



Public trust in bullion banking services and community financial inclusion: A topic modeling and sentiment analysis of the TRING application

Immanuel Nicholas Fransepta Samosir^{1,*}

¹ Statistics of Pematangsiantar City, Pematangsiantar, North Sumatra 21100, Indonesia.

*Correspondence: immanuelsamosir9@gmail.com

Received Date: November 10, 2025

Revised Date: February 13, 2026

Accepted Date: February 28, 2026

ABSTRACT

Background: Trust is a precondition for the inclusive use of digital financial services, particularly for low-income households and micro-entrepreneurs who rely on gold as a store of value and a source of emergency liquidity. In Indonesia, the launch of bullion banking services in 2025 and the migration of Pegadaian's digital services to the TRING application have moved gold savings, pawning, and trading onto a single mobile platform, yet evidence on how the public experiences this transition remains limited. This study examines public trust in TRING, operated by Pegadaian and Pegadaian Syariah, and interprets it through the lens of community financial inclusion and grassroots economic empowerment. **Methods:** This research applies a quantitative text-mining approach to 2,000 Google Play Store reviews posted between 16 December 2025 and 11 January 2026. The workflow combines web scraping, Indonesian text preprocessing, sentiment labeling with a pre-trained Indonesian RoBERTa model, Latent Dirichlet Allocation (LDA) topic modeling, Welch's t-test, temporal analysis, and five supervised classifiers evaluated with standard metrics and confidence intervals. **Findings:** LDA identified five topics: platform usability, transaction reliability, customer service, gold investment features, and security and trust. Overall sentiment was moderately positive (60.05% positive, 39.95% negative). Security, verification, and account-access issues dominated one-star reviews, usability dominated five-star reviews, and negative reviews were more than twice as long as positive ones. Random Forest reproduced the transformer-based labels with 93.5% accuracy (95% CI: 90.6% to 95.5%), with no meaningful difference among the five classifiers. **Conclusion:** Public trust in digital bullion banking is conditional and experience-based. Access and verification barriers during platform migration pose the greatest risk of excluding less digitally experienced users, which calls for assisted onboarding and community-based digital and financial literacy support alongside technical improvements. The findings are limited by single-platform, short-window data and automated labels that were validated only indirectly. **Novelty/Originality of this article:** This study reframes app-store reviews as a low-cost, bottom-up indicator of community trust in inclusive financial infrastructure and provides early empirical evidence on public trust in Indonesia's bullion banking application during its migration phase, linking text-mining results to financial inclusion and community empowerment outcomes.

KEYWORDS: digital bullion banking; financial inclusion; public trust; sentiment analysis; topic modeling.

1. Introduction

The digital transformation of financial services has fundamentally reshaped how individuals interact with investment products, particularly in emerging economies where digital platforms increasingly reduce entry barriers to formal financial markets (Lee & Shin, 2018; Thakor, 2020). In Indonesia, one of the most notable developments in this

Cite This Article:

Samosir, I. N. F. (2026). Public trust in bullion banking services and community financial inclusion: A topic modeling and sentiment analysis of the TRING application. *Community Service for Sustainable Community Journal*, 3(1), 68–90. <https://doi.org/10.61511/csjsc.v3i1.2026.3356>

Copyright: © 2026 by the author. This article is distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).



transformation is the rapid growth of digital gold investment services, which enable retail investors to access precious metal assets through mobile applications. Traditional constraints associated with gold investment, such as high minimum purchase requirements, physical storage concerns, and complex transaction procedures, have been substantially mitigated through digitalization (Senyo & Osabutey, 2020).

Among these innovations, the TRING application, operated by Pegadaian and Pegadaian Syariah, represents a new generation of digital bullion banking services in Indonesia. Launched in October 2025 to replace the Pegadaian Digital and Pegadaian Syariah Digital applications, TRING consolidates conventional and Shariah-based services, including gold savings, gold pawning, gold deposits, and gold installments, within a single application (CNN Indonesia, 2026). This transformation reflects the increasing sophistication of digital gold investment services and their positioning as formal financial instruments rather than supplementary retail products. The shift coincided with the launch of Indonesia's first bullion banking services, operated by Pegadaian and Bank Syariah Indonesia, in February 2025. Pegadaian's bullion customers grew from 3.2 million in February 2025 to 5.6 million in February 2026, while public gold savings at Pegadaian rose from 10.5 to 19.25 tons over the same period (ANTARA News, 2026). This rapid growth underscores the strategic importance of understanding public trust and user perceptions toward digital bullion banking services.

Trust is widely recognized as a central determinant of financial technology adoption, particularly in services involving high-value assets such as gold (Stewart & Jürjens, 2018). Prior studies consistently demonstrate that user trust significantly influences both initial adoption and continued usage of digital financial platforms (Ryu, 2018; Hu et al., 2019). In the context of digital gold investment, trust operates at multiple levels simultaneously. Users must place confidence not only in the technological infrastructure that records and processes transactions, but also in the institutional capability of service providers to securely store physical gold reserves and ensure alignment between digital records and underlying assets. The absence of direct physical possession intensifies the importance of perceived system reliability, security, and transparency (Arner et al., 2016).

Beyond its commercial dimension, digital gold has a distinct community relevance in Indonesia. Pegadaian has long served lower-income households and micro-entrepreneurs, and it belongs to the state-owned ultra micro holding together with Bank Rakyat Indonesia and *Permodalan Nasional Madani*/National Civil Capital (Bank Rakyat Indonesia, 2025). Gold savings that can be accumulated in small amounts and pawned for emergency liquidity function as a household savings and safety-net instrument, which is central to financial inclusion and to the sustainable development goals on poverty reduction and access to financial services (United Nations, 2015; Demirgüç-Kunt et al., 2022). Yet national survey data show that financial inclusion in Indonesia (80.51%) still outpaces financial literacy (66.46%), and that Shariah financial literacy is considerably lower at 43.42% (Otoritas Jasa Keuangan & Badan Pusat Statistik, 2025). When access expands faster than understanding, trust becomes the bridge that determines whether digital channels empower communities or expose them to new forms of exclusion and risk (Gabor & Brooks, 2017; Ozili, 2018). Examining public trust in TRING therefore concerns not only fintech performance but also whether digital bullion banking can serve as sustainable financial infrastructure for grassroots communities.

Despite the growing body of literature on sentiment analysis in financial technology applications, several important gaps remain. Previous studies on Pegadaian-related applications have predominantly focused on earlier versions of the Pegadaian Digital platform, using long historical datasets that span initial development phases and predate major system upgrades. These studies primarily emphasize classification accuracy and technical performance of machine learning models, with limited attention to the evolving nature of digital bullion banking services or the underlying trust mechanisms shaping user perceptions. As a result, existing findings may not adequately reflect the characteristics and user expectations associated with newer platforms such as TRING.

Moreover, much of the existing research treats sentiment analysis as a descriptive tool, without explicitly grounding the analysis in established theories of trust, technology acceptance, or perceived risk. The lack of theoretical integration limits the ability to interpret user sentiment as an indicator of broader trust dynamics. Additionally, few studies combine topic modeling and sentiment analysis to simultaneously explore thematic structures and emotional evaluations within user discourse, particularly in the context of digital bullion banking that integrates institutional guarantees, physical asset backing, and Shariah compliance. More importantly for community development, prior review-mining studies rarely interpret user sentiment as evidence of whether digital financial services support or hinder inclusion among the communities they are meant to serve. The contribution of this study is conceptual as well as methodological: it treats aggregated user reviews as a bottom-up signal of community trust in inclusive financial infrastructure.

To address these gaps, this study examines user-generated reviews of the TRING application collected from the Google Play Store between 16 December 2025 and 11 January 2026, shortly after the consolidation of Pegadaian's digital services into a single platform, using an integrated approach that combines topic modeling and sentiment analysis. This research pursues four interrelated objectives. First, it identifies the dominant topics that characterize user discussions of the TRING application, revealing which service dimensions are most salient to users. Second, it analyzes the sentiment polarity of user reviews to assess overall user satisfaction and trust-related perceptions. Third, it develops a lightweight classification model that approximates the transformer-based sentiment labels, enabling low-cost, continuous monitoring of public trust indicators in digital bullion banking services. Fourth, it interprets these findings of community financial inclusion and grassroots economic empowerment, identifying where trust breakdowns may exclude vulnerable users and how community-based interventions could respond. Collectively, these objectives contribute to both theoretical understanding of trust in digital financial services and practical insights for building inclusive and sustainable bullion banking platforms.

1.1 Trust in digital financial services

From a theoretical perspective, trust in digital financial services can be explained through several complementary frameworks. Institution-based trust theory posits that trust is shaped by perceptions of institutional legitimacy, regulatory safeguards, and formal mechanisms that reduce uncertainty (Zucker, 1986; Stewart & Jürjens, 2018). In bullion banking, institutional trust becomes critical because users rely on financial institutions to manage assets they cannot directly observe. Technology trust theory further emphasizes that trust in digital platforms is influenced by perceptions of system security, operational reliability, and consistency of service performance (McKnight et al., 2002). Failures in application performance, transaction processing, or data accuracy can therefore directly erode user trust. Perceived risk theory suggests an inverse relationship between perceived risk and trust, where concerns regarding system failures, asset loss, or transaction uncertainty negatively affect user confidence and satisfaction (Featherman & Pavlou, 2003).

