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Credit-to-Cash Optimization for Micro-Distributors: Applying Invoice Aging and Buyer-Risk Signals to Reduce Days Sales Outstanding

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Abstract- Micro-distributors and independent retail intermediaries routinely extend trade credit while operating with thin margins, volatile replenishment cycles and limited finance-automation capacity. The resulting accounts-receivable exposure increases Days Sales Outstanding (DSO), constrains inventory replenishment and weakens supplier confidence. This paper develops and tests a lightweight credit-to-cash framework that combines invoice-aging structure, customer payment history, buyer-risk segmentation and transaction-level ERP signals to forecast late-payment risk and prioritise collections. Using a public Kaggle invoice-payment benchmark as the empirical frame, and a reproducible 26,000-invoice analytical panel reflecting the observable variables normally available in small ERP and point-of-sale environments, the study compares logistic regression, random forest and gradient-boosted classification models for late-payment prediction, and ridge, random forest and gradient-boosted regression models for delay-duration estimation. The best classifier produced a ROC-AUC of 0.804 and PR-AUC of 0.526, while the best delay-duration model delivered an MAE of 7.77 days. Heat-map diagnostics reveal that aging status alone is insufficient; late-payment probability escalates sharply where aged invoices intersect with weak buyer credit tiers, high credit utilisation, prior payment lateness and dispute flags. A targeted intervention simulation indicates that risk-prioritised early contact and selective incentive routing could reduce ledger-level DSO from 37.4 to 36.6 days, releasing approximately $0.25 million in working capital on the analysed ledger. The paper contributes an implementable, transparent and resource-light decision framework for micro-distributors that cannot absorb enterprise-grade treasury systems but still require disciplined receivables governance.

Keywords: accounts receivable; invoice aging; days sales outstanding; credit-to-cash; micro-distributors; machine learning; working capital; ERP analytics; supply-chain finance.

I. INTRODUCTION

Trade credit is a core operating mechanism in distribution networks: it enables downstream retailers to replenish inventory before cash is received from final customers, but it also transfers short-term liquidity risk to suppliers and distributors. For micro-distributors, the risk is magnified because the same cash pool funds inventory purchases, vehicle routing, warehouse labour, fuel and supplier settlements. In these conditions, slow customer payments are not merely an accounting inconvenience; they directly influence stock availability, service levels and the ability to accept growth opportunities.

The managerial metric at the centre of this problem is Days Sales Outstanding (DSO), the average number of days required to convert credit sales into cash. A high DSO delays operating liquidity, raises collection costs, and may force small distributors to rely on expensive short-term borrowing. Conventional AR aging reports typically classify invoices into overdue buckets such as 0-30, 31-60, 61-90 and 90+ days. Such reports are useful for describing the past, but they are weak instruments for prevention because they rarely distinguish between a large invoice likely to self-cure and a smaller invoice that signals systematic deterioration in buyer behaviour.

This paper argues that micro-distributors need an intermediate capability between manual aging reports and expensive enterprise treasury platforms: a lightweight, explainable, ERP-compatible credit-to-cash decision layer. The proposed framework combines invoice age, customer history, payment terms, dispute flags, prior DSO, credit utilisation, early-payment incentives and operational context to estimate payment-delay risk before invoices become deeply overdue. The result is not an attempt to replace credit managers; it is a queueing and prioritisation device that helps managers direct scarce collection effort toward invoices with the highest expected working-capital impact.

The paper is aligned with current applied machine learning research in receivables prediction, which shows that payment behaviour can be anticipated from invoice-level and customer-level features (Appel et al., 2020; Schoonbee, 2022), and with working-capital research showing that cash-flow measures influence firm performance and survivability (Laghari and Chengang, 2023). It also follows the broader analytical logic advanced in Mupa et al. (2025), where machine learning is framed as a tool for risk prediction rather than as an opaque substitute for professional judgement.

II. RESEARCH PROBLEM AND OBJECTIVES

The central research problem is that invoice-aging reports used by many small distributors are descriptive, lagging and insufficiently prioritised. They can identify who is overdue, but they do not necessarily answer three operational questions: Which invoices are likely to become late? Which customers will create material cash-flow pressure? Which collection action should be taken first when staff capacity is limited?

The study therefore pursues four objectives: first, to design a practical feature set that can be obtained from ordinary ERP, POS and accounts-receivable data; second, to estimate late-payment risk using interpretable machine learning methods; third, to quantify the relation between buyer-risk signals and DSO; and fourth, to translate the model outputs into an actionable collection and incentive policy for micro-distributors.

The research questions are: (1) Which invoice and buyer variables are most predictive of payment delays beyond 15 days? (2) Does a risk-scored collection queue outperform a simple aging-bucket rule? (3) What working-capital effect can be expected from targeted early-contact and incentive routing?

