Risk Signal Convergence and Corporate Vulnerability in Ghana: Developing A Multi-Domain Early-Warning Model

Samuel Opata Sackitey*

Doctoral Researcher, Research Specialization: Operations Research and Business Analytics | Head, Quality Assurance and Professional Education Department | Lecturer, Mountville International University College, Ghana | Coordinator/Tutor, Institute of Commercial Management (ICM), United Kingdom

DOI: https://doi.org/10.47772/IJRISS.2026.100900504

Received: 28 September 2026; Accepted: 03 October 2026; Published: 15 October 2026

ABSTRACT

Corporate early-warning research often models financial, operational, market and macroeconomic indicators as separate predictors even though vulnerability may emerge from their concurrence. This study developed and empirically demonstrated the Risk Signal Convergence Framework (RSCF), an explainable multi-domain architecture for corporate early warning in Ghana. A quantitative longitudinal secondary-data design was applied to seven non-financial firms listed on the Ghana Stock Exchange over 2019–2024. Of 42 potential firm-year observations, 31 met the analytical eligibility rules and five were classified as forward vulnerable. Financial, operational, market and macroeconomic adverse signals were combined into convergence breadth, depth, persistence and an overall RSCF score, while Forward Corporate Vulnerability was measured one period ahead from observable stress outcomes. The mean RSCF score was 0.360 (SD = 0.253), the mean Forward Corporate Vulnerability Index was 0.263, and vulnerable-state prevalence was 16.1%. In exploratory stratified cross-validation, the financial-only logistic specification produced a receiver operating characteristic area under the curve of 0.638; the multi-domain specification increased this to 0.792, and the convergence-enhanced specification to 0.815, with a precision-recall area under the curve of 0.434. Logistic regression showed stronger overall discrimination than Random Forest and Extreme Gradient Boosting in the verified core panel, while Shapley Additive Explanations identified convergence depth as the leading tree-model attribution. Given the small and imbalanced sample, these results are interpreted as preliminary evidence of operational feasibility and incremental-information potential rather than conclusive proof of predictive superiority. The principal contribution is conceptual and methodological; the RSCF makes cross-domain concurrence an explicit, reproducible and explainable early-warning construct.

Keywords: Corporate vulnerability; early-warning systems; risk signal convergence; explainable artificial intelligence; Ghana

INTRODUCTION

Corporate vulnerability as an operations-research problem

Corporate vulnerability is not usually triggered by a single deteriorating ratio. It develops through interacting pressures that constrain cash, operating capacity, financing flexibility and market confidence. This is particularly important for firms operating in volatile environments because the same accounting position can carry different implications under different inflation, interest-rate or exchange-rate conditions. Contemporary distress research has therefore moved beyond single-score models toward richer combinations of financial, market, macroeconomic and non-financial information, while machine-learning methods increasingly capture nonlinear patterns that conventional specifications may overlook (Altman et al., 2020; Ciampi et al., 2021; Mousavi et al., 2023). This article treats early warning as an operations-research problem of signal integration under uncertainty. The practical decision is not merely whether a firm is currently profitable, but whether the configuration of available information at time t indicates a materially

elevated probability of vulnerability at time t + 1. Such a framing requires a disciplined architecture for converting heterogeneous indicators into comparable adverse signals, combining them without losing their domain meaning, and testing whether their concurrence adds predictive information. This is compatible with the broader movement toward decision-support systems that combine predictive power with transparency rather than treating classification accuracy as the sole objective (Deng et al., 2024; Černevičienė & Kabašinskas, 2024).

Ghana as an analytically valuable setting

Ghanaian firms operate within a business environment in which company-specific conditions can interact sharply with macroeconomic movements. A liquidity deterioration may coincide with exchange-rate depreciation, higher financing costs, weaker market returns or shrinking operating margins, so the informational meaning of any single accounting ratio depends partly on the wider state in which the firm is operating. Recent distress research therefore supports combining firm fundamentals with market and macroeconomic information, while emerging evidence from Ghana also shows that firm resilience differs across organizational and exposure conditions rather than being uniform across enterprises (Habib et al., 2020; Mousavi et al., 2023; Ackah et al., 2025). The Ghanaian setting is consequently suitable for a reproducible secondary-data panel built from audited financial statements, stock-market information and official macroeconomic statistics without creating artificial observations.

The empirical sample focused on non-financial firms listed on the Ghana Stock Exchange because banking and insurance institutions operate with sector-specific balance-sheet structures and prudential rules that make conventional liquidity and leverage ratios non-comparable. Financial firms were therefore excluded from the primary analysis rather than pooled mechanically with industrial, consumer, telecommunications, energy or other non-financial companies. This design choice followed the wider distress literature's emphasis on contextual calibration and the value of models tailored to the characteristics of the population being predicted (Ciampi et al., 2021; Ben Jabeur et al., 2023).

Research problem

Despite substantial progress in corporate distress prediction, three problems remain important. First, many models are variable-rich but conceptually flat: ratios are entered as parallel predictors without theorizing when simultaneous deterioration across distinct domains should count as stronger evidence than a severe movement in only one domain. Second, machine-learning studies often achieve high discrimination but provide limited conceptual explanation of how predictor combinations form a coherent risk mechanism. Third, organizational resilience research emphasizes the ability to maintain function and recover from adversity, yet it continues to face measurement challenges and is rarely connected to operational early-warning architectures based entirely on observable firm and environmental data (Hillmann & Guenther, 2021; Prayag et al., 2024).

The gap addressed here is therefore not simply another bankruptcy model. Recent reviews show that contemporary distress prediction increasingly combines multiple data classes and advanced algorithms, yet conceptual integration of those signals remains less developed than predictive model comparison (Ciampi et al., 2021; Zhao et al., 2024). The present article proposes that vulnerability information is created when adverse states converge across financial, operational, market and macroeconomic domains, because simultaneous weakening can reduce the firm's room for substitution, adaptation and recovery. This logic is consistent with organizational-resilience research, which emphasizes that resilience is multidimensional and depends on the organization's capacity to sustain and reconfigure resources under adversity (Hillmann & Guenther, 2021; Prayag et al., 2024).

Purpose and objectives

The purpose of this article is to develop and empirically demonstrate the Risk Signal Convergence Framework (RSCF) as an explainable multi-domain early-warning architecture for corporate vulnerability in Ghana.

The specific objectives are;

- Construct reproducible adverse signals from audited financial, operational, market and macroeconomic variables.
- Develop a Risk Signal Convergence Index capturing concurrence, depth and persistence.
- Construct a one-year-ahead Forward Corporate Vulnerability Index from observable stress outcomes.
- Compare the predictive contribution of convergent signals with isolated-domain and conventional ratio models.
- Use explainable machine learning to identify which signal configurations drive global and firm-specific vulnerability predictions.

Research questions

The study is guided by four questions:

- To what extent does multi-domain signal convergence predict one-year-ahead corporate vulnerability among Ghanaian firms?
- Does the predictive value of convergent signals exceed the predictive value of isolated financial, operational, market or macroeconomic indicators?
- Do nonlinear machine-learning models identify meaningful interaction thresholds that are missed by an additive logistic benchmark?
- Which risk domains and signal combinations contribute most to predicted vulnerability after model explanation?

Contribution

The article's primary contribution is conceptual: it defines risk signal convergence as a measurable state of concurrent adverse information across economically distinct domains. Methodologically, it specifies a reproducible sequence separating signal engineering, convergence construction, forward-outcome measurement and explanation. The empirical component demonstrates that the framework can be operationalized with verifiable Ghanaian secondary data; it is not presented as definitive external validation or as proof of universal predictive superiority. For Operations Research and Business Analytics, the contribution lies in transforming heterogeneous observations into a transparent early-warning architecture whose assumptions, outputs and explanations can be audited and independently tested (Ciampi et al., 2021; Mousavi et al., 2023; Deng et al., 2024; Hillmann & Guenther, 2021).

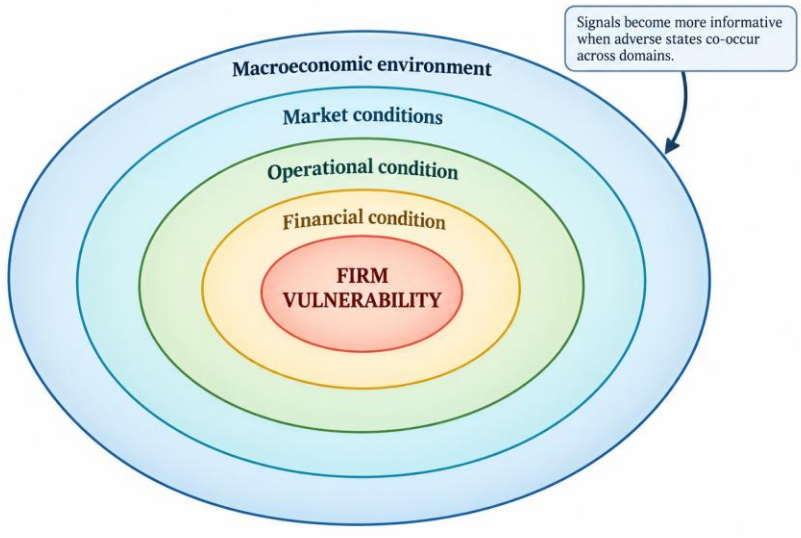


Figure 1: Multi-layer risk architecture underlying the Risk Signal Convergence Framework.

Source: Author's conceptual development.

This figure illustrates the logic of the Risk Signal Convergence Framework. It shows that firm vulnerability is shaped by nested financial, operational, market and macroeconomic conditions rather than by a single indicator. This multi-layer view is consistent with recent resilience scholarship that treats organizational outcomes as products of interacting capabilities and environmental pressures, and with distress research showing gains from integrating accounting, market and macroeconomic information (Hillmann & Guenther, 2021; Mousavi et al., 2023; Prayag et al., 2024). As adverse signals emerge simultaneously across these domains, their concurrence is expected to contain more early-warning information than the magnitude of an isolated ratio.

LITERATURE REVIEW

Conceptual Review

From financial distress prediction to corporate vulnerability

Financial distress prediction has evolved from ratio-based classification toward models that use larger variable sets, longer horizons and nonlinear algorithms. Altman et al. (2020) show that prediction horizon, variable selection and decision cut-offs materially affect distress-model efficiency. A systematic review by Ciampi et al. (2021) similarly identifies a strong movement toward artificial intelligence, machine learning, macroeconomic inputs and new categories of information, while emphasizing the value of combining multiple classes of predictive variables. These developments support a shift from retrospective failure classification toward forward-looking vulnerability analysis.

Corporate vulnerability is broader than legal bankruptcy. In the present article it refers to a measurable weakening of the firm's capacity to preserve liquidity, service obligations, sustain productive operations and absorb environmental shocks over the next period. This avoids treating bankruptcy, often rare in small listed samples, as the only meaningful endpoint. It also aligns the empirical problem with organizational resilience scholarship, which conceptualizes resilience around maintaining functions, mobilizing resources and recovering from adversity, while recognizing that measurement remains a central challenge (Hillmann & Guenther, 2021).

