period from December 1, 2024, to May 24, 2026. After going through the manual labeling and pre-processing stages of data, a total of 1,042 comments were obtained, classified into three sentiment categories, namely positive, negative, and neutral. The research stages include* preprocessing, *tokenization,* label mapping, *data splitting using* the stratified splitting *method, and* fine-tuning *the IndoBERT model for three* epochs. *The results of the evaluation showed that the model achieved an accuracy value of 95.19%, a* precision *of 95.36%, a* recall *of 95.19%, and* an F1-score *of 95.25%. The results of the sentiment analysis showed that neutral sentiment dominated with a percentage of 82.73%, followed by negative sentiment of 9.21% and positive sentiment of 8.06%. These findings indicate that most users are still at the stage of seeking information, asking questions, or sharing experiences related to the digitization of MSMEs. This study proves that IndoBERT has a very good performance in classifying Indonesian sentiment on social media data.*

Keywords: *Sentiment Analysis, Digitization of MSMEs, TikTok, IndoBERT, Natural Language Processing.*

INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) play a vital role in supporting Indonesia's economic development. According to the Ministry of Cooperatives and SMEs of the Republic of Indonesia, MSMEs contribute approximately 61% of Indonesia's Gross Domestic Product (GDP) and account for nearly 97% of national employment. These figures highlight the strategic importance of MSMEs as a key pillar of the Indonesian economy, contributing significantly to job creation and economic stability. As information and communication technologies continue to evolve, digitalization has become an essential strategy for enhancing MSME competitiveness through the adoption of digital platforms for marketing, sales, and customer engagement (LinkUMKM,2022).

Among various social media platforms, TikTok has emerged as one of the fastest-growing digital platforms and has become increasingly popular among MSMEs for marketing and customer engagement activities. Through short-form video content, live streaming, and social commerce features, TikTok enables

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businesses to reach wider audiences and interact directly with consumers. (Azizah et al., 2026) reported that the integration of social media and digital technologies can enhance customer engagement and expand market reach for MSMEs. Consequently, the growing presence of MSMEs on TikTok has generated a substantial volume of user comments containing opinions, experiences, support, and criticism related to MSME digitalization (Azizah et al., 2026).

User-generated comments on TikTok provide valuable insights into public perceptions of MSME digitalization. However, the large volume of data and the unstructured nature of social media text make manual analysis inefficient and time-consuming. Therefore, automated approaches based on Natural Language Processing (NLP) are required to process and classify public opinions effectively. Sentiment analysis is one of the most widely used NLP techniques for identifying and categorizing opinions into positive, negative, and neutral sentiments. (Habib Ismail & Turipanam Alamanda, 2025) demonstrated that sentiment analysis of TikTok data can provide comprehensive insights into public responses toward emerging social and economic phenomena.

Recent advancements in Transformer-based language models have significantly improved sentiment classification performance compared with traditional machine learning approaches. One of the most widely adopted models for Indonesian-language text processing is IndoBERT**.** (Wilie et al., 2021) introduced IndoBERT as a Transformer-based language model pre-trained on large-scale Indonesian corpora, enabling a deeper understanding of linguistic context. Furthermore, (Wilie et al., 2021) reported that IndoBERT achieved strong performance across various Indonesian sentiment classification tasks. Similarly, (Manoppo et al., 2025) obtained an accuracy of 84.94% when applying IndoBERT to analyze public sentiment regarding Indonesia's 12% Value Added Tax (VAT) policy.

Although IndoBERT has been successfully applied to sentiment analysis in various domains, including public policy, social media discussions, and brand perception, studies specifically investigating public perceptions of MSME digitalization based on TikTok comments remain limited. Most existing research has focused on product reviews, brand reputation, or public policy issues. Furthermore, studies that combine manually annotated TikTok comments with IndoBERT-based sentiment classification in the context of MSME digital transformation remain scarce. This gap highlights the need for further investigation into how the public perceives MSME digitalization through social media interactions.

