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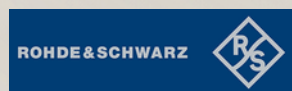
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Knowledge-Sharing Behavior Recognition in Social Media Text with Probability Calibration

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Abstract—Identifying knowledge-sharing behavior from social media text is a challenging task due to the short and informal nature of user-generated content and the difficulty of obtaining reliable confidence estimates from classifiers. This study presents a text-based recognition framework for classifying knowledge-sharing behavior into three categories in Indonesian social media posts. Multiple machine learning models are evaluated across four text representation configurations, resulting in 24 experimental combinations. The best-performing model, a class-balanced Linear Support Vector Machine with TF-IDF bigram features, achieves a Macro-F1 score of 0.7538 on a cleaned dataset of 10,963 posts. Beyond predictive performance, this study examines probability calibration as a means of improving the reliability of confidence outputs. Sigmoid calibration reduces the Expected Calibration Error from 0.1320 to 0.0319 without degrading classification performance, and enables more stable coverage-accuracy tradeoffs under confidence thresholding. The results show that calibration substantially improves the trustworthiness of model predictions, offering practical value for social media analytics and user behavior profiling.

Index Terms—knowledge-sharing behavior, social media, text classification, probability calibration, confidence estimation

I. INTRODUCTION

Social media has become one of the main places where people share knowledge, ask questions, and express opinions, producing large volumes of informal text every day [1], [2]. Being able to automatically recognize what kind of knowledge-sharing activity a post represents opens up a range of practical applications, from monitoring community dynamics to building behavioral profiles for talent assessment [3].

This study works with Indonesian posts from Twitter/X, annotated into three categories based on communicative intent:

general (sharing information or opinions), *complaint* (expressing dissatisfaction or grievances), and *inquiry* (asking questions or seeking clarification). Distinguishing these categories matters because each reflects a different role in knowledge exchange, and tracking their proportions across a user's activity is a concrete way to characterize how that person participates in online communities. The classification task is harder than it might appear. Indonesian social media posts are short, often just a few words, and the writing style is informal with abbreviations, colloquial expressions, and occasional code-switching. More importantly, the three categories overlap in vocabulary: a short post asking a rhetorical question can read like a complaint, and many general posts contain embedded questions. These overlaps mean that clean lexical separation is not always available, and the choice of text representation affects how much of the relevant signal a classifier can extract.

Two aspects of the representation choice are worth examining separately: whether TF-IDF weighting outperforms raw count encoding, and whether adding bigram features alongside unigrams improves performance. Systematic comparisons across both dimensions, and across multiple classifier families, are available for English tasks but remain sparse for Indonesian social media text [4], [5].

A separate issue is what happens to the probability scores that classifiers produce alongside their predictions. These scores are commonly treated as reliable estimates of confidence, but in practice they are often poorly calibrated: a model that outputs 80% confidence is not necessarily right 80% of the time. When these scores are used to decide which predictions to act on, such as filtering posts for review or ranking users by behavioral signal strength, a miscalibrated

model can mislead the selection even when its overall accuracy looks acceptable. Expected Calibration Error (ECE) measures how far the calibration is off, and sigmoid calibration (Platt scaling) is a lightweight method to correct it after training [14], [15]. Whether this correction works well in a multi-class short-text setting for Indonesian has not been tested.

This study evaluates all of these aspects together: text representation choices, classifier selection, probability calibration, and the interaction between post length and classification difficulty. The main contributions are:

- 1) A systematic comparison of 24 model-representation combinations (6 classifiers $\times$ 4 text representations) for recognizing three knowledge-sharing behavior categories from Indonesian social media text.
- 2) A representation ablation analysis examining the independent effects of vectorizer type (TF-IDF vs. count) and n-gram range (unigram vs. bigram) across all classifier families.
- 3) An evaluation of sigmoid-based probability calibration using ECE and a coverage-accuracy analysis under confidence thresholding.
- 4) A text-length error analysis showing how post length interacts with classification difficulty across behavioral categories.