Financial risk signals

Financial ratios remain indispensable because they summarize solvency, liquidity, profitability and cash-generating capacity. Yet recent work indicates that their value depends on horizon, interactions and model form. Ben Jabeur et al. (2023) demonstrate the utility of Extreme Gradient Boosting and feature-importance engineering for bankruptcy prediction, while Nguyen et al. (2025) show that ensemble models can be combined with Shapley Additive Explanations to reveal the contribution of specific predictors over horizons extending beyond one year. The implication for the present article is that financial signals should be retained as a core domain but should not be assumed to carry the entire early-warning burden.

The financial domain therefore emphasized deterioration and threshold breaches rather than raw ratios alone. The selected signals included weakening current liquidity, rising leverage, falling interest coverage, negative operating cash flow relative to assets, declining return on assets and erosion of retained earnings. The direction of change matters because a firm with a moderate but rapidly deteriorating ratio may be more informative for early warning than a firm with a stable but structurally low ratio.

A further implication of the recent literature is that financial indicators should be interpreted as a profile rather than as independent alarms. Reviews of financial distress identify liquidity, leverage, profitability and cash-flow measures as recurring determinants, but also emphasize that comprehensive models are needed because the same ratio can have different predictive value across horizons, sectors and economic states (Habib et al., 2020; Ciampi et al., 2021; Zhao et al., 2024). This supports the present study's use of standardized adverse states and domain-level aggregation instead of relying on a single fixed-score model.

Operational risk signals

Operational deterioration often precedes visible insolvency because stress first appears in the firm's ability to turn resources into revenue and cash. Asset turnover, inventory conversion, receivables collection, operating margin and cost intensity can therefore carry distinct information from balance-sheet solvency measures. This distinction matters for operations research: vulnerability can emerge when the production-and-conversion system loses efficiency even before financing ratios cross conventional distress boundaries. Operational indicators are especially relevant to the proposed convergence logic because they offer an internal-process domain against which financial stress can be compared. A simultaneous decline in asset turnover and operating margin, for example, suggests a different mechanism from leverage deterioration alone (Ackah et al., 2025). The model therefore treats operating deterioration as a separate signal family rather than absorbing it into a generic financial score.

Operational measures are also theoretically important because financial distress has consequences for production, working-capital management and resource conversion before formal insolvency necessarily occurs. Habib et al. (2020) identify operational consequences as a distinct stream within the financial-distress literature, while recent Ghanaian resilience evidence shows that continuity, sales and productivity can respond differently to major shocks (Ackah et al., 2025). These findings justify treating operating margin, asset turnover, inventory days, receivable days and cost intensity as a separate information domain in the Risk Signal Convergence Framework.

Market risk signals

Market-based variables provide a forward-looking dimension because prices and trading behavior aggregate investor expectations before accounting statements are released. Distress research increasingly benefits from combining accounting and market data; Mousavi et al. (2023), in a dynamic evaluation of distress prediction models, report stronger performance for configurations combining financial accounting, market and macroeconomic information than for narrower information sets. The RSCF therefore includes negative abnormal return, realized volatility, maximum drawdown and trading-liquidity deterioration where the relevant Ghana Stock Exchange series are available.

Market signals were treated cautiously because thin trading and missing observations can affect some Ghanaian securities. The methodology therefore applied availability rules and model specifications that did not require unsupported market observations. This ensured that the empirical implementation remained grounded in verifiable data.

Market information is valuable because it can incorporate changing expectations before audited accounting data are published. Zhou et al. (2022) combine financial ratios, market variables and macroeconomic conditions in a recurrent-distress survival framework, while Mousavi et al. (2023) report stronger aggregate performance when financial accounting, market and macroeconomic information are used together. The implication is not that market prices are always superior, but that their incremental information can strengthen early warning when liquidity and trading completeness are adequate.

Macroeconomic risk signals

Macroeconomic conditions alter the meaning of firm-level weakness. Inflation can compress real demand and raise costs; exchange-rate depreciation can increase imported-input and foreign-currency debt burdens; high interest rates can raise financing costs; and slower economic growth can weaken sales. The importance of combining macroeconomic information with firm data is well established in the modern distress literature and is highlighted in recent reviews and dynamic model evaluations (Ciampi et al., 2021; Mousavi et al., 2023).

The RSCF does not assume that a macroeconomic variable alone makes each firm vulnerable. Instead, macro signals enter as common environmental states whose effect is expected to be conditional on firm-level financial and operational weakness. This is where convergence becomes analytically useful: a large

exchange-rate shock should be more informative when the affected firm simultaneously exhibits weak cash coverage, falling operating margins or substantial foreign-currency exposure disclosed in its annual report.

The empirical role of the macroeconomic domain is therefore contextual rather than deterministic. Macroeconomic conditions can alter financing costs, demand, input prices and the burden of foreign-currency exposure, yet their predictive contribution is expected to depend on firm-level sensitivity and contemporaneous internal weakness. Modern reviews and multi-source prediction studies accordingly recommend modelling macroeconomic conditions jointly with firm variables instead of treating them as stand-alone explanations of distress (Habib et al., 2020; Ciampi et al., 2021; Mousavi et al., 2023; Zhao et al., 2024).

Explainable machine learning and early-warning decision support

Complex ensemble methods can capture nonlinearities and interactions, but their use in financial decisions raises interpretability concerns. Recent finance research increasingly combines high-performing algorithms with explainable artificial intelligence. Zhang et al. (2022) show how explainable artificial intelligence can be integrated into financial-distress prediction, while Deng et al. (2024) build an interpretable ensemble forewarning model for listed companies. The systematic review by Černevičienė and Kabašinskas (2024) confirms that explainability is increasingly central in financial applications because predictive performance alone does not establish trust or decision usefulness. For the present study, explainability was not an ornamental post-processing step; it formed part of model validity. The RSCF makes a substantive claim that concurrence across distinct risk domains matters. Shapley Additive Explanations were therefore used to examine whether the fitted tree model assigned meaningful importance to convergence variables and interaction patterns and whether those explanations were economically coherent at global and firm-year levels (Nguyen et al., 2025). Explainability also has a substantive role in theory testing. Zhang et al. (2022) show that Shapley Additive Explanations, partial-dependence analysis and counterfactual explanations can make financial-distress models more transparent to external users. Deng et al. (2024) similarly combine ensemble learning with Shapley Additive Explanations in a listed-company forewarning model, and Nguyen et al. (2025) demonstrate that feature contributions can be interpreted over prediction horizons of one to five years. These developments support using explanation tools to determine whether convergence variables genuinely contribute to predictions rather than merely increasing model complexity.

THEORETICAL REVIEW

Dynamic Capabilities Theory

Dynamic capabilities theory provides one theoretical foundation for linking changing risk conditions to future vulnerability. In contemporary resilience research, dynamic capabilities describe the organization's capacity to sense threats and opportunities, integrate knowledge, reconfigure resources and renew routines as conditions change. Prayag et al. (2024), using dynamic capabilities and a crisis-management lens, show that different capabilities become salient before, during and after disruption, supporting a process view in which resilience depends on timely reconfiguration rather than on a static stock of resources. Applied to the present study, concurrent financial, operational, market and macroeconomic deterioration can be interpreted as evidence that the firm's adaptive room is narrowing, thereby increasing the probability of forward vulnerability (Prayag et al., 2024). The dynamic-capabilities perspective is particularly useful for explaining why persistence matters. A temporary adverse signal may be absorbed through cash buffers, operational adjustments or financing flexibility, whereas repeated multi-domain stress suggests that the organization has been unable to restore or reconfigure critical resources quickly enough. Recent organizational-resilience research therefore supports a temporal interpretation of resilience in which preparation, response and recovery capabilities unfold over stages rather than appearing as a single contemporaneous attribute (Hillmann & Guenther, 2021; Prayag et al., 2024). The persistence component of the Risk Signal Convergence Framework operationalizes this theoretical expectation using observable secondary data.

Organizational Resilience and Systems Perspective

Organizational resilience provides a second theoretical lens. Hillmann and Guenther (2021) demonstrate that resilience has been conceptualized through multiple organizational, ecological and systems-oriented traditions and argue that measurement clarity remains a central challenge. A systems perspective is appropriate for the present article because a firm is not represented by one financial ratio; it is a connected configuration of financing, operations, market relationships and exposure to the external economy. Weakness in one subsystem may be offset by strength elsewhere, but simultaneous deterioration across several subsystems can reduce redundancy and adaptive capacity (Hillmann & Guenther, 2021). This systems logic explains the framework's emphasis on breadth and depth. Breadth captures how many distinct risk domains are active, while depth captures how strongly those domains are adverse. The conceptual proposition is therefore not that every negative observation indicates vulnerability, but that vulnerability becomes more credible when independent channels provide mutually reinforcing evidence. This approach responds to calls for clearer, more parsimonious measurement of resilience while retaining a multidimensional view of organizational functioning (Hillmann & Guenther, 2021; Ackah et al., 2025).

Information Integration and Signal-Convergence Logic

A third theoretical strand comes from the modern financial-distress literature itself, which increasingly treats prediction as an information-integration problem. Habib et al. (2020) classify determinants across firm fundamentals, macroeconomic conditions and governance, while Ciampi et al. (2021) identify growing use of artificial intelligence, non-financial information and multiple predictor classes. Mousavi et al. (2023) provide direct evidence that models combining financial accounting, market and macroeconomic information can outperform narrower information sets. These studies support the proposition that the joint configuration of heterogeneous signals can contain information that is not captured by a single domain alone.

The Risk Signal Convergence Framework extends this integration logic by converting simultaneity itself into an explicit construct. Rather than asking a black-box algorithm to discover every interaction without theoretical structure, the framework measures domain activation, breadth, depth and persistence before comparing additive and nonlinear models. This creates a bridge between theory-driven feature engineering and data-driven prediction, which is consistent with current recommendations to combine predictive accuracy, conceptual transparency and explainability in financial risk analytics (Zhang et al., 2022; Deng et al., 2024; Zhao et al., 2024; Černevičienė & Kabašinskas, 2024).

Theoretical Synthesis for the Present Study

Taken together, dynamic capabilities theory explains why adaptive capacity and temporal persistence matter; organizational-resilience and systems thinking explain why vulnerability should be understood across interdependent domains; and information-integration research explains why combining heterogeneous signals can improve early warning. The resulting theoretical expectation was that corporate vulnerability at time t + 1 would increase as adverse conditions at time t became broader, deeper, more persistent and more interactive. The Risk Signal Convergence Framework converted that expectation into measurable quantities evaluated with longitudinal secondary data and explainable predictive models (Hillmann & Guenther, 2021; Mousavi et al., 2023; Prayag et al., 2024; Zhao et al., 2024).

