E-ISSN: 2774-5694 P-ISSN: 2776-7388 OPEN ACCESS

International Journal of Management Science and Information Technology
IJMSIT

Volume 6 (2), July-December 2026, 1415-1423
DOI: https://doi.org/10.35870/ijmsit.v6i2.7849

A Machine Learning-Based Risk Classification Model for Hot Rolled Coil (HRC) Import Delays Using Supply Chain Visibility Indicators

Amadea Syahbani Rachela Putri [1*], Wiwik Handayani [2]
[1*,2] Management Study Program, Faculty of Economics and Business, Universitas Pembangunan Nasional "Veteran", Surabaya City, East Java Province, Indonesia

Email: 22012010385@student.upnjatim.ac.id [1*], wiwik.em@upnjatim.ac.id [2]

Article history:
Received July 4, 2026
Revised July 20, 2026
Accepted July 27, 2026

Abstract

Delays in importing Hot Rolled Coil (HRC) raw material can disrupt production continuity and generate operational losses for manufacturing companies that depend on imported supply. This study aims to develop a risk classification model for HRC raw material import delays based on Supply Chain Visibility indicators, using a risk scoring approach combined with machine learning at PT Berjaya Mandiri Indonesia. A quantitative descriptive approach was applied to 200 historical HRC import records from 2020 to 2025. Six risk indicators were weighted through a risk scoring method to produce Low, Medium, and High-Risk labels, which subsequently served as the learning target for three classification algorithms Naïve Bayes, Decision Tree, and Random Forest evaluated using stratified 5-fold cross-validation. Decision Tree and Random Forest achieved the highest average accuracy at 97.0%, with Decision Tree marginally outperforming Random Forest on macro-F1 (0.965 versus 0.962) and consequently selected as the final model on grounds of computational efficiency and interpretability. A confirmation interview with four company practitioners indicated that the model possesses good face validity. The integration of risk scoring and machine learning produced a risk classification model that consistently automates the manual risk-scoring rules; however, the high accuracy obtained reflects consistency in replicating a deterministic label rather than predictive capability over an independent outcome, so further predictive validation is still required before the model is applied operationally.

Keywords:
Supply Chain Visibility; Risk Scoring; Machine Learning; Import Delay; Supply Chain Risk Management.

1. INTRODUCTION

The growth of international trade has increased the complexity of global supply chains, particularly in manufacturing sectors that depend on imported raw materials (Dubey et al., 2023). The steel industry is one of the sectors most exposed to disruption from demand fluctuations, distribution uncertainty, and shifting dynamics in global trade. Hot Rolled Coil (HRC) is the principal raw material for hollow-pipe production, so import delays have a direct impact on the continuity of a company's production process (Ivanov, 2021). Dependence on imported raw materials requires companies to manage supply chain risk in a systematic and adaptive manner (Zhao et al., 2023), a need further reinforced by the growing use of artificial intelligence and predictive analytics in modern supply chain management to accelerate risk identification and response to distribution disruptions (Nwamekwe & Igbokwe, 2024).

Supply Chain Visibility (SCV) is a critical factor in controlling import delay risk, as it encompasses transparency of shipment information, documentation, customs processes, and overall distribution status (Alfaqiyah et al., 2025; Zheng & Brintrup, 2025). Low supply chain visibility increases the risk of production disruption and operational uncertainty (Wieland & Durach, 2021), whereas the integration of digital technology has been shown to improve the accuracy, speed, and effectiveness of decision-making in modern supply chains

(Dubey et al., 2023). Machine learning offers a data-driven analytical approach to identifying delay patterns and arrival-time deviations more accurately than conventional, reactive methods (Ordibazar et al., 2025; Zheng & Brintrup, 2025), however, a persistent barrier to broader adoption of machine learning in supply chain decision-making is limited explainability, particularly for practitioners who must trust and act on model outputs without a technical background (Kosasih et al., 2024). One relevant approach is risk scoring, which groups risk levels according to defined parameters in an objective and measurable way, enabling companies to prioritize mitigation according to the level of urgency (Dubey et al., 2023; Ordibazar et al., 2025). The Supply Chain Risk Management (SCRM) framework further emphasizes that risk in import supply chains is inherently complex and multidimensional, involving multiple parties, activities, and cross-border distribution stages, such that a disruption at any single stage can affect the entire operational system (Alvarenga et al., 2023; Ivanov, 2021; Wieland & Durach, 2021).

