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A practical early-warning framework for SME credit deterioration in emerging-market banking

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Abstract
Small and medium-sized enterprises (SMEs) are vital to employment, supply chains and inclusive growth, yet their credit deterioration is often detected late in emerging-market banking systems. This paper develops an operational early-warning framework for identifying SME credit weakening before formal default or non-performing loan recognition. Using a framework-construction design grounded in recent credit-risk analytics, fintech lending, relationship-banking, explainable machine-learning and model-governance literature, the study synthesises borrower financial, account-conduct, relationship, sector-macroeconomic and network-fragility signals into a bank-usable architecture. The resulting EWS-SME framework converts heterogeneous deterioration signals into four watchlist bands: Green, Amber, Orange and Red. Each band is linked to predefined managerial actions, escalation timing, reason codes and monitoring responsibilities. The framework also specifies a validation protocol based on borrower-month panel data, out-of-time testing, imbalanced-class metrics, calibration, lead-time analysis, operational workload assessment, fairness review, override tracking and model-drift monitoring. The paper contributes by reframing SME credit monitoring as a deterioration-management process rather than a default-classification exercise. Its practical value is a staged implementation route that allows emerging-market banks to begin with reliable structured data and progressively incorporate soft information, textual notes, sector overlays and network variables. The framework is especially relevant for banks seeking earlier borrower engagement, more disciplined watchlist governance and stronger resilience in SME portfolios.

Keywords: SME credit risk, early-warning systems, emerging-market banking, credit deterioration, explainable machine learning, relationship lending, model governance, non-performing loans

Introduction

Small and medium-sized enterprises (SMEs) occupy a central position in emerging-market financial systems. They sustain local employment, connect suppliers and distributors, and absorb shocks that would otherwise transmit quickly to households and larger firms. Yet SMEs are also among the most difficult borrowers for banks to monitor. Their financial statements may be delayed or unaudited, collateral values can be volatile, owner-manager finances may overlap with business cash flows, and market conditions can change before formal accounts reveal stress. These features create a structural information gap between the time when borrower deterioration begins and the time when a bank recognises formal delinquency or non-performing loan status.

In many emerging-market banks, SME monitoring still depends heavily on periodic reviews, relationship-manager judgement and backward-looking arrears thresholds. These tools remain important, but they are often insufficient for early intervention. A borrower may display reduced deposit turnover, repeated overdraft excesses, rising utilisation, delayed receivables, inventory pressure, management disputes or a deteriorating sector outlook months before a missed instalment occurs. If such signals remain fragmented across branch notes, core banking systems, spreadsheets and credit files, the bank loses the opportunity to engage the borrower while remedial action is still feasible.

Recent credit-risk research has improved default prediction through machine learning, alternative data, digital footprints, textual analytics and network variables. Studies show that non-linear models can improve ranking performance under some conditions, and that non-traditional data may add value when conventional credit files are thin (Berg *et al*., 2020; Dumitrescu *et al*., 2022; Gambacorta *et al*., 2024) [2, 8, 13]. However, an early-warning system is not only a statistical classifier. A useful system must provide sufficient lead time, explain the drivers of warning signals, assign cases to manageable watchlist bands, define responsible officers, discipline human overrides and remain stable when macroeconomic conditions change.

This paper addresses that practical gap by developing EWS-SME, an early-warning framework for SME credit deterioration in emerging-market banking. The framework is designed for banks that wish to strengthen SME portfolio monitoring without relying immediately on opaque or data-intensive black-box models. It combines structured borrower information, account-conduct behaviour, relationship and soft-information indicators, sector-macroeconomic overlays and network or supply-chain fragility. These signal layers are converted into warning bands linked to documented actions: borrower contact, watchlist review, collateral reassessment, restructuring consideration, remedial transfer and governance reporting.

The study makes three contributions. First, it reframes SME credit monitoring from a default-prediction problem into a deterioration-management process. Second, it proposes a layered architecture that integrates model-based scoring with rule-based triggers, relationship judgement, explainability outputs and governance controls. Third, it specifies a validation protocol that banks can apply to borrower-month or loan-month panel data, including out-of-time testing, calibration, precision-recall metrics, lead-time analysis, workload assessment and drift monitoring. The purpose of the study is therefore to develop a practical, transparent and governable early-warning framework that can be adapted by emerging-market banks before, during and after periods of SME stress.

