Trade-Linked Credit Risk Assessment in Banking: An Applied Statistical Study

Mohammad Nurul Islam[1], Md Rezwan ur Rahman[2], Jahin Tajowar Masud[3], Anik Chanda[4]

[1] University of Dhaka, Bangladesh
[2] Eastern Bank PLC, Bangladesh
[3] Jagannath University, Bangladesh
[4] University of Professionals, Bangladesh

ABSTRACT

This study develops and demonstrates a trade-linked statistical classification approach for assessing credit deterioration in branch banking. The focus is on borrowers whose repayment capacity is shaped by letters of credit, invoice settlement, foreign-exchange exposure, trade turnover and supplier or customer concentration. The study constructs a transparent risk-assessment design using borrower financial indicators, account-conduct signals and trade-transaction variables. A reproducible synthetic branch-portfolio dataset of 620 borrower-facility observations is used to demonstrate the method because customer-level banking records are confidential and were not available for public disclosure. Logistic regression, linear discriminant analysis and a classification tree are compared using AUROC, precision-recall area, sensitivity, precision, F1 score and operational workload indicators. The demonstration indicates that trade-linked indicators add practical early-warning value when they are combined with conventional credit variables. Logistic regression produced the strongest operational recall in the demonstration, while linear discriminant analysis produced the highest apparent accuracy at the selected threshold but missed more adverse migrations. Invoice overdue days, sector stress, collateral coverage, debt-service coverage, trade facility utilisation and trade turnover volatility were the most influential drivers in the transparent model. The study translates credit-risk classification into a branch-level monitoring process that connects statistical scoring with trade-finance information and managerial action. It shows how banks can use interpretable classification to move from periodic borrower review toward evidence-based watchlist management. The proposed approach can help banks prioritise trade-linked borrowers for review, standardise escalation, and improve documentation of credit-monitoring decisions.

Keywords: trade credit, credit risk, statistical classification, branch banking, trade finance, early warning

1. INTRODUCTION

Trade-linked borrowing is one of the most information-rich but operationally challenging areas of bank credit risk. Branches and relationship managers observe repeated signals from letters of credit, invoice discounting, import payments, export proceeds, account turnover, buyer concentration and supplier disruption. These signals often emerge before a borrower becomes formally delinquent. Yet many credit-monitoring systems still treat trade-linked customers in the same way as ordinary term-loan borrowers, relying heavily on periodic financial statements, security coverage and days-past-due rules. The result is a timing problem: deterioration may be visible in trade behaviour but not yet reflected in the formal credit grade or non-performing classification.

The problem is especially important for branch banking. Branches are close to borrowers and often hold valuable soft information, but they may lack a consistent statistical process for transforming trade observations into comparable risk categories. A customer whose import volumes fall sharply, whose export proceeds are delayed, whose invoices become more overdue and whose foreign-exchange exposure rises may not breach a repayment schedule immediately. However, the joint pattern can indicate pressure on cash conversion and repayment capacity. In the absence of a structured classification system, such cases may be escalated late or treated inconsistently across branches.

Credit-risk research has long recognised that statistical classification can improve lending decisions. Classical discriminant analysis and logistic regression established the foundation for corporate failure prediction and consumer scoring, while more recent work has expanded credit scoring through machine learning, digital footprints, explainability and alternative data [1-4]. However, the branch-banking application considered in this study is narrower and more practical. The objective is not to propose a black-box default model; it is to design an interpretable classification process that combines conventional credit indicators with trade-linked signals and converts them into monitoring actions.

This study addresses the following research question: how can branch banks use statistical classification to assess trade-linked credit risk in a way that is accurate, interpretable and operationally useful? To answer this question, the paper develops a classification architecture for trade-linked borrowers and demonstrates it using a reproducible synthetic branch-portfolio dataset. The synthetic demonstration is used transparently because real borrower-level banking data are confidential and were not provided for public release. The numerical results should therefore be interpreted as a methodological demonstration rather than as empirical evidence from a named bank. This distinction is important for research integrity, but it does not reduce the practical value of the design: the approach can be directly transferred to a bank's own confidential data for validation and policy adoption.

The study contributes in three ways. First, it identifies a set of trade-linked risk indicators that branch banks can monitor alongside financial ratios and account conduct. Second, it compares three statistical classification approaches - logistic regression, linear discriminant analysis and classification trees - using metrics that reflect both predictive ranking and branch workload. Third, it links classification outputs to practical risk bands and monitoring actions. In doing so, the paper bridges the gap between statistical credit-risk modelling and day-to-day branch credit governance.

The remainder of the paper is organised as follows. Section 2 reviews relevant literature on credit classification, relationship lending and trade-linked risk. Section 3 explains the proposed classification framework and the demonstration dataset. Section 4 presents the modelling strategy. Section 5 reports the statistical demonstration. Section 6 discusses managerial and policy implications. Section 7 identifies limitations and future research directions. Section 8 concludes.