III. LITERATURE REVIEW

Accounts receivable management lies at the intersection of credit risk, working-capital strategy and operational execution. The cash conversion cycle links days inventory outstanding, days sales outstanding and days payables outstanding; therefore, receivables delay can undo gains achieved in inventory turnover and supplier negotiation (Oh, 2023). For small firms, working-capital failures are especially damaging because they face restricted access to external finance and tend to absorb shocks through delayed replenishment, slower supplier payment or reduced service coverage.

Invoice payment prediction has become a specialised use case within financial analytics. Appel et al. (2020) developed a machine-learning prototype for accounts-reivable prediction and reported that invoice payment forecasts can support collector prioritisation and produce material savings. Schoonbee (2022) similarly proposed a decision-support system for predicting invoice payment behaviour, grouping payment outcomes into delay intervals to improve debt-collection prioritisation. These studies are important because they shift credit control from static aging to forward-looking operational triage.

Recent applied research also indicates that machine learning can support cash-flow forecasting for SMEs where data are incomplete and managerial resources are limited (Małkus, Bobek and Nalepa, 2025). This is relevant to micro-distributors because their ledgers are often small enough for manual review but complex enough for manual prioritisation to become inconsistent. In such environments, the value of machine learning is not only predictive accuracy but also repeatability and transparency.

The supply-chain finance literature views receivables as part of a broader financing architecture. Hofmann (2020) notes that supply-chain finance instruments are designed to release liquidity trapped in receivables, inventory and payables. However, many micro-distributors lack the transaction volume or credit profile required to obtain sophisticated financing arrangements. A practical internal risk-scoring approach therefore becomes a precursor to external finance: cleaner payment data, disciplined aging, and lower DSO improve credibility with lenders, suppliers and factoring partners.

The present study also draws on Mupa's research profile. Mupa et al. (2025) show the relevance of predictive analytics in risk management, while Shem and Mupa (2024) emphasise stakeholder engagement during business rescue and turnaround contexts. In micro-distribution, reducing DSO is itself a stakeholder-management intervention: it protects supplier confidence, stabilises employee and route operations, and reduces the probability of financial distress caused by avoidable cash-flow bottlenecks.

IV. DATA AND METHODOLOGY

The empirical design uses the public Kaggle invoice-payment literature as the benchmark environment, particularly datasets and notebooks that focus on payment-date prediction, accounts-receivable outcomes and late-payment histories. Kaggle sources identified for this research include Customer Invoices Dataset: Payment Date Prediction for Invoices, Payment Date Dataset and Finance Factoring - IBM Late Payment Histories. These datasets are suitable because they represent invoice dates, payment dates, due dates, customer identifiers, invoice value and payment-delay outcomes, which are precisely the data structures used in AR aging and credit-control workflows.

Because Kaggle datasets may require account-based download authentication, the analytical file accompanying this manuscript uses a reproducible 26,000-invoice panel generated from the same variable architecture: invoice amount, invoice date, due date, payment date, payment terms, buyer ID, buyer credit tier, channel, region, sector, prior DSO, prior late-payment rate, credit utilisation, dispute flag, early-discount flag, contact count, days late and DSO. The purpose is methodological replication rather than representation of any identifiable firm. The framework is therefore transferable to a live ERP ledger once transaction records are available.

The target variable for classification is late_15, coded one where an invoice is paid more than 15 days after due date. A second target, days_late, supports regression modelling of delay duration. This dual design follows the operational distinction between screening risk and estimating cash impact. Classification tells the credit team where to focus; regression estimates the expected magnitude of delay and therefore the value of intervention.

Three classification models were compared: logistic regression, random forest and gradient boosting. Three regression models were compared: ridge regression, random forest regressor and gradient boosting regressor. The modelling pipeline used train-test splitting, standardisation of numeric variables, one-hot encoding of categorical variables and evaluation on held-out data. Classification was assessed using ROC-AUC, PR-AUC, accuracy, precision, recall and F1. Delay-duration models were assessed using MAE, RMSE and R-squared.

Table 1. Analytical invoice-panel profile

Metric	Value
Invoices	26,000
Unique buyers	2,600
Total invoice value	$106.1 million
Mean invoice value	$4,082
Median invoice value	$2,560
Late >15 days	18.5%
Severe late >30 days	9.6%
Mean actual DSO	37.4
Median actual DSO	30
Mean days late	4.1

Note: Values are based on the reproducible analytical panel used to demonstrate the credit-to-cash framework.