In Indonesia, the trust formation process is further complicated by the integration of Islamic finance principles within digital bullion banking services, particularly through Pegadaian Syariah. Compliance with Shariah principles, clarity of contracts (*akad*), and transparency in asset management introduce additional evaluative dimensions for Muslim users, shaping expectations and trust assessments beyond purely technical considerations (Darmansyah et al., 2020). Consequently, trust in digital bullion banking emerges as a multidimensional construct influenced by technological performance, institutional credibility, perceived risk, and religious compliance.

1.2 Digital gold savings, financial inclusion, and community economic empowerment

Financial inclusion refers to access to, and effective use of, affordable formal financial services by individuals and businesses, and it is increasingly delivered through digital

channels (Demirgüç-Kunt et al., 2022; Ozili, 2018). Digital finance can lower transaction costs and reach underserved communities, and fintech has been positioned as an instrument for achieving the sustainable development goals, particularly targets 1.4 and 8.10 on equal access to economic resources and financial services (Arner et al., 2020; United Nations, 2015). Research on savings among low-income households shows that simple, trusted, and accessible savings instruments help households smooth consumption, cope with shocks, and invest in small enterprises (Karlan et al., 2014). In Indonesia, gold is widely held by households, and the bullion banking initiative explicitly aims to mobilize an estimated 1,800 tons of gold owned by the public (Bank Rakyat Indonesia, 2025). Pegadaian's gold savings and gold-backed pawning products translate this practice into formal financial services that can be accessed in small amounts.

Access alone, however, does not guarantee empowerment. Empowerment involves the ability to make and act on strategic choices, which depends on resources, agency, and the achievements that follow (Kabeer, 1999). In financial terms, users must understand, trust, and be able to operate the services they are offered, and financial literacy has been shown to strengthen the link between access and actual use (Grohmann et al., 2018). Digitalization can also create new exclusions when services require stable connectivity, digital identity verification, and familiarity with app-based procedures, shifting risks to users who are least able to manage them (Gabor & Brooks, 2017). Trust therefore functions as the mechanism through which digital access is converted into sustained participation and economic benefit at the community level, and breakdowns in trust are an early signal that inclusion gains may not be sustained.

1.3 User-generated reviews as community feedback and text-mining approaches

User-generated reviews on digital platforms provide a valuable and authentic source of data for examining these trust dynamics. Unlike structured surveys that may constrain responses through predefined questions, online reviews capture spontaneous user experiences and concerns using natural language (Verkijika & Neneh, 2021). The Google Play Store, as one of Indonesia's primary application distribution platforms, hosts a large volume of such reviews that reflect diverse user perspectives across demographic and geographic segments. Analyzing this data enables researchers to identify recurring themes, evaluate user sentiment, and detect emerging issues that may not yet be formally recognized by service providers (Genc-Nayebi & Abran, 2017; Khalid et al., 2015).

Recent advances in computational text analysis have introduced topic modeling and sentiment analysis as powerful tools for extracting insights from large-scale textual data. Topic modeling techniques, particularly latent dirichlet allocation (LDA), allow the identification of dominant themes that structure user discourse, revealing which aspects of a service users consider most salient. Sentiment analysis complements this approach by quantifying the emotional polarity of user feedback, distinguishing between positive and negative evaluations. The integration of these methods provides a comprehensive understanding of both what users discuss and how they evaluate digital services (Suryono et al., 2021). Such approaches are especially relevant in fintech research, where user perceptions are complex and continuously evolving.

From a community engagement perspective, app-store reviews are a form of bottom-up, unsolicited feedback from service users. Organizations that systematically listen to and act on such feedback move from transactional toward more transformational forms of community engagement (Bowen et al., 2010). Analyzing reviews thus provides a scalable channel through which the concerns of dispersed users, including those in remote areas without easy access to physical outlets, can inform service design and community-based support.

2. Methods

2.1 Research design and data collection

This research employs a quantitative approach utilizing text mining and machine learning techniques to analyze user-generated content from the TRING application. The study adopts a cross-sectional design, examining user reviews posted over a four-week window to capture contemporary perceptions of digital bullion banking services. Although the design is cross-sectional, review timestamps allow descriptive analysis of short-term temporal variation within the observation window. The research framework integrates topic modeling, sentiment analysis, and classification modeling to provide comprehensive insights into public trust dynamics (Chakraborty et al., 2020). This methodological approach enables systematic extraction of latent themes within user discourse while simultaneously quantifying emotional valence and developing predictive capabilities for continuous trust monitoring.

User reviews were collected from the Google Play Store, Indonesia's primary platform for Android application distribution, and cover reviews posted between December 16, 2025 and January 11, 2026. The Google Play Store was selected as the data source due to its widespread usage in Indonesia and the public availability of its review pages (Genc-Nayebi & Abran, 2017). The data collection employed web scraping techniques using Python programming language with the google-play-scraper library, which enables systematic extraction of publicly displayed review metadata, including review text, user ratings, timestamps, and reviewer identifiers (Khalid et al., 2015). Reviewer identifiers were not used in the analysis and are not reported.

The final dataset comprised 2,000 user reviews posted between 16 December 2025 and 11 January 2026. The dataset therefore does not represent the full review history of the application; it captures the period shortly after the migration of Pegadaian's digital services to TRING. Each collected review comprises several attributes: the original review text (content), numerical rating on a five-point scale (score), timestamp indicating date and time of posting (at), and unique reviewer identifier. The dataset exhibits natural variation in review length, ranging from brief single-sentence comments to detailed multi-paragraph assessments, reflecting authentic user engagement patterns with the platform.

2.2 Data preprocessing

Raw text data from user reviews requires systematic preprocessing to enhance analytical quality and computational efficiency (Vijayarani et al., 2015). The preprocessing pipeline implemented in this research comprises five sequential stages. First, text cleaning, which constitutes the initial preprocessing stage, removes non-informative elements that do not contribute semantic value. This process eliminates special characters, punctuation marks, numerical digits, URLs, and excessive whitespace while converting all text to lowercase to ensure case-insensitive processing (Haddi et al., 2013). Second, normalization, which addresses character encoding inconsistencies and standardizes unicode representations, particularly important for Indonesian text which may contain diacritical marks or mixed-script content (Wilie et al., 2020).

Third, slang word standardization, a stage that converts informal language, abbreviations, and colloquial expressions commonly found in social media discourse into their formal Indonesian equivalents (Arifin et al., 2020). This step is critical for Indonesian text analysis due to prevalent informal language usage in digital communication. Fourth, stemming, which reduces words to their root forms, consolidates morphological variants and decreases vocabulary dimensionality (Adriani et al., 2007). For Indonesian text, the Sastrawi stemming algorithm was employed, which implements rule-based morphological analysis specifically designed for Indonesian language characteristics, including affixation patterns. Fifth, stopword removal, a stage that eliminates high-frequency function words

that carry minimal semantic content, such as articles, prepositions, and conjunctions (Saif et al., 2014). A customized Indonesian stopwords list was compiled, combining standard linguistic stopwords with domain-specific common terms identified through frequency analysis. Negation and intensifier terms (e.g., *tidak*/no and *sangat*/very) were deliberately retained because they carry sentiment information. The complete preprocessing pipeline produces the "ulasan_bersih" (cleaned review) field, transforming original user reviews into standardized, computationally tractable text suitable for subsequent analytical procedures. The preprocessing sequence is illustrated in the research framework diagram.

2.3 Sentiment labelling

Sentiment classification was performed using the robustly optimized bidirectional encoder representations from transformers pretraining approach (RoBERTa), a transformer-based deep learning model that has demonstrated superior performance in sentiment analysis tasks across multiple languages (Liu et al., 2019). The implementation utilized a pre-trained Indonesian RoBERTa model fine-tuned on sentiment classification tasks, accessible through the hugging face transformers library (Wolf et al., 2020). RoBERTa employs masked language modeling and dynamic masking techniques to learn robust contextual representations of text.

The sentiment classification process operates on preprocessed review text, generating binary sentiment labels (positive or negative) for each review. The model architecture processes tokenized text through multiple transformer layers, producing contextualized embeddings that capture semantic relationships. This automated labeling approach enables consistent sentiment annotation across the entire dataset while leveraging state-of-the-art natural language understanding capabilities. Because the labels are generated automatically rather than by human annotators, their validity was assessed through convergent evidence from star ratings, which are an independent, user-provided evaluation of the same experience. The distribution of sentiment labels across the five rating levels was examined for this purpose. The labels are therefore interpreted as model-based estimates of sentiment polarity rather than as ground truth.