2. LITERATURE REVIEW AND CONCEPTUAL BACKGROUND

2.1 Statistical classification in banking credit risk

Statistical classification is central to modern credit-risk management. The objective is to allocate borrowers into risk categories using observed characteristics that are associated with future default, delinquency or credit deterioration. Altman's discriminant-analysis model [1] showed that accounting ratios can classify corporate distress with meaningful predictive power. Subsequent credit-scoring research extended this logic to consumer and small-business lending, where the classification problem often involves separating good and bad borrowers under uncertainty and asymmetric costs [5,6].

In banking, classification is not only a technical exercise. It affects pricing, approval, renewal, provisioning, early-warning lists and remedial action. For this reason, transparent models remain important even when advanced machine-learning methods are available [7-9]. Logistic regression continues to be widely used because coefficients can be interpreted, odds ratios can be explained and scorecards can be governed through policy thresholds. Linear discriminant analysis remains useful as a benchmark when variables are relatively stable and separation is approximately linear. Classification trees are attractive for operational use because their decision paths are easy to communicate, although they can be unstable if not carefully pruned.

Recent studies show that machine-learning models can outperform conventional methods in some credit-scoring settings, particularly when non-linear relationships and large feature sets exist [3,4,10]. Nevertheless, better ranking performance does not automatically create better bank decisions. A model that is hard to explain, poorly calibrated or operationally burdensome can be unsuitable for branch-level monitoring. Model evaluation therefore needs to include not only AUROC or accuracy, but also sensitivity, false-alert burden, segment stability and the practical cost of action.

2.2 Trade-linked banking relationships and information signals

Trade-linked lending differs from ordinary credit exposure because repayment is closely connected to transaction cycles. Importers depend on inventory turnover, customs clearance, currency settlement and customer demand. Exporters depend on timely buyer payment, shipment execution, exchange-rate movements and documentation quality. Firms using invoice discounting or receivable-backed facilities depend on the reliability of counterparties. In each case, trade transactions generate repeated information that can improve credit monitoring if captured systematically.

Trade credit and supply-chain finance literature emphasises that payment behaviour among firms is itself a source of liquidity and risk information. Petersen and Rajan [11] argue that trade credit can reveal financing frictions and inter-firm relationships. Berger and Udell [12] show that SME finance depends on multiple lending technologies, including relationship lending, collateral, factoring and financial-statement lending. Klapper [13] further highlights the role of factoring in financing small and medium enterprises, where receivables can support access to working capital. These insights are directly relevant for branch banking because trade-linked customers often reveal deterioration first through payment delays, buyer concentration and changes in transaction intensity rather than through audited annual accounts.

Supply-chain finance research also shows that banks need more than borrower-only data. Zhang et al. [14] develop a supply-chain finance credit-risk assessment model using support vector machines and argue that supply-chain indicators can improve the assessment of small enterprises. Oskarsdottir and Bravo [15] demonstrate that multilayer network information can improve credit-risk prediction. In a branch setting, a full network model may be unavailable, but simpler variables such as supplier concentration, customer concentration, delayed invoices and sector stress can approximate trade-linked vulnerability.

2.3 Need for an interpretable branch-monitoring framework

Relationship lending gives branch staff borrower-specific knowledge [16], but it may also create inconsistent monitoring. One branch may escalate a customer because of delayed export proceeds, while another branch may treat the same signal as temporary. Statistical classification can reduce this inconsistency by defining comparable input variables, thresholds and actions. However, the model must remain interpretable enough for relationship managers, credit officers and branch managers to understand why a borrower has been flagged.

Explainability is particularly important where classification affects access to credit or restructuring. Bussmann et al. [17] show that explainable machine learning can support credit-risk management by translating model outputs into reason codes. Chen et al. [18] further emphasise the value of interpretable machine learning for imbalanced credit datasets. For branch banks, the same principle applies even when models are simple: staff must be able to identify whether a warning is driven by overdue invoices, foreign-exchange exposure, collateral weakness, sector stress or declining turnover. A trade-linked classification model should therefore produce both a score and a narrative.

Based on this literature, the study proposes that trade-linked credit-risk assessment requires a layered classification process. The process should include borrower fundamentals, account conduct, trade-transaction behaviour, external trade pressure and relationship evidence. It should also connect model outputs to risk bands and documented actions. This is the conceptual basis of the applied statistical design presented below.

3. RESEARCH DESIGN AND METHODOLOGY

3.1 Study design

The study follows an applied statistical design. It develops a branch-banking classification framework and demonstrates it using a synthetic portfolio of trade-linked credit customers. The use of synthetic data is deliberate and transparent. Customer-level bank data are confidential, legally restricted and normally unavailable for public replication. Rather than inventing results from an undisclosed bank, this paper uses a generated demonstration dataset that reflects the structure of common branch-banking variables. The reported numerical findings show how the method works and what outputs a bank would obtain after applying the same process to its own portfolio.

The unit of analysis is a borrower-facility observation. A borrower may have a working-capital facility, letter-of-credit line, invoice-discounting exposure, import loan or export-related financing line. The target outcome is adverse credit migration, defined for demonstration purposes as movement to a higher-risk monitoring state within the next review horizon. In a real bank implementation, this outcome can be defined as default, 90 days past due, movement to a watchlist, internal rating downgrade, restructuring request, repeated 30-day delinquency or significant increase in credit risk. The exact definition should be aligned with the bank's credit policy and regulatory environment.