Therefore, this study aims to analyze public perceptions of MSME digitalization through sentiment analysis of TikTok comments using the IndoBERT model. The dataset was collected through web scraping using Apify and manually annotated into positive, negative, and neutral sentiment categories. Subsequently, the data underwent preprocessing, tokenization, and IndoBERT fine-tuning to develop a sentiment classification model capable of identifying public perceptions of MSME digitalization. The findings of this study are expected to provide valuable insights for MSME practitioners and policymakers in supporting the digital transformation of MSMEs in Indonesia.

LITERATURE REVIEW

Digitization of MSMEs

Micro, Small, and Medium Enterprises (MSMEs) are sectors that make an important contribution to the Indonesian economy. The development of digital technology encourages MSMEs to adopt various digital platforms to improve operational efficiency, expand market reach, and increase business competitiveness. Digitization of MSMEs includes the use of social media, marketplaces, digital payments, and data-based technology to support business activities.

According to Omrani et al. (2024) andPurnomo et al. (2024), digital transformation is an important factor in improving the performance and sustainability of MSMEs in the digital economy era. In addition, he explained that the digitalization of MSMEs can increase market access, operational efficiency, and help business actors adapt to changes in consumer behavior in the digital era.

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TikTok as a Digitalization Platform for MSMEs

TikTok has grown from a short video-based entertainment platform to a digital marketing medium that is widely used by MSME actors. Through short videos, live streaming, and social commerce features, TikTok allows businesses to reach consumers more widely and build more intensive interactions with customers.

(Azizah et al., 2026), stated that the integration of social media and digital technology is able to increase customer *engagement* and expand the market reach of MSMEs. User activity on TikTok also produces various comments that reflect opinions, experiences, questions, support, and criticism related to business activities and the digitalization of MSMEs, so that they can be used as a source of data to understand public perception.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on the interaction between computers and human language. NLP allows computers to understand, process, analyze, and produce human language in the form of text and speech. The technology is widely used in a variety of applications, such as text classification, chatbots, language translation, and sentiment analysis (Pratiwi, 2025). In this study, NLP was used to process TikTok users' comments so that they could be analyzed automatically using the IndoBERT model.

Sentiment Analysis

Sentiment analysis is a technique in *Natural Language Processing* (NLP) that is used to identify, classify, and analyze user opinions or perceptions of a topic based on text data. Through sentiment analysis, a text can be grouped into positive, negative, or neutral categories so that it can be used to understand the tendency of public opinion towards an issue. According to sentiment analysis, social media is used to examine users' reactions and opinions to events or policies that develop in society. In this study, sentiment analysis was used to identify TikTok users' perceptions of the digitization of MSMEs based on comments collected from the TikTok platform (Sanjaya et al., 2024)

IndoBERT

IndoBERT is a Transformer-based language model designed to better understand the Indonesian context compared to traditional text classification approaches. introduced IndoNLU which includes the IndoBERT pre-trained model for various Indonesian natural language processing tasks (Wilie et al., 2021).

Various studies show that IndoBERT performs well in sentiment classification tasks. reported that IndoBERT was able to produce high classification performance on various Indonesian-language datasets. In addition, it obtained an accuracy of 84.94% in the sentiment analysis of the 12% VAT policy, which shows the effectiveness of IndoBERT in understanding the context of Indonesian texts (Rafiandi Andhika et al., 2025;Manoppo et al., 2025)

Research GAP

Various previous studies have applied sentiment analysis using IndoBERT to product reviews, brand perception, and public opinion on government policies. However, research that specifically analyzes public perception of the digitalization of MSMEs using TikTok comments in Indonesia is still relatively limited. In addition, the use of TikTok comment data collected through Apify, manually labeled, and classified using IndoBERT in the context of MSME digitization is still rarely found in the literature.

Based on the research gap, this study aims to analyze public perception of the digitalization of MSMEs through TikTok comments using the IndoBERT model. This research is expected to contribute to enriching the Indonesian sentiment analysis study as well as providing insight for MSME actors and policymakers in supporting the digital transformation of MSMEs in Indonesia.