II. RELATED WORK

Multi-class social media text classification. Prior studies have applied multi-class classification to social media content in domains including mental health [6], sentiment analysis [7], and cyberbullying detection [8]. A recurring finding is that linear models outperform tree-based alternatives on sparse, high-dimensional text representations, and that class imbalance handling consistently improves minority-class performance [9], [10]. Multi-class settings introduce additional complexity compared to binary formulations, as adjacent label boundaries are often less sharply defined [11].

Topic-aware and feature-integrated classification. Text-only features remain the dominant baseline, though topic distributions have been shown to improve classification stability in social media contexts [12], [13]. Representation choices, including vectorizer type and n-gram range, influence model behavior differently under class imbalance, but systematic comparisons across multiple combinations remain limited.

Probability calibration in classification. Calibration methods such as Platt scaling and isotonic regression have been studied in general machine learning settings [14], and the Expected Calibration Error has been established as a standard evaluation metric [15]. Their application to social media text classification remains limited: models achieving strong aggregate performance may still produce overconfident or underconfident probability outputs, reducing practical utility when predictions must be filtered or ranked by confidence.

III. METHODOLOGY

Fig. 1 illustrates the overall methodology workflow, from data preparation through confidence-based evaluation.

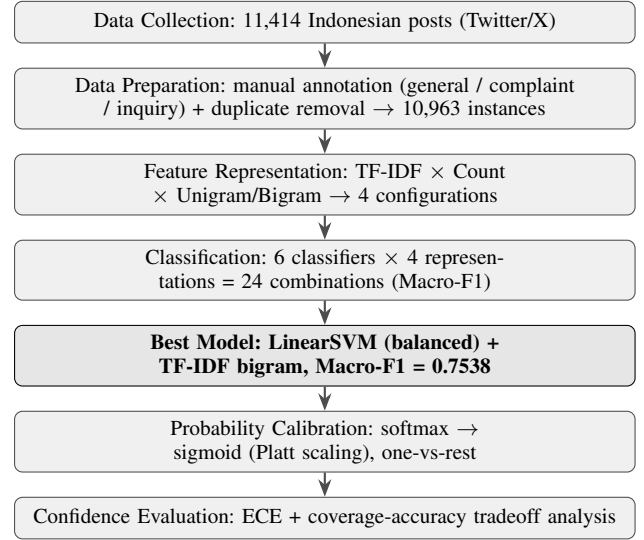


Fig. 1. Methodology workflow.

TABLE I
REPRESENTATIVE EXAMPLES PER KNOWLEDGE-SHARING BEHAVIOR CATEGORY

Class	Original (Indonesian)	English Translation
General	Hari ini ada gerhana matahari cincin. Yang di Jabodetabek hanya bisa lihat gerhana matahari sebagian.	Today there is an annular solar eclipse. Those in Greater Jakarta can only see a partial eclipse.
Complaint	Terus tri cuek aja ya, nggak ditanggapi sama sekali. Padahal sudah banyak sekali yg komen di sini. Nggak care sama sekali!	Tri keeps ignoring us, not responding at all. So many people have already complained here. They do not care at all!
Inquiry	Telur palsu itu sesungguhnya benar ada atau nggak sih? Kalau pun benar ada, apa iya biaya produksinya lebih murah dari telur asli?	Do fake eggs actually exist? And if they do, is their production cost really cheaper than real eggs?

A. Data Preparation

The dataset consists of Indonesian social media posts collected from Twitter/X and manually annotated into three functional communication categories [16]–[18]: *general* (posts not explicitly containing complaints or information-seeking intent), *complaint* (posts expressing dissatisfaction, problems, or grievances), and *inquiry* (posts formulated as questions or requests for information). These categories reflect distinct communicative roles commonly observed in social media discourse rather than sentiment polarity. Table I shows one representative example per category.