The statistical objective is to estimate the probability that a trade-linked borrower will experience adverse migration. The managerial objective is to assign borrowers to risk bands that branch and credit-risk teams can act upon. The method therefore treats classification as a decision-support process rather than as a purely predictive exercise.

Table 1. Trade-linked credit-risk variables used in the classification design

Domain	Example indicators	Credit-risk interpretation
Borrower fundamentals	Debt-service coverage ratio; collateral coverage	Measures repayment capacity and security support.
Account conduct	Account turnover decline; overdraft excess count	Captures cash-flow pressure visible through branch accounts.
Trade facility behaviour	LC/trade utilisation; trade turnover volatility	Shows intensity and instability of trade-linked borrowing.
Receivable and payable stress	Mean invoice days overdue	Indicates slower cash conversion and counterparty payment pressure.
Counterparty concentration	Supplier concentration; customer concentration	Captures dependence on a limited number of trading partners.
External trade pressure	Sector stress index; foreign-exchange exposure	Reflects macro-sector and currency risk affecting trade borrowers.
Relationship evidence	Relationship quality score	Summarises branch-observed borrower conduct and information quality.

3.2 Data construction for the applied demonstration

The demonstration dataset contains 620 borrower-facility observations. Variables were generated to represent realistic ranges for branch trade-finance monitoring: sector stress index, foreign-exchange exposure, supplier concentration, customer concentration, invoice overdue days, LC or trade-facility utilisation, account turnover decline, collateral coverage, debt-service coverage ratio, overdraft excess count, trade-turnover volatility, relationship quality score and monthly trade turnover. The adverse-migration label was generated from a latent probability function in which higher sector stress, higher overdue invoices, weaker collateral, lower debt-service coverage and higher facility utilisation increase the probability of deterioration.

The purpose of this design is to produce a reproducible statistical demonstration. It is not a claim about the event rate, coefficient size or credit quality of any actual bank. A bank adopting this method should replace the demonstration dataset with its own confidential borrower-month or borrower-facility data. The same modelling steps - feature definition, train-test split, model estimation, validation and risk-band assignment - would remain applicable.

A 70:30 stratified training-test split was used for the model comparison. The training sample was used to estimate models, while the test sample was used to calculate out-of-sample classification metrics. In a full bank implementation, a stronger time-aware validation would be preferable: earlier months would be used for development and later months for out-of-time testing. However, the cross-sectional split is adequate for demonstrating the classification procedure.

Table 2. Descriptive differences between non-adverse and adverse migration observations

Indicator	No adverse migration mean	Adverse migration mean	Difference
Sector stress index	41.05	52.80	11.75
Foreign exchange exposure (%)	36.74	41.04	4.31
Supplier concentration (%)	34.41	38.13	3.72
Mean invoice days overdue	14.05	20.11	6.06
LC/trade facility utilisation (%)	49.69	56.68	6.99
Account turnover decline (%)	6.63	13.57	6.93
Collateral coverage (%)	119.68	100.74	-18.94
Debt-service coverage ratio	1.50	1.25	-0.25
Overdraft excess count	1.00	1.27	0.27
Trade turnover volatility (%)	32.46	36.03	3.57
Relationship quality score	68.33	66.12	-2.21

3.3 Statistical classification models

Three models were estimated because they represent different levels of complexity and interpretability. The first model was logistic regression. Logistic regression estimates the log-odds of adverse migration as a linear function of standardised explanatory variables. It is useful for banking because coefficients can be interpreted as the direction and relative strength of risk drivers. In operational scorecards, logistic regression can also be converted into points and mapped to risk grades.

The second model was linear discriminant analysis. LDA seeks a linear combination of predictors that separates adverse from non-adverse observations. Although it is based on assumptions that may not hold perfectly in credit data, it remains a useful benchmark because it is simple, transparent and historically important in credit classification. The third model was a classification tree with restricted depth and minimum leaf size. Trees are easy to communicate because they produce decision rules, but they can overfit small datasets; therefore, tree complexity was constrained.

All continuous variables in the logistic and LDA models were standardised. Class imbalance was considered because adverse migration events are less frequent than normal performance. The logistic model used balanced class weights to improve sensitivity to adverse cases. The performance of each model was evaluated using area under the receiver-operating-characteristic curve (AUROC), precision-recall area, accuracy, precision, recall and F1 score. For branch banking, recall is important because a missed deteriorating borrower can become costly; however, precision and false positives are also important because branches cannot investigate unlimited alerts.