Literature Review

1. SME lending, information opacity and monitoring delay

SME lending differs from large-corporate lending because borrower opacity is higher and information production is more localised. Small firms often depend on a narrow customer base, informal supplier arrangements, owner-specific expertise and cash-flow cycles that are not fully captured in audited statements. Relationship lending helps banks interpret these conditions, but the value of relationship information depends on the quality of recording, the experience of the officer and the consistency of internal review. When relationship knowledge remains informal, it may improve individual judgement but fails to support portfolio-level monitoring.

Digital lending and fintech research shows that non-traditional information can improve credit assessment when conventional files are incomplete. Berg *et al*. (2020) [2] show that digital footprints can contain predictive information for credit scoring, while Frost *et al*. (2019) [6] explain how BigTech and digital platforms can reshape financial intermediation through data advantages. In small-business lending, Gopal and Schnabl (2022) [9] document the expansion of finance companies and fintech lenders, highlighting how technology-based credit providers can enter segments in which banks face monitoring frictions. These studies suggest that banks must modernise their data use, but they do not imply that relationship banking should be abandoned. For emerging-market SMEs, the challenge is to combine high-frequency bank data with disciplined use of local borrower knowledge.

2. Credit scoring, machine learning and model performance

The credit-scoring literature increasingly demonstrates the value of machine-learning models for detecting non-linear and interaction effects. Moscato *et al*. (2021) [14] compare machine-learning approaches for credit score prediction, and Gunnarsson *et al*. (2021) [10] caution that deep-learning benefits depend on the dataset, feature structure and governance context. Dumitrescu *et al*. (2022) [13] show that logistic regression can be improved through non-linear decision-tree effects, offering a useful middle ground between interpretability and predictive flexibility. Markov *et al*. (2022) [13] further summarise recent credit-scoring trends and emphasise the continuing importance of careful model selection, evaluation and implementation.

For banks, performance should not be judged by ranking accuracy alone. Alonso Robisco and Carbó Martínez (2022) [1] argue that model risk-adjusted performance matters because a technically strong model can still create poor decisions when it is unstable, poorly calibrated or difficult to govern. This point is critical for emerging-market SME portfolios, where training data may be short, missingness may be non-random, macroeconomic shocks can alter relationships between variables and borrower behaviour can shift quickly after currency, inflation, interest-rate or supply-chain stress. An early-warning framework must therefore include validation, calibration, challenger models, drift checks and documented use limitations.

3. Alternative, textual and network information

A growing body of research examines unstructured or relational information in credit-risk prediction. Stevenson *et al*. (2021) [16] show that textual loan assessments can provide useful information for small-business default prediction, while Kriebel and Stitz (2022) [12] demonstrate the predictive potential of user-generated text in peer-to-peer lending. Network-based research also indicates that default risk may propagate through borrower relationships, shared geography or sectoral connections. Oskarsdóttir and Bravo (2021) [15], for example, show that multilayer network information can improve credit-risk prediction by modelling borrower interconnectedness.

These findings are highly relevant for emerging-market banks, but they require cautious translation into practice. Textual notes can reflect genuine borrower stress, but they can also contain inconsistent language, subjective impressions or biased descriptions. Supply-chain and connected-borrower data may reveal concentration or contagion risk, but they must be handled at an appropriate level of aggregation and privacy control. Accordingly, EWS-SME treats alternative and soft information as governed signal layers rather than uncontrolled inputs. Relationship-manager notes should be coded using standard taxonomies, network indicators should be auditable, and all high-risk flags should be accompanied by reason codes that can be reviewed by credit-risk staff.

4. Explainability, fairness and governance

Explainability is increasingly central to credit-risk analytics. Bussmann *et al*. (2021) [3] show how explainable machine learning can support credit-risk management by translating complex model outputs into interpretable drivers. Chen *et al*. (2024) [4] emphasise the value of interpretable methods for imbalanced credit-scoring datasets, where rare default events make simple accuracy misleading. In an SME early-warning context, explanation is not optional. Relationship managers must understand why a borrower has been flagged, credit committees must be able to justify interventions, and internal validators must verify that the model relies on economically plausible drivers.