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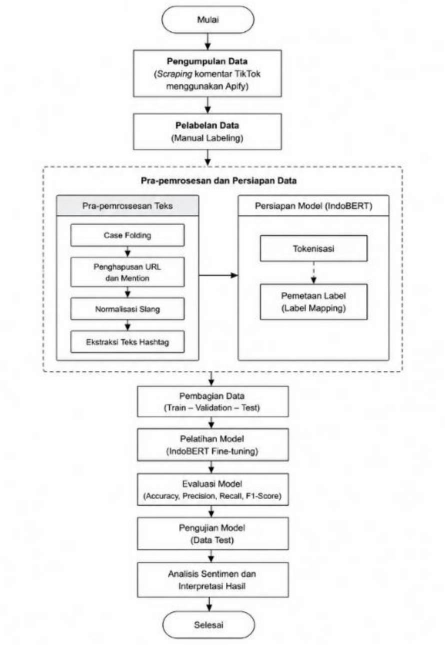
METHODS

This study applies a quantitative approach with a sentiment analysis method based on *Natural Language Processing* (NLP). The research process includes several main stages, namely data collection, data labeling, text pre-processing, model preparation, model training, model evaluation, and analysis of sentiment classification results. The model used in this study is IndoBERT (indobenchmark*/indobert-base-p1*), which is a Transformer-based model that has been trained using a large number of Indonesian language corpus and is designed for a wide range of natural language processing tasks. IndoBERT is used to classify sentiment into three categories, namely positive, negative, and neutral. This model was chosen because it has a good ability to understand the Indonesian language context compared to traditional classification methods such as Naïve Bayes and Support Vector Machine (Wilie et al., 2021).

NLP-based methods allow sentiment analysis to be carried out automatically on unstructured text data from social media. In this study, TikTok comments were used as a data source to understand public perception of the digitalization of MSMEs. Previous studies have shown that Transformer-based models, especially IndoBERT, are able to perform well on the task of classifying sentiment in Indonesian because it can understand the *bidirectional context* of words and capture semantic relationships between words more effectively than conventional methods (Wilie et al., 2021).



Gambar 1. Metodologi Penelitian

FIGURE 1. Research Methodology

In this study, the methodology used can be seen in Figure 1. The research stage begins with the process of collecting TikTok comment data using *web scraping* techniques through the Apify platform. The data was collected then through the labeling stage (*manual labeling*) to group comments into three sentiment categories, namely positive, negative, and neutral. Once the labeling process is complete, the data enters the pre-processing and data preparation stages to improve the quality of the text before being used in the model training process. The pre-processing stage of text includes *case folding*, URL and *mention* removal, *slang normalization*, and text extraction from *hashtags*.

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Furthermore, the preparation of the IndoBERT model was carried out which included the process of tokenization and label *mapping* by converting sentiment labels into numerical representations. Referring to the research, the NEUTRAL label is mapped to a value of 0, NEGATIVE to a value of 1, and POSITIVE to a value of 2. After the stage is completed, the dataset is divided into a training set (Manoppo et al., 2025), a validation set, and test *data* with a proportion of 80%, 10%, and 10%.

Training data was used for the *fine-tuning process* of the IndoBERT model, while validation data was used to monitor model performance during the training process. After the training process is complete, the model is evaluated using *the Accuracy*, *Precision*, *Recall*, and *F1-Score* metrics to measure the performance of the sentiment classification. The evaluated model is then tested using test data to find out the model's generalization ability against data that has never been seen before. The last stage is sentiment analysis and interpretation of the classification results to obtain an overview of public perception of the digitalization of MSMEs based on TikTok user comments.

Data Collection

In this study, data were collected from the TikTok platform using *web scraping* techniques through the Apify service. Data collection is focused on user comments related to MSME digitalization, digital marketing, online business, and business development through digital platforms. The data collected is stored in CSV format to facilitate processing and analysis.

Based on the *scraping* process carried out, 1,299 TikTok user comments were obtained. After a data selection and cleansing process to eliminate irrelevant comments, duplicates, and blank data, a total of 1,042 comments were obtained, which were used as research datasets. The collected comments span from December 1, 2024 (earliest date) to May 24, 2026 (most recent date).

Data Labeling

After the data collection process is completed, the next stage is manual data *labeling*. The labeling process is carried out by reading and interpreting the content of each comment based on the context of the discussion of MSME digitalization. Each comment is then classified into three sentiment categories, namely positive, negative, and neutral.