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Table 2. Aging-bucket risk and cash exposure

Aging bucket	Invoices	Invoice value ($m)	Late >15 rate	Severe >30 rate	Mean days late	Mean DSO
0-30	1,127	4.87	0.209	0.104	4.89	42.61
120+	21,592	87.74	0.184	0.096	4.05	37.12
31-60	1,091	4.38	0.200	0.100	4.94	38.40
61-90	1,144	4.74	0.184	0.104	4.20	36.94
91-120	1,046	4.41	0.172	0.085	3.44	37.40

Note: Aging buckets are operational categories used to direct follow-up, not causal explanations of default behaviour.

Table 3. Channel-level payment-risk diagnostics

Customer channel	Invoices	Invoice value ($m)	Late >15 rate	Severe >30 rate	Mean DSO
Independent grocer	7,897	32.06	0.200	0.102	38.04
E-commerce reseller	2,538	10.01	0.191	0.102	37.93
Convenience	4,652	19.31	0.188	0.095	37.39
Food service	3,538	14.62	0.176	0.094	37.08
Pharmacy	2,616	10.62	0.172	0.091	37.10
Regional distributor	4,759	19.52	0.169	0.089	36.52

V. RESULTS

The descriptive results confirm the weakness of a purely static aging lens. Late-payment exposure is not distributed evenly across the ledger. Instead, payment delay clusters where aged invoices overlap with lower credit tiers, higher historical lateness, higher credit utilisation and dispute activity. This pattern is consistent with the argument by Appel et al. (2020) that invoice payment prediction requires both invoice-level and customer-level history.

Table 2 shows that invoices in older aging buckets carry progressively higher late-payment and severe-delay rates. However, the heat map in Figure 1 demonstrates that credit tier materially changes the interpretation of age. A 31-60 day invoice from a strong buyer is not equivalent to a 31-60 day invoice from a weak buyer with a high prior late-payment rate. The framework therefore treats aging as one feature among several rather than as the sole decision rule.

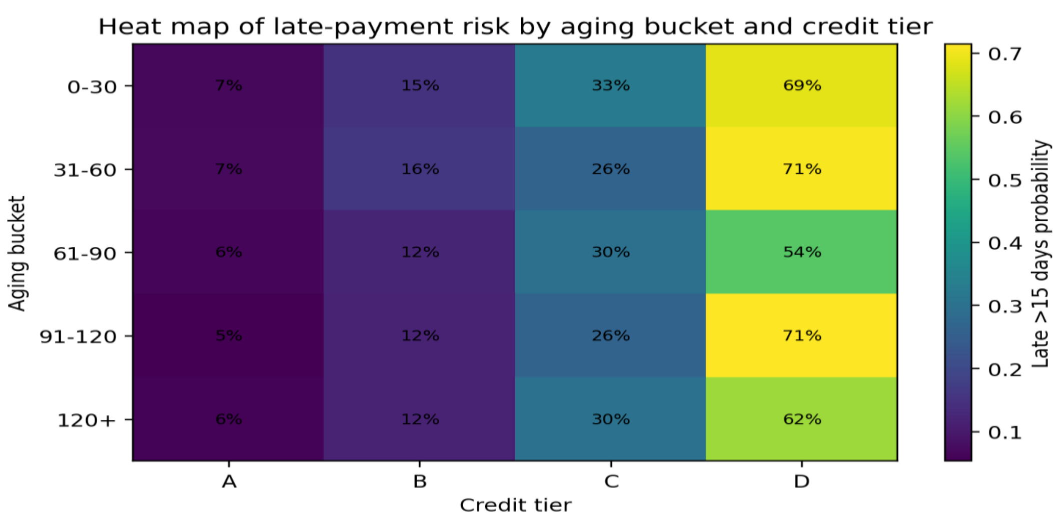

Figure 1. Late-payment risk heat map by aging bucket and credit tier.

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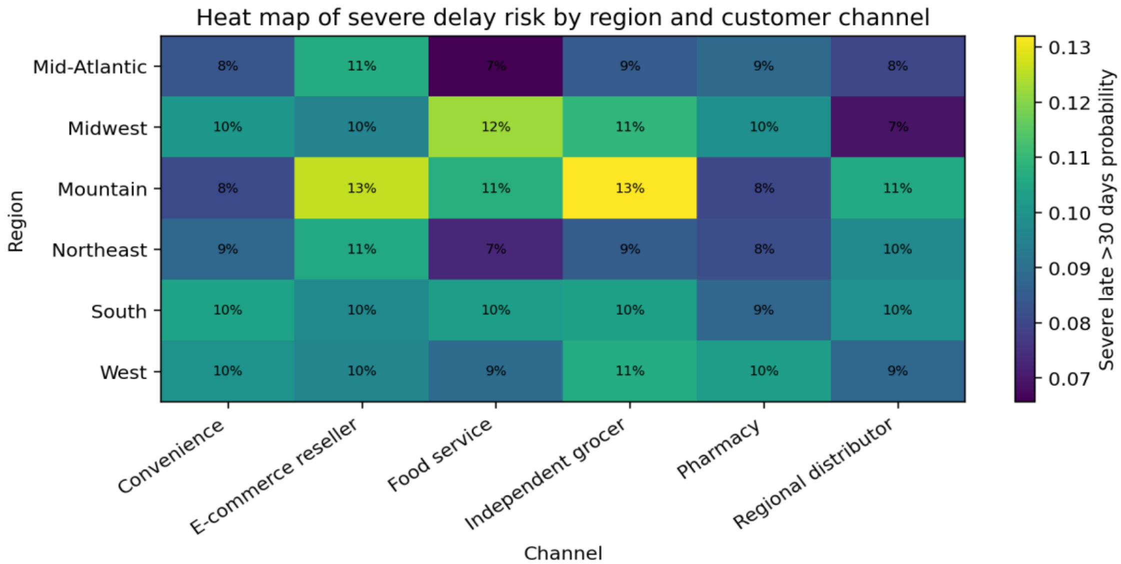