Fairness and segmentation must also be monitored. Fuster *et al*. (2022) [7] show that machine learning can affect inequality in credit markets, and Howell *et al*. (2024) [8] find that lender automation can produce differential access outcomes across borrower groups. Although their contexts differ from many emerging markets, their lesson is broader: automated models may reinforce historical bias or unstable proxy relationships unless segment-level performance is reviewed. For SME banking, relevant segments may include sector, region, firm size, collateral status, formality level and owner characteristics where lawfully and ethically available. A robust early-warning system should distinguish legitimate risk differentiation from unjustified exclusion or excessive false alarms in vulnerable borrower groups.

Materials and Methods

1. Research design

This study uses a framework-construction research design. The objective is not to estimate a proprietary default model on confidential bank data, but to develop a bank-implementable early-warning architecture that can be empirically validated in future applications. Framework construction is appropriate because the problem is organisational as well as statistical: banks need a structured way to define deterioration, integrate heterogeneous signals, assign warning bands, govern judgement and test whether warnings arrive early enough for intervention.

The framework was developed through synthesis of recent high-quality literature on SME lending, credit scoring, fintech data, machine learning, textual information, network risk, explainability, fairness and model governance. The design logic followed four steps. First, the banking problem was defined as early detection of credit deterioration rather than legal default classification. Second, evidence from prior studies was grouped into signal domains that can be operationalised by banks. Third, the domains were converted into a modular scoring and watchlist architecture. Fourth, validation metrics and governance controls were specified so that the framework can be tested, challenged and improved using borrower-level panel data.

2. Definition of deterioration and unit of analysis

Credit deterioration is defined as a material weakening in a borrower's repayment capacity, repayment behaviour or risk profile before formal default, non-performing loan recognition or write-off. This definition includes arrears migration, repeated short-term extensions, internal rating downgrade, and significant increase in credit risk, covenant breach, restructuring request, forbearance consideration, adverse relationship evidence and sector-driven stress. The definition is broader than default because the purpose of early warning is to identify actionable stress while remedial options still exist.

For empirical implementation, the preferred unit of analysis is the borrower-month or loan-month. A minimum implementation dataset should include borrower identifier, facility type, exposure, maturity, collateral type, sector, region, internal rating, days past due, utilisation, repayment history, account turnover, restructuring events and watchlist status. Banks with richer data can add management accounts, tax-record proxies, digital payment information, relationship-manager notes, customer concentration, supplier dependence and sector indicators. The panel structure is essential because SME deterioration is dynamic: the direction and persistence of signal changes often matter more than the value of any single variable at one point in time.

3. Framework-construction criteria

The proposed design was assessed against six construction criteria. Lead-time orientation requires the framework to identify deterioration before default recognition. Layered signal construction requires the score to combine borrower financial stress, account conduct, relationship information, sector-macroeconomic pressure and network fragility. Model pluralism permits statistical, machine-learning and expert-rule components to coexist with clear role definitions. Actionability requires every warning band to trigger a defined managerial response. Explainability requires borrower-level reason codes and portfolio-level driver review. Governance requires monitoring of data quality, overrides, calibration, drift, workload and fairness. These criteria were used to organise the EWS-SME framework presented in the results section.

4. Validation protocol

The validation protocol is designed for banks that can access historical borrower-month data. A transparent baseline model, such as logistic regression using conventional financial and account-conduct variables, should be compared with one or more challenger models, such as penalised logistic regression, random forest or gradient boosting. The model-development process should use time-aware data splits rather than random splitting. A stronger design trains on earlier periods, tunes thresholds on a validation period and evaluates performance on a later out-of-time period that includes a stress or post-stress window where possible.

Because serious SME deterioration events are usually rare, accuracy is not an adequate metric. The validation protocol therefore recommends discrimination, calibration, lead-time, workload, stability and fairness measures. It also requires outcome tracking after model warnings. A system that flags many borrowers but does not improve contact timing, restructuring discipline or arrears migration may be analytically impressive but operationally weak. The framework therefore evaluates early warning as a decision system, not only as a prediction model.

Results and Discussion

1. EWS-SME architecture

The core result of the study is EWS-SME, a modular early-warning architecture for SME credit deterioration. The architecture begins with five signal layers: borrower financial stress, account-conduct behaviour, relationship and soft information, sector-macroeconomic pressure, and network or supply-chain fragility. These layers are processed through feature engineering and data-quality controls, combined through a calibrated score, expert rules and sector overlays, and translated into an explainability dashboard and watchlist bands. Figure 1 summarises this architecture.

