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Bankruptcy Prediction Models for SMEs Using Machine Learning and Auditing Standards: An Integrated Early-Warning and Assurance Framework

Abstract

Small and medium-sized enterprises (SMEs) account for a large share of employment and credit portfolios, yet their failure dynamics are difficult to predict due to heterogeneous reporting quality, limited disclosures, and non-linear distress pathways. This paper proposes an integrated framework that combines machine-learning (ML) bankruptcy prediction with audit-oriented evidence requirements aligned with International Standards on Auditing (ISAs). It synthesizes classical models (Altman-type discriminant analysis and Ohlson-type logistic regression) with modern ensemble learners (Random Forest and gradient boosting/ XGBoost), and maps model outputs to the auditor's structured responsibilities: risk assessment (ISA 315 Revised 2019), responses to assessed risks (ISA 330), fraud considerations (ISA 240 Revised), and going concern evaluation (ISA 570 Revised 2024). Results indicate that ML can improve discrimination under class imbalance and complex interactions, but only when governance controls prevent data leakage, model drift, and "automation bias." The paper concludes with an implementable early-warning and assurance blueprint for banks and audit practices in candidate-country contexts.

Keywords: SME distress; bankruptcy prediction; machine learning; Random Forest; XGBoost; audit evidence; ISA 315; ISA 330; ISA 570; going concern; model risk management

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Introduction

SMEs form the economic backbone of most countries, representing the majority of firms and a substantial fraction of private-sector employment and value creation. Notwithstanding their macroeconomic relevance, SMEs frequently face structural vulnerabilities: constrained access to long-term finance, weaker collateral positions, concentrated customer bases, limited diversification, and high exposure to sectoral or local shocks. Consequently, SME distress and bankruptcy are recurring phenomena with significant negative externalities—credit losses for banks and suppliers, employment shocks, erosion of tax bases, and disruption of supply chains. The practical policy and managerial challenge is early detection: identifying distress sufficiently early to enable restructuring, covenant renegotiation, risk-based monitoring, or orderly exit rather than abrupt failure.

Bankruptcy prediction is traditionally rooted in accounting ratios and statistical classification. Altman's multivariate discriminant analysis introduced a parsimonious approach that combines ratios capturing profitability, liquidity, leverage, and activity into a composite score separating distressed from non-distressed firms. This logic remains influential due to interpretability and ease of implementation, particularly where data availability is limited. Similarly, Ohlson's logistic regression framework advanced probabilistic prediction of failure and provided a methodological basis for estimating default likelihoods rather than binary classification alone. These classic models remain widely used as baseline tools in banking and credit analytics because they are transparent, computationally simple, and can be communicated to decision-makers.

However, SME bankruptcy prediction introduces distinctive complications. First, SMEs often exhibit heterogeneity in accounting quality, frequency of reporting, and adherence to financial reporting standards, which weakens the reliability of ratio-based signals. Second, distress pathways in SMEs tend to be nonlinear and abrupt: a liquidity crunch due to delayed receivables, loss of a key customer, supply disruption, or regulatory changes can cause fast transitions from apparent stability to acute distress. Third, class imbalance is structurally severe: in most datasets, bankruptcies are a small minority of observations, which can cause conventional classifiers to optimize accuracy by favoring the majority class and missing the events of interest. Fourth, relevant predictive signals increasingly extend beyond traditional ratios: payment arrears, invoice disputes, tax or social contribution delays, and sectoral macro variables can provide earlier warning but complicate modeling and governance.

Machine learning has emerged as a practical response to these limitations. ML algorithms can capture nonlinear relationships, complex interactions, and high-dimensional signals, and can be tuned for imbalance-sensitive objectives (e.g., recall at acceptable false-positive rates). Empirical research in corporate failure prediction frequently shows strong performance for ensemble methods such as Random Forest and gradient boosting (including XGBoost), especially when validation is rigorous and feature engineering is carefully controlled. Yet higher predictive power does not automatically translate into better decisions; instead, it introduces new risks: overfitting, unstable performance under economic regime shifts, and opacity that undermines accountability.

In high-stakes settings—credit decisions, covenant enforcement, restructuring triggers, and audit judgments—model governance and assurance are non-negotiable. This is particularly true when decision-makers may exhibit "automation bias": the tendency to over-rely on algorithmic outputs and discount contradictory human judgment or contextual evidence. The risk is not only technical; it is organizational. A well-performing model can still produce harmful outcomes if it is embedded in weak controls, used without documented evidence review, or deployed without drift monitoring.

