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Temporal Supplier Risk Prediction and Prioritization

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Abstract: ***Supplier performance directly affects manufacturing continuity, cost and delivery commitments, yet conventional scorecards are retrospective and may hide gradual deterioration. This paper presents a temporal supplier risk prediction and prioritization framework that uses Month N operational behaviour to estimate a supplier's Low, Medium or High risk category in Month N+1. The workflow covers supplier-month aggregation, 47 temporal features (lags, rolling statistics, trend and deterioration indicators, risk history and business exposure), engineered target labels, chronological validation and a nine-month out-of-time (OOT) test. Five classifiers are compared with a persistence baseline on 1,450 supplier-month observations spanning 39 months. HistGradientBoosting achieves the best overall OOT result (54.32% accuracy, 48.93% Macro-F1, 0.7039 ROC-AUC), while Extra Trees reaches 85.51% high-risk recall, showing a trade-off between overall performance and high-risk screening. Predictions are combined with delivery, quality, exposure and deterioration signals into a transparent priority score and rule-based intervention recommendations delivered through a Power BI dashboard. Because the labels are engineered rather than independently observed, the system is positioned as an early-warning aid for human review.***

Keywords: ***supplier risk, temporal machine learning, multi-class classification, out-of-time evaluation, feature engineering, risk prioritization, decision support***

I. INTRODUCTION

Supplier networks supply raw materials, components and services on which manufacturing depends, so a supply disruption can affect production schedules, inventory, customer commitments and cost. Supplier monitoring typically relies on indicators such as on-time delivery, delay duration, defect rate and scrap. A single monthly average can hide a worsening pattern: a supplier that is slowly deteriorating may look acceptable until a threshold is crossed and an operational problem appears.

This work asks whether current and historical supplier behaviour can be turned into temporal features that support next-month risk classification, and how the predictions can be presented so procurement teams know which suppliers to review first. The contributions are: (i) a leakage-controlled Month N to Month N+1 prediction pipeline with chronological and out-of-time evaluation; (ii) a benchmark of five classifiers against a persistence baseline; and (iii) a decision-support layer that links predicted risk to deterioration, business exposure, evidence and recommended intervention in a Power BI dashboard. The implementation is a project-level prototype and makes no claim of live ERP integration or autonomous procurement action.

The problem addressed is the difficulty of identifying suppliers whose operational risk may increase in the next period using only static or retrospective summaries. Table I contrasts conventional monitoring with the proposed approach. The objectives are to prepare and validate operational data, aggregate it into supplier-month observations, engineer temporal features, construct Low, Medium and High labels, predict Month N+1 risk from Month N information, compare models with a persistence baseline under chronological evaluation, and combine predicted risk with deterioration and exposure to produce prioritized interventions.

TABLE I CONVENTIONAL MONITORING VERSUS PROPOSED SYSTEM

Aspect	Conventional	Proposed
Orientation	Current or historical KPI review	Next-period risk prediction
Time behaviour	Periodic, static summaries	Lag, rolling and trend features
Risk output	Scorecard or rating	Predicted Low/Medium/High
Evaluation	Often descriptive	Chronological and OOT testing
Prioritization	Manual rules	Risk, deterioration and exposure
Explanation	KPI display	Risk domain and evidence
Action	Manual follow-up	Dashboard-supported intervention

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II. RELATED WORK

Machine learning is increasingly applied to supplier evaluation. Hybrid frameworks combining prediction and clustering have been used to assess and segment supplier risk in automotive supply chains [1], and systematic reviews report that data-driven methods can improve on traditional supplier qualification [2]. Gradient boosting has been effective for predicting supplier delivery and quality performance in engineer-to-order settings [3], while temporal convolutional networks have been used to forecast late-delivery risk from time-dependent records [4]. Treating supplier assessment as a multi-class problem rather than a binary one has also been explored [5], and reviews of sustainable supplier selection stress combining several indicators in a structured analytical approach [6]. Delay-prediction studies further show the value of proactive risk management [7], [8], and broader reviews of AI in purchasing and supply risk management [9], [10] identify the need for practical, interpretable decision support. Few of these works pair a time-aware next-month classifier, strict out-of-time testing and an actionable prioritization layer, which is the gap addressed here.