The positive category is given to comments that show support, benefits, or optimistic views on the digitalization of MSMEs. The negative category is given to comments that contain criticism, complaints, obstacles, or views that are less supportive of the implementation of MSME digitalization. Meanwhile, the neutral category is given to comments that are informative, questionable, or do not clearly show positive or negative sentiment tendencies. An example of the results of manual data labeling can be seen in Table 1.

TABLE 1. Examples of Data Labeling Results

Data	Sentiment Label
"I love how MSMEs are now using TikTok to reach more customers!"	Positive
"MSMEs are now easier to reach customers through TikTok."	Positive
"What are the benefits of digitalization for MSMEs?"	Neutral

The presentation of the distribution of the amount of data in each sentiment category after the labeling process is completed can be seen in Figure 2.

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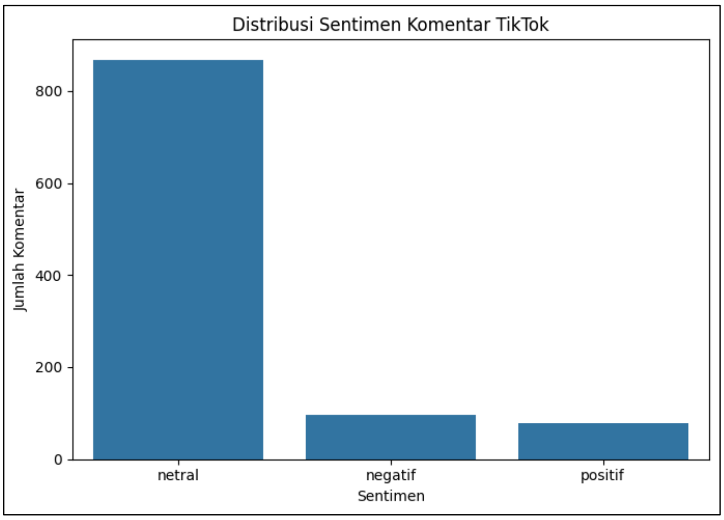

FIGURE 2. Distribution of Labeling Sentiment Data

Figure 2 shows the distribution of sentiment data from manual labeling, consisting of positive, negative, and neutral categories. Based on the labeling results, the neutral category has the highest amount of data compared to the positive and negative categories. This shows that most of TikTok users' comments related to the digitization of MSMEs are informative, discussative, or do not show strong sentiment tendencies. The distribution of the data is then used as a basis for the training and evaluation process of the IndoBERT model.

Pre-processing of Data

Pre-processing is carried out after the data labeling process is completed. This stage aims to clean and standardize text data so that it can be processed optimally by the IndoBERT model. According toRafiandi Stuart O'Neill et al. (2025),*preprocessing* is an important stage in sentiment analysis because it can improve the quality of the data and help the model understand the context of the text better. In this study, *the preprocessing* process includes *case folding* by converting the entire text to lowercase, removing URLs, *mentions*, numbers, special characters, and excess spaces, as well as slang *normalization* using an Indonesian slang dictionary. In addition, text extraction from *hashtags* is carried out to preserve information that is still relevant to the context of the comment. This stage aims to reduce *noise* in the data so as to produce a cleaner dataset that is ready to be used in the tokenization process and training of the IndoBERT model (Habib Ismail & Turipanam Alamanda, 2025).

Preprocessing IndoBERT

Data that has gone through *the preprocessing* stage is then prepared so that it can be processed by the IndoBERT model. This stage aims to convert text data into a format that is compatible with the Transformer model architecture. In this study, the IndoBERT *preprocessing* process consists of two main stages, namely tokenization and label *mapping*. Both stages are carried out using the Transformers library from Hugging Face, which supports the implementation of the IndoBERT model (indobenchmark*/indobert-base-p1*) (Wilie et al., 2021).

a) Tokenization
Tokenization is the process of converting *preprocessed text data* into numerical representations in the form of token sequences that can be understood by the IndoBERT model. This process is done using *the AutoTokenizer from* the indobenchmark/indobert-base-p1 *checkpoint* available in the Transformers Hugging Face library. Each comment will be converted into an ID token along with *an attention mask* that is used as input in the model training process (Wilie et al., 2021).