Auditing standards provide a structured basis for integrating predictive analytics into credible professional workflows. ISA 315 (Revised 2019) strengthens the auditor's risk identification and assessment process by emphasizing an enhanced understanding of the entity, its environment, and internal control, alongside a robust approach to identifying risks of material misstatement. ISA 330 frames the auditor's required responses to assessed risks, enabling a disciplined "signal-to-procedure" mapping: elevated distress signals should trigger specified audit procedures rather than subjective escalation. Going concern is the critical bridge. ISA 570 (Revised 2024) strengthens consistency and transparency related to going concern matters and is effective for audits of periods beginning on or after 15 December 2026. In addition, ISA 240 (Revised) reinforces auditor responsibilities relating to fraud and is aligned in effective timing with the going concern standard; this is relevant because distress, liquidity pressure, and fraud risk often co-occur in practice.

Accordingly, this paper argues that the most robust approach is not "ML versus auditing," but an integrated early-warning and assurance framework in which model outputs act as risk indicators that trigger evidence-based investigation. The framework is designed for SME contexts in candidate countries where data availability and reporting quality may be uneven, and where banks and auditors must balance predictive ambition with governance realism.

Research questions

- **RQ1:** Which model families provide practical performance advantages for SME bankruptcy prediction under class imbalance and out-of-time validation requirements?
- **RQ2:** How can model outputs be mapped to audit evidence and procedures aligned with ISA 315/330/240/570?
- **RQ3:** Which governance controls reduce model risk while preserving interpretability and defensibility?

Materials and Methods

2.1 Research design

This study employs a standards-informed design methodology. It does not introduce a new dataset; instead, it develops an implementable blueprint by synthesizing: (i) bankruptcy prediction theory and empirical ML benchmarking, and (ii) ISA-based assurance requirements that determine how predictive signals should be converted into documented professional actions.

2.2 Conceptual model and variables

The method assumes access to three categories of SME signals commonly available to banks and auditors:

1. **Financial statement variables** (ratio features)

- Liquidity (current ratio, quick ratio, cash conversion)
- Leverage (debt-to-equity, interest coverage)
- Profitability (EBIT margin, ROA)
- Activity (inventory turnover, receivables days)

2. **Behavioral/payment variables**

- Days past due (DPD) trajectories
- Payment reversals, arrears frequency
- Supplier payment delays (where available)

3. **Contextual variables**

- Sector and region indicators
- Macro proxies (growth, inflation, energy price exposure proxies where relevant)

2.3 Model families (classical and ML)

The framework compares and integrates two model categories:

- **Classical baselines**
    - Discriminant analysis (Altman-type) for interpretability and benchmarking
    - Logistic regression (Ohlson-type) for probability outputs and calibration
- **ML models**
    - Random Forest: robust to nonlinearity and interactions; resilient to noisy features
    - Gradient boosting / XGBoost: typically high accuracy in tabular prediction; effective with heterogeneous feature scales

2.4 Validation strategy and performance measures

To avoid unrealistic performance estimates, the method requires:

- **Out-of-time validation**: training on earlier periods and testing on later periods to reflect real monitoring deployment.
- **Class imbalance management**: cost-sensitive learning, class weighting, and threshold tuning rather than naive accuracy optimization.
- **Metrics**: AUC-PR (precision-recall) for rare event prediction, recall at fixed false-positive rates, and calibration metrics (e.g., Brier score) to ensure probability usefulness.

2.5 Governance and control design

A core methodological contribution is governance integration:

- **Leakage prevention**: features must be defined "as-of" the prediction date; any post-event variables must be excluded.
- **Data lineage and version control**: feature definitions, transformations, and data sources must be documented and versioned.
- **Model documentation ("model card")**: purpose, target definition, training window, validation results, limitations, and monitoring plan.
- **Drift monitoring**: periodic checks for performance degradation and distribution shifts; triggers for recalibration/retraining.

2.6 Assurance mapping to ISAs

The method explicitly maps high-risk predictions to audit evidence requirements:

- Under **ISA 315 (Revised 2019)**, a high-risk model signal is treated as a risk indicator affecting the auditor's risk assessment and planned audit approach.
- Under **ISA 330**, the model signal triggers specific responses (substantive procedures and, where relevant, tests of controls) focused on cash flows, covenant compliance, subsequent events, and management plans.
- Under **ISA 570 (Revised 2024)**, model outputs inform the intensity of going concern procedures and disclosure evaluation; effectiveness date is recognized for implementation planning.
- Under **ISA 240 (Revised)**, distress signals combined with anomalies elevate fraud-risk procedures, recognizing aligned effective dates.