III. METHODOLOGY

The system is a sequence of modular Python scripts, each reading the files written by the previous stage, followed by a Power BI report (Fig. 1). The architecture has data-preparation, analytics-and-modelling and decision-support layers: the preparation layer validates, cleans and aggregates records; the temporal layer creates inputs available by Month N; target engineering creates the next-month class label; the modelling layer benchmarks classifiers chronologically; and the decision-support layer combines predictions with evidence and exposure before exposing them through Power BI.

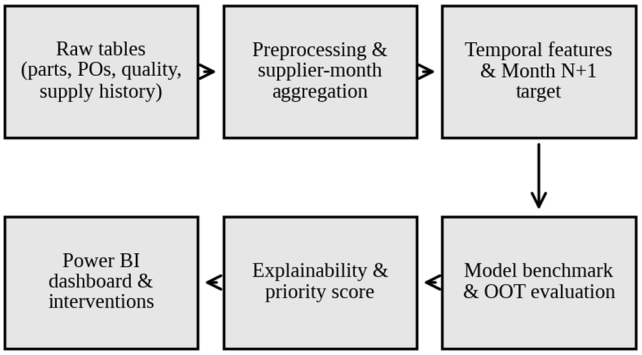


Fig. 1 Overall architecture, from raw procurement tables to the decision-support dashboard

A. Data and Supplier-Month Aggregation

The data is prepared from four raw tables (parts master, purchase orders, quality incidents and supply-chain history) covering January 2022 to March 2025. Records are validated for required fields and numeric types, and transaction-level records are aggregated into supplier-month observations using sums, rates, counts or latest values as appropriate to each field. The resulting modelling table has 1,450 observations over 39 monthly periods (Table II). The first 30 months (2022-01 to 2024-06) form the training period and the final nine months (2024-07 to 2025-03) form the OOT test set.

TABLE II DATASET AND MODELLING SUMMARY

Item	Value
Modelling observations	1,450
Monthly periods	39
Engineered input features	47
Training (30 months)	1,172 obs.
OOT test (9 months)	278 obs.
Prediction horizon	Month N → N+1
Target classes	Low, Medium, High

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Preprocessing follows the workflow in Fig. 2. Required supplier, period and operational fields are confirmed; quantitative indicators are converted to numeric types; missing and invalid values are inspected; supplier-period uniqueness is checked after aggregation; and chronological order is preserved in all partitions. Aggregation uses sums, averages, rates, counts or the latest available value according to the business meaning of each field, which gives a consistent unit of analysis for lag and rolling calculations.

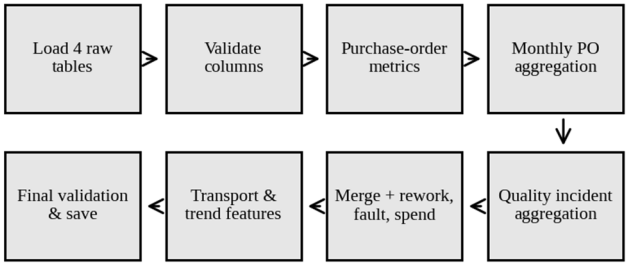


Fig. 2 Data preparation workflow

B. Temporal Feature Engineering

Forty-seven features are built from Month N or earlier information only. They comprise nine current operational indicators (late-delivery rate, average days late, short-delivery rate, route-deviation flag, transit-delay rate, quality-event rate, scrap quantity, rework-cost ratio and supplier-fault rate); six trend and history flags; two business-exposure measures (spend share and critical-component exposure); nine lag-1 values; eleven rolling 3-period means and standard deviations; and ten acceleration, worsening-streak and risk-history features. Together they describe both the current state and the recent trajectory of a supplier (Table III).