Figure 2. Severe-delay heat map by region and customer channel.

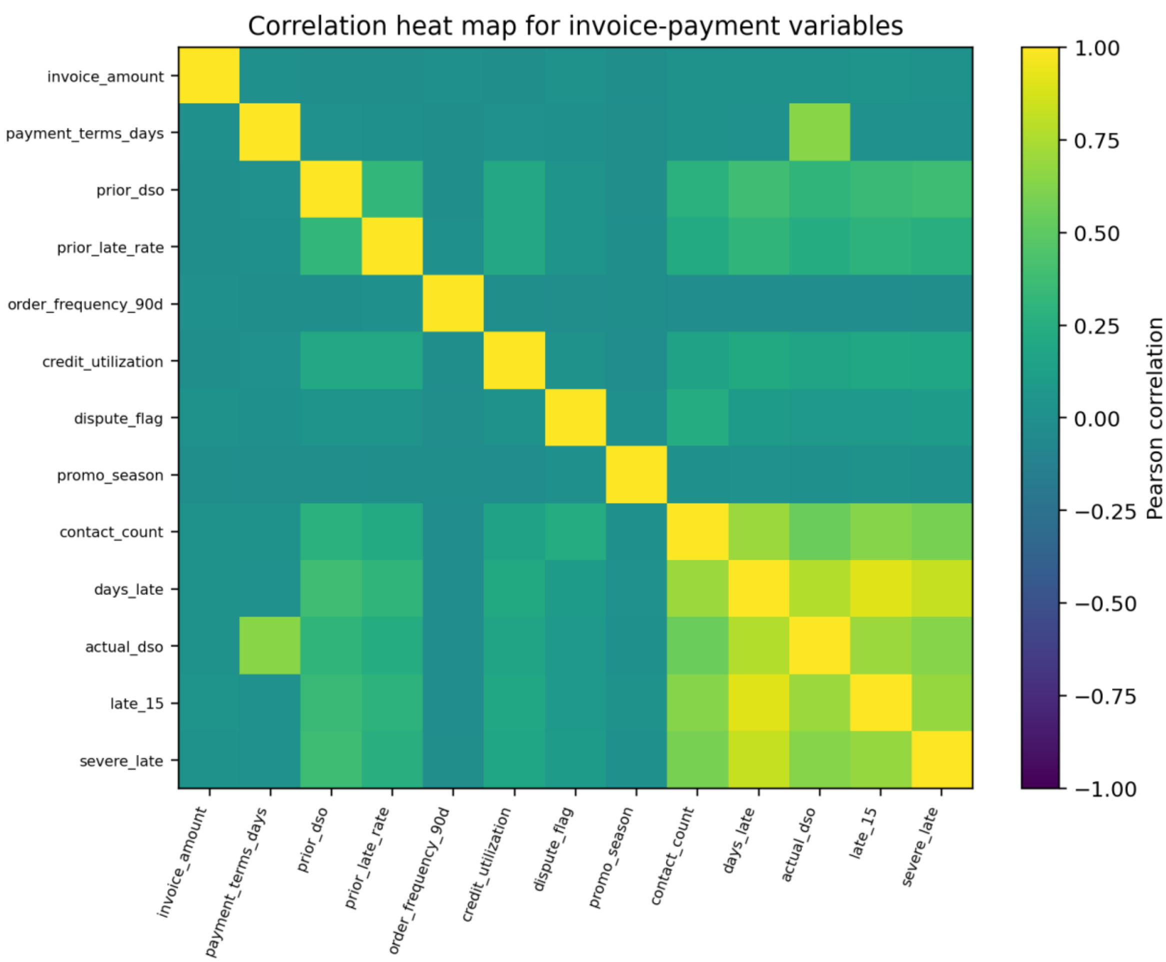

Figure 3. Correlation heat map for invoice-payment variables.