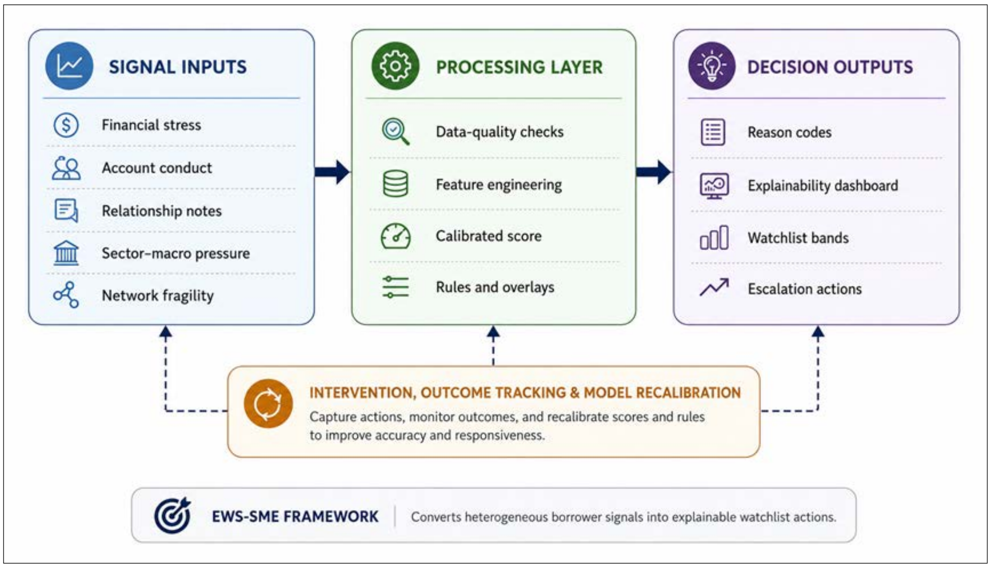

Fig 1: EWS-SME architecture for emerging-market banking

The key principle is cumulative evidence. A single adverse signal may reflect temporary liquidity management or data noise. A repeated pattern across layers is more likely to indicate genuine deterioration. For example, a borrower with high utilisation may not be distressed if deposit turnover remains strong and sector conditions are stable. By contrast, high utilisation combined with declining turnover, repeated cheque returns, a sector downturn and a relationship-manager note about loss of a major customer should trigger escalation. This layered design makes the framework more robust than single-trigger watchlists and more usable than opaque model-only scores.

2. Signal layers and operational indicators

Table 1 translates the five signal layers into operational indicators. The list is not intended to be universal. Banks should adapt indicators to product type, sector, data maturity and local regulation. Working-capital portfolios may emphasise utilisation, overdraft excesses and deposit turnover, while term-loan portfolios may emphasise repayment delays, covenant deterioration and collateral value. Export-oriented SMEs may require exchange-rate and foreign-demand indicators, whereas domestic trading firms may require inventory, receivable and supplier-payment signals.

Table 1: Signal domains for SME credit deterioration

Signal layer	Operational indicators	Suggested frequency	Warning rationale
Borrower financial stress	Revenue decline; margin erosion; weak operating cash flow; rising leverage; lower debt-service coverage; growing reliance on short-term debt.	Quarterly or semi-annual; monthly where management accounts are available.	Captures weakening repayment capacity before formal delinquency.
Account conduct behaviour	Days past due; limit utilisation; overdraft excess; cheque returns; unpaid bills; reduced deposit turnover; frequent short extensions.	Daily to monthly.	Provides high-frequency evidence when statements are delayed.
Relationship and soft information	Management change; site-visit concerns; inventory build-up; delayed receivables; customer loss; governance dispute; unplanned requests.	Event-based with monthly review.	Captures observable stress that is not always in structured data.
Sector-macroeconomic pressure	Interest-rate changes; inflation; currency depreciation; energy prices; import limits; commodity shocks; sector sales index.	Monthly or quarterly.	Adjusts borrower risk for external shocks affecting SME clusters.
Network and supply-chain fragility	Customer concentration; supplier dependence; related-party exposure; delayed receivables from major buyers; connected-borrower stress.	Monthly to quarterly.	Identifies contagion and concentration risk beyond borrower-only models.