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b) Label Mapping
The sentiment label that has been determined at the data labeling stage needs to be converted into a numerical format in order to be processed by the classification model. This stage is done by mapping each sentiment category to a unique integer value. Referring to the study (Manoppo et al., 2025), the NEUTRAL label is mapped to a value of 0, the NEGATIVE label is mapped to a value of 1, and the POSITIVE label is mapped to a value of 2. This mapping is consistently applied to all training, validation, and testing data as a target (*ground truth*) used during the training and evaluation process of the model.

Data Splitting

After the IndoBERT preprocessing process is completed, the next step is to divide the dataset into three subsets, namely 80% for training data (833 data), 10% for validation data (104 data), and 10% for test data (105 data). Data splitting is carried out to ensure that the model can be optimally trained and evaluated. In this study, *the stratified splitting* method was used to maintain the distribution of sentiment classes (positive, negative, and neutral) in each subset of data. In addition, *a random state* parameter of 42 is used to ensure that the data splitting process can be reproduced consistently. Training data is used for the *fine-tuning* process of the IndoBERT model, validation data is used to monitor model performance during the training process and determine the best model, while test data is used to evaluate the model's generalization ability against previously unseen data (Manoppo et al., 2025)

Model Training

This stage carries out a sentiment classification model training process using IndoBERT (indobenchmark*/indobert-base-p1*), which has been pre-trained using the Model Indonesian Language corpus, and then fine-tuning is carried out (Wilie et al., 2021). using training data that has gone through *the preprocessing* and tokenization stages. The training was conducted to classify TikTok comments into three sentiment categories, namely neutral, negative, and positive. The training process utilizes the Hugging Face Transformers and PyTorch frameworks with several training parameters shown in Table 2.

TABLE 2. IndoBERT Model Training Parameters

Parameter	Value	Remarks
Models	IndoBenchmark/Indobert-Base-P1	IndoBERT base model
num_labels	3	Sentiment categories (Neutral, Negative, Positive)
num_train_epochs	3	Number of training iterations
per_device_train_batch_size	16	Number of samples per batch
learning_rate	2e-5	Model learning pace
weight_decay	0.01	Model regularization
warmup_steps	500	Initial adjustment stage of learning rate
random_state	42	Experimental reproducibility

The training parameters shown in Table 2 are used for the *fine-tuning* process of the IndoBERT model on the research dataset. The parameter setting aims to produce optimal model performance in classifying sentiment on TikTok's comments related to the digitization of MSMEs.

Model Evaluation

Once the model training process is complete, the next stage is an evaluation to measure the model's performance and generalization capabilities on data that has not been used during the training. The evaluation was carried out on *the test set,* which constituted 10% of the total dataset and was separated using *the stratified splitting method* to maintain the distribution of sentiment classes in the original data.

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The evaluation process was carried out by comparing the model's prediction results against the actual label on the test data. The evaluation metrics used in this study include:

a) Accuracy: The correct proportion of the prediction of the total sample.
b) Precision: The proportion of the correct positive predictions to all the positive predictions that the model produces.
c) Recall: The proportion of correct positive predictions to all the data that should be included in the class.
d) F1-Score: The harmonious average between *precision* and *recall values*.

These metrics are used to provide an overview of the model's overall performance in classifying sentiment on TikTok's comments related to the digitization of MSMEs. The use of Accuracy, Precision, Recall, and F1-Score is a commonly used approach in the evaluation of sentiment classification models based on *Natural Language Processing* (Rafiandi Andhika et al., 2025).

Due to the imbalanced distribution of sentiment classes in the dataset, particularly the dominance of neutral comments, Precision, Recall, and F1-Score were reported using the weighted-average approach. This approach considers the proportion of samples in each class, providing a more representative evaluation of overall model performance under class imbalance conditions. The implementation of these evaluation metrics follows the Scikit-learn documentation (Scikit-learn Developers, 2025). The use of weighted-average metrics is also recommended for multi-class classification tasks with imbalanced class distributions because it accounts for the contribution of each class according to its support in the dataset (Grandini et al., 2020).