Empirical Review

Evidence from Financial and Multi-Domain Distress Models

Empirical distress research consistently shows that predictive performance depends on the information set, horizon and estimation design. Altman et al. (2020) compare several estimation methods for long-horizon bankruptcy prediction and show that method choice, variable selection and decision cut-offs materially affect efficiency. Almaskati et al. (2021), using United States public firms, similarly find that adding governance information improves bankruptcy prediction and that estimation method influences out-of-

sample performance. These results caution against treating one ratio set or one classifier as universally optimal and support the present study's nested-model comparison strategy.

Evidence also supports combining information from multiple domains. Zhou et al. (2022) model recurrent financial distress in Chinese listed firms with duration dependence, event factors, financial ratios, market variables and macroeconomic conditions. Mousavi et al. (2023) compare static and dynamic distress models and find that configurations combining financial accounting, market and macroeconomic information perform better in aggregate than narrower information sets. The present study builds on these findings by making cross-domain concurrence an explicit predictor rather than allowing multiple variables to enter only as parallel covariates.

Evidence from Machine Learning and Explainability

Recent machine-learning studies show substantial value in nonlinear classification but also expose the need for transparent explanation. Ben Jabeur et al. (2023) develop an Extreme Gradient Boosting model with feature-importance engineering and report stronger predictive accuracy than several alternative machine-learning and feature-selection combinations. Zhang et al. (2022) demonstrate an explainable artificial-intelligence architecture for financial distress using Shapley Additive Explanations, partial-dependence plots and counterfactual explanations. Deng et al. (2024) likewise report strong forewarning performance from an interpretable ensemble-learning approach for listed companies. Nguyen et al. (2025) extend this evidence by comparing Random Forest, Light Gradient Boosting Machine, Extreme Gradient Boosting and Natural Gradient Boosting for French firms over prediction horizons of one to five years, then using Shapley Additive Explanations to interpret individual and global predictions. Taken together, these studies suggest that an internationally competitive early-warning article should evaluate both discrimination and interpretability. This is why the present design retains logistic regression as a transparent benchmark while comparing Random Forest and Extreme Gradient Boosting and subsequently explaining the best-performing tree model (Nguyen et al., 2025; Černevičienė & Kabašinskas, 2024).

Evidence on Persistence, Recovery and Ghanaian Firm Resilience

Persistence is empirically important because distress can recur rather than appearing as a one-time event. Zhou et al. (2022) show that recurrent distress can be modelled with survival methods that incorporate duration dependence alongside financial, institutional, market and macroeconomic variables. This evidence supports the present article's persistence term, which distinguishes temporary signal activation from repeated cross-domain stress. It also reinforces the need for chronological validation because the informational value of a distress model can change across time and economic regimes (Mousavi et al., 2023). Ghana-specific evidence also indicates that resilience outcomes are heterogeneous. Ackah et al. (2025), using firm-level panel data from 2018 to 2021, find that special-economic-zone status did not automatically confer resilience during the coronavirus disease shock; operational continuity, sales recovery and productivity responses varied, with pre-shock performance and exposure structures remaining important. Although their study addresses a different institutional setting and outcome, it strengthens the case for measuring Ghanaian firm vulnerability through observable operational and financial outcomes rather than assuming resilience from organizational labels alone.

Empirical Studies Table of Literature (ESTOL)

Table 1 consolidates the empirical evidence most directly relevant to the article. The studies differ in geography, outcome definitions, data structures and analytical methods, but collectively show four recurring lessons: multi-source information can improve prediction, temporal structure matters, nonlinear models can capture additional patterns, and explainability is increasingly required for decision usefulness. None of the reviewed studies operationalizes breadth, depth and persistence of cross-domain adverse states as a dedicated Ghanaian Risk Signal Convergence construct, leaving a clear space for the present article (Altman et al., 2020; Zhou et al., 2022; Mousavi et al., 2023; Deng et al., 2024; Nguyen et al., 2025).

Table 1. Empirical Studies Table of Literature (ESTOL)

Author(s) / year	Context / data	Methodology	Key findings	Limitation / gap	Relevance to Risk Signal Convergence Framework
Altman et al. (2020)	European small and medium-sized enterprises; long-horizon financial and non-financial data	Compared logistic regression, neural networks and alternative estimators across prediction horizons.	Efficiency varies with estimation method, variable selection and decision cut-offs.	Cross-domain concurrence is not modelled as a construct.	Supports horizon-aware benchmarking and sensitivity analysis.
Almaskati et al. (2021)	United States public firms, 2000–2015	Compared bankruptcy models with governance information and out-of-sample evaluation.	Governance information improves prediction; estimation method materially affects accuracy.	Focuses on bankruptcy and governance rather than multi-domain stress.	Supports incremental-information testing and model comparison.
Zhou et al. (2022)	Chinese listed firms with recurrent distress events	Stratified survival analysis using financial, event, market and macroeconomic variables.	Distress recurrence contains duration dependence and benefits from several predictor classes.	Outcome is a market-specific distress designation.	Supports persistence and temporal structure in forward vulnerability.
Zhang et al. (2022)	Financial-distress prediction setting	Ensemble prediction with Shapley Additive Explanations, partial-dependence and counterfactual explanations.	Explanation methods improve transparency of black-box distress predictions.	Emphasizes explanation rather than a convergence construct.	Supports global and local explanation of framework predictions.
Ben Jabeur et al. (2023)	Corporate bankruptcy data with multiple candidate predictors	Extreme Gradient Boosting with feature-importance selection compared with seven machine-learning algorithms.	Feature-importance-engineered Extreme Gradient Boosting improves predictive accuracy.	Algorithm-centred; simultaneous domain activation is not theorized.	Supports nonlinear benchmarking and feature-importance analysis.
Mousavi et al. (2023)	Static and dynamic distress models	Malmquist Data Envelopment Analysis-based	Dynamic models and combined financial, market	Evaluates model performance	Directly supports multi-source inputs and time-aware

	evaluated across periods	multi-period performance evaluation.	and macroeconomic information show stronger aggregate performance.	rather than constructing convergence.	evaluation.
Deng et al. (2024)	Chinese listed companies	Interpretable ensemble forewarning with hyperparameter optimization and Shapley Additive Explanations.	The ensemble approach improves forewarning and explains feature contributions.	Country-specific model with limited explicit theory of domain concurrence.	Supports explainable ensemble early warning.
Nguyen et al. (2025)	French firms across industries; one-to five-year horizons	Compared Random Forest, Light Gradient Boosting Machine, Extreme Gradient Boosting and Natural Gradient Boosting, then applied Shapley Additive Explanations.	Ensembles perform strongly and Shapley values explain global and individual forecasts.	Uses bankruptcy rather than broader forward vulnerability.	Supports multi-horizon prediction and explanation architecture.
Ackah et al. (2025)	Ghanaian firms, 2018–2021 panel around the coronavirus disease shock	Firm-level panel fixed-effects estimation of resilience and recovery.	Resilience differs across firms; special-economic-zone status does not automatically improve continuity, sales recovery or productivity.	Different institutional question and no capital-market early-warning model.	Provides Ghana-specific evidence that resilience is heterogeneous and observable.

Research Gap Synthesis

The literature provides increasingly sophisticated tools for corporate distress prediction, but it offers less conceptual clarity about the information created when adverse conditions co-occur across distinct domains. Recent reviews emphasize broader predictor sets, improved feature engineering, dynamic evaluation and explainability, yet most empirical models still represent financial, operational, market and macroeconomic variables as separate inputs or algorithmic features rather than as a theoretically specified convergence state (Ciampi et al., 2021; Zhao et al., 2024).

Organizational-resilience research, meanwhile, continues to identify measurement clarity as a challenge and shows that resilience depends on configurations of capabilities and exposures rather than a single indicator (Hillmann & Guenther, 2021; Prayag et al., 2024; Ackah et al., 2025). The present study addresses this intersection by defining and testing Risk Signal Convergence through breadth, depth, persistence and interaction intensity, then examining whether those features add out-of-time predictive value beyond conventional ratio and single-domain models.

Table 2. Literature-to-gap positioning of the article

Recent literature direction	What is established	Remaining limitation addressed here	RSCF response
Long-horizon distress prediction	Prediction varies by horizon, variables and decision cut-offs (Altman et al., 2020).	Indicators are commonly modeled as parallel predictors.	Models concurrence, persistence and domain depth explicitly.
Multi-source default prediction	Combining multiple information categories is a priority (Ciampi et al., 2021).	No dedicated construct for cross-domain concurrence.	Introduces Risk Signal Convergence as the focal construct.
Dynamic performance evaluation	Combined accounting, market and macro information can improve performance (Mousavi et al., 2023).	Model comparison may remain performance-centric.	Adds theory, explainability and decision architecture.
Machine learning distress models	Extreme Gradient Boosting and ensemble models capture nonlinear patterns (Ben Jabeur et al., 2023; Deng et al., 2024).	Black-box interaction effects can be difficult to interpret.	Uses Shapley Additive Explanations plus explicit convergence variables.
Organizational resilience	Resilience is valuable but difficult to measure consistently (Hillmann & Guenther, 2021).	Survey-heavy and construct ambiguity may limit operational early warning.	Uses observable vulnerability outcomes and secondary data.

CONCEPTUAL FRAMEWORK

Risk Signal Convergence Framework (RSCF)

Core construct: risk signal convergence

Risk signal convergence is defined in this study as the degree to which adverse conditions are simultaneously active across economically distinct risk domains for the same firm and observation period. The construct has four attributes: breadth, referring to the number of active domains; depth, referring to the severity of adverse signals within domains; persistence, referring to repeated activation across adjacent periods; and interaction intensity, referring to nonlinear amplification when specific domains are jointly adverse. This multidimensional specification is consistent with resilience research that conceptualizes organizational response as a dynamic combination of anticipation, coping, adaptation and resource-reconfiguration capabilities rather than as a single static attribute (Duchek, 2020; Conz & Magnani, 2020; Zhang et al., 2023). The construct also assumes partial substitutability of corporate buffers: strength in liquidity, financing flexibility, operating capacity or other resources can temporarily offset weakness elsewhere, whereas simultaneous deterioration across several domains reduces the scope for compensation and adaptation. Empirical work on resource deployment and dynamic capabilities similarly shows that organizational resilience depends on the availability and reconfiguration of complementary resources under adverse conditions (Do et al., 2022; You et al., 2023).

Signal standardization

Each candidate variable was oriented so that larger adverse-state values consistently represented greater risk. Continuous and binary indicators were transformed according to their economic direction, and binary signals

identified whether the relevant adverse condition was activated. Such orientation is consistent with contemporary distress modelling, where heterogeneous financial and non-financial predictors must be transformed into analytically comparable risk information without erasing their economic meaning (Altman et al., 2020; Ciampi et al., 2021; Zhao et al., 2024). In the RSCF, standardization therefore served as a measurement bridge between heterogeneous source variables and the higher-order convergence construct.