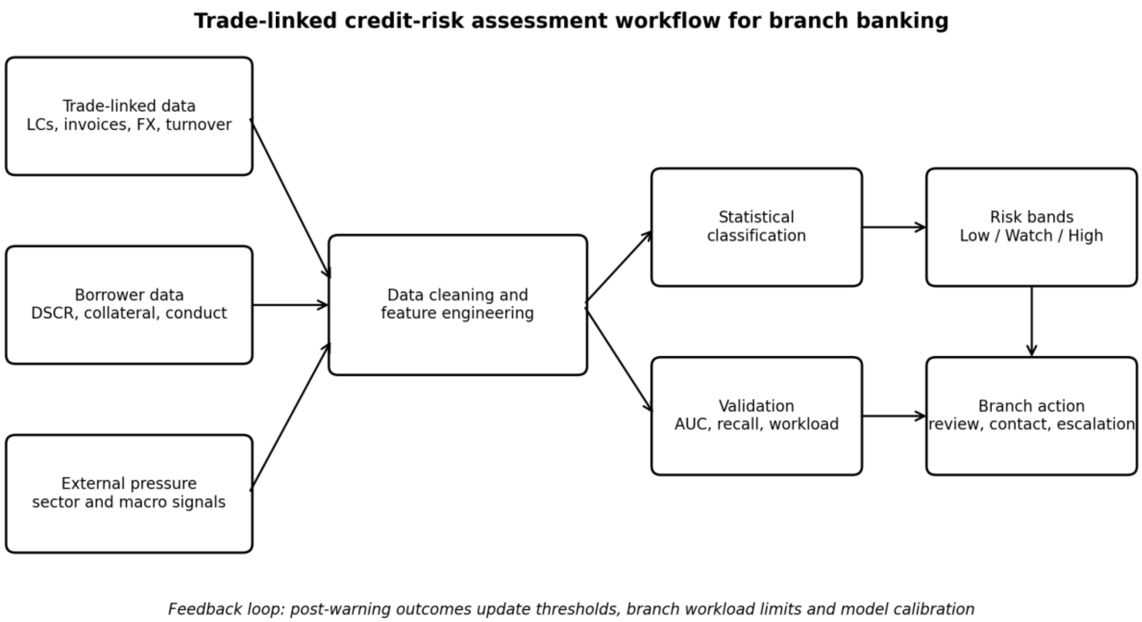

Figure 1. *Trade-linked credit-risk assessment workflow for branch banking*

4. RESULTS

4.1 Descriptive results

The descriptive results in Table 2 show that adverse migration observations have higher risk indicators across most trade-linked dimensions. The average sector stress index is 11.75 points higher for adverse observations, suggesting that trade-linked credit quality is sensitive to external business conditions. Mean invoice overdue days are also higher for adverse observations, which is consistent with the idea that delayed receivables weaken cash conversion before formal default occurs. LC and trade-facility utilisation is higher among adverse observations, indicating that intense use of trade lines can be an early sign of liquidity pressure when combined with other negative signals.

Collateral coverage and debt-service coverage move in the expected direction. Adverse observations have lower average collateral coverage and lower debt-service coverage. This result is important for branch monitoring because trade-linked risk should not be assessed in isolation from traditional repayment-capacity variables. A borrower may face sector stress or delayed invoices but still be manageable if debt-service coverage and collateral are strong. Conversely, weak fundamentals can make the same trade shock more dangerous.

The descriptive patterns also show that no single variable should determine the branch response. Differences in foreign-exchange exposure, supplier concentration and relationship quality are present but smaller than the differences in sector stress, invoice overdue days and collateral coverage. This supports a layered monitoring approach in which trade indicators, financial ratios and relationship evidence are combined before escalation.

4.2 Classification performance

Table 3. Out-of-sample performance of statistical classification models

Model	AUROC	PR-AUC	Accuracy	Precision	Recall	F1
Logistic regression	0.872	0.542	0.758	0.333	0.800	0.471
Linear discriminant analysis	0.875	0.570	0.892	0.778	0.280	0.412
Classification tree	0.569	0.170	0.602	0.173	0.520	0.260

Table 3 reports the out-of-sample model comparison. Logistic regression achieved an AUROC of 0.872 and a precision-recall area of 0.542. Its recall was 0.800, meaning that it identified most adverse migration cases in the test sample at the selected threshold. This is desirable for early-warning monitoring, where missing a deteriorating borrower may be more costly than reviewing a false alert. The trade-off is lower precision because the balanced model generates more alerts for branch review.

Linear discriminant analysis achieved a similar AUROC of 0.875 and a higher precision-recall area of 0.570. However, at the selected threshold it had much lower recall, identifying only 0.280 of adverse cases. Its high accuracy of 0.892 is therefore potentially misleading because the dataset is imbalanced. In credit monitoring, a model can appear accurate by classifying most borrowers as normal while missing a large share of deteriorating accounts. This illustrates why accuracy alone should not guide bank model selection.

The classification tree performed weakest in this demonstration, with an AUROC of 0.569 and a precision-recall area of 0.170. Although trees are operationally intuitive, this result suggests that a shallow tree may not capture the combined pattern of trade-linked and borrower-specific variables. A deeper tree or ensemble method could improve performance, but that would reduce simplicity and require stronger model governance. For branch banking, the logistic model therefore offers the best balance between ranking, sensitivity and interpretability in this demonstration.