Each post was preprocessed before feature extraction. User mentions, hashtags, and URLs were removed; all text was lowercased. Common informal tokens, including abbreviations and colloquial forms typical of Indonesian Twitter (e.g., *nggak*, *yg*, *aja*), were normalized to their standard equivalents, while domain-specific informal expressions were retained to preserve behavioral markers. Indonesian stopwords were then removed. A duplicate audit removed 451 identical text-label pairs,

TABLE II
DATA PREPARATION SUMMARY

Split	Total	General	Complaint	Inquiry
Original	11,414	–	–	–
After dedup	10,963	3,899	3,665	3,399
Train (80%)	8,770	3,119	2,932	2,719
Test (20%)	2,193	780	733	680

reducing the corpus from 11,414 to 10,963 instances. The final class distribution is moderately balanced: general 3,899 (35.6%), complaint 3,665 (33.4%), and inquiry 3,399 (31.0%). The dataset was split into training and test sets using stratified sampling to preserve class proportions, as shown in Table II.

B. Feature Representation

Four text representation configurations were evaluated:

- TF-IDF with unigram features (vocabulary: 3,924 terms)
- TF-IDF with unigram-bigram features (vocabulary: 5,430 terms)
- Count vectorizer with unigram features
- Count vectorizer with unigram-bigram features

These four settings treat vectorizer type (TF-IDF vs. count) and n-gram range (unigram vs. bigram) as independent factors, crossed consistently across all classifiers. TF-IDF weighting reduces the influence of frequent function words by scaling each term’s count by how rarely it appears across documents; count vectorization retains the raw frequency. Bigram features extend the vocabulary with adjacent word pairs, capturing short phrase-level patterns that unigrams cannot distinguish. For example, from the complaint fragment *nggak ditanggapi sama sekali*, the unigram setting yields only the isolated tokens *nggak*, *ditanggapi*, *sama*, and *sekali*, whereas the bigram setting additionally produces the pairs *nggak ditanggapi* (not responded to) and *sama sekali* (at all). The latter is a fixed collocation whose meaning does not follow from *sekali* alone (very/once). Such patterns are specific to complaint posts. The unigram setting cannot capture them because it treats each word independently. A minimum document frequency of 3 and a maximum of 95% were applied to both vectorizer types to remove very rare and near-universal terms.

C. Classification Models

Six classifiers were evaluated: Logistic Regression (LR), LR with class balancing, Linear SVM, Linear SVM with class balancing, Random Forest, and XGBoost. Linear models were included as the primary candidates because they are known to perform well on sparse, high-dimensional text features, where classification signals are spread across many individual words rather than concentrated in feature interactions [9], [10]. Class-balanced variants were added alongside the standard versions to test whether correcting for mild imbalance provides a consistent gain across all linear families. Random Forest and XGBoost were included as contrastive baselines: they can capture nonlinear feature interactions through ensemble splits, which may be useful if some categories are distinguishable by word co-occurrence patterns rather than individual terms.

Combined with four representations, this yields 24 experimental combinations. Macro-F1 was used as the primary evaluation metric to give equal weight to all three classes under the observed mild imbalance.

D. Probability Estimation and Calibration

Since LinearSVM does not produce direct probability outputs, decision scores are first converted to pseudo-probabilities using softmax. Sigmoid calibration (Platt scaling) [14] is then applied using a one-vs-rest scheme to improve the alignment between confidence scores and actual correctness rates. Calibration quality is measured using Expected Calibration Error (ECE) [15]:

$$\text{ECE} = \sum_{m=1}^M \frac{|B_m|}{n} |\text{acc}(B_m) - \text{conf}(B_m)| \quad (1)$$

where B_m denotes a confidence bin, $\text{acc}(B_m)$ is the empirical accuracy within the bin, and $\text{conf}(B_m)$ is the mean predicted confidence.

E. Confidence-Based Evaluation

A threshold τ is applied to retain only predictions whose confidence exceeds the threshold. The tradeoff between coverage (proportion of retained predictions) and accuracy is analyzed before and after calibration. Additionally, confidence distributions of correct and incorrect predictions are compared to assess whether confidence scores function as informative reliability signals.

IV. RESULTS AND DISCUSSION

A. Data Preparation and Corpus Profile

The duplicate removal stage reduced the dataset by 3.9% (451 instances), ensuring that repeated text-label pairs do not inflate test performance. The final class distribution across general (35.6%), complaint (33.4%), and inquiry (31.0%) is moderately balanced, reducing the risk that aggregate metrics mask category-level performance differences.