A number of prior studies have examined supply chain risk management from various methodological angles. Pettawali and Hernadewita (2024) and Pettawali et al. (2025) applied an integrated SCOR and House of Risk (HOR) approach to identify risk events and risk agents in the andesite mining and furniture industries respectively, finding that low supply chain transparency emerged as the risk agent with the highest Aggregate Risk Potential. (Handayani et al., 2022) combined AHP and FMEA to prioritize risk on a scoring basis, while (Tarigan & Saniatul Mutmainah, 2023) applied the HOR method to raw material procurement and found inventory control to be the mitigation action with the highest effectiveness-to-difficulty ratio. Machine learning-based approaches have gained increasing adoption in recent years: (Rezki & Mansouri, 2024) compared Random Forest, Gradient Boosting, Logistic Regression, Decision Tree, K-Nearest Neighbors, and Support Vector Machine for predicting shipment delays, with Gradient Boosting and Random Forest showing the strongest performance. (Widayanti et al., 2026) achieved 94.2% accuracy using Gradient Boosting to predict supply chain disruption risk based on supplier reliability and inventory cycle duration, while (Nezianya et al., 2024) noted that machine learning applications in SCRM including demand forecasting, supplier risk assessment, and real-time visibility enhancement continue to face challenges related to data quality and implementation cost. (Zheng & Brintrup, 2025) showed that generative AI and knowledge graphs can enhance SCV by improving the detection of relationships among supply chain entities.

The research gap lies in the still-limited integration of Supply Chain Visibility indicators with machine learning-based risk classification models in the context of raw material import delay (Zheng & Brintrup, 2025). Most prior studies rely on descriptive, priority-scoring approaches (HOR, AHP-FMEA) that have not systematically exploited historical company data for automated classification (Dubey et al., 2023; Ordibazar et al., 2025). Historical data, however, can serve as the basis for developing a machine learning model capable of identifying import delay risk levels more consistently (Zheng & Brintrup, 2025).

PT Berjaya Mandiri Indonesia is a hollow-pipe manufacturer that depends on HRC imports from China and Vietnam. Internal company data show that import delays have reached up to 60 days, resulting in a production capacity decline of approximately 75–100 tons per month and increased operating costs from emergency purchases at higher prices from local suppliers. The ten worst delay cases recorded during 2020–2025 amounted to a cumulative estimated loss exceeding IDR 600,000,000, with customs clearance recurring as the most frequent point of delay, followed by the shipping and inland distribution stages. The urgency of this study lies in the high risk of HRC import delay and its impact on reduced production output and potential unmet market demand, while conventional strategies such as advance ordering and forecasting remain only partially effective owing to price fluctuations and limited storage capacity.

Based on the foregoing, this study aims to develop a risk classification model for HRC raw material import delay based on Supply Chain Visibility indicators, using a risk scoring and machine learning approach at PT Berjaya Mandiri Indonesia (Dubey et al., 2023; Ordibazar et al., 2025). The model is intended to classify import delay risk levels into Low, Medium, and High-Risk categories based on historical data patterns, thereby supporting a more systematic, data-driven approach to risk identification and contributing to the supply chain risk management literature that applies machine learning to operational decision-making (Ivanov, 2021).

2. RESEARCH METHOD

This study employed a quantitative descriptive approach (Creswell & Creswell, 2018) to measure risk variables numerically and describe import delay patterns based on actual data without manipulating the research variables. The research subjects were 12 employees of the import unit of PT Berjaya Mandiri Indonesia, drawn from the Procurement, Import-Export, Logistics and Warehouse, and PPIC (production planning and inventory control) divisions. The research object was 200 historical HRC import transactions from 2020 to 2025 and their impact on production schedules. Primary data were collected through direct observation of the import process, structured interviews, and transaction documentation; secondary data comprised Bills of Lading, invoices, packing lists, purchase orders, and shipping schedules.

Six risk indicators were used as research variables: delay days and customs clearance duration (Culot et al., 2024); import document completeness and document clarification duration (Dubey et al., 2023); and shipment monitoring status and Estimated Time of Arrival (ETA) deviation (Zhao et al., 2023). Delay days and customs clearance duration are ex-post in nature known only after the shipment or clearance process is complete so the resulting model functions to automate risk classification for transactions that have already occurred, rather than to predict risk prior to a transaction taking place (ex-ante).