The signal layers also support staged implementation. A bank with limited data can begin with repayment history, utilisation, account turnover and internal rating migration. As data maturity improves, it can add structured relationship flags, sector stress indices, transaction patterns, textual note coding and connected-borrower indicators. The framework is therefore practical for emerging-market banks because it does not require full digital maturity on day one.

3. Warning score and borrower-band assignment

The EWS-SME score is a monitoring overlay rather than a replacement for the bank's approved probability-of-default or expected-loss model. A simplified representation is as follows:

EWS_it = f (PD migration_it, account conduct_it, financial stress_it, soft flags_it, sector pressure_st, network fragility_it, governance adjustment_it).

In this notation, i represents the borrower, t the monitoring period and s the borrower sector. For advanced banks, the first component can be a calibrated default probability, staging probability or expected-loss migration. For banks with less mature systems, the score may initially be a weighted rule-based index, later benchmarked against supervised learning models. In either case, the output should be mapped to watchlist bands that correspond to clear actions. Table 2 presents an illustrative banking structure.

Table 2: Illustrative watchlist bands and management actions

Band	Score	Meaning	Primary action	Escalation timing
Green	0-34	No material deterioration signal.	Routine monitoring and normal feature updates.	Monthly portfolio report.
Amber	35-49	Early or weak deterioration; signal may be temporary.	Relationship-manager contact, cash-flow verification and documented action note.	Within 10 business days.
Orange	50-69	Persistent or multi-layer deterioration.	Watchlist movement, repayment-plan review, documentation tightening, collateral and sector review.	Credit-risk review within 15 business days.
Red	70-100	Severe deterioration or imminent default risk.	Intensive monitoring/remedial transfer, restructuring or forbearance review and provisioning/staging assessment.	Immediate escalation.

Thresholds in Table 2 are illustrative and must be calibrated to the bank's portfolio history, risk appetite and operational capacity. A low threshold may provide earlier warnings but overwhelm relationship managers with false alerts. A high threshold may reduce workload but miss the window for intervention. Therefore, threshold selection should consider statistical performance and branch-level capacity. Figure 2 defines early-warning lead time as the interval between the first actionable warning and formal default or non-performing classification.

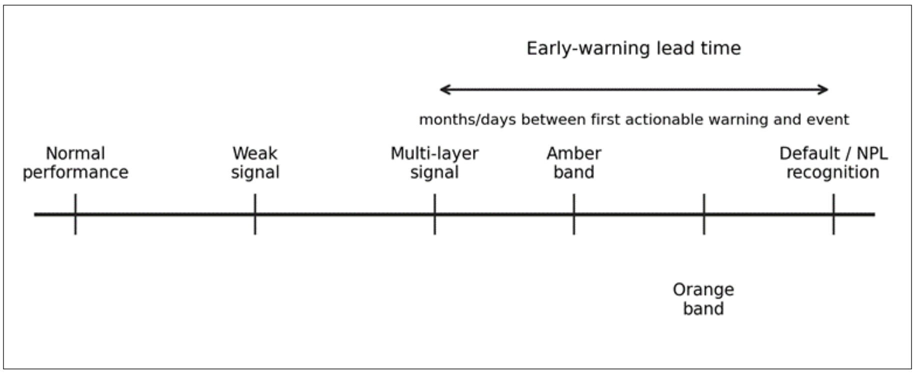

Fig 2: Event-time definition of credit deterioration and lead time

4. Model development, calibration and validation

The validation protocol must evaluate whether EWS-SME improves practical credit monitoring. Table 3 sets out recommended validation areas. Discrimination measures assess whether deteriorating borrowers receive higher scores than stable borrowers. Calibration measures assess whether predicted or banded risks correspond to observed deterioration rates Lead-time measures assess whether warnings occur early enough for borrower contact, documentation tightening, collateral review or restructuring assessment. Workload measures protect the system from generating more warnings than branch teams can reasonably investigate. Stability and fairness measures examine whether performance changes across time, sectors, regions, collateral status and firm size.

