

Classification of High-Risk Provinces for Fintech Lending Based on TWP90 from LPBBTI OJK Using Interpretable Model for Artificial Intelligence Ethical Transparency

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Abstract – The growth of the fintech lending industry (LPBBTI) in Indonesia has expanded access to financing but has also increased credit risk, as reflected in the 90-day Default Rate (TWP90). This condition demands proactive regional risk monitoring, while existing approaches are still dominated by historical descriptive analysis. This study aims to develop a high-risk provincial classification as a transparent and accountable early warning system. The research methodology uses multi-sheet data integration from the Financial Services Authority (OJK) LPBBTI Statistics to create a provincial-monthly panel dataset covering supply, demand, and transaction activity. The Logistic Regression model was used as the baseline model due to its interpretability and support for decision auditability. Model evaluation using a time-based split approach during the May–July 2025 test period demonstrated good performance, with an ROC-AUC of 0.8598, an accuracy of 0.8462, and a precision of 0.8000. The results of feature analysis indicate that scale and activity indicators, particularly the outstanding amount, the number of active borrowers, and the value of disbursed funds, contribute significantly to risk probability. Although detection sensitivity (recall: 0.5333) still needs improvement, this study provides a measurable, relevant regional risk-ranking framework for regulatory decision-making.

Kata Kunci – Fintech lending, TWP90, Risk Classification, Machine Learning, Transparency

I. INTRODUCTION

The growth of fintech lending (peer-to-peer lending) has expanded access to financing across regions in Indonesia, but has also increased exposure to credit risk and consumer protection risks[1]. Rising defaults could put pressure on the industry's sustainability and the quality of its funding portfolio, necessitating a more proactive, data-driven approach to risk monitoring. Within its regulatory framework, the Financial Services Authority (OJK) defines LPBBTI as a service that connects lenders and borrowers through an electronic system[2]. The operational provisions and strengthening of LPBBTI governance are now set out in POJK 40 of 2024 (effective December 27, 2024), along with the technical provisions for their implementation in SEOJK 19/SEOJK.06/2025, which emphasizes the importance of risk mitigation and provider compliance. One risk indicator used in the fintech lending industry is the 90-Day Default Rate (TWP90), which measures the level of default/negligence in settling obligations beyond 90 days from the due date[3]. This indicator is used as a proxy for funding quality and is frequently highlighted in public communications and stability monitoring. In Indonesia, the Financial Services Authority (OJK) also periodically publishes LPBBTI statistics in spreadsheet format, containing aggregate

indicators such as outstanding balances, lender-borrower activity, transactions, and risk measures, including the TWP90[4]. The statistical dataset is spread across several tables/sheets that reflect different perspectives (e.g., category, activity, and position/outstanding), so cross-sheet integration can yield a more comprehensive risk signal than using a single table.

However, conventional risk monitoring remains predominantly descriptive, for example, reviewing TWP90 trends or outstanding data over time. This approach is informative for historical evaluation, but less supportive of operational early warning requirements, namely identifying provinces likely to be in the highest-risk group during a given period based on previous indicator patterns and associated factors.

This study formulates the problem as a monthly classification of “high-risk” provinces using TWP90 quantile-based labels (e.g., the 75th percentile per month). With this relative definition, the research focuses on distinguishing provinces within the highest-risk group each month, making the model relevant for dynamic monitoring over time and across regions.

The main contribution of this study is to develop multi-sheet features from OJK's LPBBTI statistics (e.g., scale/outstanding signals, account and transaction activity intensity, and indicator changes/deltas) to predict TWP90-

based High-Risk labels. This approach is expected to produce a more scalable, replicable, and readily integrated framework as the basis for an early warning system at the regional level.

In addition to the predictive aspect, this study emphasizes transparency as one of the pillars of AI ethics through the use of interpretable models[5]. Model transparency and explainability are considered essential to ensure that prediction rationales can be audited, communicated to stakeholders, and used for responsible decision support, rather than as a "black-box decision." This principle of transparency/explainability aligns with international guidelines on trustworthy AI and AI risk governance.