Each indicator was scored 1–3 (ordinal numerical indicators: delay days, customs clearance duration, ETA deviation, document clarification duration) or 0–2 (binary categorical indicators: document completeness, monitoring status) according to the severity of its impact. A preliminary fishbone (Ishikawa) diagram with 4M+1E categories (Man, Method, Material, Machine, Environment) was first constructed from structured interviews with company practitioners to map plausible causes of import delay; the frequency counts recorded at this interview-based stage served as an initial qualitative reference rather than a final, data-verified count. These interview-based counts were subsequently refined against the complete 200-transaction dataset through formal Pareto analysis, which represents the final, data-verified frequency distribution of delay-cause categories used in this study. The frequency results from the Pareto analysis are conceptually distinct from the variable weights: weights were determined from practitioners' qualitative severity judgments through an FMEA-based approach, so a category may occur infrequently yet still carry a high weight because of its significant impact when it does occur. The weights applied were: import document completeness (30%), delay days (20%), customs clearance duration (15%), ETA deviation (15%), shipment monitoring status (10%), and document clarification duration (10%).

The weighted score for each transaction was summed and normalized to a 0–100 scale using the actual maximum weighted score of 2.6, then classified into Low Risk (score 0–45), Medium Risk (score 46–70), and High Risk (score 71–100). The thresholds were set by proportionally dividing the 0–100 scale and were checked against the quantile distribution of the actual data (the threshold of 45 approximates the 29.5th percentile, score 46.94; the threshold of 70 approximates the 53.0th percentile, score 70.13). A sensitivity analysis shifting the thresholds by ±5 and ±10 points showed that the risk category distribution is fairly sensitive to threshold changes the proportion of High Risk ranged from 32.0% to 57.5% depending on the threshold used indicating that the thresholds applied in this study are a practical convention rather than the result of an independent statistical optimization.

The Decision Tree, Random Forest, and Naïve Bayes classifiers were each trained using their default scikit-learn hyperparameter configurations (notably, an unconstrained maximum depth for the Decision Tree), with a fixed random seed (random_state = 42) applied throughout for reproducibility. The risk labels (Low/Medium/High) resulting from risk scoring were subsequently used as the supervised learning target for three classification algorithms: Naïve Bayes, Decision Tree, and Random Forest, with the same six indicators used as input variables. Because the labels are a direct derivation of the weighted scoring formula applied to the same input variables, the role of machine learning in this study is that of an automation and consistency-validation mechanism for the manual risk-scoring rules not a predictive tool for an outcome that is independent and not yet known. The dataset was split into training and testing sets using an 80:20 single-split scheme, supplemented by stratified 5-fold cross-validation that preserved the proportion of each risk class in every fold, in order to obtain a more stable performance estimate given that the single-split test set (40 transactions) is susceptible to random variation, particularly for the smaller medium class. Model performance was evaluated using accuracy, precision, recall, F1-score per class, macro-F1, and the confusion matrix. This study was limited to the model development stage and did not proceed to system implementation, since evaluating an implemented system requires an operational observation period beyond the scope of this research (Larsen et al., 2025). To obtain evidence of practical relevance, a confirmation interview was conducted with four practitioners from the Procurement, Import-Export, PPIC, and Warehouse divisions as domain experts, serving as a face validity test of the model's variables, weights, and classification outputs not a test of predictive validity against an actual outcome that remains unknown.

3. RESULTS AND DISCUSSION

3.1. Delay Cause Mapping and Risk Category Distribution

A preliminary fishbone (Ishikawa) diagram was constructed from structured interviews with company practitioners to map plausible causes of import delay across the 4M+1E categories, prior to the completion of formal Pareto analysis on the full transaction dataset.