B. Baseline and Representation Comparison

Table III shows that across all 24 combinations, linear models consistently outperform tree-based alternatives. Random Forest and XGBoost remain in the Macro-F1 range of 0.60–0.62, while linear classifiers cluster above 0.70, reflecting the suitability of linear decision boundaries for sparse, high-dimensional text vectors. The best configuration overall is Linear SVM with class balancing and TF-IDF bigram features (Accuracy = 0.7551, Macro-F1 = 0.7538). Class weighting consistently provides a small but stable gain over the unweighted variant across all linear model families.

Across all 24 combinations, the overall mean Macro-F1 is 0.6990, with linear classifiers contributing a mean of 0.7480 and tree-based models contributing a mean of 0.6030. At the representation level, TF-IDF achieved a mean Macro-F1 of 0.7021 compared to 0.6969 for count-based encoding. Bigram settings provided a marginal but consistent advantage over

TABLE III
BEST RESULT PER MODEL FAMILY (TF-IDF BIGRAM, 24 COMBINATIONS TOTAL)

Model	Accuracy	Macro-F1
LinearSVM_balanced	0.7551	0.7538
LinearSVM	0.7519	0.7503
LR_balanced	0.7492	0.7481
LR	0.7487	0.7465
RandomForest	0.6211	0.6165
XGBoost	0.6097	0.6037

TABLE IV
PER-CLASS PERFORMANCE OF THE BEST MODEL

Class	Precision	Recall	F1
General	0.7671	0.7641	0.7656
Complaint	0.7625	0.7885	0.7753
Inquiry	0.7325	0.7088	0.7205

unigram-only features (0.6997 vs. 0.6993). Neither gap is large in absolute terms, but both are consistent across all six classifiers without exception, which suggests they reflect a real signal rather than noise. Even the weakest configuration, count vectors with bigrams, still reaches Macro-F1 0.7474 under a balanced linear model. The representation choice therefore shifts the result only slightly once a linear classifier is in place.

C. Class-Wise Performance

Per-class results for the best model, shown in Table IV, indicate that complaint posts are most reliably recognized (F1 = 0.7753), followed by general posts (F1 = 0.7656), while inquiry posts remain the most difficult category (F1 = 0.7205). This ranking reflects the directness of lexical cues in complaint posts, whereas inquiry posts share surface vocabulary with both other categories, making their boundary less distinct for a linear separator.

D. Text Length and Classification Difficulty

Table V breaks down accuracy on the test set by post length. The pattern is not monotonic. Very short posts in the 1–5 token group reach accuracy 0.7856, which then drops to 0.7135 in the 6–10 group before recovering at longer lengths (0.7600 for 11–20 tokens, 0.8000 for 21–50). The 6–10 token range is both the most error-prone and the most common: 712 of the 2,193 test instances fall in that band.

The drop at 6–10 tokens is likely caused by ambiguity rather than data scarcity. In that range, complaint and inquiry posts tend to look alike on the surface: short, direct statements with overlapping vocabulary and no extended context to disambiguate intent. Very short posts with one strong class-specific

TABLE V
LENGTH-BASED ACCURACY ON THE TEST SET (BEST MODEL)

Length (tokens)	Count	Accuracy
1–5	751	0.7856
6–10	712	0.7135
11–20	650	0.7600
21–50	80	0.8000

TABLE VI
CALIBRATION SUMMARY OF THE BEST MODEL

	Accuracy	Macro-F1	ECE	Brier
Before calibration	0.7551	0.7538	0.1320	0.1234
After calibration	0.7533	0.7520	0.0319	0.1147