II. Research Methodology

The research method used to classify high-risk provinces in fintech lending is based on the TWP90 indicator from the LPBBTI OJK statistics. The description includes the research design and data scope, the multi-sheet integration process into a monthly provincial panel dataset, the pre-processing stage and the formation of High-Risk labels based on TWP90 quantiles, the selection of an interpretable classification model to support transparency (ethical principles of Artificial Intelligence), as well as a time-based validation scheme and performance evaluation metrics used to assess the model's capabilities in the context of early warning of regional risks.

A. Research Design

This study employs a quantitative design with a supervised machine learning approach to address a binary classification problem at the provincial and monthly levels. The primary objective is to identify the provinces with the highest relative risk (i.e., high risk) in a given month, based on the aggregate LPBBTI indicator. To maintain compliance with the operational early warning scenario, the evaluation uses a time-based data split to prevent information leakage from future to past periods[6].

B. Data Sources and Scope

The research data comes from the LPBBTI Statistics published by the Financial Services Authority (OJK) on the Fintech Data and Statistics channel. The dataset is a monthly spreadsheet containing LPBBTI industry indicators by location (province) and period. The data scope follows the statistical files used in the research pipeline, utilizing several key sheets to build multi-perspective features: supply/lender, demand/borrower, risk & exposure, including TWP90, as well as accumulated activity and scale.

C. Unit of Analysis and Dataset Structure

The unit of analysis is a province×month panel, where 1 row represents 1 province in 1 month. The final dataset is saved as `prov_month_features.csv` and arranged chronologically per province to allow for the calculation of time-based features (lag, growth, accumulated delta).

D. Target Variables and Predictor Variables

The primary risk indicator uses the 90-Day Default Rate (TWP90), which represents defaults/delays of over 90 days

on LPBBTI funding. This indicator is commonly used as a summary of funding quality and is frequently reported in industry statistics/communications.[7].

E. Pre-processing and Feature Construction

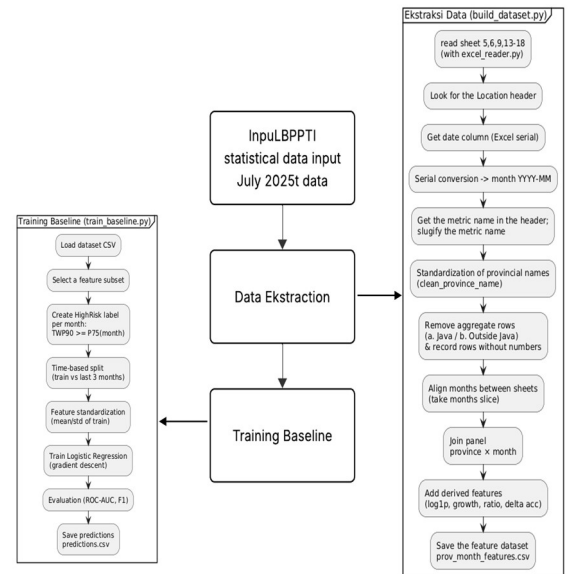


Figure 1. Preprocessing Stages

1. Data extraction from multi-sheet Excel

The data source is the file `STATISTIK LPBBTI July 2025.xlsx`, which contains various thematic tables on different sheets. The sheets used are sheets 5, 6, 9, and 13 through 18, each representing aspects of supply, demand, risk, and accumulated activity. Reading is performed using the dedicated `excel_reader.py` module (without `pandas`) using the `read_sheet_as_rows(...)` function, so that the initial data is represented as raw rows. The goal of this step is to ensure that all sheets are uniformly accessible and ready for further processing without relying on the `DataFrame` structure.

2. Identify Time and Metric Headers

Most sheets have a location (province) row + time column format. The script automatically:

- Looks for header rows containing the text "Location" or "Locations" as the starting point for the data.
- Identifies date header rows containing Excel serial numbers (e.g., 45474, 45839).
- Converts these serial numbers to YYYY-MM month format (e.g., 45474 → 2024-07).
- Reads the metric header row (usually the text below the date header) to determine the name of the numeric variable.