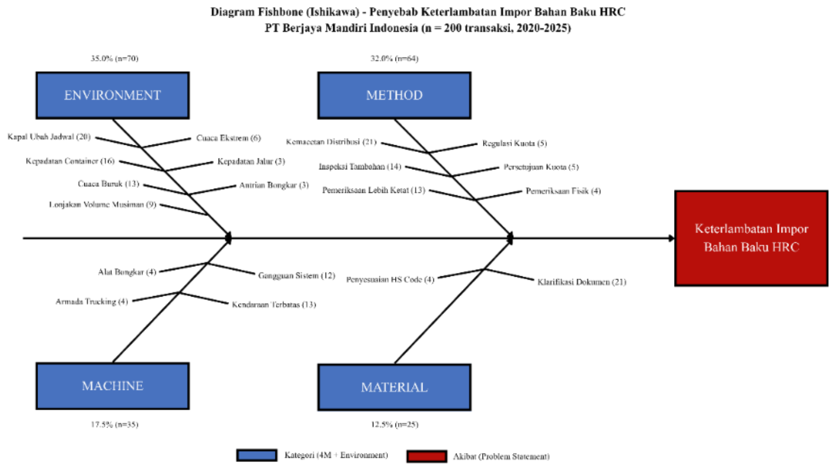

Figure 1. Fishbone (Ishikawa) Diagram of HRC Import Delay Causes
(interview-based frequency counts, n = 194 recorded instances)

The interview-based counts underlying Figure 1 were subsequently cross-checked and refined against the complete 200-transaction dataset through formal Pareto analysis (Figure 2). The category-level totals in Figure 1 (n = 194 recorded instances) do not fully coincide with the data-verified Pareto totals in Figure 2 (n = 200 transactions); this study treats the Pareto results in Figure 2 as the final, authoritative frequency distribution, while Figure 1 is retained as a record of the qualitative cause-mapping process that preceded it.

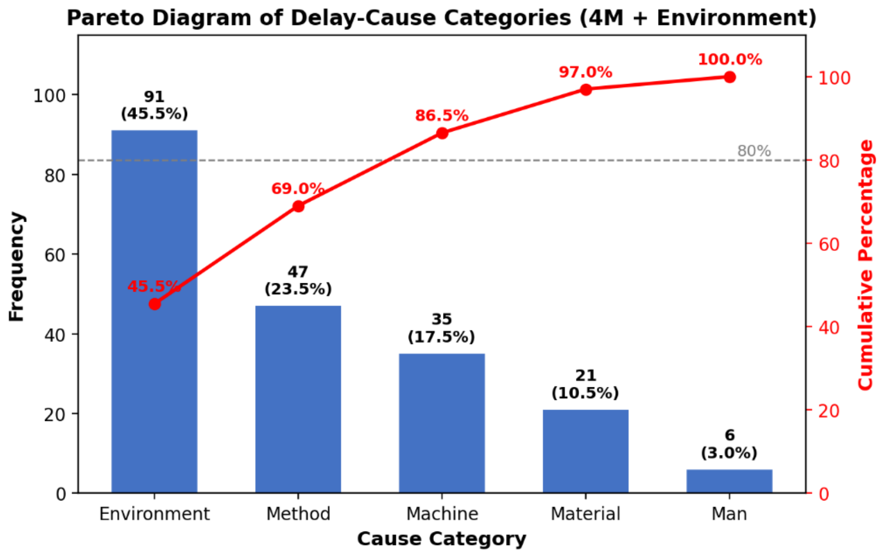

Figure 2. Pareto Diagram of Delay-Cause Categories, Final Data-Verified Distribution
(n = 200 transactions, 2020–2025)

Environment (45.5%) and Method (23.5%) jointly account for 69.0% of recorded delay-cause instances, exceeding the 80% cumulative threshold only when Machine (17.5%) is included. This distribution informed, but was not used to directly derive, the FMEA-based severity weights described above; the two are intentionally decoupled, as explained in Section 2.