TABLE III FEATURE GROUPS

Feature group	**Count**
Current operational and transport indicators	9
Trend and history flags	6
Business exposure	2
Lag-1 history	9
Rolling 3-period statistics	11
Acceleration, streak and risk history	10
Total	47

C. Target Engineering

A domain-informed composite risk score is computed from late-delivery rate (weight 0.35), normalized average days late (0.20), quality-event rate (0.30) and normalized scrap quantity (0.15). Class boundaries are learned from training-period scores only: the 25th percentile separates Low from Medium and the 85th percentile separates Medium from High, giving roughly 25% Low, 60% Medium and 15% High. Normalization parameters are fitted on the training period and frozen. The label is shifted one month so that features at Month N predict the class at Month N+1. Because the label is engineered from operational indicators, the evaluation measures how well models predict this constructed target rather than an independently observed incident (Table IV). Fig. 3 shows the Month N to Month N+1 prediction flow.

TABLE IV RISK-SCORE COMPONENTS AND WEIGHTS

Component	**Weight**
Late-delivery rate	0.35
Average days late (normalized)	0.20
Quality-event rate	0.30
Scrap quantity (normalized)	0.15

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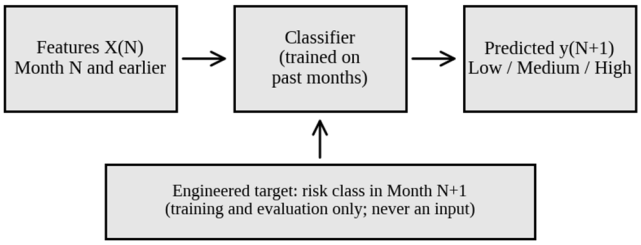


Fig. 3 Month N to Month N+1 prediction flow

D. Prevention of Temporal Leakage

Only Month N or earlier information is used as input; the N+1 target and future-derived columns are excluded; train and test partitions preserve chronological order; imputation and scaling are fitted on training data only; and the OOT period is kept separate from model development and selection. Feature timestamps are audited to confirm that they precede the target timestamp.

E. Models and Validation

Logistic Regression (balanced and standard variants), Random Forest, Extra Trees, HistGradientBoosting and XGBoost are compared with a persistence baseline that predicts the Month N class for Month N+1 (random_state = 42 throughout). A random split is unsuitable for monthly data, so three rolling validation folds (18, 22 and 26 training months, each followed by four validation months) are used inside the training period for model and threshold selection. The historical selection score weights accuracy (35%), high-risk precision (25%), high-risk F1 (25%) and Macro-F1 (15%), with the high-risk threshold tuned between 0.25 and 0.70 on historical data only. Fig. 4 illustrates the split and Table V lists the model configurations.

TABLE V MODEL CONFIGURATION (RANDOM_STATE = 42)

Model	**Key configuration**
Logistic Regression	C = 0.5, balanced class weights, max_iter = 5000
LR Standard	C = 1.0, no class weighting, max_iter = 5000
Random Forest	900 trees, max_depth = 10, min_samples_leaf = 2, balanced weights
Extra Trees	900 trees, max_depth = 12, min_samples_leaf = 2, balanced weights
HistGradientBoosting	max_iter = 350, learning_rate = 0.04, max_leaf_nodes = 15, L2 = 1.0
XGBoost	700 estimators, max_depth = 3, learning_rate = 0.03, subsample = 0.85, reg_lambda = 3.0