Metric names are then normalized using the `slugify()` function for consistency: lowercase letters are removed, spaces are replaced with `_`, and non-alphanumeric characters are removed. This ensures that each numeric value has an explicit identifier (province, month, metric).



3. Standardize province names as join keys

Because province names appear across many sheets with varying spellings, the `clean_province_name()` function is used to standardize location names. This process includes removing prefixed numbers (e.g., "1. BANTEN"), tidying up spacing, converting to uppercase, and correcting any simple typos. This standardization is crucial for consistently joining data across sheets at the provincial level.

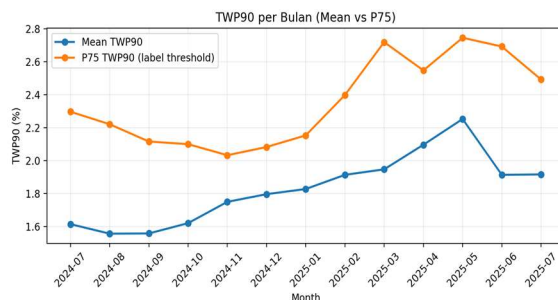


Figure 2. TWP90 per month

4. Filtering non-provincial rows

Some sheets include aggregate rows such as "Java" or "Outside Java," which are not units of analysis. These rows are skipped. Additionally, rows labeled with provinces but with all metric values blank are also discarded because they are typically notes or footers, not actual observational data.

5. Time alignment between sheets

Each sheet has a different time span. To ensure consistency in the final dataset, the script retrieves available month slices across all sheets. The month sequence follows the chronological order of Sheet 9 (risk & exposure), which serves as the primary reference. This approach ensures that each dataset row has relatively complete features and is not mixed with partial months.

6. Selecting key metrics per sheet (best-effort)

To prevent the dataset from becoming too large and noisy, only relevant metrics were selected from each sheet. The selection was done by substring matching on the normalized metric names.

- Sheet 9 (required): `twp90`, `outstanding`, and `active_borrower_entities`.
- Sheet 6 (demand): `borrower_accounts` and `disbursement` (if available).
- Sheet 5 (supply): `lender_accounts` and `lender_fund`.
- Sheets 13–18 (accumulation): one key metric per sheet was selected due to its cumulative nature and recurring monthly.

This approach maintains a balance between signal comprehensiveness and feature complexity.

7. Join a province × month panel

After all sheets are projected into the same month list, a join process is performed to form the final panel. The base row is determined by the (province, month) combination in Sheet 9, then columns from other

sheets are filled in if available. The final result is a single-panel table written to `highrisk_ml/data/derived/prov_month_features.csv`.

8. Derived feature creation (feature engineering)

After the panel dataset was created, the data was grouped by province and sorted by month to enable time-based calculations. The derived features created included:

- Scale transformation: `outstanding_log = log1p(outstanding)` to stabilize scale differences between provinces.
- Monthly change (growth): `outstanding_growth` and `disbursement_growth` as the difference between the current month and the previous month.
- Normalized ratio: `outstanding_per_active` and `disbursement_to_outstanding` to make metrics more comparable across regions.
- Delta of accumulation variables: all `acc_*` are transformed into `delta_acc_*` to represent monthly activity, not historical totals. For all lag-based features, the first month is automatically set to None because it lacks a t-1 reference.

F. Model Performance Evaluation

Model performance was evaluated using the following classification metrics:

- ROC-AUC to assess the model's ability to distinguish between positive and negative classes across a threshold.
- Precision, Recall, and F1-score to assess the accuracy of high-risk predictions and sensitivity to high-risk cases. In cases of imbalanced class distribution, precision-recall metrics are often more informative than ROC curves alone.
- Accuracy, as a summary of the proportion of correct predictions, should be interpreted with caution when the classes are imbalanced [8].

G. Model Performance Evaluation

This research incorporates AI ethics into the transparency/explainability principle by selecting interpretable models and reporting interpretations based on feature coefficients. Transparency supports auditability (traceability of prediction rationales), increases user trust, and facilitates responsible use of models for decision support. This principle aligns with international guidelines such as the OECD AI Principles (transparency & responsible disclosure) and the NIST AI RMF 1.0 framework, which emphasize trustworthiness and AI risk management through transparent practices[9].