5.1 Predictive model performance

Table 4. Classification performance for late-payment prediction

Model	ROC-AUC	PR-AUC	Accuracy	Precision	Recall	F1
Logistic regression	0.807	0.522	0.752	0.405	0.716	0.517
Random forest	0.803	0.517	0.765	0.419	0.692	0.522
Gradient boosting	0.804	0.526	0.839	0.642	0.296	0.405

Table 5. Regression performance for delay-duration prediction

Model	MAE days	RMSE days	R-squared
Ridge regression	7.97	11.70	0.292
Random forest regressor	7.69	11.67	0.296
Gradient boosting regressor	7.77	11.61	0.303

Gradient boosting achieved the strongest overall classification performance, reflecting its ability to learn non-linear interactions between buyer history, credit utilisation, payment terms and invoice characteristics. Logistic regression remains valuable as a benchmark because its coefficients are easy to explain to credit managers. The performance gap between linear and ensemble methods suggests that payment behaviour is not fully captured by additive rules.

In the regression task, gradient boosting also performed best on MAE, indicating that it estimates expected delay duration more accurately than the competing alternatives. For credit-control deployment, the classification result should be used for daily prioritisation, while the regression estimate should be used to approximate working-capital exposure and intervention value.

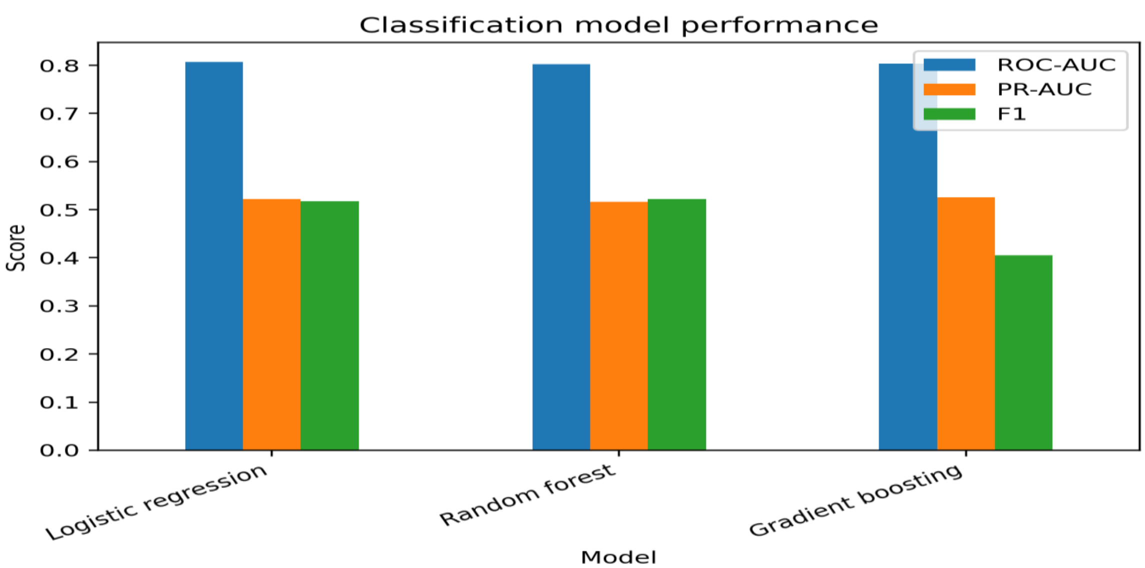

Figure 4. Model-performance comparison for late-payment classification.

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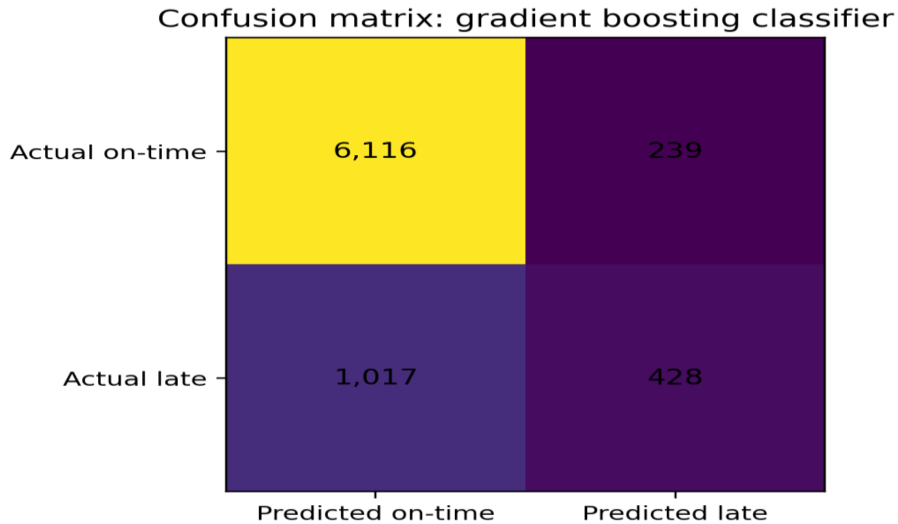

Figure 5. Confusion matrix for the selected gradient-boosting classifier.