Model Testing

Tests were carried out on models that have gone through the training process using several examples of comments related to the digitization of MSMEs. This test was carried out to determine the model's ability to classify various forms of public opinion into positive, negative, and neutral sentiment categories. The model that has been trained aims to see IndoBERT's ability to understand the context of the language used by TikTok users, both in the form of support for the digitization of MSMEs, criticism of the challenges faced by business actors, and informative or neutral comments. The test results were used to ensure that the model was able to identify sentiments according to the meaning contained in the comments and provide a classification that is appropriate to the context of the discussion of MSME digitalization.

RESULTS AND DISCUSSION

This section presents the results of the implementation of the IndoBERT model in classifying sentiment on TikTok user comments regarding the digitization of MSMEs. The discussion included the data collection process, model performance evaluation, sentiment distribution analysis, and interpretation of the dominant words that appeared in each sentiment category. All stages were carried out to obtain an overview of TikTok users' perceptions of the issue of MSME digitalization based on comments given on various related content.

At the data collection stage, TikTok comments were obtained using scraping techniques through the Apify platform. Data collection was carried out on several uploads that discussed the digitization of MSMEs, digital marketing, the use of marketplaces, and the use of social media as a means of business development. The collected data is then stored in CSV format and combined into a single research dataset. The comment time range used in this study covers the period from December 1, 2024, to May 24, 2026. After the data collection process is completed, sentiment labeling is carried out manually into three categories, namely neutral, negative, and positive. Furthermore, the data is processed through pre-processing stages, which include case folding, URL and mention removal, normalization of non-standard words, tokenization using the IndoBert tokenizer, and label mapping before being used in the model training process.

Figure 3 shows the flow of research data collection carried out using Apify on the TikTok platform to produce a dataset that is ready to be used for sentiment analysis.

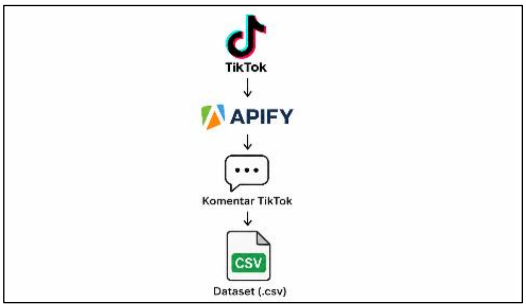

FIGURE 3. Data Collection Process

After all stages of data preparation were completed, the IndoBERT model (*indobenchmark/IndoBERT-base-p1*) was trained using training data and evaluated using validation data. The training process was carried out over three epochs to obtain the model with the best classification ability. The evaluation was carried out using several metrics that are commonly used in sentiment analysis, namely accuracy, precision, recall, and F1-score.

TABLE 3. IndoBERT Model Evaluation Results

Parameter	Value
Accuracy	0.951923
Precision	0.953623
Recall	0.951923
F1-Score	0.952543
Validation Loss	0.177680

Based on Table 3, the IndoBERT model achieved an accuracy of 95.19%, a precision of 95.36%, a recall of 95.19%, and an F1-score of 95.25%. This value shows that the model has an excellent ability to classify the sentiment of TikTok comments related to the digitization of MSMEs. A high precision value indicates that most of the predictions the model generates correspond to the actual label, while a high recall value indicates the model's ability to recognize data on each sentiment class effectively. In addition, an F1-score value close to 1 indicates a good balance between precision and recall, so that the model can be said to have stable and consistent performance.

To see the development of the model training process in each *epoch*, observations were made of the values *of training loss*, *validation loss*, *accuracy*, *precision*, *recall*, and *F1-score,* as shown in Table 4.

TABLE 4. Training and Validation Metrics Summary

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1
1	0.875717	0.698451	0.663462	0.859590	0.663462	0.712927
2	0.391217	0.261434	0.903846	0.920207	0.903846	0.909708
3	0.132321	0.177680	0.951923	0.953623	0.951923	0.952543

Based on Table 4, the value of *training losses* has decreased consistently from 0.8757 in the first *epoch* to 0.1323 in the third *epoch*. This decrease shows that the model is increasingly able to learn the patterns contained in the training data. In addition, *validation losses* also experienced a significant decrease from 0.6984 to 0.1777, indicating that the improvement in model performance occurred not only in the training data, but also in validation data that had never been used during the training process. In line with the decrease in *the value of loss*, the *accuracy metric* increased from 66.35% in the *first epoch* to 95.19% in the third *epoch*. Similar improvements were also seen in *the precision*, *recall*, and *F1 scores*, which reached 95.36%, 95.19%, and 95.25%, respectively, in the *third epoch*. These results show that the IndoBERT

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model is able to study the characteristics of the data well and has a high generalization ability to validate data.