2.7 Limitations

The framework requires disciplined implementation; without robust validation, documentation, and evidence mapping, the predictive system may increase rather than reduce risk. The method also acknowledges that explainability tools support review but do not establish causality.

Results

3.0 Overview of results

The results are presented as an implementable architecture for SME bankruptcy prediction that is both analytically effective and professionally defensible.

Result A: ML ensembles can outperform classical models in discrimination, particularly under nonlinear patterns and mixed feature spaces, but only with out-of-time validation and leakage control.

Result B: Classical baselines remain essential as governance anchors and interpretability checks.

Result C: Operational value is maximized using a two-stage workflow (ML screening → evidence-based review) rather than automated decisions.

Result D: ISA-aligned mapping converts model outputs into structured, auditable work, reducing automation bias and strengthening accountability.

These results are summarized visually in **Figure 1** and operationally specified in **Table 1**, both discussed below.

3.1 Model comparison and practical performance logic

In SME contexts, predictive performance depends on how well a model handles nonlinearity, interactions, and sparse/variable quality data. Logistic regression and discriminant analysis provide stable baselines and are often robust when the ratio signal is strong and accounting quality is consistent. However, they may struggle when distress is driven by interaction effects (e.g., moderate leverage becomes critical when liquidity deteriorates) or when early warning signals arise in behavioral variables (arrears trajectories) that do not fit linear assumptions.

Ensemble models—Random Forest and gradient boosting—are better suited to these realities. Random Forest reduces variance through bagging and can capture variable interactions without strict parametric assumptions, making it practical in noisy SME datasets. Gradient boosting methods such as XGBoost often deliver strong predictive power by sequentially learning from residual errors and can handle complex boundaries, but they are more sensitive to overfitting if validation is weak.

The most defensible approach is a **stacked governance portfolio**: retain an interpretable baseline (logistic regression or ratio composite) and deploy an ensemble model as the primary screening tool. Disagreement between models is treated as a governance signal that triggers review of data quality and edge cases, rather than as an invitation to pick the most convenient output. This approach improves resilience under drift and supports transparent communication to credit committees and audit reviewers.

3.1.1 Audit and assurance alignment (prediction-to-evidence mapping)

Audit defensibility requires that model outputs are not treated as conclusions. Under **ISA 315 (Revised 2019)**, a high predicted distress probability is incorporated as a risk indicator that affects the auditor's understanding of risk, internal control implications, and planned procedures. Under **ISA 330**, the auditor must implement responses to assessed risks; this can be operationalized via a standardized evidence checklist: testing management cash-flow forecasts, assessing financing availability, recalculating covenant compliance, and evaluating subsequent events.

Going concern evaluation is the focal use case. **ISA 570 (Revised 2024)** requires strengthened consistency and transparency regarding going concern matters and is effective for audits of periods beginning on or after 15 December 2026, providing a clear horizon for firms to modernize their going concern procedures and documentation. Model signals should intensify the evaluation of management's plans, sensitivity analyses, and disclosure adequacy.

Where distress indicators co-occur with anomalies (unusual related-party transactions, aggressive revenue recognition patterns), fraud risk must be escalated consistent with **ISA 240 (Revised)**, which also has an effective date aligned with the going concern standard.

Numbered lists can be added as follows

The following implementation controls are recommended to ensure professional and model governance integrity:

1. **Define the event and timing precisely** (bankruptcy, insolvency filing, covenant default, or restructuring trigger) and lock it to an "as-of" prediction date.
2. **Implement out-of-time validation** with at least one full-year (or multi-quarter) holdout to mimic deployment conditions.
3. **Treat class imbalance explicitly** using cost-sensitive loss functions and calibrated thresholds; report AUC-PR and recall at fixed false-positive rates.
4. **Prevent data leakage** by excluding post-event signals and ensuring features reflect only information available at prediction time.
5. **Use human-in-the-loop decisions**: no adverse credit or audit conclusion should be driven solely by the model without documented evidence review.
6. **Provide explainability for review** (feature importance, case-level explanations) strictly as decision support, not causal proof.
7. **Monitor drift**: track calibration and discrimination over time; define retraining triggers and governance approvals.
8. **Map every high-risk flag to an evidence checklist** aligned with ISA 315/330/570, including cash-flow forecast testing and subsequent events review.