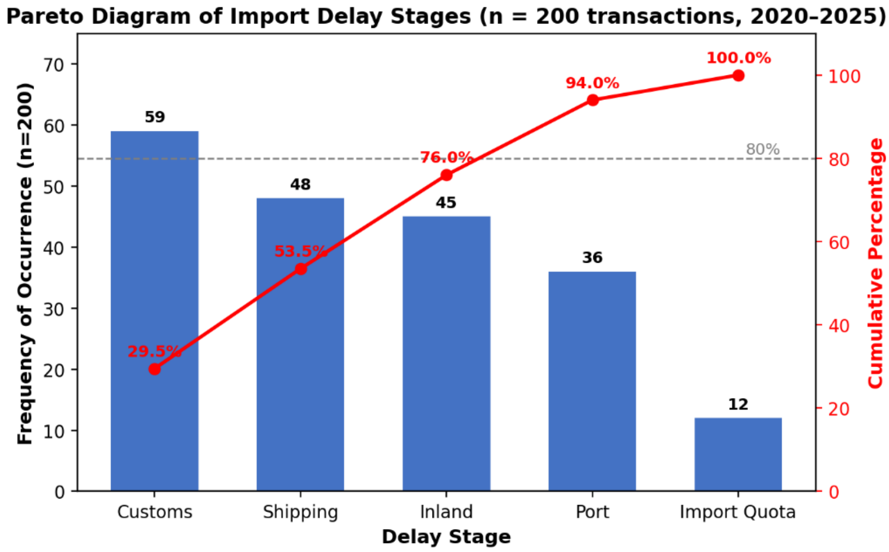

Figure 3. Pareto Diagram of Import Delay Stages (n = 200 transactions, 2020–2025)

At the process-stage level, customs clearance was the single most frequent point of delay (59 occurrences, 29.5%), followed by shipping (48) and inland distribution (45); together these three stages account for 76.0% of recorded delay instances, while port handling (36) and import-quota processing (12) were comparatively less frequent.

Risk scoring applied to 200 HRC import transactions from 2020 to 2025 produced the following risk category distribution.

Table 1. Risk Category Distribution from Risk Scoring (n = 200)

Risk Category	Number of Transactions	Percentage
High Risk	94	47.0%
Low Risk	59	29.5%
Medium Risk	47	23.5%

The High-Risk category represents the largest proportion of the dataset, indicating that the company's import activity carries a dominant level of delay risk that requires systematic management. This finding supports Supply Chain Risk Management theory, which holds that risk in global supply chains is multidimensional and arises from uncertainty at multiple stages of the process (Dubey et al., 2023; Ordibazar et al., 2025), and indicates that import risk management at PT Berjaya Mandiri Indonesia requires a more systematic approach than reliance on managerial experience alone (Wieland & Durach, 2021).

3.2. Model Comparison: Single-Split and Cross-Validation

Evaluation of the classification models on the single-split 80:20 scheme produced the following accuracy results: Naïve Bayes 85.0%, Decision Tree 87.5%, and Random Forest 90.0%. Because the single-split evaluation has methodological limitations arising from the small test-set size, an additional evaluation was conducted using stratified 5-fold cross-validation.

Table 2. Stratified 5-Fold Cross-Validation Results

Model	Mean Accuracy	Mean Macro-F1
Naïve Bayes	87.5% (±4.8%)	0.832 (±0.067)
Decision Tree	97.0% (±2.1%)	0.965 (±0.026)
Random Forest	97.0% (±2.6%)	0.962 (±0.034)

Decision Tree and Random Forest achieved an identical top mean accuracy (97.0%), outperforming Naïve Bayes (87.5%). Between the two, Decision Tree marginally outperformed Random Forest on macro-F1 (0.965 versus 0.962), a difference of 0.003. Naïve Bayes consistently showed weaker performance in identifying the medium category (F1-score 0.68) compared with Decision Tree and Random Forest (F1-score 0.93), suggesting that the probabilistic independence assumption underlying Naïve Bayes is less suited to distinguishing risk categories near the class boundaries. The narrow margin by which Decision Tree outperformed Random Forest on macro-F1 (0.003) indicates that the two algorithms have broadly comparable classification capability; given the deterministic relationship between the label and the input variables (discussed further in Section 3.4), a single Decision Tree structure is sufficient to consistently replicate the risk-scoring mapping function without requiring the added complexity of an ensemble approach, so Decision

Tree was selected as the final model on grounds of computational efficiency and interpretability rather than superior predictive capability. This preference for an intrinsically interpretable model over a marginally different ensemble alternative is consistent with Heydarbakian & Spehri (2022) who likewise found that among interpretable classifiers applied to supply chain resilience data, Decision Tree offered strong classification performance while preserving the transparency that practitioners require to trust and act on model outputs.