To obtain a more detailed picture of the classification capabilities of the model in each sentiment class, the confusion matrix, as shown in Figure 4, is used.

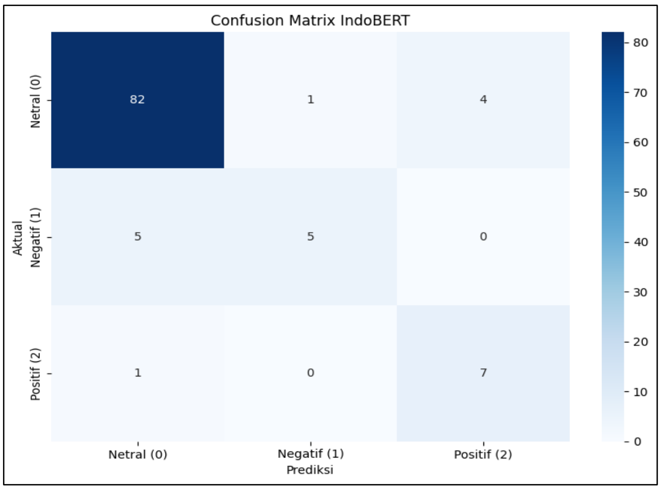

FIGURE 4. Confusion Matrix Model IndoBERT

Based on Figure 4, the model managed to correctly classify 82 neutral data, 5 negative data, and 7 positive data. In the neutral class, there was 1 data point that was incorrectly predicted as negative and 4 data points that were incorrectly predicted as positive. Meanwhile, in the negative class, 5 data points were found that were incorrectly predicted as neutral. The positive class showed relatively good performance with only 1 data point incorrectly classified as neutral. These results show that the model has an excellent ability to recognize the neutral comments that dominate the dataset. However, there are still some misclassifications found in the negative and positive classes that have less data than the neutral class.

This condition shows a *class imbalance* in the research dataset. Data imbalances have the potential to affect the model's ability to optimally study the characteristics of minority classes. Despite this, the model still produces high *precision*, *recall*, and *F1 scores*, which are 95.36%, 95.19%, and 95.25%, respectively. Therefore, the model's performance can still be considered very good in classifying the sentiment of TikTok's comments regarding the digitization of MSMEs, even though the distribution of classes is unbalanced.

Considering the imbalanced class distribution, weighted-average Precision, Recall, and F1-Score were employed to ensure that the reported evaluation metrics adequately reflected the contribution of each sentiment class.

After the model shows good performance at the evaluation stage, the model is used to make predictions on the entire TikTok comment dataset. The results of the overall sentiment classification are presented in Table 5.

TABLE 5. Prediction Sentiment Distribution

Sentiment	Quantity	Percentage (%)
Neutral	862	82,73
Negatives	96	9,21
Positive	84	8,06

Based on Table 5, neutral sentiment dominated the classification results with a total of 862 comments or 82.73% of the total data. Meanwhile, negative sentiment amounted to 96 comments or 9.21%, and positive sentiment amounted to 84 comments or 8.06%. The dominance of neutral sentiment shows that most TikTok users do not explicitly support or reject the digitalization of MSMEs. Comments that fall into the neutral category generally contain questions, sharing experiences, discussions, or informative responses regarding the use of digital technology in business activities. These findings indicate that users are still at the stage of seeking information and understanding the process of digitizing MSMEs before forming stronger opinions.

To gain a deeper understanding of the topics that are often discussed in each sentiment category, visualizations were carried out using WordCloud. The results of the visualization of positive sentiment are shown in Figure 5.