Figure 1: mandatory figure

Figure 1. Integrated SME distress early-warning and audit-assurance workflow
Data inputs (ratios + payment behavior + sector/macros) → ML screening (RF/XGBoost) + baseline model → governance checks (leakage, calibration, drift) → risk classification → evidence-based review (ISA 315/330) → going concern conclusion and disclosure evaluation (ISA 570 Revised 2024) → feedback loop (monitoring and model updates).

Table 1: mandatory table

Table 1. Feature clusters, predictive interpretation, and audit/credit evidence actions

Feature cluster	Typical distress signal	Predictive implication	Evidence action (audit/credit file)
Liquidity	declining quick ratio; negative OCF	near-term cash stress	test cash-flow forecasts; review short-term funding
Leverage	rising debt burden; covenant proximity	higher PD and LGD risk	recalculate covenants; verify financing availability
Profitability	margin collapse; persistent losses	deterioration in viability	test turnaround assumptions; sensitivity analysis
Payment behavior	arrears frequency; DPD trend worsening	early distress indicator	reconcile aging; review subsequent payments/events
Governance anomalies	unusual related-party patterns	combined distress + fraud risk	escalate fraud procedures (ISA 240 Revised)

Discussion

This paper's central argument is that technical performance improvements in bankruptcy prediction are valuable only when embedded in governance and assurance structures that prevent misuse and preserve accountability. The discussion therefore evaluates model performance, organizational use, and professional standards integration.

4.1 Predictive gains versus decision quality

The literature frequently reports superior discrimination for ensemble methods in failure prediction. In SME contexts, this advantage is plausible because distress signals are often interaction-driven: a moderate leverage ratio is not necessarily problematic unless liquidity collapses; profitability declines may not be alarming unless accompanied by deteriorating payment behavior. ML captures such patterns more flexibly than linear models. Nevertheless, the key operational question is not only "which model predicts best," but "which model improves decisions under institutional constraints." False negatives can be costly, but excessive false positives can generate monitoring overload and relationship damage. Therefore, risk appetite and operational capacity must shape threshold selection and workflow design.

4.2 Model risk and governance

Model risk is often underestimated. The most damaging failures frequently arise from leakage and validation errors rather than algorithm choice. If a dataset includes post-event information (e.g., legal filing dates, post-default restructuring indicators) that inadvertently enters feature definitions, performance will appear artificially high but collapse in production. Likewise, random train-test splits can inflate results when firms' time-series patterns leak across folds. Hence, the governance controls specified in the Methods section—out-of-time testing, leakage checks, and drift monitoring—are not optional technicalities; they are requirements for credible deployment.

4.3 Explainability and defensibility

Regulators, audit inspectors, and courts typically demand defensible reasoning. While sophisticated explainability tools can provide case-level insights, they should be treated as interpretive aids, not as evidence of causality. A stable baseline model, combined with an ensemble model and documented evidence review, is often more defensible than a single opaque "best model." This is especially relevant in candidate-country contexts where institutional capacity for advanced model validation may be uneven.

4.4 Automation bias and professional skepticism

Automation bias is a material threat to professional judgment. Credit officers may accept model outputs without challenging them; auditors may over-weight risk scores and under-weight contradictory evidence. The mitigation is procedural and cultural: require documented human review; define an evidence checklist; and enforce professional skepticism. The ISA framework provides a practical structure: treat model outputs as risk indicators (ISA 315) and mandate documented responses (ISA 330).

4.5 Going concern and fraud interplay

Going concern procedures can be strengthened by early-warning analytics, but the direction of inference must be controlled. The model flags risk; the auditor collects evidence and evaluates management's assessment and disclosures. ISA 570 (Revised 2024) strengthens transparency expectations and provides an effective date (15 December 2026) that encourages firms to upgrade their procedures now. Additionally, fraud risk can intensify under distress—through manipulation of revenue, capitalization of expenses, or related-party transactions. ISA 240 (Revised) supports escalation when distress signals co-occur with anomalies.

4.6 Practical implementation in banks and audit firms

The best operational design is a two-stage model. Stage 1 uses ML to prioritize cases. Stage 2 conducts evidence-based review with standardized documentation. This reduces workload, supports consistent decisioning, and preserves accountability. For banks, it enables earlier restructuring engagement. For auditors, it supports a disciplined, evidence-led going concern assessment.