Domain scores and convergence index

Let the adverse signal for variable k, firm i and year t take a value between zero and one after scaling. For each risk domain d, the domain score is the arithmetic mean of its component signals. The overall Risk Signal Convergence Index is then formed from weighted domain scores and an explicit concurrence premium that increases when several domains are simultaneously active. The use of domain-level aggregation is consistent with evidence that distress prediction benefits from combining multiple classes of financial, market, operational and macroeconomic information rather than relying exclusively on one predictor family (Ciampi et al., 2021; Mousavi et al., 2023; Zhao et al., 2024). Equal domain weights were retained as the primary specification to preserve interpretability and avoid allowing sample-specific algorithmic weights to redefine the conceptual structure.

Forward corporate vulnerability

The dependent construct was the Forward Corporate Vulnerability Index (FCVI), measured at t + 1 using observable adverse outcomes rather than subjective assessments. This forward orientation reflects the distinction between a firm's present risk configuration and its subsequent capacity to preserve function, absorb stress and recover, a distinction emphasized in contemporary resilience and distress research (Duchek, 2020; Conz & Magnani, 2020; Zhou et al., 2022). Its core components were negative operating cash flow, negative or materially weak return on assets, inadequate interest coverage, negative working capital and severe market drawdown where market data were available. A binary vulnerable-state label was generated when at least two applicable core outcomes were simultaneously adverse, while the continuous index represented the proportion of applicable adverse outcomes, allowing vulnerability to be captured before formal bankruptcy becomes the only observable endpoint (Zhao et al., 2024).

Propositions

The framework yielded four testable propositions. First, higher risk signal convergence at time t was expected to be associated with greater Forward Corporate Vulnerability at time t + 1. Second, the predictive gain from a multi-domain convergence index was expected to exceed that of any single-domain score. Third, the relationship was expected to become nonlinear as multiple domains became concurrently adverse. Fourth, persistent convergence across adjacent periods was expected to provide stronger early-warning information than one-period convergence alone. These propositions were grounded in evidence that distress prediction improves when heterogeneous information is integrated, that nonlinear algorithms can capture interaction effects, and that resilience depends on dynamic resource reconfiguration across time (Ben Jabeur et al., 2023; Mousavi et al., 2023; Do et al., 2022; You et al., 2023).

$$D_{d,it} = \frac{1}{K_d} \sum_{k=1}^{K_d} s_{k,it}$$ **Where:** D denotes the risk-domain score; d identifies the domain; i identifies the firm; t identifies the year; K_d is the number of indicators in domain d; k indexes the indicators; and $s_{k,it}$ is the standardized adverse signal for indicator k.	**(1)**
$$B_{it} = \sum_{d=1}^{4} \mathbb{I}(D_{d,it} \geq \tau_d)$$ **Where:** B is convergence breadth; d indexes the four risk domains; $D_{d,it}$ is the score for domain d; τ_d	**(2)**

is the activation threshold for domain d; and the indicator function equals one when the domain is active and zero otherwise.

$$RSC_{it} = \sum_{d=1}^{4} w_d D_{d,it} + \lambda \left[\frac{B_{it}(B_{it}-1)}{6} \right] \quad (3)$$

Where: RSC is the Risk Signal Convergence Index; w_d is the weight assigned to domain d, with the weights summing to one; $D_{d,it}$ is the domain score; B_{it} is breadth; and λ controls the size of the concurrence premium. The denominator six is the maximum number of pairwise domain combinations when four domains are active.

$$PERSIST_{it} = \frac{RSC_{it} + RSC_{i,t-1}}{2} \quad (4)$$

Where: PERSIST measures two-period convergence persistence; RSC_{it} is the current-year convergence index and $RSC_{i,t-1}$ is the immediately preceding-year convergence index for the same firm.

$$FCVI_{i,t+1} = \frac{1}{J} \sum_{j=1}^{J} v_{j,i,t+1} \quad (5)$$

Where: FCVI is the Forward Corporate Vulnerability Index; J is the number of applicable forward vulnerability outcomes; j indexes those outcomes; and $v_{j,i,t+1}$ equals one when outcome j is adverse for firm i in year t+1 and zero otherwise.

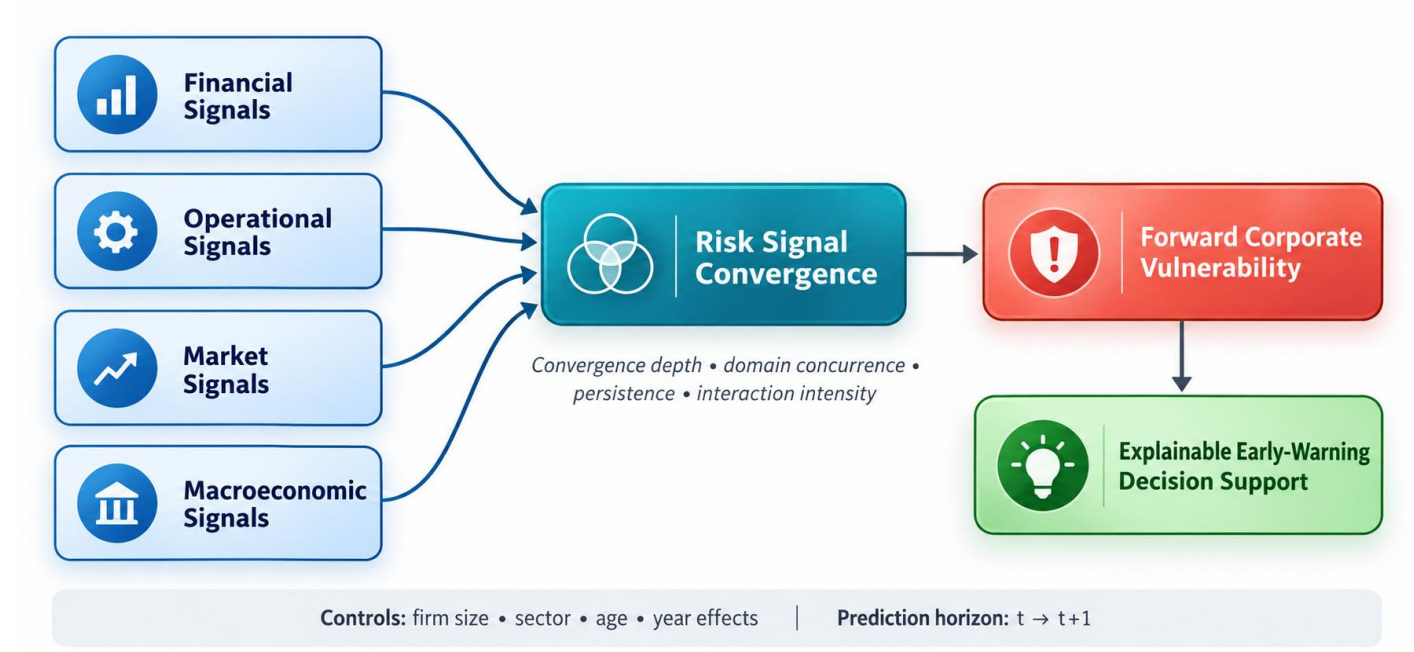


Figure 2. Pictorial form of Risk Signal Convergence Framework (RSCF).

Table 3. RSCF constructs, dimensions and observable indicators

Construct/domain	Indicative observable measures	Risk orientation	Primary source
Financial signals	Current ratio; debt-to-assets; interest coverage; operating cash flow/assets; return on assets;	Low liquidity/profitability/cash coverage and high	Audited annual reports and financial statements

	retained earnings/assets	leverage = adverse	
Operational signals	Asset turnover; operating margin; inventory days; receivable days; cost-to-sales ratio	Falling turnover/margin or rising conversion days/cost intensity = adverse	Annual reports and notes
Market signals	Annual return; realized volatility; maximum drawdown; trading turnover/liquidity	Negative returns, high volatility/drawdown, deteriorating liquidity = adverse	Ghana Stock Exchange market reports / price data
Macroeconomic signals	Inflation; cedi depreciation; policy rate/interest rate; real GDP growth	High inflation/depreciation/rates and growth slowdown = adverse	Bank of Ghana; Ghana Statistical Service; World Bank/International Monetary Fund
Corporate vulnerability	Negative operating cash flow; weak/negative return on assets; interest coverage below one; negative working capital; severe drawdown	More simultaneous adverse outcomes = greater vulnerability	Derived from firm-year and market data

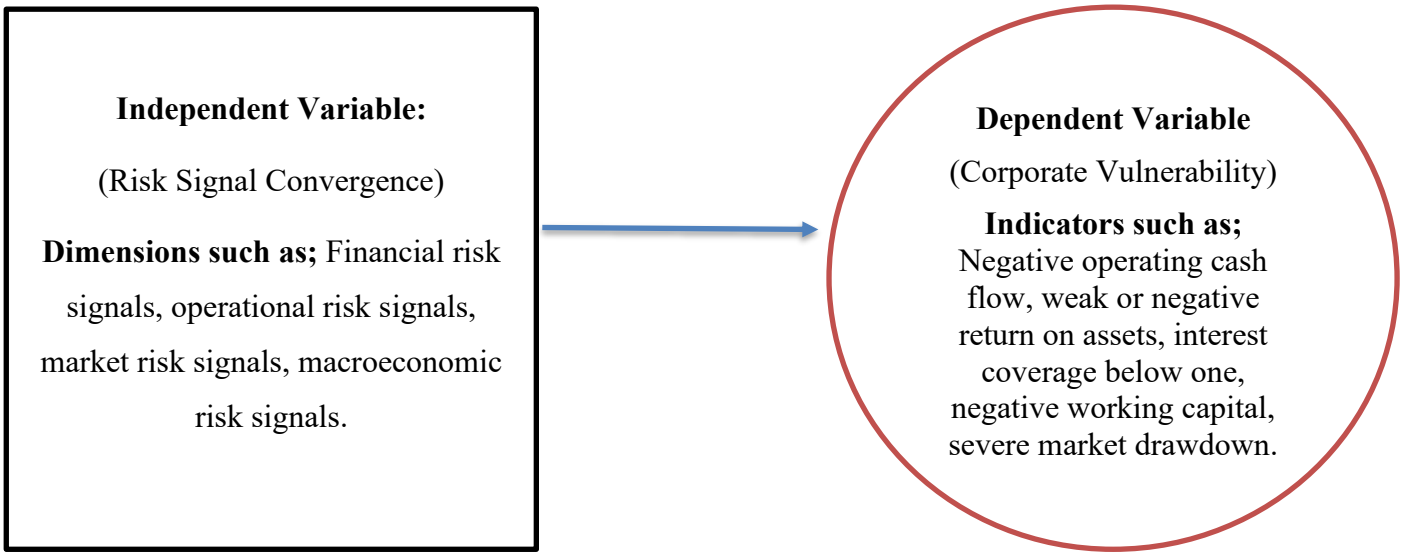


Figure 2.1: **Detailed Conceptual Framework (Risk Signal Convergence Framework-RSCF).**

Source: Author's conceptual development.