FIGURE 5. Wordcloud Positive Sentiment

In positive sentiment, the dominant words include *semangat* (enthusiasm), *untung* (profit), *jualan* (sales), *bagus* (good), *maju* (progress), and *online*. The appearance of these words indicates that many TikTok users perceive MSME digitalization positively, particularly in terms of business growth, increased sales opportunities, profitability, and broader market access. The prominence of words such as *semangat* and *maju* also reflects optimism toward the adoption of digital technology in business activities. Furthermore, the results of wordcloud visualization on negative sentiment are shown in Figure 6.

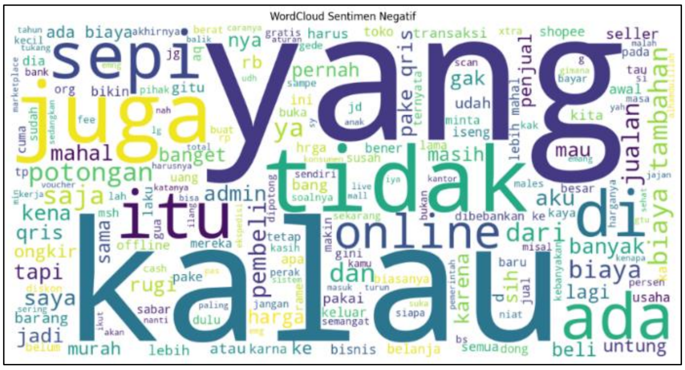

FIGURE 6. Wordcloud Negative Sentiment

The negative sentiment word cloud reveals several frequently occurring terms, including *sepi* (low sales), *mahal* (expensive), *potongan* (platform fees or deductions), *rugi* (loss), and *ongkir* (shipping costs). These terms indicate that negative perceptions of MSME digitalization are primarily associated with concerns regarding sales performance, operational costs, platform fees, and logistics expenses.

Overall, the results of the study show that the IndoBERT model is able to classify TikTok comment sentiment regarding the digitization of MSMEs with excellent performance. In addition, sentiment distribution analysis shows that the majority of users give neutral responses, while positive and negative sentiments appear in relatively balanced proportions. These findings indicate that the discourse on the

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digitalization of MSMEs on TikTok is still dominated by information and experience-sharing activities, while support and criticism for digitalization appear in smaller quantities. These results can be input for the government, business actors, and digital platform providers in designing more effective digital mentoring and literacy programs for MSMEs.

CONCLUSIONS

This study aimed to analyze the sentiment of TikTok users' comments on the digitalization of MSMEs in Indonesia using the Natural Language Processing (NLP) approach based on the Transformer model, namely IndoBERT. The research data was obtained through scraping TikTok comments using Apify, followed by manual labeling, text preprocessing, tokenization, and label mapping before being used in the model training process. The IndoBERT model (indobenchmark/IndoBERT-base-p1) was fine-tuned with an 80% training, 10% validation, and 10% testing data split over three epochs.

The results show that the IndoBERT model performs very well in classifying TikTok comment sentiment related to MSME digitalization. The model achieved an accuracy of 95.19%, precision of 95.36%, recall of 95.19%, and F1-score of 95.25%, demonstrating that IndoBERT can effectively understand the Indonesian context and is suitable for social media sentiment analysis tasks.

Sentiment distribution analysis revealed that neutral sentiment was dominant (82.73%), followed by negative (9.21%) and positive (8.06%). This dominance of neutral sentiment indicates that most TikTok users are still seeking information, asking questions, sharing experiences, or discussing digitalization without showing an explicit attitude supporting or rejecting it. This finding highlights that the digital transformation process in MSMEs still requires education, mentoring, and the enhancement of digital literacy so that MSME actors can optimally understand and utilize digital technologies.

For future research, several improvements can be considered, including expanding data sources to other social media platforms such as Instagram, X, and Facebook to obtain a more representative analysis. Future studies may also address class imbalance using techniques such as SMOTE, class weighting, or targeted data collection to increase the number of positive and negative sentiment samples. In addition, comparing the performance of IndoBERT with other Transformer-based models and exploring aspect-based sentiment analysis may provide deeper insights into public perceptions of MSME digitalization.

Overall, this study demonstrates that IndoBERT is effectively applied for identifying public sentiment regarding MSME digitalization on social media.

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