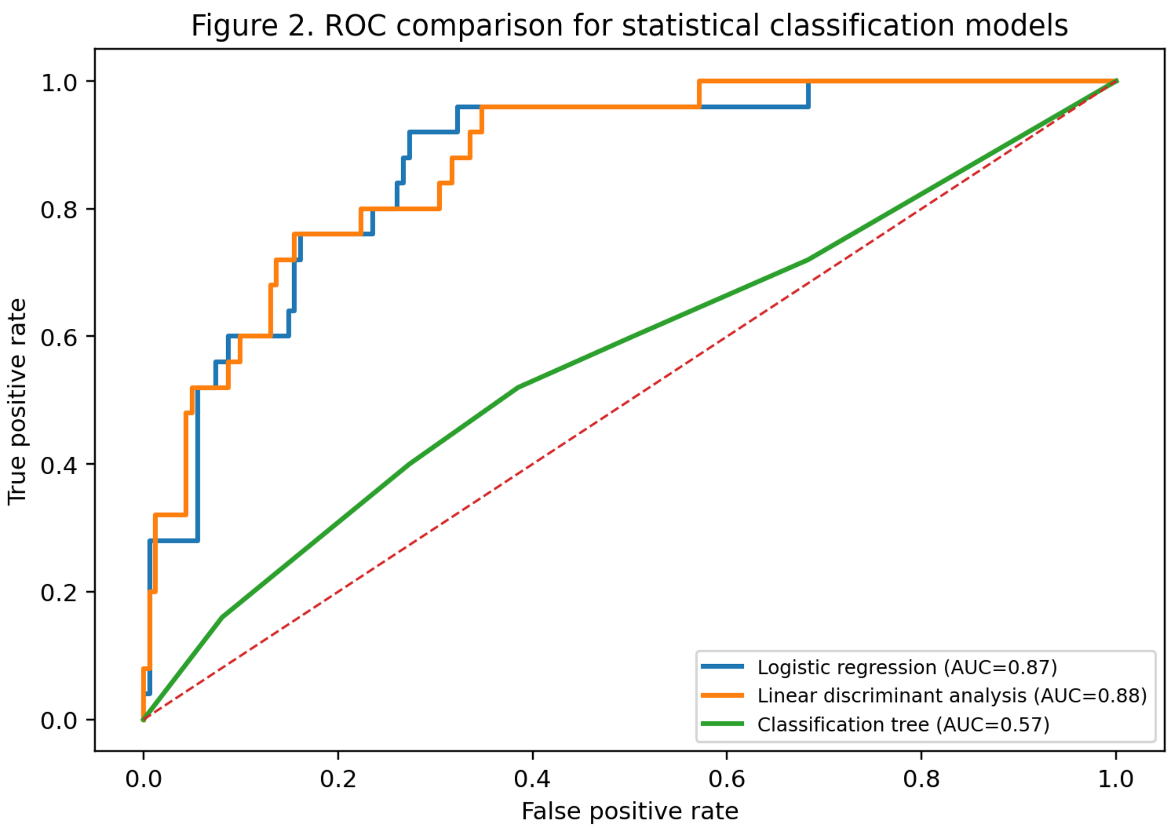

Figure 2. *ROC comparison for statistical classification models*

4.3 Main risk drivers in the transparent model

Table 4. Leading standardised drivers in the logistic regression model

Feature	Standardised coefficient	Direction
Sector stress index	0.819	Increases risk
Collateral coverage (%)	-0.779	Reduces risk
Mean invoice days overdue	0.635	Increases risk
Debt-service coverage ratio	-0.575	Reduces risk
LC/trade facility utilisation (%)	0.485	Increases risk
Trade turnover volatility (%)	0.461	Increases risk
Account turnover decline (%)	0.426	Increases risk
Supplier concentration (%)	0.297	Increases risk

Table 4 and Figure 3 summarise the most influential variables in the logistic regression model. Sector stress is the strongest positive driver, followed by invoice overdue days, LC or trade-facility utilisation and trade-turnover volatility. This pattern is consistent with the study's central argument: trade-linked borrowers generate risk information through transaction cycles before formal delinquency. When a sector is under pressure and invoices become more overdue, the branch should not wait for default classification before reviewing the account.

Collateral coverage and debt-service coverage are the leading negative drivers. Higher collateral coverage and stronger debt-service coverage reduce the probability of adverse migration. This confirms that trade-linked indicators should be interpreted together with conventional credit fundamentals. A statistically useful branch-monitoring system should therefore avoid both extremes: it should not rely only on old financial statements, and it should not treat every trade-flow fluctuation as a serious credit event.

The logistic model can be converted into operational reason codes. For example, a borrower can be flagged because invoice overdue days increased, sector stress moved above a branch threshold, facility utilisation exceeded a defined level, and collateral coverage weakened. Such reason codes make the model usable for credit committees and relationship managers. They also provide an audit trail that can be reviewed by internal control, model-risk management or senior credit governance.