Explanation of the Conceptual Framework

The conceptual framework for this study is the Risk Signal Convergence Framework (RSCF). It explains how multiple adverse signals arising from different areas of a firm and its external environment can combine to increase the likelihood of future corporate vulnerability. Rather than treating individual financial ratios or market indicators as isolated predictors, the framework assumes that risk becomes more informative when adverse conditions occur simultaneously across several domains. This position is supported by contemporary distress reviews that favour broader information sets and by organizational-resilience

scholarship that treats resilience as a multidimensional and process-based capability (Ciampi et al., 2021; Zhao et al., 2024; Duchek, 2020; Conz & Magnani, 2020; Zhang et al., 2023).

The framework begins with four major risk-signal domains: financial signals, operational signals, market signals and macroeconomic signals. Financial signals capture liquidity, leverage, debt-service capacity, profitability and cash generation, while operational signals reflect the efficiency with which resources are converted into revenue and cash. Recent distress research shows that firm fundamentals remain central to prediction but become more informative when interpreted alongside non-financial, market and environmental information (Habib et al., 2020; Ciampi et al., 2021; Zhao et al., 2024). Resilience research likewise emphasizes that organizations draw simultaneously on financial, operational and adaptive resources when responding to disruption (Do et al., 2022; You et al., 2023). The selected operational indicators therefore include asset turnover, operating margin, inventory days, receivable days and cost-to-sales ratio because they capture resource-conversion stress that may precede visible insolvency.

The third domain comprises market risk signals, which introduce a forward-looking component through annual returns, realized volatility, maximum drawdown and trading turnover or liquidity. The fourth domain captures macroeconomic risk through inflation, cedi depreciation, the policy or interest rate and real Gross Domestic Product growth. Empirical research demonstrates that combining accounting, market and macroeconomic information can improve distress-model performance, while recurrent-distress studies confirm that time-varying market and macroeconomic conditions matter for the evolution of corporate stress (Zhou et al., 2022; Mousavi et al., 2023; Zhao et al., 2024). These domains are therefore treated as complementary sources of evidence rather than interchangeable predictors.

At the centre of the framework is Risk Signal Convergence, defined as the extent to which adverse signals from the four domains occur together for the same firm within the same observation period. The construct is represented by breadth, depth, persistence and interaction intensity. Breadth identifies the number of adverse domains, depth reflects the severity of the active domains, persistence captures repeated activation across time, and interaction intensity allows the combined effect of multiple domains to become nonlinear. The multidimensional treatment is consistent with capability-based resilience research, which shows that resilience is composed of several complementary dimensions and evolves across phases rather than being adequately represented by a single indicator (Duchek, 2020; Conz & Magnani, 2020; Zhang et al., 2023). The RSCF extends that logic into corporate early warning by making cross-domain concurrence directly measurable.

The logic of the framework is based on partial substitutability of corporate buffers. Temporary weakness in profitability may be absorbed by strong liquidity, low leverage or stable cash flows, while market volatility may remain manageable when operating fundamentals are sound. Resource-based and dynamic-capability evidence indicates that resilience is strengthened when organizations can mobilize, recombine and redeploy complementary resources in response to changing conditions (Do et al., 2022; You et al., 2023). As several domains deteriorate together, however, the firm has fewer compensating strengths available, supporting the expectation that Forward Corporate Vulnerability rises more sharply as convergence broadens, deepens and persists.

The dependent construct is Forward Corporate Vulnerability, measured at period $t + 1$ so that the framework functions as an early-warning model rather than a contemporaneous description of weakness. Observable adverse outcomes include negative operating cash flow, weak or negative return on assets, interest coverage below one, negative working capital and severe market drawdown. Capability-based resilience studies distinguish between current exposure and the subsequent ability to absorb, cope, adapt and recover, while financial-distress research shows that deterioration can recur and become visible before formal bankruptcy (Duchek, 2020; Zhang et al., 2023; Zhou et al., 2022). These insights support a forward vulnerability outcome rather than legal bankruptcy alone.

The framework hypothesized that higher Risk Signal Convergence at time t would be associated with greater Forward Corporate Vulnerability at time $t + 1$. It further proposed that a multi-domain convergence measure would add predictive information beyond any single domain, that the relationship could become nonlinear

after several domains became simultaneously adverse, and that persistent convergence would be more informative than a one-period signal. These expectations are consistent with evidence on long-horizon prediction, recurrent distress, multi-source model performance, nonlinear ensemble methods and the role of dynamic capabilities in sustaining resilience under continuing pressure (Altman et al., 2020; Zhou et al., 2022; Mousavi et al., 2023; Ben Jabeur et al., 2023; You et al., 2023).

Conceptually, the framework can therefore be summarized as:

Financial Risk Signals + Operational Risk Signals + Market Risk Signals + Macroeconomic Risk Signals → Risk Signal Convergence → Forward Corporate Vulnerability

The contribution of the Risk Signal Convergence Framework lies in shifting attention from the isolated magnitude of individual indicators to the pattern, concurrence and persistence of adverse signals across multiple domains. This gives the framework a distinctive Operations Research and Business Analytics orientation because it combines multi-criteria signal aggregation, temporal prediction, nonlinear interaction analysis and explainable decision support. Contemporary research supports both the multidimensional operationalization of resilience and the use of transparent explanation when complex models are deployed for financial decisions (Zhang et al., 2023; Zhang et al., 2022; Deng et al., 2024; Černevičienė & Kabašinskas, 2024; Nguyen et al., 2025).

METHODOLOGY

Research design

The study adopted a quantitative longitudinal research design using secondary firm-year and macroeconomic data. The firm-year was the unit of analysis. Predictors were measured at year t and Forward Corporate Vulnerability at year t + 1, thereby preserving temporal ordering between risk signals and the subsequent outcome (Mousavi et al., 2023; Zhao et al., 2024).

The empirical design combined explanatory and predictive analysis. Logistic regression provided the interpretable benchmark, while Random Forest and Extreme Gradient Boosting were estimated to examine nonlinearities and interactions. Model performance was evaluated with receiver operating characteristic area under the curve, precision-recall area under the curve, F1 score, balanced accuracy and Brier score, consistent with contemporary distress-prediction practice (Ben Jabeur et al., 2023; Deng et al., 2024; Nguyen et al., 2025).

Population, sampling frame and observation period

The primary population comprised non-financial companies listed on the Ghana Stock Exchange with verifiable annual financial and market information. The verified analytical archive covered 2019–2024 and contained seven non-financial firms, producing a 42-row potential firm-year grid. After application of the predefined analytical eligibility rules, 31 firm-year observations contained both a computable Risk Signal Convergence Framework score and a one-year-ahead vulnerability classification.

Banks, insurers and other regulated financial institutions were excluded from the primary model because their leverage, liquidity and asset structures are not directly comparable with those of non-financial firms. Persistence was computed only for firms with consecutive usable observations, consistent with the temporal structure of the convergence construct (Ciampi et al., 2021; Zhao et al., 2024).

Data sources and data provenance

The study used verifiable secondary sources. Firm accounting data were extracted from audited annual reports and financial statements available through the Ghana Stock Exchange and issuer publications. Market variables were obtained from Ghana Stock Exchange market information, while macroeconomic

variables were obtained from Bank of Ghana and World Bank series. Extracted observations retained source, period and provenance identifiers.

Missing observations were not fabricated. Where a value could not be verified, it remained missing and was handled through the predefined analytical rules. The data architecture therefore preserved a clear separation between source-reported values, reproducibly derived measures and unavailable observations.

Variable construction and measurement

Financial signals were computed from audited statement values. Current ratio was measured as current assets divided by current liabilities; leverage as total liabilities divided by total assets; interest coverage as earnings before interest and tax divided by the absolute value of finance cost; return on assets as profit after tax divided by average total assets; and operating cash-flow intensity as operating cash flow divided by average total assets.

Operational measures included asset turnover, operating margin, inventory days, receivable days and cost intensity subject to verified availability (Habib et al., 2020; Zhao et al., 2024).

Financial and operational measurement equations

$$CR_{it} = \frac{CA_{it}}{CL_{it}}$$

Measurement formula M1. Where: CR is the current ratio; CA is current assets; CL is current liabilities; i denotes the firm; and t denotes the fiscal year.

$$LEV_{it} = \frac{TL_{it}}{TA_{it}}$$

Measurement formula M2. Where: LEV is leverage; TL is total liabilities; and TA is total assets.

$$ICR_{it} = \frac{EBIT_{it}}{|FC_{it}|}$$

Measurement formula M3. Where: ICR is interest coverage; EBIT is earnings before interest and tax; and FC is finance cost. The absolute value ensures that a finance-cost line reported with a negative accounting sign does not reverse the economic interpretation.

$$ROA_{it} = \frac{PAT_{it}}{(TA_{it} + TA_{i,t-1})/2}$$

Measurement formula M4. Where: ROA is return on assets; PAT is profit after tax; TA is total assets; and the denominator is average total assets across the current and previous fiscal years.

$$OCFI_{it} = \frac{OCF_{it}}{(TA_{it} + TA_{i,t-1})/2}$$

Measurement formula M5. Where: OCFI is operating cash-flow intensity; OCF is net cash generated from operating activities; and the denominator is average total assets.

$$ATO_{it} = \frac{REV_{it}}{(TA_{it} + TA_{i,t-1})/2}$$

Measurement formula M6. Where: ATO is asset turnover; REV is revenue; and average total assets measure the asset base used to generate revenue.

$$OM_{it} = \frac{OP_{it}}{REV_{it}}$$

Measurement formula M7. Where: OM is operating margin; OP is operating profit; and REV is revenue.

$$ID_{it} = 365\left(\frac{INV_{it}}{COGS_{it}}\right)$$

Measurement formula M8. Where: ID is inventory days; INV is inventory; COGS is cost of goods sold; and 365 converts the turnover relation into an annual number of days.

$$RD_{it} = 365\left(\frac{AR_{it}}{REV_{it}}\right)$$

Measurement formula M9. Where: RD is receivable days; AR is trade receivables; and REV is annual revenue.

$$CI_{it} = \frac{COGS_{it}}{REV_{it}}$$

Measurement formula M10. Where: CI is cost intensity; COGS is cost of goods sold; and REV is annual revenue. Higher values indicate that a larger share of revenue is absorbed by direct operating cost.

[M4.4-P02] Market measures were computed where trading data were verifiable. Annual return was calculated from year-end price changes, and available high-low information was used to derive drawdown and range-based market-risk proxies. Macroeconomic indicators were aligned to the relevant year and oriented so that adverse movements in inflation, cedi depreciation, policy rates and economic growth were represented consistently (Mousavi et al., 2023; Zhao et al., 2024).