2.4 Topic modelling

Topic modeling employs latent dirichlet allocation (LDA), a generative probabilistic model that discovers latent thematic structures within document collections (Blei et al., 2003). LDA assumes each document comprises a mixture of topics, and each topic consists of a distribution over words. The model estimates these distributions through variational inference, revealing interpretable topic structures. The LDA model specification is,

$$P(\theta, z, w \mid \alpha, \beta) = P(\theta \mid \alpha) \prod_{n=1}^N P(z_n \mid \theta) P(w_n \mid z_n, \beta) \quad (\text{Eq. 1})$$

where θ represents document-topic distributions, z denotes topic assignments, w indicates observed words, α and β are Dirichlet priors, and N is the number of words in the document. Prior to LDA application, preprocessed text undergoes vectorization using Count Vectorization, which transforms text into document-term matrices (Salton & McGill, 1983). The number of topics was set to $K = 5$, a choice guided by the distinctiveness and interpretability of the resulting topics in the context of bullion banking services, in line with the recommendation that topic models be validated through human interpretation (Maier et al., 2018). Formal coherence-based selection of K was not performed and is acknowledged as a limitation.

Topic interpretation involves examining the top-weighted terms for each topic, with the author assigning semantically meaningful labels based on term coherence and contextual relevance to digital bullion banking services. The model generates topic-document distributions, enabling analysis of topic prevalence across the review corpus and

identification of dominant themes in user discourse. Each review was assigned to its dominant topic, defined as the topic with the highest document-topic probability, and topic prevalence was computed as the sum of document-topic probabilities across the corpus. The distribution of dominant topics across rating levels was then used to identify which themes characterize satisfactory versus unsatisfactory user experiences.

2.5 Sentiment analysis and classification modelling

Beyond binary classification, comprehensive sentiment analysis examines distributional characteristics, temporal patterns, and associative relationships between sentiment and other review attributes (Liu, 2012). Temporal sentiment trends are analyzed through time-series aggregation, computing daily sentiment proportions to identify patterns, shifts, or stability in user perceptions over the observation period. A three-day moving average was applied to reduce daily volatility. Then, cross-tabulation analysis examines relationships between sentiment and rating scores, providing a descriptive convergent validity check on the consistency between numerical ratings and textual sentiment expressions. Review length analysis investigates whether sentiment polarity correlates with review verbosity, examining whether users experiencing strong emotions (positive or negative) tend to write more extensively. Word count serves as the length metric, and the difference in mean length between negative and positive reviews was tested using Welch's t-test, which does not assume equal variances, with Cohen's d as the effect size. Heatmaps of negative review counts by day of week and hour of day were used descriptively to locate periods of concentrated complaints.

Classification modeling develops supervised machine learning models to predict sentiment labels from review text, enabling automated sentiment monitoring for future reviews (Pang & Lee, 2008). Because the target labels are produced by RoBERTa, the classifiers are designed as lightweight surrogates that approximate the transformer labels at a lower computational cost; their accuracy therefore measures agreement with the RoBERTa labels rather than with human judgment. The modeling process employs term frequency-inverse document frequency (TF-IDF) vectorization, which weights terms based on their discriminative power:

$$TF - IDF(t, d) = TF(t, d) \times IDF(t) \quad (\text{Eq. 2})$$

where

$$TF(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \quad (\text{Eq. 3})$$

$$IDF(t) = \log\left(\frac{N}{|\{d \in D: t \in d\}|}\right) \quad (\text{Eq. 4})$$

Here, $f_{t,d}$ represents the frequency of term t in document d , N denotes the total number of documents, and D indicates the document collection.

TF-IDF vectorization parameters include maximum features (1500), n-gram range (1 to 3) for capturing unigrams through trigrams, minimum document frequency (3), maximum document frequency (0.85), and sublinear term frequency scaling applying logarithmic scaling to term frequencies. The dataset undergoes stratified train-test splitting with 80% allocated to training and 20% to testing. Class imbalance, if detected with imbalance ratio exceeding 1.5, is addressed through synthetic minority over-sampling technique (SMOTE), which generates synthetic examples for the minority class (Chawla et al., 2002). Because the positive-to-negative ratio in this dataset was 1.503 (1,201 to 799), which exceeds this threshold, SMOTE was applied. The 95% confidence interval for test-set accuracy was computed using the Wilson score method (Wilson, 1927).

Five classification algorithms are trained and compared to identify optimal performance: logistic regression, multinomial naive Bayes, support vector machine (SVM),

random forest, and gradient boosting. Each algorithm represents distinct machine learning paradigms, providing a comprehensive performance comparison. First, logistic regression, a linear classification model that estimates the probability of an observation belonging to a particular class using the logistic function. In text classification tasks, the model learns a linear relationship between TF-IDF-weighted textual features and the log-odds of sentiment classes (Hosmer et al., 2013). Logistic Regression estimates class probability as:

$$P(y = 1 | x) = \frac{1}{1 + \exp(-(\beta_0 + \beta^T x))} \quad (\text{Eq. 5})$$

where β_0 and β^T are learned coefficients. Second, multinomial naive Bayes, a probabilistic classifier based on Bayes' theorem with the assumption of conditional independence among features. The model is particularly well suited for text data represented by word frequencies or TF-IDF weights, as it models the likelihood of term occurrences within each sentiment class (McCallum & Nigam, 1998). Multinomial naive Bayes applies:

$$P(y | x) = P(y) \prod_{i=1}^n P(x_i | y) \quad (\text{Eq. 6})$$

where $P(y)$ represents prior probability, and $P(x_i|y)$ denotes conditional probability of feature x_i given class y .

Third, the support vector machine (SVM), a discriminative classification algorithm that aims to identify the optimal hyperplane that maximizes the margin between classes. In sentiment analysis, SVM is effective in handling high-dimensional feature spaces by focusing on support vectors that are most informative for class separation (Cortes & Vapnik, 1995). Support Vector Machine optimization is defined as:

$$\min_{w,b,\varepsilon} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \varepsilon_i \quad (\text{Eq. 7})$$

subject to $y_i(w^T x_i + b) \geq 1 - \varepsilon_i$ and $\varepsilon_i \geq 0$, where w represents the weight vector, b is bias, C is the regularization parameter, and ε_i are slack variables. Fourth, random forest, an ensemble learning method that constructs multiple decision trees using bootstrap sampling and random feature selection. Each tree produces an independent prediction, and the final classification is determined through majority voting (Breiman, 2001). Random forest prediction follows majority voting:

$$\hat{y} = \text{mode}\{h_1(x), \dots, h_T(x)\} \quad (\text{Eq. 8})$$

where $h_t(x)$ represents the prediction of the t -th tree, and T denotes the total number of trees (set to 100). Fifth, gradient boosting, an ensemble method that builds models sequentially, where each new weak learner is trained to correct the errors made by previous models. By iteratively minimizing a loss function using gradient-based optimization, Gradient Boosting can capture complex and non-linear patterns in text data (Friedman, 2001). Gradient Boosting updates the ensemble as:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (\text{Eq. 9})$$

where $F_m(x)$ represents the ensemble after m iterations, $h_m(x)$ is the m -th weak learner, and γ_m is the step size of the m -th update, scaled by the learning rate.

Model evaluation employs multiple metrics to assess classification performance comprehensively. Model performance is evaluated using accuracy, precision, recall, and F1-score:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (\text{Eq. 10})$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (\text{Eq. 11})$$

$$Recall = \frac{TP}{TP+FN} \quad (\text{Eq. 12})$$

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (\text{Eq. 13})$$

where TP , TN , FP , and FN represent true positives, true negatives, false positives, and false negatives, respectively.

3. Results and Discussion

3.1 Data preparation results

This section presents the results of the processes conducted prior to the substantive analysis. It reports the outcomes of data scraping, text preprocessing, and sentiment labeling. First, data collection through web scraping was carried out on the TRING application available on the Indonesian Google Play Store. The scraping process yielded a total of 2,000 user reviews posted between 16 December 2025 and 11 January 2026, which were stored in CSV format. Overview of the raw data obtained from the scraping process (Table 1).

Table 1. Overview of the raw data

No	Content	Score	At
1	<i>sangat membantu saat tidak bisa lgsung datang ...</i>	5	2026-01-11 13:20:49
2	<i>Bang, Tolong balikin system aplikasinya...</i>	2	2026-01-11 13:10:25
3	<i>mau di pakai transaksi malah harus update...</i>	1	2026-01-11 13:03:48
...	...	...	...
2000	<i>Aplikasi Tring! ini benar benar game changer...</i>	5	2025-12-16 20:14:15

The raw data obtained from the scraping process were subjected to data preprocessing to facilitate subsequent labeling and modeling stages. The preprocessing results indicate that there were zero missing values and no reviews written entirely in English; therefore, no data were removed from the dataset. Text preprocessing was then conducted through several stages, including text cleaning, normalization, slang word standardization, stemming, and stopword removal. An overview of the text data before and after preprocessing is presented below (Table 2).