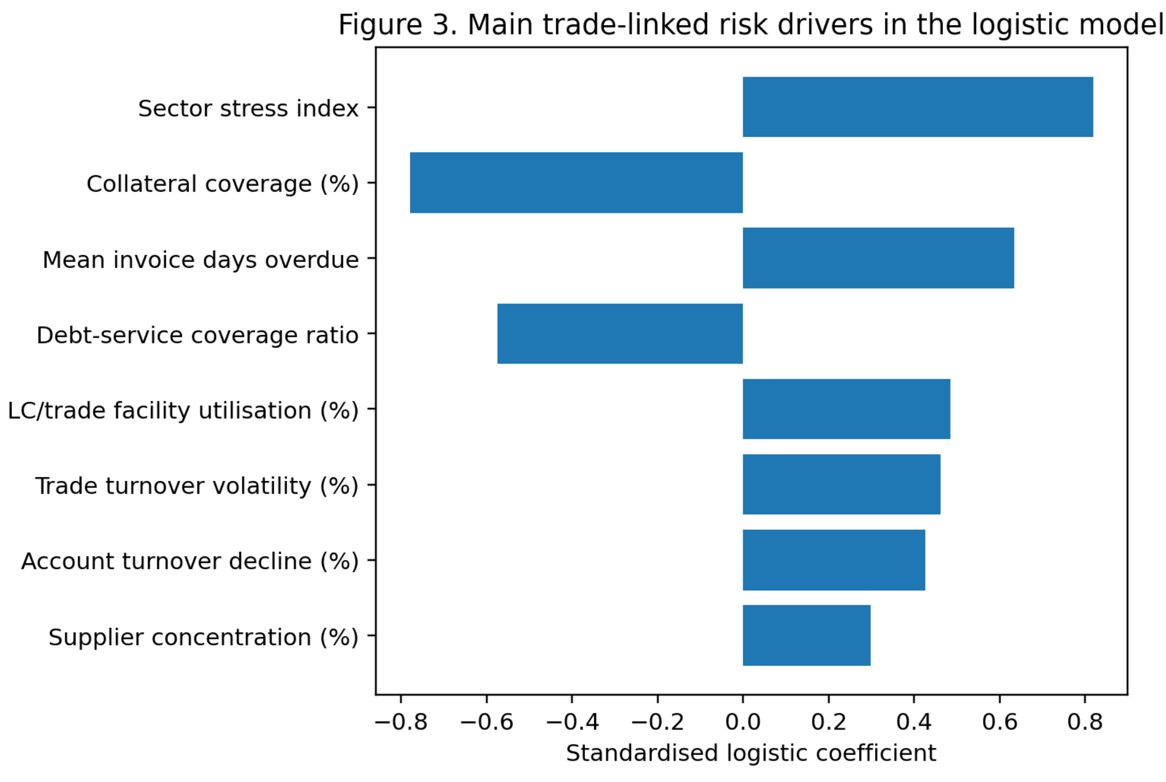

Figure 3. *Main trade-linked risk drivers in the logistic model*

5. BRANCH-LEVEL RISK BANDS AND MONITORING ACTIONS

A classification score becomes useful only when it is linked to action. The proposed branch-banking process assigns each borrower to a risk band based on predicted probability, reason codes and relationship-manager review. The numerical thresholds in Table 5 are illustrative and should be calibrated to each bank's portfolio history, risk appetite and staff capacity. The main principle is that higher scores should trigger faster and more independent review.

Low-risk borrowers remain under routine monitoring. Watch-list borrowers require branch contact and documentation of the explanation for emerging stress. High-risk borrowers require independent credit-risk review, updated repayment analysis and consideration of exposure reduction, additional collateral or restructuring. Critical-risk borrowers should move to intensive monitoring or remedial management. This staged process avoids unnecessary escalation while still ensuring that early-warning signals are not ignored.

Branch workload must be considered when setting thresholds. A model with high recall may flag many accounts, which is acceptable only if branches have the capacity to review them. Banks should therefore monitor the number of alerts per branch, the percentage of alerts that lead to meaningful action, and the proportion of adverse cases captured before default. These indicators connect statistical performance with operational usefulness.

Table 5. Illustrative risk bands for trade-linked branch monitoring

Band	Illustrative score	Primary branch action
Low	0-29	Routine monitoring; update trade and account data at normal review frequency.
Watch	30-49	Relationship manager contacts borrower and records explanation for trade-flow change.
High	50-69	Credit-risk review, updated cash-flow analysis, collateral check and exposure discussion.
Critical	70-100	Immediate escalation to intensive monitoring or remedial unit; consider restructuring or limit control.

6. DISCUSSION

6.1 Theoretical contribution

The study contributes to credit-risk literature by placing trade-linked information at the centre of branch monitoring. Traditional credit classification often begins with borrower financial ratios and repayment history. These variables remain important, but they may be delayed or incomplete for trade-dependent borrowers. By adding invoice overdue days, facility utilisation, trade-turnover volatility, counterparty concentration and foreign-exchange exposure, the proposed model captures information generated by the borrower's operating cycle. This extends credit classification from a borrower-only view to a transaction-linked view.