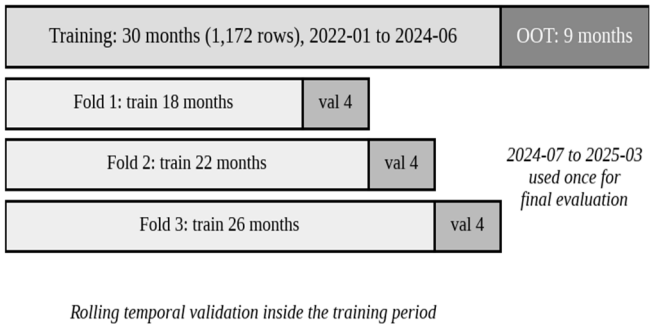


Fig. 4 Chronological training and out-of-time evaluation split with rolling validation folds

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F. Evaluation Metrics

Accuracy is the fraction of predictions that match the engineered target class, but it can mislead when classes are imbalanced. Macro-F1 averages the per-class F1 scores equally so that a common class cannot dominate the summary. High-risk recall is the proportion of actual high-risk observations that are correctly identified, which matters when missing a risky supplier is costly; higher recall may come with more false positives, so it is read together with precision. ROC-AUC summarizes class discrimination from predicted probabilities and is a complementary measure that must not be read as percentage accuracy.

G. Software Environment

Data preparation, feature engineering, modelling, explainability and dashboard-data preparation are implemented in Python with pandas and NumPy for tabular processing, scikit-learn and XGBoost for the classifiers and metrics, and Matplotlib for feature-importance plots. The pipeline consists of eleven scripts covering the raw-data audit, supplier-month aggregation, target engineering, temporal modelling, exposure-weighted prioritization, operational priority scoring, coefficient-based explainability, risk-reason generation, rule-based interventions and dashboard preparation. The four-page decision-support dashboard is built in Microsoft Power BI Desktop from the prepared CSV tables. Tables VI and VII summarize the requirements and scripts.

TABLE VI SOFTWARE AND HARDWARE REQUIREMENTS

Category	**Requirement**
Operating system	Windows 10 or later (for Power BI Desktop)
Language	Python 3
Data processing	pandas, NumPy
Machine learning	scikit-learn; XGBoost (optional)
Explainability plots	Matplotlib
Visualization	Microsoft Power BI Desktop
Data formats	CSV and JSON
Processor and RAM	Dual-core 2 GHz or better; 4 GB minimum, 8 GB recommended
Storage and display	5 GB free disk; 1366 × 768 or higher

TABLE VII IMPLEMENTATION SCRIPTS

Script	**Purpose**
data_audit.py, data_audit_temporal.py	Raw-data and temporal coverage audit
data_processing.py	Supplier-month aggregation and features
build_prediction_pairs.py	Target engineering and N to N+1 pairs
modelling_final.py	Modelling, validation and OOT evaluation
exposure_prioritization.py	Exposure-weighted prioritization
phase4_decision_support.py	Operational priority score
phase5_model_explainability.py	Coefficient-based explainability
phase6 (two scripts)	Risk reasons and rule-based interventions
phase7_dashboard_preparation.py	Power BI data preparation

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IV. PRIORITIZATION AND DECISION SUPPORT

The model outputs are converted into actionable review lists in three steps. First, an explainability stage refits the selected model on historical data only and reports global coefficient importance and row-level reasons, verified to reproduce the saved probabilities. Second, a transparent priority score from 0 to 100 combines the model high-risk probability (30%), delivery risk (25%), quality risk (20%), strategic exposure (15%) and deterioration (10%), with bands Low (<25), Moderate (25–50), High (50–75) and Critical (≥75). A complementary exposure-weighted score multiplies expected risk severity (Low 0, Medium 0.5, High 1) by business exposure (70% spend share, 30% critical-component exposure). Third, deterministic rules on the component scores assign risk domains, evidence, an intervention level (Immediate intervention, Corrective action, Enhanced monitoring or Routine monitoring), an action owner and a review cadence; all future-outcome fields are excluded. Table VIII gives the priority-score components and Fig. 5 the overall data flow.