Table 2. Text preprocessing result

No	Before	Score	After
1	<i>Sangat membantu saat tidak bisa lgsung datang ke kantor...</i>	5	<i>Sangat bantu tidak bisa langsung datang kantor... (very helpful, can't come directly to the office)</i>
2	<i>Bang, tolong balikin system aplikasinya ke tahun 2020...</i>	2	<i>Bang tolong balikin sistem aplikasi tahun 2020... (bro, please return the application system to 2020...)</i>
3	<i>Mau di pakai transaksi malah harus update...</i>	1	<i>Mau pakai transaksi malah harus update.. (i want to use it for transactions but i have to update it...)</i>
...	...	...	...
2000	<i>Aplikasi tring! Ini benar benar game changer...</i>	5	<i>Aplikasi tring benar-benar game changer... (tring application is really a game changer...)</i>

The clean and tidy dataset was subsequently subjected to the labeling process. In this stage, each review was automatically assigned a sentiment label using the RoBERTa-based system. In this study, a label of 1 was assigned to reviews expressing positive sentiment,

while a label of 0 was assigned to reviews expressing negative sentiment. The results of the sentiment labeling for the clean dataset are presented below (Table 3).

Table 3. Data labelling result

No	Review	Score	Label	Sentiment
1	<i>sangat membantu saat tidak bisa lgsung datang ...</i>	5	1	Positive
2	<i>Bang, Tolong balikin system aplikasinya...</i>	2	0	Negative
3	<i>mau di pakai transaksi malah harus update...</i>	1	0	Negative
...	...	...	...	...
2000	<i>Aplikasi Tring! ini benar benar game changer...</i>	5	1	Positive

3.2 Topic modelling: Identifying user concerns and expectations in bullion banking services

The LDA analysis successfully identified five primary topics from 2,000 user reviews of the TRING application, revealing the multifaceted nature of user engagement with digital bullion banking services. The topic modeling analysis provides crucial insights into what users prioritize when evaluating digital gold investment platforms, particularly in the context of emerging financial technologies in Indonesia's growing digital economy. Table 4 presents the highest-ranked terms for each topic, alongside human-assigned interpretive labels based on term coherence and contextual relevance to digital bullion banking services (Table 4).

Table 4. Identified topics and representative terms from LDA analysis

No	Topic	Top terms (ranked by probability)
1	Platform usability & interface	Application, easy, usable, navigation, features, design, simple, practical, fast, access, menu, display, responsive
2	Transaction processing & reliability	Transaction, buy, sell, process, fast, smooth, failure, error, time, confirmation, delay, completed, automatic
3	Customer service & support	CS (customer service), service, response, help, complaint, answer, chat, phone, slow, professional, complaint
4	Gold investment features	Gold, investment, price, grams, savings, installments, physical, digital, print, withdrawal, balance, asset
5	Security & trust	Safe, data, personal, account, verification, password, protection, fraud, doubt, trust, guarantee

Topic 1 “platform usability & interface” emerges as the most frequently discussed theme, reflecting users' primary concern with the ease of navigating and operating the application. High-frequency terms such as *mudah* (easy), *simpel* (simple), and *praktis* (practical) indicate that interface design significantly influences user evaluations. Reviews within this topic emphasize the importance of straightforward navigation pathways, clear visual hierarchies, and minimal steps required to complete core functions. This finding corroborates technology acceptance literature demonstrating that perceived ease of use constitutes a fundamental determinant of user satisfaction and continued usage intentions in financial technology applications (Ryu, 2018). For digital bullion banking specifically, where users may possess varying levels of financial literacy and technological proficiency, intuitive interface design reduces cognitive barriers to adoption and enhances accessibility across diverse user segments.

Topic 2 “transaction processing & reliability” addresses the operational performance of transaction mechanisms, encompassing gold purchasing, selling, and account management functions. The prominence of terms such as *cepat* (fast), *lancar* (smooth), *gagal* (failed), delay, and error reveals that transaction speed and reliability represent critical evaluation criteria. Users express strong preferences for instant transaction confirmation and seamless processing without interruptions. Conversely, transaction failures, prolonged pending

statuses, and processing errors generate substantial dissatisfaction and trust erosion. This pattern reflects the high-stakes nature of financial transactions, where even minor delays or technical glitches can trigger anxiety regarding fund security and platform competence (Arner et al., 2016). The central role of transaction reliability in user discourse underscores the necessity for robust technical infrastructure and redundancy mechanisms to maintain continuous operational integrity.

Topic 3 “customer service & support” captures user experiences with institutional support mechanisms, including customer service responsiveness, problem resolution effectiveness, and communication quality. Terms such as *respon* (response), *lambat* (slow), and *bantu* (help) indicate that support service quality substantially shapes overall platform evaluations. Users experiencing technical difficulties or transactional issues evaluate platforms not solely based on problem occurrence, but critically on the quality and timeliness of institutional assistance in resolving these problems. Effective customer service functions as a trust repair mechanism, mitigating negative sentiment arising from technical failures and demonstrating institutional commitment to user welfare (Özkan et al., 2020). Conversely, delayed responses, unhelpful assistance, or unresolved complaints amplify dissatisfaction and signal institutional indifference, accelerating trust deterioration.

Topic 4 “gold investment features” encompasses substantive discussions of product-specific functionalities unique to bullion banking services, including gold accumulation mechanisms, price tracking, physical gold withdrawal options, and portfolio management tools. The prevalence of terms such as *investasi* (investment), *tabungan* (savings), *cicil* (installment), *fisik* (physical), and *cetak* (print/convert) reflects users' engagement with core value propositions of digital gold platforms. Reviews within this topic evaluate whether platform features align with investment objectives, facilitate flexible accumulation strategies, and provide transparent mechanisms for converting digital holdings to physical gold. This theme highlights that beyond technological functionality, users assess whether the platform effectively serves their financial goals and investment preferences. The discussion of physical gold conversion options specifically addresses a distinctive trust dimension in digital bullion banking: users' need for assurance that digital records correspond to tangible assets that can be redeemed when desired (Darmansyah et al., 2020).

Topic 5 “security & trust” directly addresses users' perceptions of platform safety, data protection, and fraud prevention mechanisms. High-salience terms include *aman* (safe), *data*, *verifikasi* (verification), *password*, *proteksi* (protection), and *percaya* (trust). Although this topic exhibits lower prevalence compared to usability and transaction processing themes, its presence underscores that security concerns remain salient for a significant user segment, particularly in the context of financial services involving valuable assets. Users express both confidence in security measures (citing multi-factor authentication, one-time password verification, and encryption) and anxieties regarding potential vulnerabilities (mentioning fraud risks, data breaches, and scams). This ambivalence reflects the inherent tension in digital financial services, where users must balance convenience benefits against perceived security risks (Featherman & Pavlou, 2003). The explicit discussion of security features suggests that transparent communication regarding protective measures can enhance perceived trustworthiness and reduce adoption barriers among risk-averse users. The co-occurrence of security terms with verification and password terms also indicates that this topic captures the practical difficulty of accessing accounts, a distinction that becomes important when topics are compared across rating levels.

Based on the topics and terms identified in Table 4, topic prevalence was calculated for each topic as the sum of its document-topic probabilities across all 2,000 reviews, so that the total across topics equals the number of reviews. The distribution of topic prevalence across all identified topics is presented below (Figure 1).

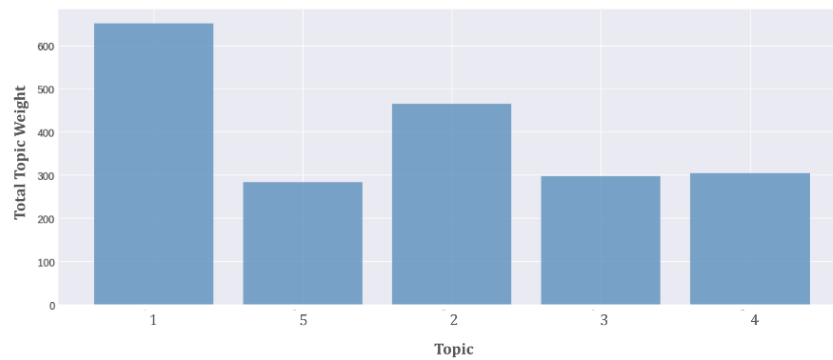


Fig. 1. Distribution of topics in TRING app reviews

The distribution of topics across the corpus (Figure 1) shows that operational functionality (topics 1 and 2, approximately 56% of total topic prevalence) dominates user attention, while institutional factors (topics 3 and 5, approximately 29%) and product-specific features (topic 4, approximately 15%) receive substantial but secondary emphasis. This pattern indicates that for digital bullion banking platforms, technological performance and reliability form the foundation of user trust, upon which institutional credibility and product attractiveness are subsequently evaluated. The distribution of topics across user rating levels is also presented (Figure 2).