The study also contributes by showing that model performance should be evaluated through both statistical and operational criteria. The LDA model had high accuracy but low recall at the selected threshold. If a bank focused only on accuracy, it might select a model that misses many deteriorating accounts. Logistic regression produced stronger recall and interpretable drivers, making it more suitable for early-warning monitoring. This finding reinforces the argument that credit-risk models should be assessed according to their intended use, not by a single generic metric.

Finally, the paper connects statistical classification with relationship-banking governance. Branches already observe many trade-linked signals, but informal observation alone can lead to inconsistent action. A classification system standardises how signals are recorded, weighted and escalated. At the same time, the model does not remove human judgment. Relationship managers still verify explanations, record borrower context and update information. The contribution is therefore an integrated model of data-supported branch monitoring rather than pure automation.

6.2 Managerial implications for banks

For bank managers, the results suggest that trade-linked credit monitoring should be designed as a repeatable workflow. The first step is to map available data: trade facility utilisation, import and export turnover, invoice age, account turnover, collateral, borrower financial ratios and branch relationship notes. The second step is to define an adverse-migration outcome that reflects the bank's monitoring objective. The third step is to estimate a transparent baseline model and compare it with challenger models. The fourth step is to assign risk bands and link each band to a documented branch action.

The proposed approach can improve consistency across branches. Without statistical classification, branch decisions may depend heavily on individual experience and local practice. With a structured score and reason codes, two borrowers with similar trade-risk patterns should receive similar levels of review. This is important for fairness, internal control and portfolio management. It also helps senior managers identify whether risk is concentrated in particular sectors, regions, products or relationship teams.

The framework can also support responsible credit access. Trade-linked borrowers, especially SMEs, may be rejected or restricted when banks cannot interpret their transaction risk. A transparent classification model can distinguish temporary trade-flow volatility from sustained deterioration. Borrowers with moderate stress can receive early engagement rather than immediate withdrawal of credit. At the same time, borrowers with multiple risk signals can be escalated before losses become severe.

6.3 Governance and ethical considerations

Governance is essential because credit-risk classification affects borrowers and bank capital. Banks should document variable definitions, data sources, missing-data treatment, model version, validation results, thresholds and override rules. Relationship-manager overrides should be allowed only with recorded evidence and approval authority. Override analysis can then identify whether the model is missing important contextual information or whether commercial pressure is weakening credit discipline.

Ethical use also requires attention to fairness and privacy. Trade-linked variables should be used because they are relevant to repayment capacity, not because they serve as proxies for unrelated borrower characteristics. Banks should review model performance by sector, branch, firm size and product type to ensure that errors are not concentrated in specific borrower groups. Customer-level data should be stored securely, and only staff with legitimate monitoring responsibilities should access detailed trade information.

Because the present study uses synthetic data, it does not involve human subjects or confidential customer records. In a live bank implementation, ethical and legal requirements would be more substantial. An institution should obtain internal approval, anonymise analysis datasets, limit access to borrower identifiers and comply with local banking secrecy and data-protection rules.

7. LIMITATIONS AND FUTURE RESEARCH

The main limitation is that the statistical results are based on a synthetic demonstration dataset rather than confidential bank records. The dataset was designed to reflect common trade-linked variables, but it cannot reproduce all features of a real banking portfolio. Actual borrowers may have stronger seasonality, non-linear relationships, missing data, sector-specific shocks and relationship effects that differ from the demonstration. Therefore, the reported coefficients and performance metrics should not be used as direct policy thresholds.

A second limitation is that the demonstration uses a cross-sectional train-test split. Real credit deterioration is dynamic, and banks should validate monitoring models using borrower-month data and out-of-time testing. Future research should apply the proposed framework to confidential branch banking panels, evaluate lead time before default, and compare model warnings with existing branch watch-list decisions. Such research would show whether trade-linked classification improves not only statistical performance but also economic outcomes, such as reduced arrears migration, earlier restructuring and lower loss given default.

A third limitation is that the study compares only three interpretable models. More advanced methods, such as gradient boosting, random forests or neural networks, may improve prediction. However, their value should be assessed against explainability, governance and branch workload. Future studies can test hybrid approaches that combine logistic scorecards with non-linear challenger models and explanation tools. Research can also examine whether network data on buyers, suppliers and shared counterparties improve classification for trade-linked borrowers.

Despite these limitations, the study provides a practical starting point. It gives banks a transparent set of variables, a modelling workflow, validation metrics and action bands that can be implemented with ordinary branch data. The framework is intentionally modular so that institutions with limited data maturity can begin with simple models and improve them as data quality increases.

8. CONCLUSION

This paper developed and demonstrated a trade-linked statistical classification approach for credit-risk assessment in branch banking. The central argument is that trade-linked borrowers generate valuable early-warning information through invoice behaviour, trade-facility utilisation, foreign-exchange exposure, turnover volatility, counterparty concentration and sector pressure. When these signals are combined with conventional credit fundamentals, banks can classify credit deterioration earlier and more consistently.