Table 3: Validation metrics for EWS-SME implementation

Validation area	Recommended measures	Decision relevance
Discrimination	Area under receiver operating characteristic curve; precision-recall area; Kolmogorov-Smirnov statistic; top-decile capture rate.	Tests whether deteriorating borrowers are ranked above stable borrowers.
Calibration	Brier score; calibration slope; calibration-in-the-large; decile calibration plot.	Tests whether predicted or banded risks correspond to observed event rates.
Lead time	Median months from first warning to event; share captured three or six months before event.	Tests whether warnings arrive early enough for action.
Operational workload	Number of Amber, Orange and Red cases per officer; false-alert review burden.	Prevents analytically strong models from overloading branch teams.
Stability and drift	Population stability index; feature drift; score migration; override-rate trend.	Monitors model behaviour under new economic conditions.
Fairness and segmentation	Performance and false-positive/false-negative rates by sector, region, firm size and collateral status.	Identifies unstable or unjustified differences across borrower segments.

Lead-time metrics are especially important. A default model that flags a borrower one week before default may have good ranking power but limited remedial value. An early-warning system should therefore report the median number of months between first warning and event, the share of deteriorating borrowers captured at least three or six months before the event and the proportion of false alerts requiring review. These metrics connect analytics to managerial usefulness.

Calibration and explainability should be reviewed together. If borrowers in the Orange band do not display meaningfully higher subsequent deterioration than Amber borrowers, thresholds or score construction should be revised. If the model relies on variables that are unstable, poorly recorded or weakly related to economic risk, the bank should downgrade their role. Borrower-level reason codes should identify which signals changed and why action is justified. Examples include sustained utilisation above a defined threshold, sharp decline in deposit turnover, repeated late payments, sector stress movement, coded relationship concern or connected-borrower deterioration.

5. Governance cycle and implementation roadmap

A technically strong early-warning system can fail if governance is weak. EWS-SME should therefore be embedded in a formal cycle of development, independent validation, approval, deployment, monitoring, intervention, learning and recalibration. Figure 3 presents the governance cycle. Table 4 outlines a staged implementation roadmap for emerging-market banks.