In the context of LPBBI, OJK regulations also emphasize governance and risk control, and transparency of the analytical models used for regional monitoring can help ensure consistency in decision-making and policy communication[10].

H. Implementasi dan Replikasi

The entire process is automated in a pipeline that includes: (1) building a multi-sheet dataset into a province×month panel, (2) generating HighRisk labels



based on TWP90 quantiles per month, (3) training logistic regression with standardization, and (4) time-split-based evaluation and reporting of coefficient interpretations. The dataset structure, feature definitions, and pre-processing stages are documented in the project documentation.

III. RESULTS AND DISCUSSION

The quantitative evaluation results in this study serve as an objective validation mechanism before the early warning system is implemented on a wider scale. In the context of responsible artificial intelligence governance, statistical reliability is a key prerequisite for transparency, particularly for regulators who require empirical evidence of a model's stability and discriminatory capabilities before making policy decisions. Therefore, testing was conducted using test data from May–July 2025, which represent actual operational conditions, and the model was exposed to future data that had never been used in the training process (out-of-time validation).

The data used comes from the multi-sheet integration of the OJK's LPBBTI Statistics, encompassing the dimensions of supply (lenders), demand (borrowers), risk exposure, and accumulated transaction activity, thus forming a comprehensive risk representation. The model's performance during the test period was demonstrated by an ROC-AUC of 0.8598, an accuracy of 0.8462, a precision of 0.8000, and a recall of 0.5333.

A high ROC-AUC value indicates the model's excellent ability to rank risks between provinces. Relatively high precision indicates that the majority of high-risk area predictions are highly accurate[11], This can reduce the potential for false alarms and improve the efficiency of monitoring resource allocation. However, the moderate recall value indicates that the model still misses some actual risk cases, so the detection sensitivity is not optimal[12]. These findings emphasize that models should be positioned as decision-support tools with human involvement (human-in-the-loop), rather than as fully automated policy mechanisms.

A. Model Interpretability and Feature Transparency

Within the framework of AI ethics, high predictive performance must be accompanied by model explainability to avoid "black box"-based decision-making practices. Therefore, this study chose Logistic Regression as the baseline model due to its inherent interpretability. This approach aligns with the transparency and auditability principles mandated in the NIST AI Risk Management Framework (RMF) 1.0 and the OECD AI Principles. All independent variables were standardized using Z-scores to ensure that model coefficients could be compared fairly across features with different scales[13]. Based on the coefficient estimation results, several variables show a significant contribution to increasing the probability of risk, including the size of outstanding loans, the number of active borrowing entities, the value of fund disbursements, and the delta variable, which represents temporal changes in transaction and disbursement activities[14]. These variables reflect operational and actual risk dynamics, not just historical conditions.

In contrast, the ratio of outstanding to active borrowers shows a negative relationship with the probability of default, indicating that a more even distribution of credit tends to reduce regional risk[15]. The linear model structure allows each prediction to be traced back to the contribution of individual features, so regulators or auditors can identify the main drivers of an area's risk classification[16]. These characteristics support the principles of openness and accountability as regulated in POJK Number 40 of 2024[17].