Conclusions

This paper developed a complete, implementable framework for SME bankruptcy prediction that unifies modern machine learning with audit-aligned governance and evidence requirements. The principal conclusion is that predictive analytics can materially strengthen early-warning capabilities for SME portfolios, but only if it is embedded within a professional control environment that prevents leakage, drift, and over-reliance.

First, modern ensemble models—Random Forest and gradient boosting/XGBoost—are well-suited for SME distress prediction because they capture nonlinear patterns, interactions, and mixed data sources more effectively than linear models. However, their advantage is conditional: performance must be demonstrated using out-of-time validation; imbalance must be handled transparently through appropriate metrics and threshold tuning; and data leakage must be systematically prevented through "as-of" feature engineering and versioned data pipelines.

Second, interpretability is a governance asset. Classical baselines such as logistic regression and ratio composites remain valuable as benchmarks, sanity checks, and communication tools. Their role is not to compete with ML on raw accuracy, but to anchor the decision system, strengthen defensibility, and reduce the probability that an opaque model drives outcomes without scrutiny.

Third, the paper established that the greatest operational value comes from a two-stage workflow: ML screening to allocate monitoring resources, followed by evidence-based review aligned with professional standards. In auditing, this means converting model signals into structured risk assessment and responses: ISA 315 (Revised 2019) frames how such signals influence the risk assessment; ISA 330 frames the required responses; and ISA 570 (Revised 2024) anchors going concern work and disclosure evaluation, with a clear effective date that institutions can prepare for. Where distress signals align with anomalies that suggest manipulation, fraud procedures must be escalated consistent with ISA 240 (Revised).

Finally, for candidate-country contexts and SME-heavy economies, the framework provides a pragmatic pathway: start with monitoring and prioritization; develop governance, documentation, and drift controls; build an evidence checklist aligned with ISA requirements; and only then integrate predictive analytics into higher-impact decisions. Under this approach, ML strengthens professional judgment rather than replacing it, and thereby improves both risk outcomes and accountability.

Patents

No patents are claimed. The manuscript presents a governance and methodological framework based on public-domain auditing standards and academic literature. Potential patentable outputs would arise only from future proprietary software implementations (e.g., integrated early-warning platforms, automated evidence-bundling tools, or institution-specific ML pipelines with unique feature engineering and monitoring capabilities). Such implementations are outside the scope of this academic work, which focuses on principles, controls, and standards-aligned operationalization.

Supplementary Materials

Supplementary materials may include: (i) a model card template tailored to SME distress prediction (purpose, target, training window, validation design, limitations); (ii) a leakage and "as-of" feature checklist; (iii) an evidence checklist aligned with ISA 315/330/570 for going concern procedures; and (iv) a drift monitoring dashboard specification with AUC-PR stability, calibration curves, alert thresholds, and retraining triggers. These materials are intended to support consistent deployment across banking and audit environments.

Author Contributions

Rametulla Ferati contributed to conceptualization, methodology design, synthesis of bankruptcy prediction and ML governance literature, and integration of International Standards on Auditing into an operational early-warning and assurance framework. The author developed Figure 1 and Table 1, drafted and revised all manuscript sections for academic rigor and clarity, and approved the final version for submission.

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Institutional Review Board Statement

Not applicable. The study uses publicly available standards and academic sources and does not involve human participants, clinical interventions, or collection of personal data.

Informed Consent Statement

Not applicable.

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Conflicts of Interest

The author declares no conflicts of interest.

Appendix A

Minimum prediction-to-evidence protocol: When the model flags high distress risk, require (i) updated management accounts, (ii) a 12-month cash-flow forecast with sensitivity tests, (iii) covenant recalculation and documentary evidence of financing availability, (iv) subsequent events review, and (v) documentation of management's mitigation plans and feasibility assessment. For audited entities, incorporate this into the risk assessment and responses consistent with ISA 315/330 and evaluate disclosure adequacy under ISA 570.

Appendix B

Model governance minimum controls: version control for datasets and features; leakage tests; out-of-time validation; class imbalance documentation; decision thresholds approved by a committee; explainability outputs for review; drift monitoring with defined retraining triggers; independent validation at least annually; and a prohibition on fully automated adverse decisions without documented human review.

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