3.3. Decision Tree Per-Class Performance and Confirmation Interview

For the final selected model (Decision Tree), per-class performance was evaluated on the stratified 5-fold out-of-fold predictions across the full dataset (n = 200), consistent with the aggregate figures reported in table 3.

Table 3. Decision Tree Precision, Recall, and F1-Score per Class (Stratified 5-Fold Out-of-Fold, n = 200)

Category	Precision	Recall	F1-Score	Support
High	0.98	0.98	0.98	94
Medium	0.96	0.91	0.93	47
Low	0.97	1.00	0.98	59
Accuracy			0.97	200
Macro avg	0.97	0.96	0.97	200
Weighted avg	0.97	0.97	0.97	200

Recall for the Medium category (0.91) remains the weakest among the three classes, echoing the pattern seen in the single-split evaluation and in Naïve Bayes' comparatively larger shortfall on this class consistent with the interpretation that risk scores near the Low/Medium and Medium/High boundaries are the hardest to separate.

Confirmation interviews with four practitioners from the Procurement, Import-Export, PPIC, and Warehouse divisions indicated that the six risk indicators and their weights were considered consistent with the company's operational conditions. All informants stated that the Low, Medium, and High-Risk classification outputs were consistent with the characteristics of import transactions that had actually occurred transactions with complete documentation and on-schedule customs clearance generally fell into the low-risk category, whereas transactions with delayed documentation or schedule deviation tended to be classified as high risk. The model was judged to be conceptually ready for use as a risk-identification aid, with the main remaining requirement being its integration into the company's information system for routine use. The role of information-transparency indicators shipment monitoring status, import document completeness, and ETA deviation in determining risk level supports Supply Chain Visibility theory, which holds that accurate and timely information across the supply chain improves a company's ability to detect potential disruptions and supports faster decision-making (Guo et al., 2025; Zheng & Brintrup, 2025), consistent with Zheng & Brintrup (2025), who showed that enhanced supply chain visibility through data and digital technology contributes to more accurate risk management and faster response to operational disruption (Guo et al., 2025).

3.4. Interpretation of Model Accuracy and the Circular-Labeling Issue

The high accuracy (97.0%) achieved by Decision Tree and Random Forest warrants cautious interpretation. Because the risk category label is a deterministic transformation of the same six indicator scores used as model inputs, the high and consistent accuracy across cross-validation folds including several folds reaching 100% reflects the algorithms' ability to reverse-engineer an already-known scoring function, rather than evidence of predictive capability over an outcome independent of the labeling process. This interpretation is consistent with the ex-post nature of some indicators (delay days and customs clearance duration), which are only known after a shipment has been completed.

The confirmation interview results discussed in Section 3.3 indicate that the model has good face validity in the eyes of company practitioners: the variables, weights, and classification outputs were judged plausible and consistent with operational experience. Face validity, however, is fundamentally different from predictive validity, which tests model accuracy against an actual outcome not yet known at the time the model is applied. This study was limited to face validity testing because of time constraints that precluded real-time monitoring of new import transactions following model development, so readiness for routine operational use would ideally still require further predictive validation.

3.5. Comparison with Prior Studies

Compared with prior studies that focused on risk ranking through HOR or AHP-FMEA (Handayani et al., 2022; Pettawali & Dewita, 2024; Tarigan & Saniatul Mutmainah, 2023) this study extends those approaches by automating the classification process through machine learning applied to historical data. However, unlike Rezki & Mansouri (2024) or Widayanti et al. (2026), who positioned machine learning as a tool for predicting shipment delay against an independent outcome, the role of machine learning in this study is to automate an already-established manual risk-scoring rule a conceptual distinction that matters for avoiding an unsupported claim of predictive capability.

3.6. Limitations

This study has several limitations. First, the scoring scheme combines a 1–3 ordinal scale and a 0–2 binary scale without normalization prior to weighting, so the contribution of each variable to the final risk score is not purely proportional to its assigned weight. Second, the risk category thresholds were set by proportionally dividing the 0–100 scale rather than through formal statistical optimization, and the sensitivity analysis shows that the risk category distribution can change substantially if the thresholds are shifted. Third, the Decision Tree model was trained using default scikit-learn hyperparameters (unconstrained tree depth); a supplementary grid search across tree depth, minimum split size, minimum leaf size, and split criterion found no practically meaningful improvement over this default configuration (best cross-validated macro-F1 = 0.965 for the grid search versus 0.966 for the reported default model, a difference of less than 0.001), indicating that model performance in this study is governed primarily by the deterministic structure of the labeling process rather than by hyperparameter choice. Fourth, and most fundamentally, the deterministic structure of the labeling process means that the high accuracy obtained cannot be used as grounds for claiming that the model has been validated predictively.