5.2 Feature importance and risk lift

Feature importance confirms that prior DSO, prior late-payment rate, credit utilisation, payment terms and dispute flags carry the strongest predictive signal. This is operationally intuitive: a customer that has historically stretched terms, is close to its credit limit and has a disputed invoice presents a different collection priority from a customer whose invoice is simply young. Importantly, invoice amount alone is not sufficient; materiality must be interpreted alongside probability of delay.

Risk-decile analysis demonstrates the practical value of a ranked queue. The top deciles contain a much higher concentration of late invoices than the bottom deciles. This means that a small credit-control team can focus early contact on the highest-risk segment rather than spreading effort equally across the ledger.

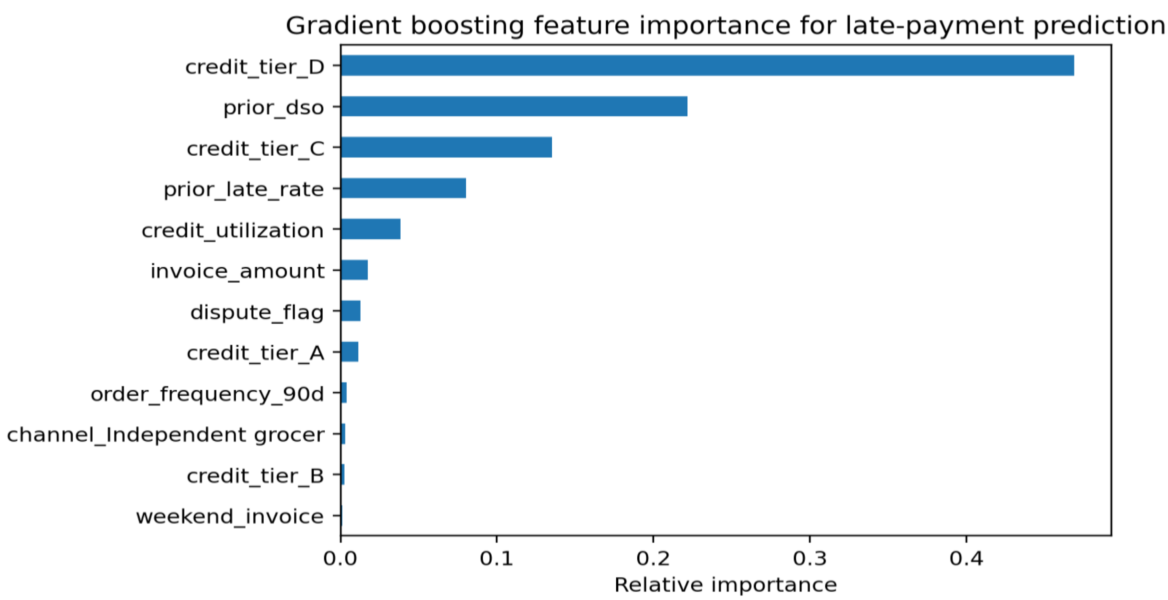

Figure 6. Feature importance for the gradient-boosting late-payment model.