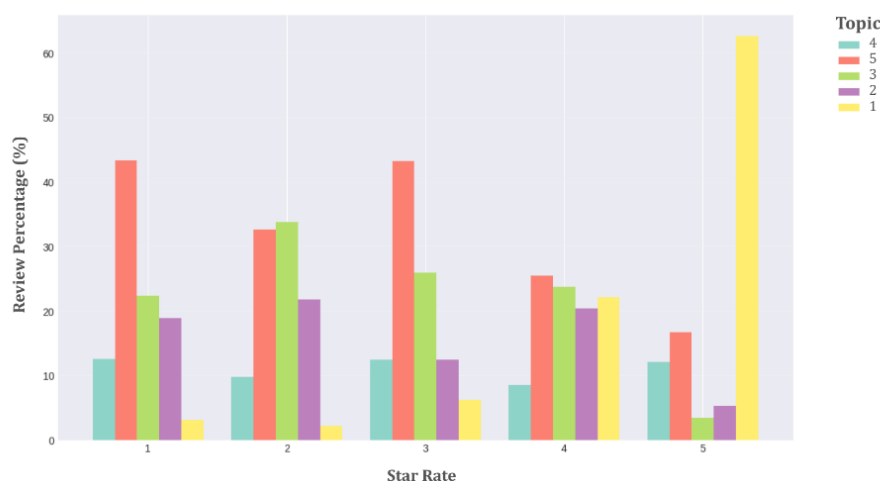


Fig. 2. Distribution of topics across user rating

Figure 2 shows that the thematic composition of reviews shifts markedly across rating levels. Topic 5 (security & trust) was the most frequent dominant topic among one-star and three-star reviews (approximately 43% in each), and together with topic 3 (customer service & support), it accounted for roughly two-thirds of two-star reviews. In contrast, topic 1 (platform usability & interface) accounted for approximately 63% of five-star reviews but less than 5% of one-star and two-star reviews. This gradient indicates that dissatisfaction is driven primarily by problems of account access, verification, and security, compounded by slow service recovery, whereas satisfaction is anchored in ease of use. The pattern is consistent with the migration of Pegadaian's digital services to TRING, which required existing customers to re-register their accounts (Pegadaian, 2025). From an inclusion perspective, access barriers of this kind are particularly consequential, because users with limited digital experience are the least able to resolve verification problems on their own.

These findings contribute to the understanding of digital financial services in emerging markets, particularly for specialized services like bullion banking that combine traditional asset management with modern digital interfaces. The topic modeling results suggest that

building public trust in such services requires not only robust technical infrastructure but also intuitive design, transparent operations, and responsive customer support systems that can address the unique concerns of users managing valuable physical assets through digital channels. For communities that rely on Pegadaian as an accessible source of savings and emergency liquidity, these requirements determine whether digital bullion banking supports, rather than hinders, financial inclusion.

3.3 Sentiment analysis: measuring public trust through user opinions

The sentiment analysis of 2,000 TRING application reviews revealed a moderately positive overall perception, with 60.05% positive sentiment (1,201 reviews) and 39.95% negative sentiment (799 reviews) (Figure 3). This distribution suggests that while the majority of users maintain favorable views of the digital bullion banking service, a substantial minority experiences significant dissatisfaction. A comparable mix of evaluations has been reported for digital banking elsewhere; Alawaji & Aloraini (2025), analyzing Arabic reviews of Saudi digital banks, found that reviews combined positive, negative, and conflicting evaluations, and that traditional machine learning classifiers remained competitive with large language models.

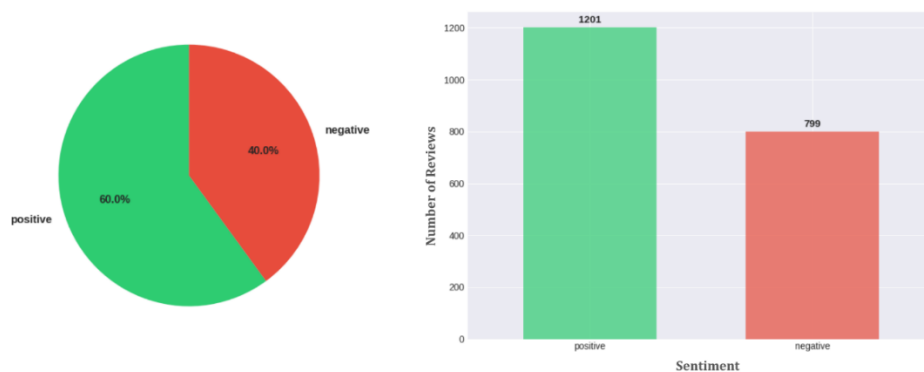


Fig. 3. Distribution of sentiment

The relationship between user ratings and sentiment polarity demonstrates strong consistency and provides convergent evidence for the validity of the automated labels. Reviews with one-star ratings showed 95.69% negative sentiment, while five-star ratings exhibited 93.23% positive sentiment (Figure 4). This strong association confirms that users' explicit ratings align closely with the emotional tone of their textual feedback. The gradient from predominantly negative sentiment at lower ratings to overwhelmingly positive sentiment at higher ratings reflects a coherent pattern where user satisfaction directly translates into positive emotional expression. Notably, four-star reviews were still predominantly negative in tone (approximately 63%), suggesting that users who rate the application favorably continue to use the review space to report problems or request improvements. This validation is important because it supports the reliability of sentiment-based trust measurement, although it does not replace human annotation (see Section 5).

When comparing the vocabulary of positive and negative reviews, distinct patterns emerge that illuminate the factors driving satisfaction versus dissatisfaction (Figure 5). Positive sentiment emphasized the application's helpfulness (*sangat bantu*), quality (*bagus, sangat bagus*), and ease of use (*mudah*), suggesting that when the platform functions as designed, users appreciate its accessibility and utility. The prominence of *gadai* (pawn) among positive reviews also indicates that users value the application as a channel for obtaining liquidity against their gold holdings, a function of direct relevance to household financial resilience. Conversely, negative sentiment concentrated on technical failures (*tidak bisa, malah, update*), access issues (login, *masuk, buka*), registration and verification (*daftar, verifikasi, password*), and unmet expectations (*mau, tetapi, sudah*). This stark contrast

indicates that user trust in bullion banking services is highly contingent on consistent technical performance and feature reliability.

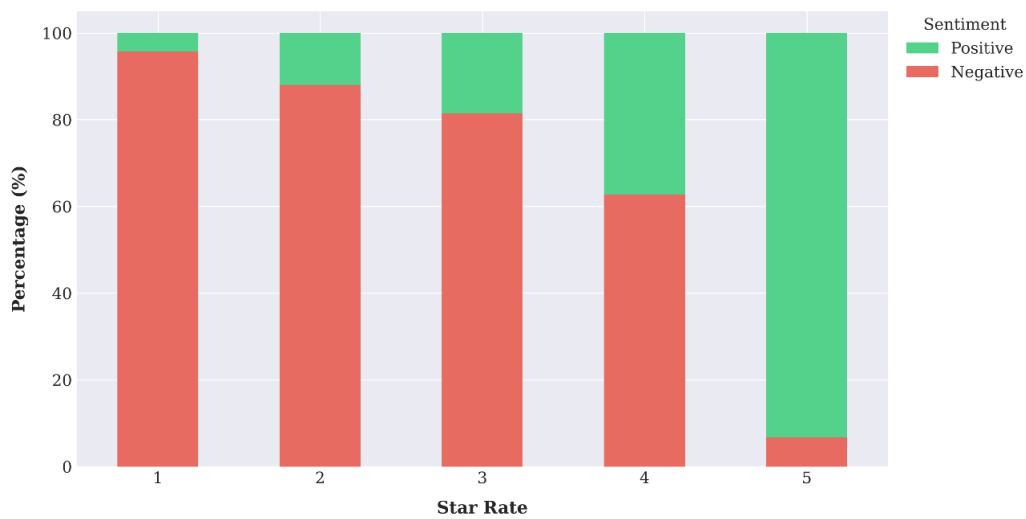


Fig. 4. Distribution of sentiment across user rating

The temporal analysis of sentiment trends provides insight into the dynamic nature of public trust in the TRING application over the observation period from 16 December 2025 to 11 January 2026 (Figure 6). Positive reviews rose sharply during the first week, peaking at close to 90 reviews per day (three-day moving average) around 21 December 2025, and then declined steadily. Negative reviews remained comparatively stable at roughly 20 to 40 per day and exceeded positive reviews between approximately 31 December 2025 and 7 January 2026, before positive reviews recovered in the final days of the window. Because the design is cross-sectional and no event data were collected, these fluctuations cannot be attributed to specific causes; they are, however, consistent with a period of service consolidation following the migration from Pegadaian Digital (CNN Indonesia, 2026). Prior research shows that functional, system, information, and service failures in mobile banking reduce usage and user satisfaction (Kamboj et al., 2022). With Pegadaian's bullion customer base growing from 3.2 million to 5.6 million within a year (ANTARA News, 2026), maintaining consistent service quality during scaling represents a significant challenge that manifests in sentiment fluctuations.