4. CONCLUSION

This study developed a risk classification model for HRC raw material import delay at PT Berjaya Mandiri Indonesia based on six Supply Chain Visibility indicators weighted through a risk-scoring method. Risk scoring applied to 200 import transactions from 2020 to 2025 showed High Risk as the largest category (47.0%), followed by Low Risk (29.5%) and Medium Risk (23.5%). Among the three algorithms evaluated through stratified 5-fold cross-validation, Decision Tree and Random Forest both achieved the highest mean accuracy (97.0%), with Decision Tree selected as the final model based on its slightly higher macro-F1 (0.965 versus 0.962) together with considerations of computational efficiency and interpretability. Confirmation interviews with four company practitioners established good face validity for the model, although predictive validity against actual outcomes was not tested in this study.

The high accuracy obtained should be interpreted as evidence of the model's consistency in automating the replication of the manual risk-scoring rule, not as proof of predictive capability over import delays that have not yet occurred, given that the risk label is a direct derivation of the same input variables. Future research is recommended to address this circular-labeling limitation by using actual delay outcomes as the target and restricting input variables to indicators available prior to the arrival of goods (an ex-ante predictive approach), so that the model's predictive capability can be tested independently. Future research is also recommended to broaden the data coverage, consider additional variables that may influence import delay, and conduct predictive validation through direct monitoring of new import transactions to support the model's readiness for operational deployment.

ACKNOWLEDGEMENTS

The authors thank the management and staff of the Procurement, Import-Export, Logistics and Warehouse, and PPIC divisions of PT Berjaya Mandiri Indonesia for providing data access and participating in the research interviews. Part of the manuscript preparation process was assisted by an AI tool (Claude, Anthropic) for language processing and drafting support; all data analysis, interpretation of results, and final conclusions remain the sole responsibility of the authors.

REFERENCES

Alfaqiyah, E., Alzubi, A., Aljuhmani, H. Y., & Öz, T. (2025). How Industry 4.0 Technologies Enhance Supply Chain Resilience: The Interplay of Agility, Adaptability, And Customer Integration in Manufacturing Firms. Sustainability (Switzerland), 17(17). Https://Doi.Org/10.3390/Su17177922

Alvarenga, M. Z., Paulo, M., & De Oliveira, V. (2023). The Impact of Using Digital Technologies on Supply Chain Resilience and Robustness: The Role of Memory Under the Covid-19 Outbreak. (28(5)), 825–842. Https://Doi.Org/10.1108/SCM-06-2022

Creswell, J. W., & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, And Mixed Methods Approaches (5th Ed.). SAGE Publications.

Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial Intelligence in Supply Chain Management: A Systematic Literature Review of Empirical Studies and Research Directions. In Computers in Industry (Vol. 162). Elsevier B.V. Https://Doi.Org/10.1016/J.Compind.2024.104132

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic Digital Capabilities and Supply Chain Resilience: The Role of Government Effectiveness. International Journal of Production Economics, 258. Https://Doi.Org/10.1016/J.Ijpe.2023.108790

Guo, X., Chen, Y., Xie, J., Wang, H., & Lei, X. (2025). Research On Supply Chain Resilience Mechanism Of AI-Enabled Manufacturing Enterprises -Based on Organizational Change Perspective. Scientific Reports, 15(1). Https://Doi.Org/10.1038/S41598-025-17138-3

Handayani, W., & Adam Yusuf, M. (2022). Analisis Dan Mitigasi Resiko Rantai Pasok Dengan Metode AHP Dan FMEA. REVITALISASI: Jurnal Ilmu Manajemen, 11(1), 43-53. doi:10.32503/revitalisasi.v11i1.2501

Heydarbakian, S., & Spehri, M. (2022). Interpretable Machine Learning to Improve Supply Chain Resilience, An Industry 4.0 Recipe. IFAC-Papersonline, 55(10), 2834–2839. Https://Doi.Org/10.1016/J.Ifacol.2022.10.160