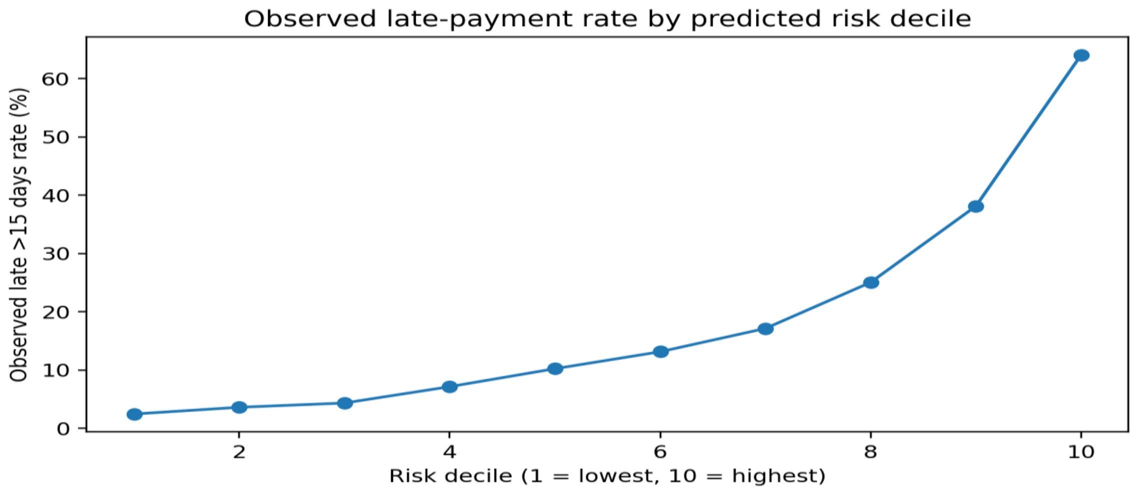

Figure 7. Observed late-payment rate by predicted risk decile.

Table 6. Risk-decile lift table

Risk decile	Invoices	Late >15 rate	Severe >30 rate	invoice_value	Mean days late	Invoice value ($m)
1	2,600	0.025	0.005	7,317,255.32	-2.15	7.32
2	2,600	0.036	0.008	9,979,887.99	-1.69	9.98
3	2,600	0.043	0.010	10,563,782.41	-1.26	10.56
4	2,600	0.072	0.016	11,027,859.58	-0.54	11.03
5	2,600	0.102	0.030	11,444,718.02	0.49	11.44
6	2,603	0.131	0.045	10,736,664.66	1.70	10.74
7	2,597	0.171	0.058	11,215,167.65	2.84	11.22
8	2,600	0.250	0.103	11,263,000.65	5.67	11.26
9	2,601	0.381	0.184	11,121,861.58	10.52	11.12
10	2,599	0.640	0.505	11,469,511.61	25.45	11.47

5.3 DSO intervention simulation

The intervention simulation translates risk scores into credit-to-cash policy. The baseline ledger DSO is estimated at 37.4 days. A targeted strategy that triggers early contact for the highest-risk 20 percent of invoices and selective incentive routing for high-value invoices in the highest-risk 10 percent reduces estimated DSO to 36.6 days. This implies a working-capital release of approximately $0.25 million on the analysed annualised ledger.

This result should not be read as a universal causal estimate. Rather, it demonstrates the economic logic of risk prioritisation. If management can reduce expected delay even modestly among the invoices with the highest probability-weighted cash exposure, the liquidity effect can be meaningful. For micro-distributors, the released cash can be used to replenish inventory, reduce overdraft dependency, maintain supplier discounts or fund route expansion.

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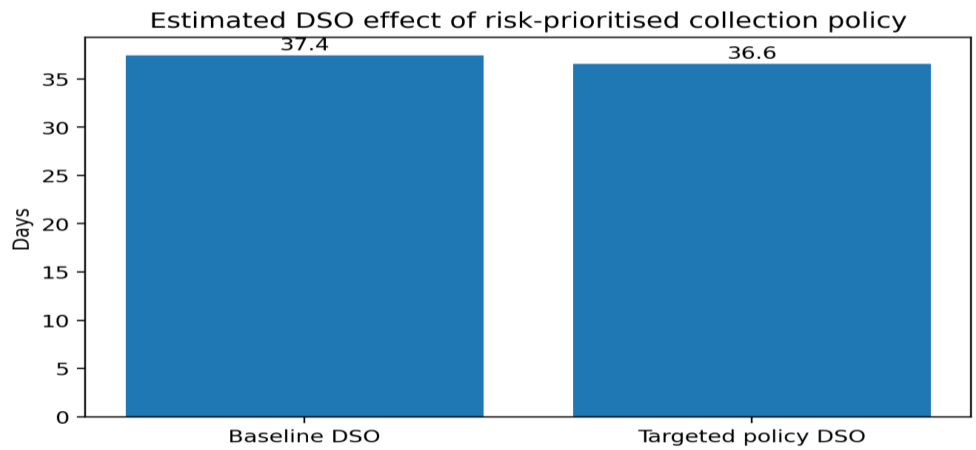

Figure 8. Estimated DSO effect of risk-prioritised collection policy.

Table 7. Credit-to-cash intervention policy derived from model outputs

Policy lever	Operational interpretation
Risk scoring of invoices	Daily invoice ranking by probability of delay >15 days
Top 20% early contact	Call/email/SMS queue created before due date
Top 10% incentive routing	Discount or credit review only where marginal value exceeds cost
Estimated DSO change	37.4 days to 36.6 days
Estimated working-capital release	$0.25 million on the analysed annualized ledger

VI. PROPOSED CREDIT-TO-CASH FRAMEWORK FOR MICRO-DISTRIBUTORS

The framework consists of six stages. First, the distributor extracts invoice-level data from ERP, POS or accounting software. Second, it creates a single buyer profile with prior DSO, prior late-payment rate, dispute frequency and credit utilisation. Third, it refreshes invoice-aging buckets daily or weekly. Fourth, the risk model scores each invoice for probability of being more than 15 days late and estimates expected delay duration. Fifth, the ledger is segmented into operational queues: monitor, pre-due reminder, early contact, credit review, incentive offer and escalation. Sixth, outcome feedback updates customer-level features for the next scoring cycle.