TABLE VIII PRIORITY-SCORE COMPONENTS

Component	Weight
Model high-risk probability	30%
Delivery risk	25%
Quality risk	20%
Strategic exposure	15%
Deterioration	10%

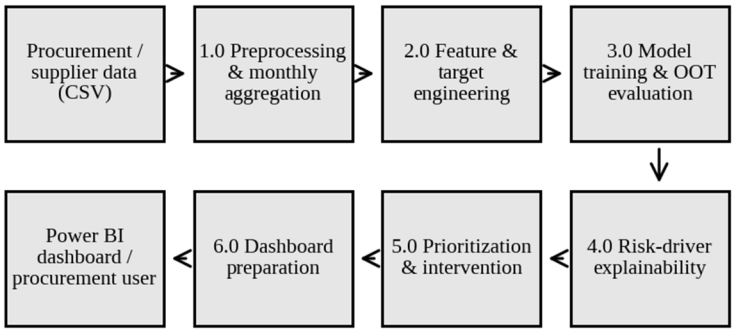


Fig. 5 Data flow from supplier procurement data to the procurement user

The results are delivered in a four-page Power BI dashboard (Executive Overview, Supplier Risk Analysis, Model Performance Analysis and Supplier Intervention & Action) covering 40 suppliers. The recommendations are decision support only; procurement staff remain responsible for confirming evidence and choosing actions.

Feasibility. *Technical:* the project uses Python data-processing and machine-learning libraries with Power BI, and can be reproduced on a standard computer with the prepared data files. *Operational:* the dashboard is organized around procurement questions (which suppliers are at risk, what evidence supports the assessment, who should be reviewed first and what action may be appropriate), so a business user need not inspect model code. *Economic:* only commonly available tools are needed and no specialized hardware is required. No monetary savings are claimed because a live deployment and controlled business evaluation were outside the project scope.

V. RESULTS AND DISCUSSION

A. *Out-of-Time Performance*

Tables IX and X and Fig. 6 report performance on the final nine-month OOT period (278 observations), which was not used for model selection. HistGradientBoosting is the strongest overall model on accuracy, Macro-F1 and ROC-AUC, whereas Extra Trees gives the highest high-risk recall (85.51%) at the cost of accuracy (42.09%). The persistence baseline is competitive (51.44% accuracy), indicating that supplier risk is temporally persistent and that the learned models add only a modest overall gain.

TABLE IX OUT-OF-TIME MODEL PERFORMANCE

Model	**Acc.**	**Macro-F1**	**HR Rec.**	**AUC**
HistGradientBoosting	54.32%	48.93%	34.78%	0.7039
Persistence baseline	51.44%	48.28%	49.28%	0.5978
XGBoost	51.44%	48.64%	44.93%	0.6985
Logistic Regression	44.24%	44.51%	79.71%	0.6711
Random Forest	44.24%	45.14%	72.46%	0.6860
Extra Trees	42.09%	40.55%	85.51%	0.7013

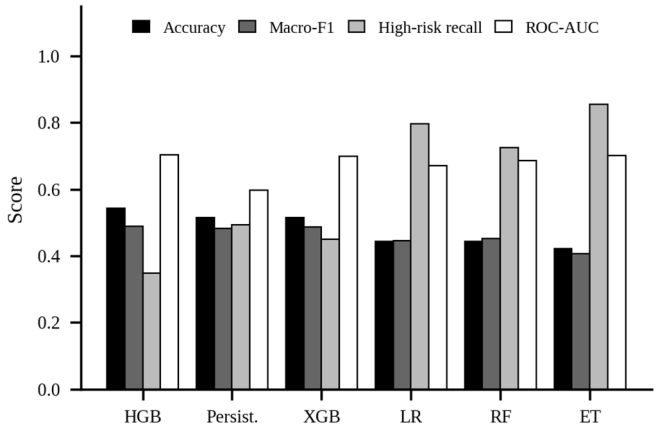


Fig. 6 Out-of-time comparison (HGB: HistGradientBoosting, Persist.: persistence baseline, XGB: XGBoost, LR: Logistic Regression, RF: Random Forest, ET: Extra Trees)