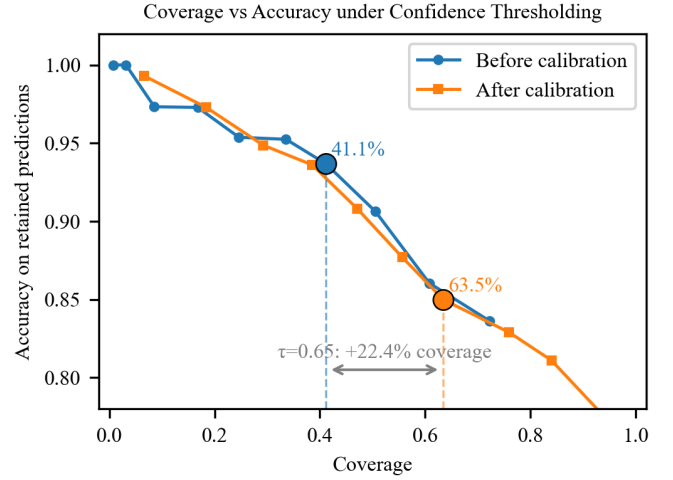


Fig. 2. Coverage-accuracy curve under confidence thresholding before and after calibration.

marker, such as a question particle or an explicit complaint term, are actually easier to classify despite having less text. Longer posts provide enough variety of vocabulary for the model to find clearer patterns. In practical terms, the posts most likely to be misclassified are the most typical ones in this corpus.

E. Calibration and Confidence Analysis

The uncalibrated model produces an ECE (see (1)) of 0.1320, indicating a substantial gap between predicted confidence and actual accuracy. After sigmoid calibration, ECE drops to 0.0319, a reduction of approximately 76%, while Macro-F1 decreases only marginally from 0.7538 to 0.7520, as reported in Table VI. The multiclass Brier Score, which measures the mean squared error of probability outputs across all classes, decreases from 0.1234 to 0.1147, corroborating the ECE improvement. Calibration therefore improves confidence reliability without meaningfully reducing predictive performance.

Fig. 2 plots the coverage-accuracy tradeoff for both models. At a confidence threshold of 0.65, the uncalibrated model retains only 41.1% of predictions at accuracy 0.9368, while the calibrated model retains 63.5% at accuracy 0.8500. The calibrated path moves more smoothly across the coverage range, making threshold selection less brittle for deployment scenarios that require a rejection option or manual review layer.

Fig. 3 shows confidence distributions of correct and incorrect predictions, supporting this pattern. Before calibration, correct predictions had a mean confidence of 0.6565 versus

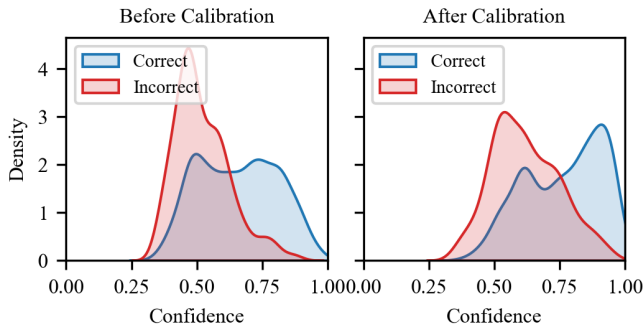


Fig. 3. Confidence distributions of correct and incorrect predictions before and after calibration.

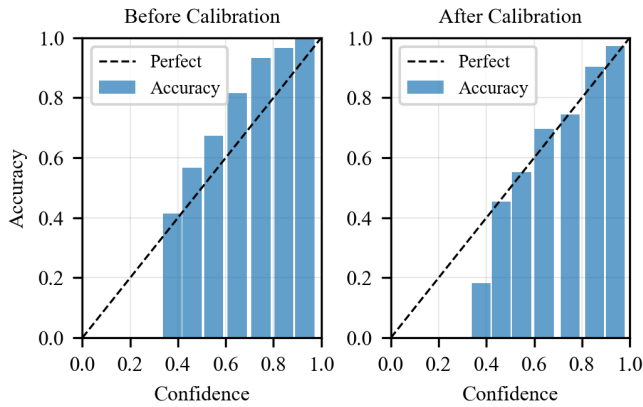


Fig. 4. Reliability diagrams before and after sigmoid calibration. Bars show empirical accuracy per confidence bin; the diagonal represents perfect calibration.

0.5202 for incorrect ones. After calibration, the separation widens to 0.7642 versus 0.6197: correct predictions shift further into the high-confidence region, while incorrect predictions remain concentrated at lower levels. This means the confidence score becomes a more informative diagnostic signal, even though label-level performance barely changes.