Market measurement equations

$$R_{it} = \frac{P_{it}}{P_{i,\,t-1}} - 1$$

Measurement formula M11. Where: R is the annual price return; P_{it} is the adjusted closing price at the end of year t; and $P_{i,t-1}$ is the adjusted closing price at the end of the preceding year.

$$r_{i,\,\tau} = \ln\left(\frac{P_{i,\,\tau}}{P_{i,\,\tau-1}}\right)$$

Measurement formula M12. Where: r is the periodic logarithmic return; τ indexes the trading period within the year; and P is the adjusted closing price.

$$RV_{it} = \sqrt{\frac{1}{n_{it}-1}\sum_{\tau=1}^{n_{it}}(r_{i,\,\tau} - \bar{r}_{it})^2}$$

Measurement formula M13. Where: RV is realized volatility; n is the number of valid return observations for firm i in year t; r is the periodic logarithmic return; and the barred r is the mean periodic return for that firm-year.

$$MDD_{it} = \min_{\tau}\left(\frac{P_{i,\tau}}{\max_{u \le \tau} P_{i,u}} - 1\right)$$

Measurement formula M14. Where: MDD is maximum drawdown; $P_{i,au}$ is the price at period τ; and the denominator is the highest price observed up to that period. More negative values indicate larger peak-to-trough losses.

$$TURN_{it} = \frac{\sum_{\tau=1}^{n_{it}} VOL_{i,\tau}}{SHARES_{it}}$$

Measurement formula M15. Where: TURN is annual trading turnover; VOL is the number of shares traded in period τ; n is the number of trading periods; and SHARES is the number of shares outstanding.

Adverse-signal rule

Adverse signals were created with pre-specified directional rules and thresholds documented before model comparison. Where a variable had a widely interpretable economic boundary, that boundary was retained, including a current ratio below one, interest coverage below one, negative profitability or negative operating cash flow. For variables without a universal economic cut-off, sector-year distributional thresholds were used so that adverse classification reflected contemporaneous context rather than an arbitrary global constant. High-risk variables were activated at or above the sector-year seventy-fifth percentile and low-risk variables at or below the twenty-fifth percentile. These rules were fixed independently of the forward-vulnerability outcome and were not tuned to maximize predictive performance, reducing the risk of outcome leakage or post-hoc threshold selection (Altman et al., 2020; Zhao et al., 2024).

Sector-year adverse-signal equations

$$s^{(H)}_{k,it} = \mathbb{I}(x_{k,it} \ge Q_{0.75,k,st})$$

Adverse-signal rule A1. Where: $s^{(H)}$ is the adverse signal for a high-risk variable; x is the observed value; $Q_{0.75,k,st}$ is the 75th percentile of indicator k within the relevant sector s and year t; and the indicator function equals one when the threshold is reached or exceeded.

$$s^{(L)}_{k,it} = \mathbb{I}(x_{k,it} \le Q_{0.25,k,st})$$

Adverse-signal rule A2. Where: s^{L} is the adverse signal for a low-risk variable; $Q_{0.25,k,st}$ is the corresponding 25th percentile; and the signal equals one when the observed value falls at or below that lower threshold.

Forward Corporate Vulnerability Index

The Forward Corporate Vulnerability Index was constructed from observable outcomes at t + 1 rather than from the same-period predictors used to build the convergence index. The binary outcome classified a firm-year as vulnerable when at least two applicable adverse outcomes were present, including negative operating cash flow, weak or negative return on assets, interest coverage below one, negative working capital and severe market drawdown. Requiring two conditions, rather than one, reduced sensitivity to an isolated noisy

observation while preserving a broader vulnerability concept than formal bankruptcy. The continuous index represented the proportion of applicable vulnerability outcomes that were adverse. Because only five binary events were observed, this classification rule is treated as a transparent operational definition rather than an optimized cut-off (Zhou et al., 2022; Zhao et al., 2024).

Risk Signal Convergence Index estimation

The Risk Signal Convergence Index used equal domain weights (0.25 per domain) as the primary specification. Equal weighting was chosen ex ante because the framework treats financial, operational, market and macroeconomic domains as conceptually distinct sources of evidence and the available sample was too small to support stable outcome-derived weights without substantial overfitting risk. Each domain score was bounded between zero and one. Breadth captured the number of active domains, depth captured the average severity of available domain scores, and the concurrence premium increased as more domains became simultaneously adverse. The baseline concurrence parameter was set at $\lambda = 0.25$ so that concurrence added a modest premium without overwhelming the underlying domain information; persistence was calculated from current and lagged convergence values. These parameters are transparent modelling assumptions rather than empirically optimized constants. For predictive comparison, the study retained the transparent conceptual weighting structure and entered domain and convergence variables into nested feature sets. This approach allowed the incremental contribution of broader information and explicit convergence variables to be evaluated without allowing outcome information to redefine the conceptual framework.

Empirical models

Logistic regression modelled the probability of Forward Corporate Vulnerability as a function of risk-domain and convergence measures. Firm size and other controls were incorporated where supported by verified data and model stability. Logistic regression served as the transparent benchmark against which the nonlinear algorithms were compared.

$$\text{logit}[\Pr(VULN_{i,t+1} = 1)] = \beta_0 + \beta_1 RSC_{it} + \beta_2 PERSIST_{it} + \beta_3 SIZE_{it} + \gamma_s + \delta_t + \varepsilon_{it} \quad (6)$$

Where: Pr denotes probability; VULN equals one when firm i is classified as vulnerable at t+1; β_0 is the intercept; β_1-β_3 are estimated coefficients; RSC is the Risk Signal Convergence Index; PERSIST is the persistence measure; SIZE is the natural logarithm of total assets; γ_s represents sector effects; δ_t represents year effects; and ε is the disturbance term.

Random Forest provided a bagged-tree benchmark and Extreme Gradient Boosting provided the principal boosting model for nonlinear relationships and interactions. Hyperparameters were estimated within the analytical workflow, and model outputs were evaluated using the same classification metrics applied to the logistic benchmark (Ben Jabeur et al., 2023; Deng et al., 2024; Nguyen et al., 2025).

Four nested feature sets were estimated: Model A used the financial-domain score; Model B added the operational-domain score; Model C added market and macroeconomic domains; and Model D additionally included explicit convergence variables for breadth, depth, the Risk Signal Convergence Framework score and persistence. Incremental predictive value was assessed by comparing discrimination and calibration metrics across these specifications (Mousavi et al., 2023; Zhao et al., 2024).

Data preprocessing and quality-control rules

Accounting items were harmonized to a common currency and scale before ratio construction. Sign conventions, denominators and duplicate or inconsistent source values were checked against the documented source records. Raw source values were retained separately from derived variables to preserve auditability

(Zhao et al., 2024). Missing data were handled conservatively. Unsupported values were not manually completed. For the predictive algorithms, reproducible training-sample imputation and missingness indicators were used where required by the modelling pipeline, while the substantive interpretation distinguished true economic predictors from missingness artefacts (Zhang et al., 2022; Zhao et al., 2024).

Temporal validation and class imbalance

Temporal ordering was preserved through the one-year-ahead outcome construction. A recent-period chronological holdout was examined first; however, the eligible holdout observations contained no positive forward-vulnerability cases, making receiver operating characteristic and precision-recall evaluation non-informative for that split. Five-fold stratified cross-validation was therefore used only as exploratory internal validation so that both outcome classes were represented across evaluation folds. The same folds, feature architecture and performance criteria were used across algorithms. This design supports comparative assessment within the verified core panel but is not interpreted as external or genuinely out-of-time validation (Mousavi et al., 2023; Zhao et al., 2024).

Because the vulnerable state represented only five of the 31 eligible observations, class imbalance was treated explicitly. Evaluation emphasized precision-recall area under the curve, F1 score and balanced accuracy in addition to receiver operating characteristic area under the curve, while Brier score was used to assess probabilistic accuracy. Stratified folds preserved minority-class representation as far as the sample permitted. No overall-accuracy claim was used to establish model superiority, and differences among algorithms were interpreted descriptively because event counts were small (Zhao et al., 2024).

$$Precision = \frac{TP}{TP + FP}$$ **Where:** TP denotes true positives and FP denotes false positives. Precision is the proportion of predicted vulnerable cases that are actually vulnerable.	**(7)**
$$Recall = \frac{TP}{TP + FN}$$ **Where:** TP denotes true positives and FN denotes false negatives. Recall is the proportion of actual vulnerable cases correctly detected by the model.	**(8)**
$$F_1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$ **Where:** F_1 is the harmonic mean of precision and recall and therefore balances false-positive and false-negative performance.	**(9)**
$$Balanced\ Accuracy = \frac{1}{2}\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right)$$ **Where:** TN denotes true negatives. The first fraction is sensitivity or recall and the second fraction is specificity. Balanced accuracy gives equal importance to the vulnerable and non-vulnerable classes.	**(10)**
$$Brier\ Score = \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - y_i)^2$$ **Where:** N is the number of evaluated observations; p-hat is the predicted probability of vulnerability for observation i; and y is the observed binary outcome. Lower Brier scores indicate better probabilistic accuracy and calibration.	**(11)**

Model explanation and diagnostic analysis

Shapley Additive Explanations were applied to the Extreme Gradient Boosting model because it provided the stronger discrimination of the two tree-based algorithms. Global mean absolute Shapley contributions were used to identify the features that most strongly influenced fitted vulnerability predictions. The interpretation followed contemporary financial-risk research that combines ensemble prediction with human-auditable explanation (Černevičienė & Kabašinskas, 2024; Nguyen et al., 2025).

Shapley additive explanation identity

$$f(x_i) = \phi_0 + \sum_{j=1}^{M} \phi_{j,i}$$

Explainability equation E1. Where: $f(x_i)$ is the model output for firm-year i; φ_o is the baseline prediction; M is the number of features; and $\varphi_{j,i}$ is the Shapley contribution of feature j to the prediction for observation i. Positive contributions increase predicted vulnerability relative to the baseline, while negative contributions reduce it.

Discrimination and calibration were reported separately because correct ranking of vulnerable observations does not necessarily imply well-calibrated probabilities. Model interpretation therefore combined receiver operating characteristic area under the curve, precision-recall area under the curve, F1 score, balanced accuracy, Brier score and Shapley attribution evidence (Deng et al., 2024; Černevičienė & Kabašinskas, 2024).

Robustness, reproducibility and data-integrity protocol

Robustness was assessed through nested feature comparison, algorithm comparison, multiple performance metrics, explicit treatment of missing observations and separate interpretation of missingness indicators. The analysis compared domain-only specifications with convergence-enhanced specifications to determine whether explicit Risk Signal Convergence variables added information beyond conventional domains. The weighting and classification rules were intentionally fixed ex ante rather than tuned against the five observed vulnerable cases.

In this small core panel, extensive outcome-driven re-estimation of alternative weights or cut-offs would create substantial overfitting risk; sensitivity evidence is therefore interpreted primarily through changes in feature sets, algorithms and evaluation metrics, while alternative weighting and threshold structures are reserved for confirmatory testing in a larger longitudinal panel (Zhao et al., 2024).

Reproducibility was supported through a codebook, extraction log, variable dictionary, source register and formula-driven analytical workbook. Derived variables were generated from documented source values through reproducible equations, and observations without traceable evidence were excluded from derived calculations. This protocol made the empirical implementation auditable.