Fig. 5. Word cloud of each sentiment

One particularly revealing finding emerged from the analysis of review length relative to sentiment. Negative reviews averaged 19.49 words with a standard deviation of 15.37 words, while positive reviews averaged only 7.64 words with a standard deviation of 9.43 words. The difference was statistically significant (Welch's $t(1197.8) = 19.49$, $p < 0.001$) and large in magnitude (Cohen's $d = 0.97$). This substantial difference suggests that dissatisfied users invest considerably more effort in articulating their complaints, providing detailed accounts of problems encountered. This pattern corroborates findings by Verkijika

& Neneh (2021), who observed that negative experiences prompt more elaborate explanations as users seek to communicate specific failures or frustrations. For bullion banking services, where financial stakes are tangible and users may feel particularly vulnerable when technical issues arise, this tendency to provide detailed negative feedback represents valuable diagnostic information for service improvement. Conversely, satisfied users tend to offer brief affirmations, suggesting that when the service meets expectations, users see little need for extensive commentary.

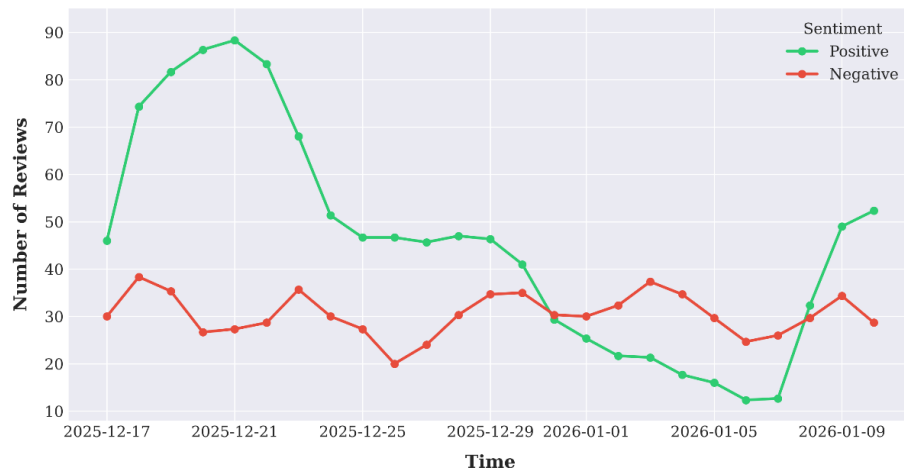


Fig. 6. Daily sentiment trends (three-day moving average)

The heatmap of negative reviews by day of week and hour of day (Figure 7) shows that complaints were concentrated in the early hours and around midday, with the largest single cell on Thursday at approximately 01:00. The time zone of the timestamps returned by the scraping library was not independently verified, so exact hours should be interpreted with caution. Because the observation window covers only four weeks, each day-hour cell aggregates at most four occurrences of that weekday, so isolated peaks may reflect single incidents rather than recurring patterns. The heatmap is therefore interpreted descriptively, as a tool for locating periods when monitoring and customer support capacity may need to be strengthened, rather than as evidence of stable weekly cycles.

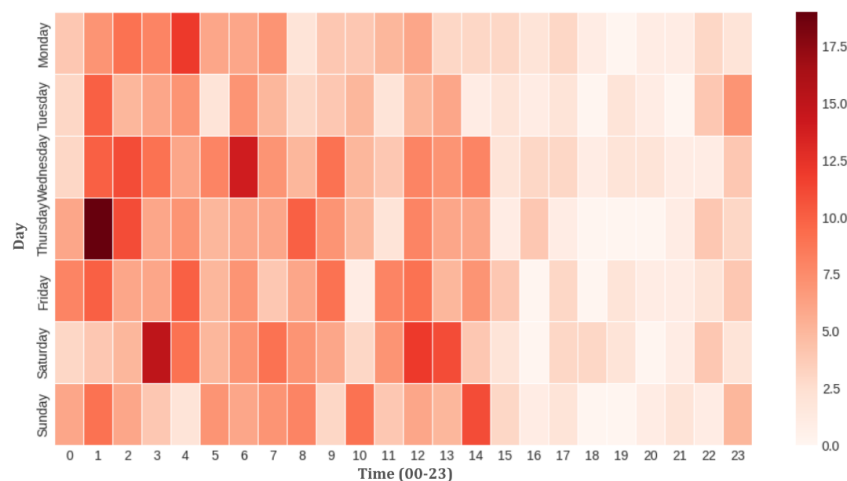


Fig. 7. Heatmap of negative reviews by day of week and hour of day

For digital bullion banking services in Indonesia's emerging fintech landscape, these sentiment patterns suggest that public trust remains conditional and responsive to service quality. The substantial user base that Pegadaian has cultivated, with 90 tons of gold under management in 2024 (Bank Rakyat Indonesia, 2025) and 5.6 million bullion customers by February 2026 (ANTARA News, 2026), demonstrates market demand for digital gold

services. However, the sentiment analysis reveals that sustaining and expanding this market requires continuous attention to the factors driving negative sentiment, particularly technical reliability, transaction success rates, and customer service responsiveness.

The integration of sentiment analysis with topic modeling provides a comprehensive framework for understanding public trust in bullion banking services. While sentiment measures the emotional valence of user experiences, topic modeling identifies the specific aspects of service delivery that generate these emotional responses. Together, these methods reveal that public trust in digital bullion banking operates at multiple levels, encompassing technical functionality, security perceptions, service quality, and overall user experience, and that maintaining trust requires excellence across all these dimensions simultaneously.

3.4 Sentiment classification modeling: Predictive framework for trust monitoring

The development and evaluation of machine learning models for sentiment classification achieved strong predictive performance, with the random forest algorithm emerging as the optimal classifier with 93.5% accuracy (Figure 8). This subsection examines the modeling process, comparative performance across algorithms, and implications for automated trust monitoring in digital bullion banking services. Because the test set contains 400 reviews, the 95% Wilson confidence interval for this accuracy is 90.6% to 95.5%. The five classifiers differed by less than two percentage points (Figure 8), well within this interval, so the models should be regarded as performing comparably rather than random forest being clearly superior. As noted in Section 3.5, these figures measure agreement with the RoBERTa labels rather than with human judgment.

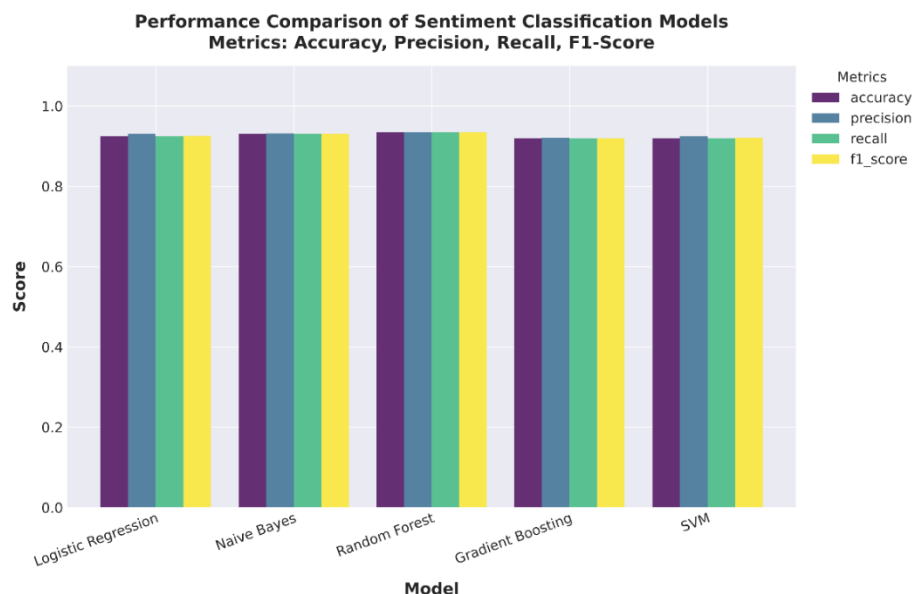


Fig. 8. Performance comparison of sentiment classification models

The performance of these classification models also supports the broader applicability of machine learning approaches to trust measurement in financial services. As digital financial platforms continue to proliferate in emerging markets like Indonesia, the ability to automatically monitor user sentiment and trust becomes increasingly important for maintaining service quality at scale. The methodological framework demonstrated in this study, combining topic modeling for interpretability with sentiment classification for automation, offers a template that other financial service providers can adapt to their specific contexts.

Looking forward, the predictive models developed in this research can evolve as the TRING application user base grows and service features expand. Regular retraining with

new review data, together with periodic human annotation of a random subsample, will ensure the models adapt to changing user concerns and remain aligned with human judgment. Because these surrogate models are far less computationally demanding than transformer-based models (Liu et al., 2019; Willie et al., 2020), they are suitable for routine monitoring by service providers, regulators, or community organizations with limited computing resources.

The achievement of 93.5% accuracy in sentiment classification represents more than a technical milestone; it demonstrates the feasibility of systematic, scalable trust monitoring for digital bullion banking services. In an industry where public confidence directly influences adoption and usage, the ability to continuously measure and respond to trust indicators provides a significant competitive advantage. For Pegadaian, as one of the two institutions designated to operate Indonesia's first bullion banking services in 2025 (Bank Rakyat Indonesia, 2025), these tools for monitoring public trust offer essential capabilities for sustaining market leadership as the digital gold investment sector continues its rapid expansion.