TABLE X HIGH-RISK PRECISION, RECALL AND F1 ON THE OOT PERIOD

Model	Prec.	Recall	F1
HistGradientBoosting	57.14%	34.78%	43.24%
Persistence baseline	54.84%	49.28%	51.91%
XGBoost	44.93%	44.93%	44.93%
Logistic Regression	44.00%	79.71%	56.70%
Random Forest	43.10%	72.46%	54.05%
Extra Trees	43.07%	85.51%	57.28%
LR Standard (selected)	51.43%	26.09%	34.62%

B. Selected Model and Interpretation

Historical rolling validation selected Logistic Regression Standard with a high-risk threshold of 0.40, so its predictions feed the explainability, prioritization and dashboard stages. On the OOT period it obtained 49.28% accuracy, 38.41% Macro-F1, 0.6703 ROC-AUC, 51.43% high-risk precision and 26.09% high-risk recall; these figures were reported for evaluation only. The choice of model or threshold should follow the operational goal: if screening for as many high-risk suppliers as possible matters most, a high-recall model such as Extra Trees may be preferred, provided the false-alarm burden is acceptable. In the dashboard snapshot, one of 40 suppliers is predicted high risk, seven fall in the moderate-priority band and the average priority score is 15.96.

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C. Dashboard Results

The Power BI dashboard translates model and prioritization outputs into four report pages that support summary monitoring, supplier-level inspection, model review and intervention planning (Table XI). Its KPIs describe the current dashboard dataset and are not permanent totals for future runs.

1) *Executive Overview.* Fig. 7 shows 40 suppliers, 7 moderate-priority suppliers, 1 predicted high-risk supplier and an average priority score of 15.96. Deterioration is the primary risk domain for 20 suppliers (50%), and the highest priority scores are 33 (SUP039) and 30 (SUP014). The page also shows a monthly high-risk probability trend so that a user gets an immediate view of the supplier-risk landscape.



Fig. 7 Executive Overview page of the Power BI dashboard

2) *Supplier Risk Analysis.* Fig. 8 shows a selected supplier (SUP001) with predicted risk (Medium), high-risk probability (3.34%), priority score (12.56) and primary risk domain (Deterioration), together with a "why risky" explanation, supporting evidence (a deterioration score of 70.0/100 and a worsening flag), the intervention level (Enhanced monitoring) and the recommended action. These fields give context for review but do not prove that a future disruption will occur.



Fig. 8 Supplier Risk Analysis page with risk, probability, priority, evidence and intervention

3) *Model Performance Analysis.* Fig. 9 lets a user select a model and compare accuracy, Macro-F1, ROC-AUC and the tuned high-risk threshold across models, making clear that no single metric fully describes a model's suitability.

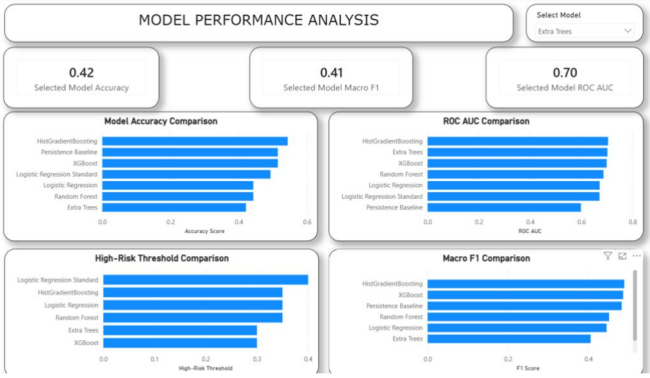


Fig. 9 Model Performance Analysis page of the Power BI dashboard

4) Supplier Intervention & Action. Fig. 10 groups recommendations by intervention level and risk domain: 15 suppliers (37.5%) require corrective action, 14 (35%) enhanced monitoring and 11 (27.5%) routine monitoring. The recommendations are rule-based decision support and are not executed automatically; procurement staff remain responsible for confirming evidence, communicating with suppliers and selecting actions.

