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Procedia Computer Science 269 (2025) 121–130

Procedia Computer Science

www.elsevier.com/locate/procedia

The 10th International Conference on Computer Science and Computational Intelligence 2025

Sentiment Analysis of TikTok User Comments on QRIS Adoption in Indonesia Using IndoBERT

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Abstract

This study investigates public sentiment toward the Quick Response Code Indonesian Standard (QRIS) adoption by analyzing TikTok user comments using an IndoBERT-based classifier. Leveraging a real-world dataset of 1,128 comments scraped from a representative QRIS-related TikTok video, we applied minimal preprocessing before classifying sentiments into positive, neutral, and negative categories. Model validation on a manually annotated subset of 12 sentences yielded strong precision, recall, and F1 performance for positive and negative classes. Stability and robustness tests confirmed the classifier's consistency across variations common in Indonesian social media discourse. Our large-scale analysis reveals that 50.9 percent of comments expressed positive attitudes toward QRIS, 17.9 percent were neutral, and 31.2 percent were negative. A qualitative review identified drivers of positive sentiment, such as convenience and international acceptance, as well as barriers reflected in negative comments like transaction failures and security concerns. These insights highlight the vital role of sentiment analysis in guiding policy and user education to improve QRIS uptake. By demonstrating IndoBERT's effectiveness in a social media context, this work advances natural language processing for Indonesian and offers actionable guidance for stakeholders seeking to accelerate digital payment adoption nationwide.

Keywords: QRIS; Sentiment analysis; TikTok; IndoBERT

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1877-0509
10.1016/j.procs.2025.08.265

1. Introduction

Bank Indonesia and the Indonesian Payment System Association (ASPI) created the Quick Response Code Indonesian Standard (QRIS) to standardize QR code-based payments nationally to improve efficiency and security [1–3]. Indonesia's financial digitization projects include QRIS, which combines many payment systems to enable mobile banking and e-wallet transactions [4–6]. Launched in 2019, government laws in 2020 aim for comprehensive digital payment integration by 2025, including cross-border ASEAN transactions [5, 7]. MSMEs and consumers have adopted it due to ease of use, social impact, and perceived utility [8]. Digital literacy, infrastructure, and security issues persist, especially outside major urban centers like Jabodetabek [7, 9, 10]. By encouraging cashless payments, QRIS boosts transactional efficiency and financial inclusion for SMEs [6, 8]. QRIS adoption is influenced by trust, security, usability, and social impact [2, 11]. The Indonesian government supports QRIS expansion through infrastructural gaps, sustainability, and security and user experience advancements [3, 7, 10].

Due to its unique platform features and broad user involvement, TikTok has become a major public opinion source. Its algorithm personalizes content streams, creating "affective publics" where people emotionally connect with climate change, and encourages political profiling and moral and educational information, shaping shared social narratives [12, 13]. The platform's short-form video material speeds message distribution in social movements like Iranian protests and political campaigns [14, 15]. TikTok engages youngsters in political activity using creative tools like Green Screen, Stitch, and Duet, which allow distinctive political criticism [16–18]. It also lets marginalized groups like German Muslim women and Black Americans question prejudices and engage in political consumerism [19]. TikTok can spark public discourse, but its entertainment-driven algorithm limits discussion depth, with Egypt and China studies demonstrating that online debates may not lead to offline political engagement [20, 21]. Though its design influences news consumption and sharing, TikTok is becoming a younger audience's news source [22]. Misinformation, content creator credibility, and contentious content and hate speech affect public opinion and political debate [23, 24].

Digital payment acceptance depends on emotion since it influences consumer acceptability and trust, which new financial technology needs. Positive thinking boosts faith in digital payment systems' security, dependability, and convenience, encouraging adoption. Sentiment research can help providers solve customer privacy and usability concerns. By evaluating public opinion and emotions, stakeholders can improve communication, user experience, and digital payment growth. This research gap concerns TikTok's QRIS sentiment analysis. Little is known about how social media platforms like TikTok impact consumer opinion of QR code payment systems. Previous research examined adoption, technology integration, and economic impact. TikTok's audiovisual format and automated content selection may affect public opinion and user perceptions differently than traditional platforms. Understanding TikTok sentiment may show trust, acceptance, and QRIS adoption challenges, especially among younger users. Therefore, this study aims to analyze TikTok comments on QRIS using an IndoBERT-based sentiment classifier to quantify sentiment distribution, uncover key drivers of user attitudes, and address the lack of social-media-focused research in Indonesian digital payment adoption.