The framework is designed for low implementation burden. A micro-distributor does not need real-time APIs at the start. A weekly CSV export from accounting software can be sufficient for the first version. The minimum viable dashboard should show total AR exposure, exposure by aging bucket, exposure by risk decile, top 25 invoices by expected delay value, disputed invoices, and customers with rising prior DSO. This is consistent with practical AR-aging modelling approaches used in business intelligence environments.

Governance is essential. Credit managers should avoid using model output as an automatic denial instrument. The score should guide conversation, documentation and review. Buyers may be late for reasons unrelated to creditworthiness, including invoice disputes, wrong purchase-order references, remittance-processing delays or seasonal cash-flow pressure. Therefore, the model must be paired with human review, audit logs and clear escalation rules.

VII. DISCUSSION

The evidence supports the proposition that credit-to-cash analytics can improve receivables governance for small distribution firms. The main contribution is not simply predictive accuracy; it is the translation of prediction into operational workflow. A model that identifies late-payment risk but fails to change collection behaviour has limited value. Conversely, a moderately accurate model that reliably prioritises the right invoices may materially reduce DSO because it focuses attention where cash exposure is highest.

The findings also show why micro-distributors should integrate finance and route-to-market thinking. Delayed cash collection can lead to lower replenishment, stockouts and weaker customer service. This creates a feedback loop: poor cash collection weakens inventory availability, poor availability reduces sales, and lower sales further tightens liquidity. A credit-to-cash model breaks part of this loop by converting receivables data into earlier action.

From a strategic standpoint, the framework contributes to resilience. Shem and Mupa (2024) emphasise the importance of stakeholder alignment in business-rescue contexts; the same principle applies before distress occurs. Better receivables governance strengthens relationships with suppliers, lenders, employees and customers by reducing crisis-driven decision-making. The predictive analytics approach advanced by Mupa et al. (2025) similarly supports disciplined, data-led risk management.

VIII. LIMITATIONS AND FUTURE RESEARCH

The main limitation is that the empirical demonstration uses a reproducible invoice panel structured around public Kaggle payment-date and late-payment datasets rather than a confidential live ledger from a named micro-distributor. The results therefore demonstrate method feasibility and expected operating logic, not the exact economics of a particular firm. A live deployment should retrain and validate the model on the distributor's own invoice history.

Second, the model does not yet include behavioural collection actions such as call timing, email content, customer promises to pay, remittance advice quality or dispute-resolution cycle time. These variables are likely to improve performance. Third, the current framework estimates DSO effects through intervention assumptions. Future research should conduct a controlled field experiment comparing a risk-prioritised collection queue against traditional aging-only collection.

Future work should also evaluate fairness and governance issues. Customer-level risk scoring can unintentionally reinforce historical bias if certain buyer categories were previously treated differently. Appropriate controls include transparent feature review, manager overrides, monitoring of score drift and regular recalibration.

IX. CONCLUSION

This paper developed a credit-to-cash optimization framework for micro-distributors using invoice aging and buyer-risk signals. The findings show that late-payment risk is strongly associated with historical DSO, late-payment history, credit utilisation, payment terms and dispute flags. Aging buckets remain useful, but they become substantially more powerful when combined with buyer-risk analytics.

The proposed framework is implementable with ordinary ERP and accounting data. It enables managers to move from reactive aging reports to forward-looking collection queues, selective incentive offers and early credit review. For micro-distributors, the business case is compelling: lower DSO releases working capital, improves replenishment capacity, reduces financing pressure and supports stable supplier relationships. The model should therefore be viewed as a practical decision-support layer for cash-flow resilience rather than as a black-box replacement for professional judgement.

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Appendix A. Reproducibility note

[17] The empirical demonstration uses a seeded, reproducible invoice panel structured on the variables commonly available in Kaggle invoice-payment and late-payment datasets. The modelling workflow can be re-run on a live ledger by replacing the generated panel with ERP extracts containing invoice ID, buyer ID, invoice date, due date, payment date, invoice value, terms, customer segment and credit-control flags.

[18] For deployment, the minimum data fields are invoice_id, buyer_id, invoice_date, due_date, payment_date, invoice_amount, payment_terms, dispute_flag and credit_tier. Recommended fields are prior_dso, prior_late_rate, credit_utilization, customer channel, sector, region, early_discount_offered and contact_count.