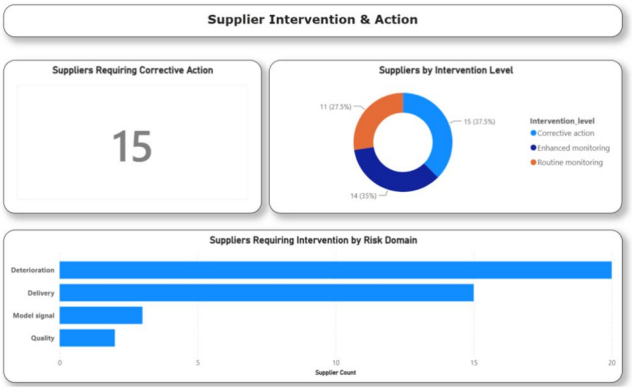


Fig. 10 Supplier Intervention & Action page of the Power BI dashboard

TABLE XI DASHBOARD PAGES AND PURPOSE

Page	**Primary purpose**
Executive Overview	Summarizes supplier counts, priority KPIs, risk domains, trends and top priorities
Supplier Risk Analysis	Inspects one supplier: risk, probability, priority, evidence and intervention
Model Performance Analysis	Compares accuracy, Macro-F1, ROC-AUC and thresholds across models
Supplier Intervention & Action	Supports action planning by intervention level and risk domain

D. Practical Use Scenario

A procurement analyst opens the Executive Overview and reviews the suppliers with the highest priority scores, then selects a supplier on the Supplier Risk Analysis page, checks the predicted risk and probability and reads the supporting evidence. The analyst reviews the suggested intervention and decides whether additional monitoring or a supplier conversation is appropriate. A supplier with a high predicted risk, worsening recent performance and high business exposure may warrant earlier review than a supplier with a similar probability but low exposure. The model therefore helps organize the review; the user makes the final decision.

E. Why Accuracy Is Moderate

The task is a three-class prediction across time with only 39 monthly periods, so later months may differ from earlier ones. Class imbalance affects the metrics, persistence in supplier risk makes the baseline comparatively strong, and the engineered target may contain noise because operational indicators are combined through domain-informed rules. These factors limit the conclusions that can be drawn from a single evaluation window, and the results should be treated as sensitive to the limited number of periods.

VI. LIMITATIONS

The risk labels are engineered rather than independently observed, so performance does not prove prediction of real disruptions. The dataset has only 39 monthly periods and a nine-month OOT window that may not represent future operating conditions. Performance is moderate, and the persistence baseline is competitive. Class-specific recall trades off against accuracy and precision, risk-driver evidence is supporting signal rather than causal proof, and the dashboard is a prototype not integrated with a live procurement or ERP platform.

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VII. CONCLUSION AND FUTURE WORK

This paper presented a leakage-controlled temporal pipeline that predicts next-month supplier risk and converts predictions into prioritized, evidence-backed interventions. On 1,450 supplier-month observations, HistGradientBoosting gave the best overall OOT result (54.32% accuracy, 0.7039 ROC-AUC) and Extra Trees the best high-risk recall (85.51%), with results that are moderate and best used as an early-warning signal for human review. Future work includes extending the data to more suppliers and longer periods, validating labels with procurement experts and observed incidents, evaluating across multiple future windows, calibrating probabilities and cost-based thresholds, monitoring drift, collecting user feedback on recommendations, and running a prospective pilot.