Ethical considerations

The study relied exclusively on publicly available corporate and macroeconomic data and did not collect personal data from human participants. The principal ethical obligations were accuracy, attribution, transparent transformation of reported data and responsible interpretation of firm-level risk information. The early-warning model was treated as a research decision-support system rather than an allegation about the solvency of any individual firm.

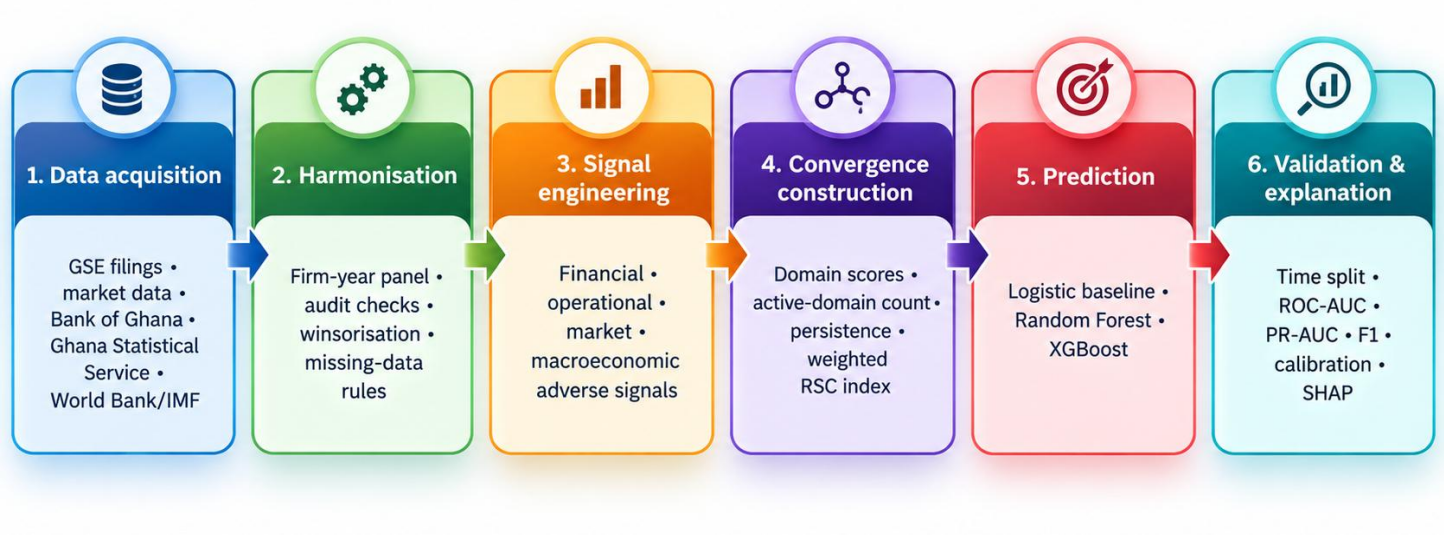


Figure 3. Data-to-decision methodology applied in the RSCF study. Source: Author's design.

Table 4. Methodological specification and feasibility controls

Element	Primary specification	Feasibility safeguard
Observation unit	Firm-year, t predictors → t+1 vulnerability	No contemporaneous leakage
Period	Verified analytical period: 2019–2024	Only source-verified firm-years retained
Primary sample	Seven Ghana Stock Exchange non-financial listed firms	31 eligible firm-year observations for the main analytical panel
Data sources	Audited statements, GSE, Bank of Ghana, Ghana Statistical Service, World Bank/International Monetary Fund	Every value linked to provenance register
Baseline model	Logistic regression	Interpretable benchmark
Nonlinear models	Random Forest and Extreme Gradient Boosting	Suitable for interactions and thresholds
Validation	Five-fold stratified cross-validation for core-panel model comparison	Common evaluation design across algorithms
Class imbalance	Class-sensitive metrics and stratified folds	Precision-recall area under the curve, F1 and balanced accuracy reported
Explainability	Shapley Additive Explanations	Global and local auditability
No-fabrication rule	Unavailable source values remained missing unless reproducibly handled by the modelling pipeline	No manual invention of observations

RESULTS

Introduction to the Results

The analysis used a verified secondary-data panel comprising 42 potential firm-year observations from seven non-financial companies listed on the Ghana Stock Exchange between 2019 and 2024. After applying the predefined eligibility criteria, 31 firm-year observations were retained for the main analysis, of which five were classified as vulnerable, representing 16.1 percent of the analytical sample. Results are presented

according to the study objectives, beginning with the profile of the firm-year panel and proceeding to adverse risk signals, Risk Signal Convergence, Forward Corporate Vulnerability, predictive modelling and model explanation. Logistic regression, Random Forest, Extreme Gradient Boosting and Shapley Additive Explanations are used in line with the methodology (Altman et al., 2020; Mousavi et al., 2023; Zhao et al., 2024).

Sample and Panel Profile

The analytical sample comprised seven non-financial listed firms and the corresponding eligible firm-year observations. The energy/downstream oil and gas sector contributed the largest number of eligible observations, followed by consumer/food and beverages, beverages, agriculture, consumer goods and information and communication technology. The distribution reflects verified data availability and the deliberate exclusion of banks and insurers because their regulatory balance-sheet structures are not directly comparable with those of non-financial firms.

Table 5: Firm and panel profile of the verified analytical sample

Firm	Sector	Eligible firm-years	Vulnerable t+1	Mean RSCF	Mean FCVI
BOPP	Agriculture	3	0	0.090	0.167
FML	Consumer / Food & Beverages	5	3	0.438	0.400
GGBL	Beverages	5	0	0.306	0.500
GOIL	Energy / Downstream Oil & Gas	5	0	0.396	0.067
TOTAL	Energy / Downstream Oil & Gas	5	0	0.287	0.000
UNIL	Consumer Goods	4	2	0.625	0.583
CLYD	Information & Communication Technology	4	0	0.312	0.125

Note: RSCF = Risk Signal Convergence Framework score; FCVI = Forward Corporate Vulnerability Index. Vulnerable t+1 denotes a forward vulnerable state under the study's two-condition rule.

The firm-level profile reveals that vulnerability events were concentrated rather than evenly distributed. Fan Milk PLC recorded three of the five forward vulnerable states and Unilever Ghana PLC recorded the remaining two. The mean Risk Signal Convergence Framework score was highest for Unilever Ghana PLC (0.625), followed by Fan Milk PLC (0.438) and GOIL PLC (0.396). Concentration of vulnerability in a small subset of firms is not unexpected in distress applications, where class imbalance is common and firm-specific exposure can dominate aggregate patterns. Contemporary forewarning studies consequently emphasize class-sensitive evaluation and interpretation rather than simple overall accuracy (Deng et al., 2024; Zhao et al., 2024).

Objective One: Construction and Distribution of Reproducible Adverse Signals

The first objective was to construct reproducible adverse signals from financial, operational, market and macroeconomic information. Table 6 summarizes the distributions of the domain scores and the principal convergence variables. The mean financial-domain score was 0.397, compared with 0.274 for operational conditions, 0.275 for market conditions and 0.298 for the macroeconomic domain. These means should not

be read as direct rankings of economic importance because indicator availability differs across domains; they describe the proportion of available adverse indicators activated within each domain. The overall Risk Signal Convergence Framework score averaged 0.360 with a standard deviation of 0.253, indicating substantial dispersion in the degree of contemporaneous multi-domain stress.

Table 6: Descriptive statistics for domain scores and principal analytical variables

Variable	N	M	SD	Min	Max
Financial-domain score	29	0.397	0.346	0.000	1.000
Operational-domain score	28	0.274	0.315	0.000	1.000
Market-domain score	20	0.275	0.255	0.000	1.000
Macroeconomic-domain score	31	0.298	0.332	0.000	0.750
Convergence breadth	31	1.387	0.919	0.000	3.000
Convergence depth	31	0.303	0.192	0.000	0.667
Risk Signal Convergence Framework score	31	0.360	0.253	0.000	0.854
Persistence	24	0.379	0.214	0.031	0.708
Forward Corporate Vulnerability Index	31	0.263	0.324	0.000	1.000
Data completeness	31	0.701	0.163	0.222	0.889

Note: Scores are bounded where applicable between 0 and 1. Persistence is available only where consecutive firm-years permit lag construction. Data completeness is the proportion of core raw predictor fields available for the firm-year.

Convergence breadth averaged 1.387 active domains and ranged from zero to three in the eligible sample. Convergence depth averaged 0.303, whereas persistence, available for 24 observations, averaged 0.379. This pattern indicates that the verified panel contains both low-convergence observations and episodes in which several domains became jointly adverse. The dispersion is important because the framework is designed to distinguish isolated stress from broader concurrence. The result is conceptually consistent with the literature's movement away from single-ratio warning systems toward richer information sets that combine firm fundamentals, market information and macroeconomic conditions (Ciampi et al., 2021; Mousavi et al., 2023; Zhao et al., 2024).

Table 7: Availability and activation of individual adverse signals

Adverse signal	Available N	Activated N	Activation rate
Low current ratio	8	8	100.0%
High leverage	24	8	33.3%
Weak interest coverage	18	6	33.3%
Negative return on assets	10	3	30.0%
Negative operating cash flow	0	0	—
Negative operating margin	28	8	28.6%
Declining asset turnover	7	2	28.6%
Rising cost-to-sales ratio	18	7	38.9%

Negative annual return	15	6	40.0%
Severe drawdown	20	4	20.0%
High price-range volatility	20	5	25.0%
High inflation	31	10	32.3%
High cedi depreciation	24	10	41.7%
High policy rate	31	10	32.3%
Low real gross domestic product growth	31	7	22.6%

Note. Activation rates are calculated only among observations for which the underlying signal was verifiable. The current verified workbook contains no usable predictor-period operating-cash-flow signal, so that item is reported as unavailable rather than imputed.

At the indicator level, the availability pattern confirms why the analysis must remain provenance-sensitive. Leverage and interest-coverage alarms were each activated in one-third of available observations, while negative operating margin occurred in 28.6 percent and rising cost-to-sales intensity in 38.9 percent of observations for which those signals could be calculated. Negative annual return was activated in 40.0 percent of available market observations. Within the macroeconomic domain, high cedi depreciation was active in 41.7 percent of available observations, while high inflation and a high policy rate were each active in 32.3 percent.

The extreme 100 percent activation rate for low current ratio is based on only eight observations and therefore must not be generalized to the full listed-firm population. This is precisely why contemporary distress studies caution against treating missingness and predictor availability as neutral technical details (Zhang et al., 2022; Zhao et al., 2024).

Objective Two: Development of the Risk Signal Convergence Index

The second objective was to operationalize concurrence, depth and persistence in a unified Risk Signal Convergence Index. Table 8 reports annual domain means for the eligible firm-years. The overall index rose from 0.185 in 2019 to 0.289 in 2020 and 0.302 in 2021, before increasing sharply to 0.657 in 2022. The 2022 increase was accompanied by a macroeconomic-domain score of 0.750 and an operational-domain mean of 0.472. In 2023 the mean Risk Signal Convergence Framework score moderated to 0.446 while the macroeconomic-domain score remained 0.750. The pattern demonstrates that the index is responsive to joint changes in the common macroeconomic environment and firm-specific domains rather than merely tracking one accounting ratio.