3.5 Implications for community financial inclusion and grassroots economic empowerment

The findings carry implications that extend beyond platform management to the communities that digital bullion banking is intended to serve. Digital gold savings allow households to accumulate a trusted asset in small amounts, and gold-backed pawning provides liquidity without forcing the sale of that asset. The prominence of *gadai* (pawn) and *bantu* (help) in positive reviews suggests that users value TRING for these safety-net functions. At the same time, the dominance of security, verification, and account-access problems in one-star reviews indicates that the main threat to inclusion is not the attractiveness of the product but the ability of users to reach and operate their accounts. In terms of Kabeeer's (1999) framework, the application expands resources, but agency depends on whether users can navigate the procedures required to use them.

These access barriers are unlikely to be distributed evenly. The gap between financial inclusion (80.51%) and financial literacy (66.46%) in Indonesia, and the lower level of Shariah financial literacy (43.42%), imply that a substantial share of users hold accounts without the knowledge needed to resolve problems independently (Otoritas Jasa Keuangan & Badan Pusat Statistik, 2025). Users in rural and remote areas, older users, and first-time investors are plausibly more affected by migration, re-registration, and verification failures, although the review data do not allow users' characteristics to be identified. For these users, a failed login may mean temporary loss of access to savings and emergency liquidity, and negative experiences shared publicly may discourage prospective users within the same social networks from adopting formal savings (Gabor & Brooks, 2017; Grohmann et al., 2018).

Several community-oriented actions follow from these findings. First, digital migration and account verification should be accompanied by assisted onboarding through Pegadaian outlets and agents, village-owned enterprises/*Badan Usaha Milik Desa*, cooperatives, and community organizations, so users who cannot resolve access problems online are not excluded. Second, financial and digital literacy programs, including university community service programs, can use the recurring pain points identified here (registration, verification, password recovery, and security awareness) as practical training content. Third, customer service responsiveness should be treated as a trust repair mechanism, particularly for complaints that involve access to funds. Finally, the lightweight monitoring framework demonstrated can be used by service providers, regulators, and community partners as a low-cost early-warning indicator of when digital channels begin to exclude the communities they serve, supporting SDG targets 1.4 and 8.10 on equitable access to economic resources and financial services (Arner et al., 2020; United Nations, 2015).

4. Conclusions

This study investigates public trust in digital bullion banking services through an integrated topic modeling and sentiment analysis of user reviews from the TRING application. By analyzing 2,000 user-generated reviews collected from the Google Play Store between 16 December 2025 and 11 January 2026, the research provides empirical evidence on how users perceive and evaluate digital gold investment services in Indonesia's emerging fintech ecosystem and relates these perceptions to community financial inclusion. The combination of LDA and sentiment classification offers a comprehensive perspective on both the substantive issues discussed by users and the emotional valence underlying their experiences.

The topic modeling results reveal five dominant themes structuring user discourse: platform usability, transaction processing and reliability, customer service and support, gold investment features, and security and trust. The distribution of these topics across rating levels demonstrates a clear gradient: low ratings are dominated by security, verification, and account-access issues together with customer service failures, whereas five-star ratings emphasize ease of use. This pattern confirms that public trust in bullion banking services is closely tied to platform performance and service quality rather than solely to the attractiveness of the investment product itself. Sentiment analysis further indicates that while a majority of users express positive sentiment toward the TRING application, a substantial proportion of negative sentiment persists. Negative reviews were significantly longer than positive reviews, providing detailed diagnostic information, and negative sentiment exceeded positive sentiment during part of the observation window. The concentration of complaints in certain day-hour periods suggests when monitoring and support capacity may need to be strengthened, although the short window limits inference about recurring patterns. These findings highlight the importance of real-time monitoring, proactive system management, and responsive customer support in maintaining trust, particularly for financial services involving valuable physical assets such as gold.

Overall, this study contributes to the growing literature on digital financial services in emerging markets by demonstrating that trust in digital bullion banking operates across multiple dimensions, including technical stability, transparency, and user experience. From a community development perspective, the results show that the main risk to inclusive participation lies in access and verification barriers rather than in product appeal. Sustaining public trust therefore requires assisted onboarding, community-based digital and financial literacy support, and responsive service recovery, so that digital bullion banking can function as sustainable savings and liquidity infrastructure for grassroots communities.

This study has several limitations. First, the data cover a single platform, a single app store, and a four-week window shortly after a major platform migration, so the findings may not generalize to other periods, to iOS users, or to users who do not write reviews; review writers are also likely to over-represent users with strong experiences. Second, sentiment labels were generated by a pre-trained model and validated only indirectly through star ratings, without human annotation of a random subsample. Third, the classification models were trained to approximate these automated labels, so their accuracy reflects agreement with the labeling model rather than with human judgment, and their stability was not assessed through k-fold cross-validation. The number of topics was also chosen on interpretive grounds rather than through formal coherence comparison. Fourth, the reviews contain no demographic or geographic information, so the implications for specific communities are inferred rather than directly observed. Future research should incorporate human-annotated validation sets, longer and multi-platform data, comparisons between conventional and Shariah service users, and field-based studies with community members to examine how trust in digital bullion banking translates into savings behavior and economic resilience.

Acknowledgement

The author thanks the users of the TRING application whose publicly available reviews made this analysis possible, and the anonymous reviewers for their constructive comments.

Author Contribution

I.N.F.S.: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Visualization, Writing – Original Draft, Writing – Review & Editing.

Funding

This research received no external funding.

Ethical Review Board Statement

Not available.

Informed Consent Statement

Not available.

Data Availability Statement

The reviews analyzed in this study were collected from publicly accessible Google Play Store pages. The processed dataset is not publicly archived.

Conflicts of Interest

The author declares no conflict of interest.

Declaration of Generative AI Use

During the preparation of this work, the author used Claude to assist with idea brainstorming, correcting coding errors, and improving the grammar, clarity, and academic tone of the manuscript. After using this tool, the author reviewed and edited the content as necessary and takes full responsibility for the content of the publication.

Open Access

©2026. The author. This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original authors and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third-party material in this article are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit: <http://creativecommons.org/licenses/by/4.0/>

References

- Adriani, M., Asian, J., Nazief, B., Tahaghoghi, S. M., & Williams, H. E. (2007). Stemming Indonesian: A confix-stripping approach. *ACM Transactions on Asian Language Information Processing*, 6(4), 1–33. <https://doi.org/10.1145/1316457.1316459>
- Alawaji, R., & Aloraini, A. (2025). Sentiment analysis of digital banking reviews using machine learning and large language models. *Electronics*, 14(11), 2125. <https://doi.org/10.3390/electronics14112125>
- ANTARA News. (2026). *Prabowo praises bullion bank for managing 153 tons of gold in one year*. <https://en.antaranews.com/news/423392/prabowo-praises-bullion-bank-for-managing-153-tons-of-gold-in-one-year>
- Arifin, A. Z., Shaufiah, Wijaya, A. Y., & Purwitasari, D. (2020). Slang word normalization in Indonesian text preprocessing for sentiment analysis. In *2020 International Electronics*

- Symposium (IES) (pp. 517–522). IEEE.
<https://doi.org/10.1109/IES50839.2020.9231784>
- Arner, D. W., Barberis, J., & Buckley, R. P. (2016). The evolution of Fintech: A new post-crisis paradigm? *Georgetown Journal of International Law*, 47(4), 1271–1319.
<https://doi.org/10.2139/ssrn.2676553>
- Arner, D. W., Buckley, R. P., Zetzsche, D. A., & Veidt, R. (2020). Sustainability, FinTech and financial inclusion. *European Business Organization Law Review*, 21(1), 7–35.
<https://doi.org/10.1007/s40804-020-00183-y>
- Bank Rakyat Indonesia. (2025). *President Prabowo inaugurates Pegadaian Gold Bank Service, BRI Group optimistic in strengthening the national economy* [Press release]. PR Newswire. <https://www.prnewswire.com/news-releases/president-prabowo-inaugurates-pegadaian-gold-bank-service-bri-group-optimistic-in-strengthening-the-national-economy-302388147.html>
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3, 993–1022.
<https://dl.acm.org/doi/abs/10.5555/944919.944937>
- Bowen, F., Newenham-Kahindi, A., & Herremans, I. (2010). When suits meet roots: The antecedents and consequences of community engagement strategy. *Journal of Business Ethics*, 95(2), 297–318. <https://doi.org/10.1007/s10551-009-0360-1>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.
<https://doi.org/10.1023/A:1010933404324>
- Chakraborty, K., Bhattacharyya, S., & Bag, R. (2020). A survey of sentiment analysis from social media data. *IEEE Transactions on Computational Social Systems*, 7(2), 450–464.
<https://doi.org/10.1109/TCSS.2019.2956957>
- Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16, 321–357. <https://doi.org/10.1613/jair.953>
- CNN Indonesia. (2026). *Pegadaian perkuat transformasi digital lewat integrasi aplikasi Tring!* <https://www.cnnindonesia.com/nasional/20260227135349-293-1332489/pegadaian-perkuat-transformasi-digital-lewat-integrasi-aplikasi-tring>
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297.
<https://doi.org/10.1007/BF00994018>
- Darmansyah, A., Fianto, B. A., Hendratmi, A., & Aziz, P. F. (2020). Factors determining behavioral intentions to use Islamic financial technology: Three competing models. *Journal of Islamic Marketing*, 12(4), 794–812. <https://doi.org/10.1108/JIMA-12-2019-0252>
- Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. World Bank. <https://doi.org/10.1596/978-1-4648-1897-4>
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451–474.
[https://doi.org/10.1016/S1071-5819\(03\)00111-3](https://doi.org/10.1016/S1071-5819(03)00111-3)
- Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 1189–1232. <https://doi.org/10.1214/aos/1013203451>
- Gabor, D., & Brooks, S. (2017). The digital revolution in financial inclusion: International development in the fintech era. *New Political Economy*, 22(4), 423–436.
<https://doi.org/10.1080/13563467.2017.1259298>
- Genc-Nayebi, N., & Abran, A. (2017). A systematic literature review: Opinion mining studies from mobile app store user reviews. *Journal of Systems and Software*, 125, 207–219.
<https://doi.org/10.1016/j.jss.2016.11.027>
- Grohmann, A., Klühs, T., & Menkhoff, L. (2018). Does financial literacy improve financial inclusion? Cross country evidence. *World Development*, 111, 84–96.
<https://doi.org/10.1016/j.worlddev.2018.06.020>
- Haddi, E., Liu, X., & Shi, Y. (2013). The role of text pre-processing in sentiment analysis. *Procedia Computer Science*, 17, 26–32. <https://doi.org/10.1016/j.procs.2013.05.005>

- Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). John Wiley & Sons. <https://doi.org/10.1002/9781118548387>
- Hu, Z., Ding, S., Li, S., Chen, L., & Yang, S. (2019). Adoption intention of fintech services for bank users: An empirical examination with an extended technology acceptance model. *Symmetry*, 11(3), 340. <https://doi.org/10.3390/sym11030340>
- Kabeer, N. (1999). Resources, agency, achievements: Reflections on the measurement of women's empowerment. *Development and Change*, 30(3), 435–464. <https://doi.org/10.1111/1467-7660.00125>
- Kamboj, S., Sharma, M., & Sarmah, B. (2022). Impact of mobile banking failure on bank customers' usage behaviour: The mediating role of user satisfaction. *International Journal of Bank Marketing*, 40(1), 128–153. <https://doi.org/10.1108/IJBM-10-2020-0534>
- Karlan, D., Ratan, A. L., & Zinman, J. (2014). Savings by and for the poor: A research review and agenda. *Review of Income and Wealth*, 60(1), 36–78. <https://doi.org/10.1111/roiw.12101>
- Khalid, H., Shihab, E., Nagappan, M., & Hassan, A. E. (2015). What do mobile app users complain about? *IEEE Software*, 32(3), 70–77. <https://doi.org/10.1109/MS.2014.50>
- Lee, I., & Shin, Y. J. (2018). Fintech: Ecosystem, business models, investment decisions, and challenges. *Business Horizons*, 61(1), 35–46. <https://doi.org/10.1016/j.bushor.2017.09.003>
- Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, 5(1), 1–167. <https://doi.org/10.2200/S00416ED1V01Y201204HLT016>
- Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., & Stoyanov, V. (2019). *RoBERTa: A robustly optimized BERT pretraining approach*. arXiv. <https://doi.org/10.48550/arXiv.1907.11692>
- Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., Pfetsch, B., Heyer, G., Reber, U., Häussler, T., Schmid-Petri, H., & Adam, S. (2018). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology. *Communication Methods and Measures*, 12(2–3), 93–118. <https://doi.org/10.1080/19312458.2018.1430754>
- McCallum, A., & Nigam, K. (1998). A comparison of event models for naive Bayes text classification. In *AAAI-98 Workshop on Learning for Text Categorization* (Vol. 752, pp. 41–48). AAAI Press. <https://www.aaai.org/Papers/Workshops/1998/WS-98-05/WS98-05-007.pdf>
- McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334–359. <https://doi.org/10.1287/isre.13.3.334.81>
- Otoritas Jasa Keuangan & Badan Pusat Statistik. (2025). *Siaran pers bersama: Indeks literasi dan inklusi keuangan masyarakat meningkat, OJK dan BPS umumkan hasil Survei Nasional Literasi dan Inklusi Keuangan (SNLIK) tahun 2025* (SP 69/OJK/GKPB/V/2025). <https://ojk.go.id/id/berita-dan-kegiatan/siaran-pers/Pages/OJK-dan-BPS-Umumkan-Hasil-Survei-Nasional-Literasi-Dan-Inklusi-Kuangan-SNLIK-Tahun-2025.aspx>
- Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, 18(4), 329–340. <https://doi.org/10.1016/j.bir.2017.12.003>
- Özkan, P., Süer, S., Keser, İ. K., & Kocakoç, İ. D. (2020). The effect of service quality and customer satisfaction on customer loyalty: The mediation of perceived value of services, corporate image, and corporate reputation. *International Journal of Bank Marketing*, 38(2), 384–405. <https://doi.org/10.1108/IJBM-03-2019-0096>
- Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1–2), 1–135. <https://doi.org/10.1561/1500000011>
- Pegadaian. (2025). *Transformasi digital Pegadaian: Dari kantor cabang ke aplikasi Tring!* <https://pegadaian.co.id/artikel/berita/transformasi-digital-pegadaian>
- Ryu, H. S. (2018). What makes users willing or hesitant to use Fintech? The moderating

- effect of user type. *Industrial Management & Data Systems*, 118(3), 541–569. <https://doi.org/10.1108/IMDS-07-2017-0325>
- Saif, H., Fernández, M., He, Y., & Alani, H. (2014). On stopwords, filtering and data sparsity for sentiment analysis of Twitter. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation* (pp. 810–817). European Language Resources Association. <https://aclanthology.org/L14-1265/>
- Salton, G., & McGill, M. J. (1983). *Introduction to modern information retrieval*. McGraw-Hill.
- Senyo, P. K., & Osabutey, E. L. (2020). Unearthing antecedents to financial inclusion through FinTech innovations. *Technovation*, 98, 102155. <https://doi.org/10.1016/j.technovation.2020.102155>
- Stewart, H., & Jürjens, J. (2018). Data security and consumer trust in FinTech innovation in Germany. *Information & Computer Security*, 26(1), 109–128. <https://doi.org/10.1108/ICS-06-2017-0039>
- Suryono, R. R., Budi, I., & Purwandari, B. (2021). Detection of fintech P2P lending issues in Indonesia. *Heliyon*, 7(4), e06782. <https://doi.org/10.1016/j.heliyon.2021.e06782>
- Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, 100833. <https://doi.org/10.1016/j.jfi.2019.100833>
- United Nations. (2015). *Transforming our world: The 2030 Agenda for Sustainable Development* (A/RES/70/1). <https://sdgs.un.org/2030agenda>
- Verkijika, S. F., & Neneh, B. N. (2021). Standing up for or against: A text-mining study on the recommendation of mobile banking apps. *Journal of Retailing and Consumer Services*, 63, 102743. <https://doi.org/10.1016/j.jretconser.2021.102743>
- Vijayarani, S., Ilamathi, M. J., & Nithya, M. (2015). Preprocessing techniques for text mining: An overview. *International Journal of Computer Science & Communication Networks*, 5(1), 7–16. <https://ijcscn.com/Documents/Volumes/vol5issue1/ijcscn2015050102.df>
- Wilie, B., Vincentio, K., Winata, G. I., Cahyawijaya, S., Li, X., Lim, Z. Y., Soleman, S., Mahendra, R., Fung, P., Bahar, S., & Purwarianti, A. (2020). IndoNLU: Benchmark and resources for evaluating Indonesian natural language understanding. In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing* (pp. 843–857). Association for Computational Linguistics. <https://doi.org/10.18653/v1/2020.aacl-main.85>
- Wilson, E. B. (1927). Probable inference, the law of succession, and statistical inference. *Journal of the American Statistical Association*, 22(158), 209–212. <https://doi.org/10.1080/01621459.1927.10502953>
- Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., ... Rush, A. M. (2020). Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations* (pp. 38–45). Association for Computational Linguistics. <https://doi.org/10.18653/v1/2020.emnlp-demos.6>
- Zucker, L. G. (1986). Production of trust: Institutional sources of economic structure, 1840–1920. *Research in Organizational Behavior*, 8, 53–111. <https://psycnet.apa.org/record/1988-10420-001>

Biographies of Author

Immanuel Nicholas Fransepta Samosir, Statistics of Pematangsiantar City, Pematangsiantar, North Sumatra 21100, Indonesia.

- Email: immanuelsamosir9@gmail.com
- ORCID: N/A
- Web of Science ResearcherID: N/A
- Scopus Author ID: N/A
- Homepage: <https://scholar.google.com/citations?user=QolrrTwAAAAJ&hl=id>