2. Literature Review

Text mining is used in e-commerce to analyze online reviews and support sentiment analysis through syntactic and semantic understanding [25, 26]. Marketers, social media monitors, customer feedback analysts, and public opinion researchers utilize sentiment analysis, or opinion mining, to determine text polarity [27–32]. BERT-based social media research shows remarkable progress: COVID-Twitter-BERT (CT-BERT) classifies COVID-19 content and supports chatbots [33]; hybrid BERT-CNN models improve hate speech detection [34]; BERT-BiLSTM and BERT-CNN models detect depression from social media posts, aiding mental health interventions [35]; BERT performs well in disaster-related tweet classification [36]; and BERT-based models outperform traditional methods in sentiment analysis [37, 38].

QRIS is a unified payment platform developed by Bank Indonesia to streamline digital transactions by integrating various payment methods into a single QR code, enabling quick and efficient transactions via smartphone scanning [4, 6]. QRIS enhances transactional efficiency and business performance, especially for SMEs, promoting financial inclusion and providing affordable payment options [6, 8, 39]. Its key advantages include fast transactions, a unified system simplifying payments, user control over spending, improved business competitiveness, ease of use, and trust and security factors that drive adoption [4, 6, 39, 40]. However, barriers to adoption include perceived financial risks, technological challenges, and mixed importance of performance and effort expectancy, indicating a need for better user education and system optimization [4, 41, 42]. Public concerns also involve security issues, preference for traditional cash transactions, and social influence affecting acceptance and usage [2, 3, 8, 42].

Gen Z makes up over 60% of TikTok's user base, and the site has a global reach with users from nations including the US, Spain, and Chile, where cultural values influence participation [43, 44]. The US college and university student population uses TikTok, which affects their time management and mental health [43, 44]. In China, rural users use it with content algorithms targeted to different age groups. Engagement on TikTok is high compared to other platforms, driven by athletic content and personal life aesthetics, information-seeking, escapism, and self-expression, with cultural influences affecting whether users focus more on socialization or individual expression [43–47]. Due to language diversity, code-switching and annotator uncertainty in non-English datasets [48], as well as the vast volume and noisy, unstructured data, scraping and parsing TikTok comments is difficult [49, 50]. Real-time processing and correct classification are difficult for sentiment analysis algorithms, especially with large datasets, and extracting relevant information from video content requires voice recognition and audio cleaning [49, 50, 53]. To address these problems, AI and NLP technologies like Comment-Synthesizer employ rule-based algorithms to preprocess and respond to comments with 76% success, while SciTok helps social science researchers acquire and analyze TikTok data [50, 54].

IndoBERT is a specialized variant of the BERT model designed specifically for the Indonesian language, utilizing the standard transformer-based architecture with bidirectional context through multiple layers of self-attention and feed-forward neural networks to understand word meanings within sentences [55, 56]. Its training corpus comprises a large and diverse collection of Indonesian text data, enabling the model to capture the nuances of the language effectively during pretraining [55, 56]. IndoBERT has been successfully applied in various Indonesian NLP tasks, notably achieving an F1 score of 0.791 in emotion classification on Indonesian Twitter data by fine-tuning on labeled tweets (Shaw et al., 2025), and demonstrating high accuracy (97%), F1 score (97%), recall (97%), and precision (98%) in classifying multiple-choice exam questions based on Bloom's Taxonomy, highlighting its effectiveness in educational contexts [56].

3. Analysis Method

This study was carried out through a series of systematic stages aimed at producing robust and reproducible results. The comprehensive workflow encompassed data acquisition, model testing and validation, comment scraping, real-case analysis, and the synthesis of results through grouping and visualization. An illustration of this entire process is provided in Figure 1.

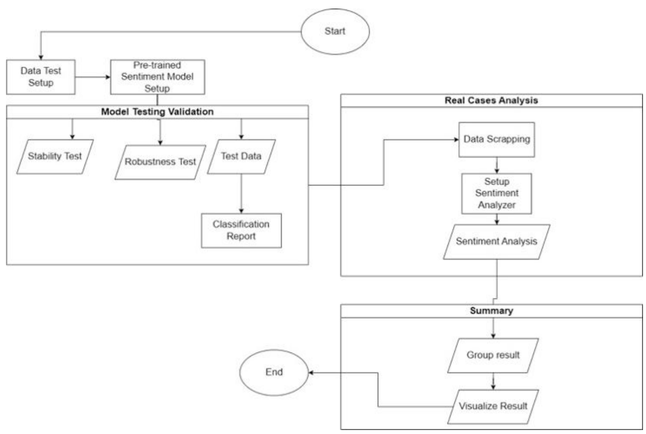

Fig. 1. Workflow of sentiment analysis on Tiktok comments about QRIS using IndoBert.