Figure 4 shows the reliability diagrams before and after calibration. Before calibration, confidence bins in the 0.4–0.7 range are overconfident: the model assigns higher probability than its actual accuracy warrants. After calibration, the bars align more closely with the perfect-calibration diagonal across all bins, confirming that the improvement in ECE reflects a genuine redistribution of probability mass rather than a change in rank ordering.

F. Discussion

The three analyses agree with one another. Linear models are the right fit for this task. Their margin over Random Forest and XGBoost holds in all four representation settings, which points to a real match between sparse text features and a linear boundary rather than a one-off result. Within the linear family, TF-IDF weighting and bigram features each add a small gain, and that gain shows up in every classifier we

tested. The calibration results add a practical angle to the same conclusion. The model with the best Macro-F1 is also the one that gains most from calibration, with ECE falling from 0.1320 to 0.0319. At a confidence threshold of 0.65 it keeps 63.5% of its predictions at accuracy 0.8500, against only 41.1% before calibration. A gap of that size is what makes confidence-based filtering usable in a real pipeline.

The per-class and length results show where the framework still struggles. Complaint posts are recognized most reliably, at an F1 of 0.7753. This fits the way complaints are written in Indonesian, where markers such as *sama sekali* and *nggak* signal dissatisfaction fairly clearly. Inquiry posts are the hardest, at F1 = 0.7205, because they often use indirect phrasing and share much of their vocabulary with general posts. Length introduces a second difficulty. The 6–10 token band is the most common in the corpus, yet its accuracy drops to 0.7135, below both the shorter and the longer posts.

Examining the 537 misclassified test instances reveals that confusion between inquiry and general is the dominant error pattern (202 cases: 105 inquiry predicted as general, 97 general predicted as inquiry). Complaint-to-inquiry confusion accounts for 172 additional errors (93 inquiry predicted as complaint, 79 complaint predicted as inquiry), while complaint-general confusion contributes 163 errors (87 general predicted as complaint, 76 complaint predicted as general). The asymmetry between inquiry and complaint confusion (172 cases) versus complaint and general confusion (163 cases) indicates that inquiry occupies a lexically intermediate position: its short indirect-phrasing style overlaps both with general opinion posts and complaint posts that embed a question. This finding reinforces the practical recommendation to route short, low-confidence posts to manual review, as the model’s weakest boundary is precisely the one hardest to resolve through representation alone.

V. CONCLUSION

This study evaluated a text-based recognition framework for knowledge-sharing behavior in Indonesian social media, comparing 24 model-representation combinations and extending the analysis to probability calibration and length-based error patterns. Sparse linear classifiers proved to be the appropriate model family for this task, with TF-IDF features consistently outperforming count-based encoding and bigram settings providing a small but consistent gain. The best model, LinearSVM with class balancing and TF-IDF bigram features, achieves Macro-F1 = 0.7538 with stable three-class performance across general, complaint, and inquiry categories. The representation ablation confirmed that both factors (vectorizer type and n-gram range) point in the same direction across all classifiers, with TF-IDF and bigram settings each providing a modest but consistent advantage. The length-based analysis found that the 6–10 token range is the most error-prone (accuracy 0.7135), despite being the most common post length in the corpus, which has practical implications for downstream filtering and review pipelines.

Sigmoid calibration substantially reduces ECE from 0.1320 to 0.0319 without degrading classification performance, and produces more informative confidence outputs: the separation between correct and incorrect predictions widens after calibration, and the coverage-accuracy tradeoff becomes more predictable under confidence thresholding. The calibrated model thus supports both accurate prediction and reliable confidence estimation within the same pipeline.

These results suggest that incorporating calibration into social media text recognition pipelines improves the practical trustworthiness of model outputs, particularly for applications requiring selective prediction or user behavior profiling. One limitation of this study is that annotation was performed without formal inter-annotator agreement measurement; future work should quantify annotation reliability to strengthen the validity of the class boundaries. Future directions include integrating topic-based behavioral features, extending the comparison to transformer-based models such as IndoBERT, applying formal statistical significance testing to the representation comparisons, and deploying the calibrated classifier within a social media talent profiling system.

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