Ivanov, D. (2021). Supply Chain Viability and the COVID-19 Pandemic: A Conceptual and Formal Generalisation of Four Major Adaptation Strategies. International Journal of Production Research, 59(12), 3535–3552. Https://Doi.Org/10.1080/00207543.2021.1890852

Kosasih, E. E., Papadakis, E., Baryannis, G., & Brintrup, A. (2024). A Review of Explainable Artificial Intelligence in Supply Chain Management Using Neurosymbolic Approaches. In International Journal of Production Research (Vol. 62, Number 4, Pp. 1510–1540). Taylor And Francis Ltd. Https://Doi.Org/10.1080/00207543.2023.2281663

Larsen, K. R., Lukyanenko, R., Mueller, R. M., Storey, V. C., Parsons, J., Vandermeer, D., & Hovorka, D. S. (2025). VALIDITY IN DESIGN SCIENCE. MIS Quarterly, 49(4), 1267–1294. Https://Doi.Org/10.25300/MISQ/2024/18064

Michelle Chibogu Nezianya, Ahmed Olanrewaju Adebayo, & Paschal Ezeliora. (2024). A Critical Review of Machine Learning Applications in Supply Chain Risk Management. World Journal of Advanced Research and Reviews, 23(3), 1554–1567. Https://Doi.Org/10.30574/Wjarr.2024.23.3.2760

Nwamekwe, C. O., & Igbokwe, N. C. (2024). Supply Chain Risk Management: Leveraging AI For Risk Identification, Mitigation, And Resilience Planning. International Journal of Industrial Engineering, Technology & Operations Management, 2(2), 41–51. Https://Doi.Org/10.62157/Ijietom.V2i2.38

Ordibazar, A. H., Hussain, O. K., Chakrabortty, R. K., Irannezhad, E., & Saberi, M. (2025). Artificial Intelligence Applications for Supply Chain Risk Management Considering Interconnectivity, External Events Exposures and Transparency: A Systematic Literature Review. Modern Supply Chain Research and Applications. Https://Doi.Org/10.1108/Mscra-10-2024-0041

Pettawali, A. F. L., & Dewita, H. (2024). Analisis Risiko Rantai Pasok Bahan Baku Dalam Memenuhi Permintaan Konsumen Pada Industri Pertambangan Andesit di Cilegon. JISI: Jurnal Integrasi Sistem Industri, 11(2), 191–212. Https://Doi.Org/10.24853/Jisi.11.2.191-212

Rezki, N., & Mansouri, M. (2024). MACHINE LEARNING FOR PROACTIVE SUPPLY CHAIN RISK MANAGEMENT: PREDICTING DELAYS AND ENHANCING OPERATIONAL EFFICIENCY. Management Systems in Production Engineering, 32(3), 345–356. Https://Doi.Org/10.2478/Mspe-2024-0033

Tarigan, Y., & Saniatul Mutmainah, S. (2023). 92-Jurnal Akuntansi. 11(1), 92.

Widayanti, R., Setiyowati, H., Yusup, M., & Rodriguez, M. (2026). Predicting Supply Chain Risks Using Machine Learning for Resilient Operations. ADI Journal on Recent Innovation (AJRI), 7(2), 137–148. Https://Doi.Org/10.34306/Ajri.V7i2.1376

Wieland, A., & Durach, C. F. (2021). Two Perspectives on Supply Chain Resilience. Journal Of Business Logistics, 42(3), 315–322. Https://Doi.Org/10.1111/Jbl.12271

Zhao, N., Hong, J., & Lau, K. H. (2023). Impact Of Supply Chain Digitalization on Supply Chain Resilience and Performance: A Multi-Mediation Model. International Journal of Production Economics, 259. Https://Doi.Org/10.1016/J.Ijpe.2023.108817

Zheng, G., & Brintrup, A. (2025). An Analytics-Driven Approach to Enhancing Supply Chain Visibility with Graph Neural Networks and Federated Learning. Http://Arxiv.Org/Abs/2503.07231

Zheng, G., & Brintrup, A. (2025). Enhancing Supply Chain Visibility with Generative AI: An Exploratory Case Study on Relationship Prediction in Knowledge Graphs. Http://Arxiv.Org/Abs/2412.03390