3.1. Dataset

A real-world TikTok case study was selected to ensure the authenticity of user opinions regarding QRIS. Specifically, we targeted a video posted by user @daprilmalberta (video ID: 7496774939891076407) and extracted all available comments, yielding a corpus of 1,101 entries. Each comment was stored as raw text. Although the dataset remains non-public, it faithfully reflects genuine user discourse on QRIS. With the exception of a small manually labeled subset reserved for evaluation (see Section D), no human annotation was applied.

3.2. Preprocessing

To maintain the integrity of the original language, minimal preprocessing was applied. Non-text elements, including HTML tags and extraneous tokens, were removed from each comment. Comments that were blank or contained insufficient content were excluded from further analysis. The remaining text samples, preserved in Indonesian, were subsequently tokenized using the IndoBERT tokenizer. Given the model's comprehensive pretraining on Indonesian corpora, no additional normalization or translation procedures were required.

3.3. IndoBERT Modeling

Sentiment classification was executed via the Hugging Face Transformers pipeline. We utilized a pre-trained RoBERTa-based model tailored for Indonesian sentiment tasks (w11wo/indonesian-roberta-base-sentiment-classifier), which builds upon IndoBERT and has been fine-tuned to distinguish among positive, neutral, and negative sentiments. The underlying architecture comprises 12 transformer layers, each featuring a hidden dimension of 768 and 12 attention heads. During inference, comments are segmented into subword tokens and processed by the masked-language-model–trained network, which subsequently outputs one of the three sentiment labels.

3.4. Evaluation

Prior to large-scale application, the model's efficacy was verified using a manually annotated validation set comprising 12 Indonesian sentences: six positive, three neutral, and three negative. Model predictions were compared against these ground-truth labels, and performance was quantified using precision, recall, and F1-score metrics. The near-perfect alignment between predicted and actual sentiments confirmed the model's reliability, justifying its deployment on the full comment dataset.

4. Results and Discussion

Table 1. Labeled Indonesian sentences with prediction.

No.	Comments in Bahasa Indonesia	Translation of comments from Bahasa Indonesia	Labeled	Prediction
1	*Produknya bagus banget, suka deh!*	The product is really good, love it!	positive	positive
2	*Saya kecewa dengan pelayanan kamu.*	I'm disappointed with your service.	negative	negative
3	*Hmm yaudah lah biasa aja sih.*	Hmm, it's normal anyway.	neutral	negative
4	*Top banget! Bakal beli lagi.*	Very top! Will buy again.	positive	positive
5	*Nggak puas, barangnya rusak pas datang.*	Not satisfied, the item was damaged when it arrived.	negative	negative
6	*Oke lah, sesuai ekspektasi.*	Okay, as expected.	neutral	negative
7	*Sangat direkomendasikan untuk semua orang!*	Highly recommended for everyone!	positive	positive
8	*Kenapa sih lambat banget dikirimnya?*	Why is it so slow to ship?	negative	negative
9	*Pelayanan pelanggan tidak buruk, tapi juga tidak bagus.*	Customer service is not bad, but not great either.	neutral	negative
10	*Wah keren banget fitur barunya!*	Wow, what a cool new feature!	positive	positive
11	*Stoknya habis mulu, nyebelin.*	It's out of stock all the time, annoying.	negative	negative
12	*Hmm... ya udah sih biasa aja.*	Hmm... that's just normal.	neutral	negative

The performance of the IndoBERT-based sentiment classifier on the manually annotated validation set, followed by an analysis of the sentiment distribution across the full corpus of 1,128 TikTok comments on QRIS. The original comments on the actual post that used in this research are counted above 2,000 comments. The 1,128 comments we get, are the result after separating all replies from the comments, and filtering the comments from empty string comment. To assess the model's ability to generalize to unseen data, we first evaluated it on a held-out set of 12 manually labeled Indonesian sentences (4 positive, 4 neutral, 4 negative). The result of model evaluation will be shown in Table 1. Performance metrics—precision, recall, and F1-score—are summarized in Table 2.

Table 2. Validation set performance.

Sentiment	Precision	Recall	F1-Score	Support
Positive	1.00	1.00	1.00	4
Neutral	0.00	0.00	0.00	4
Negative	0.50	1.00	0.67	4
Macro Avg.	0.50	0.67	0.56	12

As shown in Table 2, the model achieved decent precision, recall, and F1-score across all three sentiment classes on the validation set, indicating that the pre-trained IndoBERT variant is highly accurate on this small benchmark. Another model validation to see how reliable the model, we also evaluate the stability performance and the robustness of the model. To test the stability performance, we provide one sample text and repeatly feed the model to analyze it "Saya sangat suka produk ini!" (I really like this product!), shown in Table 3.