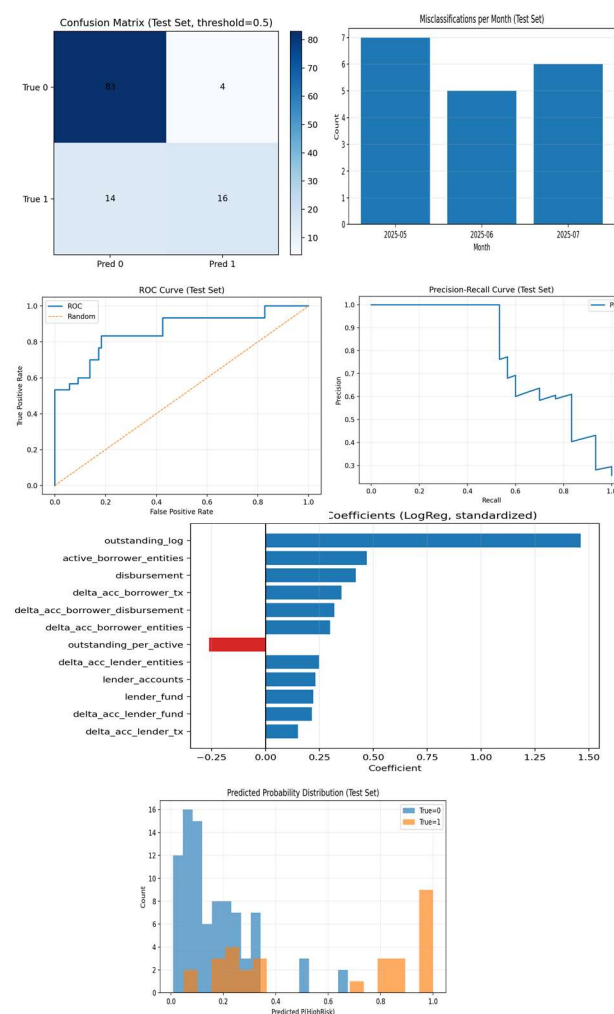


Figure 3. Evaluation Classification Results

Model evaluation was conducted in a realistic prediction scenario with a time-based split: the model was trained on the initial months and tested on the last three months (May–July 2025)[18]. On the test data, the baseline logistic regression model produced an accuracy of 0.8462, indicating that the majority of classifications were correct. The ROC-AUC value of 0.8598 indicates strong risk ranking, indicating that the model is quite effective at distinguishing high- and low-risk provinces based on predicted probabilities.

In terms of high-risk class prediction accuracy, the model achieved a precision of 0.8000, meaning that when it predicted High-Risk, the prediction was mostly correct.



However, the recall of 0.5333 indicates that the model still misses some provinces that are actually high risk (false negatives remain quite high), as reflected in the F1-score of 0.6400, which serves as a compromise between precision and recall. Overall, these results indicate that the baseline is promising for ranking-based early warning but still needs improvement to increase sensitivity to High-Risk cases (e.g., through threshold adjustments, the use of top-k metrics, or additional models/features).

B. Error Analysis and Model Stability

Error analysis was conducted to identify model limitations and potential biases due to spatial and temporal data dynamics[19]. The evaluation results indicated false-negative errors in several provinces, such as North Kalimantan and West Nusa Tenggara, suggesting that the increased risk in these regions was influenced by local factors not fully captured by standard growth features. This phenomenon reflects spatial-temporal drift in the data.

On the other hand, false positives were identified in regions with large economic scales, such as Banten Province, indicating that the model tends to be sensitive to portfolio-scale indicators, though this sensitivity does not always translate into realized risks. This finding confirms that while multidimensional data integration has improved the quality of risk signals, the baseline model still has limitations in capturing non-linear relationships and in-depth local context. Therefore, prediction results need to be combined with qualitative assessments from regional supervisors.

IV. CONCLUSION

This study successfully developed an early warning framework for fintech lending risks at the provincial-month level based on TWP90 indicators, integrating multi-sheet data from the Financial Services Authority (OJK)'s LPBBI Statistics. The baseline logistic regression model demonstrated robust, interpretable risk ranking, although detection sensitivity still needs improvement. The analysis confirmed that scale and activity indicators are the main contributors to regional risk. Further development is recommended to increase predictive sensitivity while maintaining the principles of model transparency and accountability.

In the baseline evaluation using a time-based split (tested in the last 3 months: May–July 2025), the logistic regression model showed strong performance for risk ranking, with an ROC-AUC of 0.8598, an accuracy of 0.8462, and a precision of 0.8000, indicating that the High-Risk prediction is likely accurate. However, a recall of 0.5333 indicates that some high-risk provinces are still being missed (false negatives), so for operational use as an early warning, sensitivity improvements are still needed, for example, by adjusting the decision threshold, top-k metrics, or adding additional models/features.

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