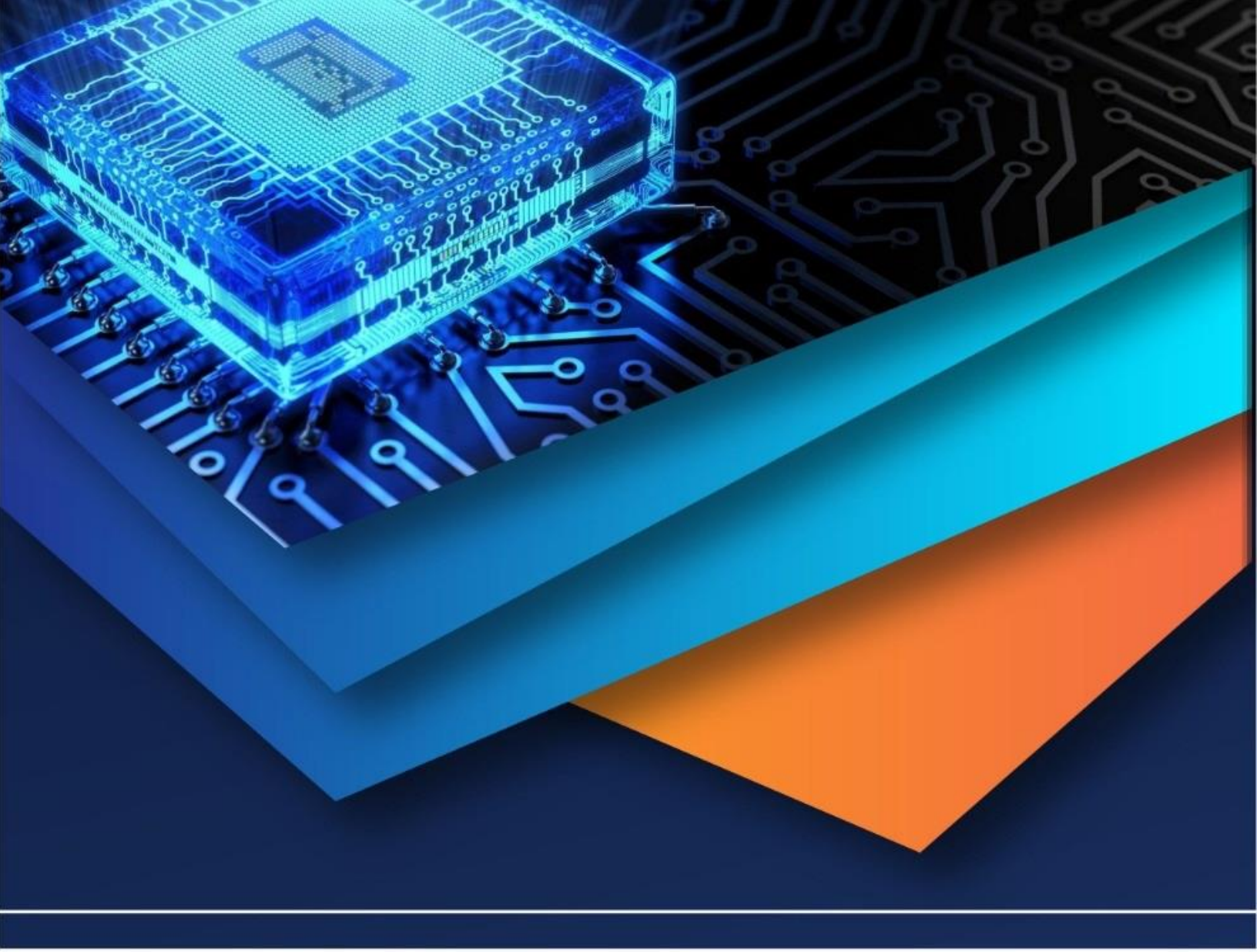
VIII. ACKNOWLEDGMENT

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