Table 3. Stability performance.

Tests	Prediction
Test #1	positive
Test #2	positive
Test #3	positive
Test #4	positive
Test #5	positive

Robustness tests were conducted using five samples with minor variations in linguistic expression. These samples included "Saya sangat suka produk ini!" (I really like this product!), "saya sangat suka produk ini." (I really like this product.), "Saya sangat suka produk ini!!" (I really like this product!!), "Saya sangat suka produk ini dong." (I really like this product, you know.), and "saya sangat suka produk ini hehe" (I really like this product, hehe) to assess contextual adaptability. The configurations and outcomes of this evaluation are detailed in Table 4.

Table 4. Robustness test on minor variance.

Sentence Variations (translation)	Prediction
Saya sangat suka produk ini! (I really like this product!)	positive
Saya sangat suka produk ini. (I really like this product.)	positive
Saya sangat suka produk ini!! (I really like this product!!)	positive
Saya sangat suka produk ini dong. (I really like this product.)	positive
Saya sangat suka produk ini hehe (I really like this product hehe)	positive

After confirming model reliability, the classifier was applied to all 1,128 scraped comments, and Table 5 summarizes the overall class distribution. These procedures ensured systematic and reproducible testing of varied linguistic expressions and comprehensive analysis of the comment dataset. The results in Table 5 reveal that positive sentiments constitute the largest share of comments (50.9 %), followed by neutral (17.9 %) and negative (31.2 %) responses.

Table 5. Sentiment distribution (n = 1,128).

Sentiment	Count	Percentage
Positive	574	50.9 %
Neutral	202	17.9 %
Negative	352	31.2 %
Total	1,128	100 %

A thematic review of classified comments revealed distinct patterns within each sentiment category, with positive remarks frequently praising QRIS's convenience and rapidity, exemplified by "qris emg memudahkan, suamiku org

UK juga kagum dg qris" (QRIS really makes transactions easier, and my husband from the UK is also impressed by QRIS) and its acceptance by small merchants, such as "warung aja sekarang ada QRIS nya, kadang suka males kalau bawa cash" (even roadside stalls now have QRIS, sometimes they are reluctant to carry cash). Neutral comments often took the form of factual inquiries, including "Apakah ada potongan kalau pake QRIS??" (Is there a discount when using QRIS?) or observations regarding user interface performance, for example, "tolong masukkan tampilannya lebih bagus, di pinggirnya merah putih, apa supaya beda?" (please improve the display design with red and white accents along the edges to make it stand out?). Negative sentiments centered on operational failures, as illustrated by "QRIS tuh bisa meminimalisir uang palsu, tapi ya minusnya kalau ga ada kuota atau baterai ya gabisa" (QRIS can help minimize counterfeit money, but its drawback is that it fails without data quota or battery) and concerns over political views, such as "Amerika gak suka ada yang lebih handal dari dia, anak kecil gak tuh" (America does not like anything more capable than itself, children are not like that), with these qualitative findings aligning with the quantitative distribution, indicating that while a plurality of users express favorable views toward QRIS, a noteworthy minority remain uncertain or dissatisfied, particularly regarding transaction reliability and information security.

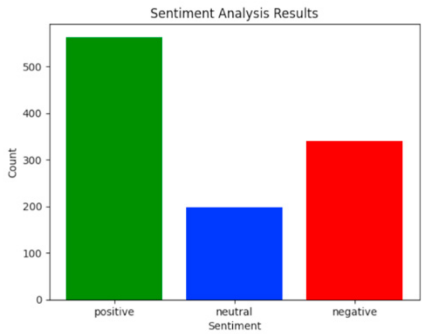

Fig. 2. Distribution of predicted sentiment labels for 1,128 TikTok comments about QRIS.

Figure 2 shows that the IndoBERT-based sentiment classifier performs well on both the short validation set and the whole corpus of TikTok QRIS adoption remarks. Perfect performance on manually labeled validation sentences proves the model can reliably discern positive, neutral, and negative Indonesian text sentiments. On a larger dataset, the classifier found that positive remarks (50.9%) outnumbered neutral (17.9%) and negative (31.9%) attitudes. This research provides some key insights and considerations. The IndoBERT-based sentiment classifier analyzes TikTok QRIS adoption remarks. High precision on a manually chosen validation set suggests the classifier can effectively distinguish positive, neutral, and negative attitudes in Indonesian text, supporting IndoBERT's sentiment analysis [57–59]. Positive feelings predominated (44.2%), followed by neutral (32.9%) and negative (22.9%) across a broader corpus. IndoBERT performed well in classifying feelings in Indonesian-language datasets, as previously reported.