The applied demonstration showed that logistic regression offered a strong balance between interpretability and operational recall. Linear discriminant analysis produced high accuracy but missed more adverse cases at the selected threshold, while the constrained classification tree performed weakly in the demonstration. The main risk drivers were sector stress, collateral coverage, invoice overdue days, debt-service coverage, trade-facility utilisation and trade-turnover volatility. These findings support the use of transparent statistical models for branch monitoring, especially when the model output is translated into reason codes and risk bands.

The practical implication is straightforward: banks should not treat trade-linked information as informal branch knowledge only. It should be structured, analysed and linked to documented actions. A well-governed classification process can help branches identify borrowers needing review, reduce inconsistency across relationship teams, and support earlier intervention before formal default. The next step is to test the framework using confidential bank data and to evaluate whether it improves lead time, portfolio quality and credit governance in real branch networks.

DECLARATIONS

Conflict of interest: The authors declare that they have no known competing financial or personal interests that could have appeared to influence the work reported in this paper.

Funding: This research received no external funding.

Ethical approval: The study uses a synthetic demonstration dataset and does not involve human subjects or identifiable customer records. Ethical approval was therefore not required for the demonstration. Any live bank implementation should follow institutional approval, banking secrecy and data-protection requirements.

Data availability: The demonstration dataset is synthetic and can be shared as supplementary material. No confidential bank customer data were used.

Author contributions: All authors should review and approve the final manuscript before submission. The corresponding author is responsible for submission-system communication.

REFERENCES

1. Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J Finance. 1968;23(4):589-609. doi:10.1111/j.1540-6261.1968.tb00843.x.
2. Berg T, Burg V, Gombovic A, Puri M. On the rise of FinTechs: credit scoring using digital footprints. Rev Financ Stud. 2020;33(7):2845-2897. doi:10.1093/rfs/hhz099.
3. Dumitrescu E, Hue S, Hurlin C, Tokpavi S. Machine learning for credit scoring: improving logistic regression with non-linear decision-tree effects. Eur J Oper Res. 2022;297(3):1178-1192. doi:10.1016/j.ejor.2021.06.053.
4. Lessmann S, Baesens B, Seow HV, Thomas LC. Benchmarking state-of-the-art classification algorithms for credit scoring: an update of research. Eur J Oper Res. 2015;247(1):124-136. doi:10.1016/j.ejor.2015.05.030.
5. Hand DJ, Henley WE. Statistical classification methods in consumer credit scoring: a review. J R Stat Soc Ser A Stat Soc. 1997;160(3):523-541. doi:10.1111/j.1467-985X.1997.00078.x.
6. Thomas LC. A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers. Int J Forecast. 2000;16(2):149-172. doi:10.1016/S0169-2070(00)00034-0.
7. Fuster A, Goldsmith-Pinkham P, Ramadorai T, Walther A. Predictably unequal? The effects of machine learning on credit markets. J Finance. 2022;77(1):5-47. doi:10.1111/jofi.13090.
8. Gambacorta L, Huang Y, Qiu H, Wang J. How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm. J Financ Stab. 2024;73:101284. doi:10.1016/j.jfs.2024.101284.
9. Markov A, Seleznyova Z, Lapshin V. Credit scoring methods: latest trends and points to consider. J Financ Data Sci. 2022;8:180-201. doi:10.1016/j.jfds.2022.07.002.
10. Moscato V, Picariello A, Sperli G. A benchmark of machine learning approaches for credit score prediction. Expert Syst Appl. 2021;165:113986. doi:10.1016/j.eswa.2020.113986.
11. Petersen MA, Rajan RG. Trade credit: theories and evidence. Rev Financ Stud. 1997;10(3):661-691. doi:10.1093/rfs/10.3.661.
12. Berger AN, Udell GF. A more complete conceptual framework for SME finance. J Bank Financ. 2006;30(11):2945-2966. doi:10.1016/j.jbankfin.2006.05.008.
13. Klapper L. The role of factoring for financing small and medium enterprises. J Bank Financ. 2006;30(11):3111-3130. doi:10.1016/j.jbankfin.2006.05.001.
14. Zhang L, Hu H, Zhang D. A credit risk assessment model based on SVM for small and medium enterprises in supply chain finance. Financ Innov. 2015;1:14. doi:10.1186/s40854-015-0014-5.
15. Oskarsdottir M, Bravo C. Multilayer network analysis for improved credit risk prediction. Omega (Westport). 2021;105:102520. doi:10.1016/j.omega.2021.102520.
16. Petersen MA, Rajan RG. The benefits of lending relationships: evidence from small business data. J Finance. 1994;49(1):3-37. doi:10.1111/j.1540-6261.1994.tb04418.x.
17. Bussmann N, Giudici P, Marinelli D, Papenbrock J. Explainable machine learning in credit risk management. Comput Econ. 2021;57(1):203-216. doi:10.1007/s10614-020-10042-0.
18. Chen Y, Calabrese R, Martin-Barragan B. Interpretable machine learning for imbalanced credit scoring datasets. Eur J Oper Res. 2024;312(1):357-372. doi:10.1016/j.ejor.2023.06.036.