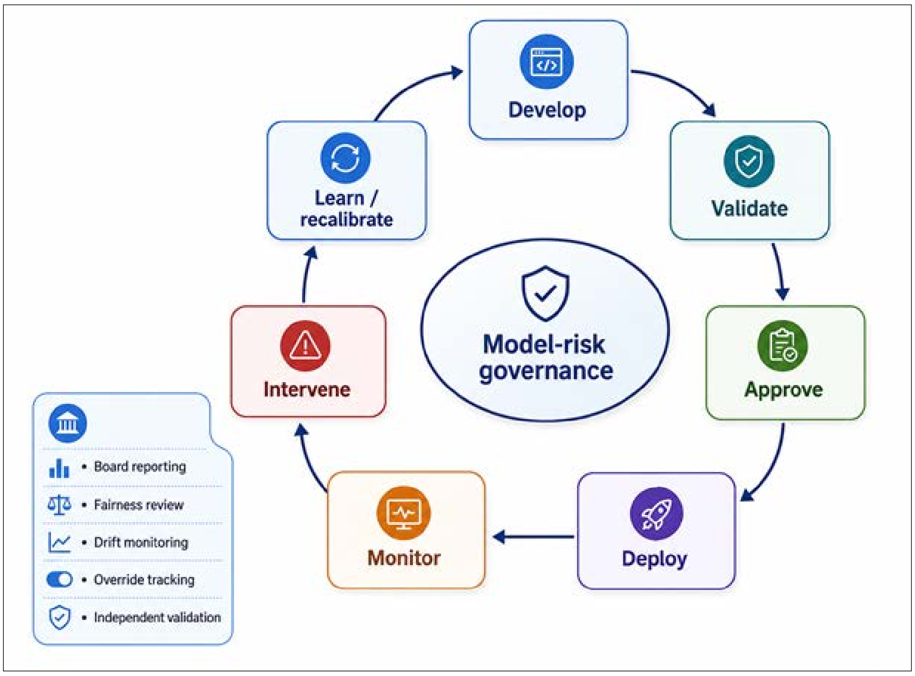

Fig 3: Governance cycle for EWS-SME implementation

Table 4: Implementation roadmap for emerging-market banks

Phase	Core activities	Output
Phase 1: Diagnostic	Map SME data, watchlist practice, non-performing loan history, relationship notes and branch workflows.	Data inventory, problem statement and governance owner.
Phase 2: Prototype	Build baseline score using reliable variables; define event labels, bands and reason codes.	Prototype scorecard, draft dashboard and initial validation.
Phase 3: Validation	Conduct out-of-time testing, calibration, lead-time analysis, workload review and segmentation checks.	Validation report, threshold recommendation and limitations.
Phase 4: Pilot	Run the framework in selected regions or sectors; compare warnings with relationship-manager judgement.	Pilot results, override taxonomy and revised thresholds.
Phase 5: Approval and rollout	Approve policy, escalation rules, model-use limitations and reporting templates.	Credit committee approval, rollout plan and staff training.
Phase 6: Monitoring	Track performance, drift, overrides, action completion and post-warning outcomes.	Quarterly monitoring pack and annual revalidation.

Override governance is a central feature of the framework. Relationship managers may possess borrower-specific knowledge that improves model interpretation, but undocumented overrides can delay recognition of genuine risk. Every override should record direction, reason, supporting evidence, approving authority and subsequent borrower outcome. Periodic override analysis can then identify whether the model is misclassifying specific borrower types or whether commercial pressure is weakening watchlist discipline.

Senior-management reporting should focus on decision usefulness rather than technical complexity alone. A quarterly monitoring pack should show migration across bands, concentrations of Orange and Red borrowers by sector and region, top deterioration drivers, action-completion rates, restructure requests, calibration results, model-drift indicators and override outcomes. This reporting makes early warning part of credit-risk appetite management rather than a stand-alone analytics project.

6. Practical, policy and inclusion implications

For banks, the framework provides a blueprint for moving from fragmented monitoring to disciplined watchlist management. It clarifies what should be monitored, how warning bands should be assigned, what actions should follow and how the system should be validated. The approach is deliberately staged: banks can begin with reliable structured variables and later add textual, alternative and network indicators. This makes the framework feasible for institutions where data maturity varies across regions, products and branches.

For supervisors and policymakers, stronger early-warning systems can support financial stability. Delayed recognition of SME stress may lead to sudden increases in non-performing loans, procyclical credit tightening and pressure on bank capital. Earlier detection allows banks to distinguish temporary liquidity strain from structural insolvency, engage viable borrowers sooner and improve provisioning discipline. The framework also supports financial inclusion because transparent and validated monitoring can reduce the tendency to withdraw from SME lending after losses. However, fairness checks are necessary to ensure that automated monitoring does not unfairly penalise smaller, less formal or geographically peripheral firms.

The framework's main limitation is that it requires empirical testing before performance claims can be made. Future studies should apply EWS-SME to confidential loan-level data from one or more banks, compare its lead time and error rates with existing watchlist processes and estimate economic outcomes such as expected-loss reduction, arrears migration and restructuring effectiveness. Cross-country applications would also show which signal layers generalise across emerging markets and which require local adaptation.

Conclusion

This paper developed EWS-SME, a practical early-warning framework for SME credit deterioration in emerging-market banking. The framework integrates borrower financial stress, account-conduct behaviour, relationship and soft information, sector-macroeconomic pressure and network fragility into an explainable watchlist architecture. It links warning bands to predefined managerial actions and embeds validation, calibration, lead-time analysis, fairness review, override governance and drift monitoring.

The central conclusion is that SME early warning should be evaluated by its ability to support timely, explainable and accountable intervention, not only by statistical accuracy. A bank that detects deterioration earlier can engage borrowers before arrears become irreversible, improve portfolio resilience and strengthen credit-risk governance. For emerging-market banks, the most promising approach is disciplined integration: data-driven signals, relationship judgement and governance controls working together in one system. The next step is empirical validation using borrower-month panel data to test whether the framework improves lead time, reduces uncontrolled arrears migration and supports better remedial decision-making.

Declarations

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Institutional Review Board Statement: Not applicable because the paper develops a conceptual framework and validation protocol and does not report research involving human participants, animals or identifiable borrower-level data.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new empirical dataset was generated or analysed in this framework-development study. Future empirical applications of the EWS-SME framework should report the availability and confidentiality restrictions of any bank-level data used for validation.

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