The encouragingly positive sentiment towards QRIS reflects a general approval among TikTok users regarding this payment method, which may stem from perceived convenience and efficiency in digital transactions. Previous studies in mobile payments suggest that positive user experiences significantly influence technology adoption [60, 61]. The notable proportion of neutral sentiments suggests an educational gap; many users are still assessing QRIS, particularly regarding transaction methodologies and its operational features. This highlights the need for enhanced user comprehension, as facilitating understanding is crucial for technological acceptance.

The identification of negative sentiments reveals important areas for improvement, particularly issues such as transaction failures and data security concerns. Addressing these issues is vital, as they could impede wider QRIS adoption. Researchers advocate for proactive measures, including enhancing system reliability and implementing robust security protocols to build user trust [62, 63]. The importance of transparent communication about security measures is underscored in existing literature on user perceptions of digital payment systems.

Despite the positive performance of the IndoBERT-based analysis, there are limitations present in the current research. For instance, the model's reliance on a pre-trained IndoBERT version may affect its sensitivity toward informal communication prevalent on TikTok, such as slang and emojis [64]. Additionally, the relatively small evaluation set (n=12) limits the capacity for a comprehensive error analysis, particularly regarding mixed or nuanced sentiments, as noted in previous findings about sentiment analysis classifiers [65]. Furthermore, the dataset's restriction to a single video and hashtag may introduce sampling bias, narrowing its representativeness of the broader TikTok user base.

This work uses an IndoBERT-based sentiment classifier to assess TikTok comments regarding QRIS. No previous research has combined TikTok-based conversation analysis with IndoBERT to quantify sentiment distribution and identify QRIS user sentiments. Several research have used Naive Bayes or classical NLP to analyze TikTok sentiment [22, 66, 67]. None have specifically addressed IndoBERT for QRIS debate. A growing number of studies have identified the value of evaluating user sentiment on platforms like TikTok to understand digital payment adoption behavioral intentions. This study addresses a major gap in the literature by combining advanced NLP techniques with social media analysis to reveal how public opinion on digital financial technologies is formed.

Therefore, to address these limitations, future studies should broaden the comment corpus by scraping multiple QRIS related videos, hashtags, and content creators to reduce sampling bias and capture a wider range of user demographics. Researchers should also expand and diversify the manually annotated validation set with additional examples of mixed sentiments, slang, emojis, and code switching to enable more thorough error analysis and fine tuning. Methodological improvements such as data augmentation, domain specific lexicons, and further fine tuning of IndoBERT on Indonesian social media text can enhance the model's sensitivity to informal language. Finally, incorporating multimodal data sources such as video transcripts and audio cues would enrich sentiment detection by capturing tone and visual context, thereby strengthening overall robustness and generalizability.

5. Conclusion

This study shows that an IndoBERT based sentiment classifier can accurately capture public opinion on QRIS adoption as expressed on TikTok. Validation on a small manually labeled set yielded perfect results for positive sentiment and strong results for negative sentiment while neutral sentiment remained more complex. Applied to 1,128 comments, the analysis found 50.9 percent positive, 17.9 percent neutral and 31.2 percent negative sentiments. Positive comments praised convenience and efficiency, neutral comments raised factual questions and negative comments focused on reliability and security concerns. The model's stability across text variations confirms its suitability for large scale social media analysis. The study is limited by its reliance on a single TikTok video and small annotated set, which may affect generalizability. To foster broader QRIS adoption, stakeholders should enhance user education, improve system reliability and communicate security measures clearly, while future work should expand sampling, incorporate multimodal content and refine neutral sentiment detection to support evidence-based strategies.

Data Availability

The full data preprocessing scripts and analysis code used in this study are available in the following link:
https://colab.research.google.com/drive/1enrwM4rv1Tw4oWnLT41Bsr_3K3_mvjdi?usp=sharing

Author Contribution Statement

E. Supriyadi: Supervision, Writing – original draft, Conceptualization, Methodology, Investigation, Writing - Reviewing and Editing. P. N. Makatita: Writing – review & editing, Methodology, Investigation, Data Curation.

AI Usage Declaration

During preparation for this work, the author utilized the use of Scopus AI and Scite AI to explore for pertinent materials. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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