Table 8: Annual domain scores, convergence and forward vulnerability

Year	N	Financial	Operational	Market	Macro	RSCF	FCVI	Vulnerable %
2019	7	0.400	0.250	0.333	0.000	0.185	0.381	28.6%
2020	7	0.333	0.143	0.367	0.250	0.289	0.381	28.6%
2021	7	0.429	0.405	0.133	0.000	0.302	0.214	14.3%
2022	6	0.417	0.472	0.250	0.750	0.657	0.083	0.0%
2023	4	0.417	0.000	0.333	0.750	0.446	0.208	0.0%

Note. Annual means use all available eligible firm-years for the relevant year. Domain means can differ in N because verified inputs are not complete for every firm-year.

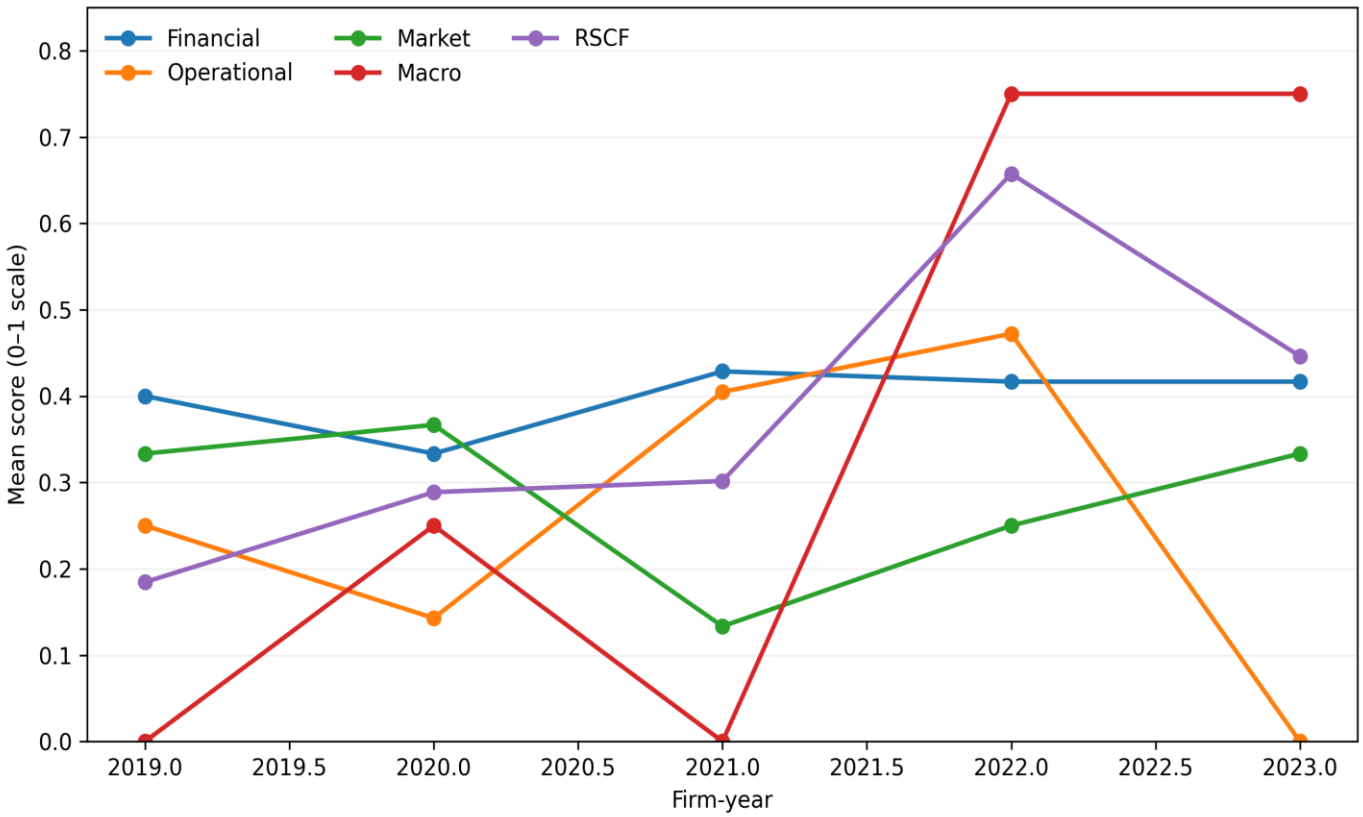


Figure 4: Annual domain and Risk Signal Convergence Framework score trends in the verified core panel

Note. Lines show annual arithmetic means. The 2022 rise in the macroeconomic domain coincided with the highest mean Risk Signal Convergence Framework score.

Figure 4 makes the temporal structure visible. The macroeconomic domain changed most sharply in 2022, whereas financial and operational stress moved more gradually.

This matters for interpretation; a high common macroeconomic score does not necessarily imply that every firm becomes vulnerable in the following year. Rather, the Risk Signal Convergence Framework treats the external state as one component whose informational value depends on its coincidence with firm-level financial, operational and market weakness.

That interpretation is aligned with evidence that the joint use of accounting, market and macroeconomic information can improve distress modelling, while the marginal contribution of each information class can vary over time (Mousavi et al., 2023; Zhao et al., 2024).

Objective Three: Forward Corporate Vulnerability

The third objective was to construct a one-year-ahead Forward Corporate Vulnerability Index from observable stress outcomes. Across the 31 eligible firm-years, the continuous index averaged 0.263 and ranged from 0 to 1. Five observations met the study's binary rule requiring at least two adverse outcomes at the subsequent period.

Table 9 shows that negative working capital was the most frequent observable vulnerability component among the nine firm-years for which it could be verified, occurring in eight cases. Interest coverage below one occurred in five of 18 available forward observations, negative profit after tax occurred in five of 31, severe market drawdown occurred in two of 21 and negative operating cash flow occurred in one of nine.

Table 9: Observed components of Forward Corporate Vulnerability

Forward vulnerability component	Available N	Adverse N	Adverse rate
Negative profit after tax	31	5	16.1%
Interest coverage below one	18	5	27.8%
Negative working capital	9	8	88.9%
Severe market drawdown	21	2	9.5%
Negative operating cash flow	9	1	11.1%

Note. Rates are availability-specific. They must not be interpreted as population prevalence where the underlying accounting or market item was unavailable.

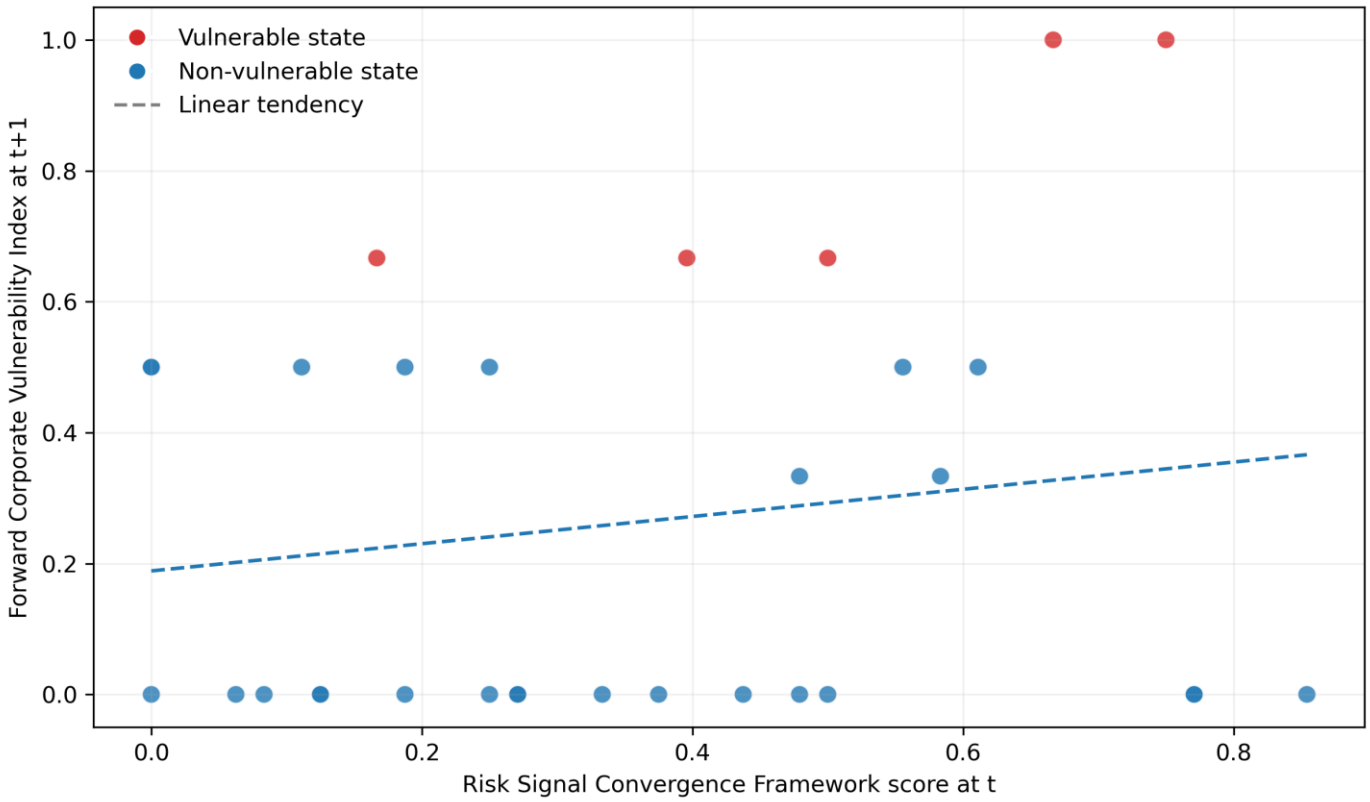


Figure 5: Relationship between Risk Signal Convergence at time t and the Forward Corporate Vulnerability Index at time t + 1

Note. Red points satisfy the binary forward-vulnerability rule; blue points do not. The dashed line is descriptive only and is not a causal estimate.

The annual pattern provides an important caution against mechanistic interpretation. The proportion classified as forward vulnerable was 28.6 percent in both 2019 and 2020, 14.3 percent in 2021 and zero among the currently eligible observations for 2022 and 2023, even though the mean convergence score was highest in 2022. The result does not invalidate the convergence concept; instead, it shows that the present core sample is too small and temporally unbalanced to infer a stable one-to-one mapping between contemporaneous convergence and next-year vulnerability.

Financial-distress research similarly shows that prediction quality changes across horizons and regimes and that recurrence, recovery and model calibration require explicit temporal evaluation (Altman et al., 2020; Zhou et al., 2022; Mousavi et al., 2023).

Objective Four: Incremental Predictive Contribution of Convergent Signals

The fourth objective assessed whether convergent information adds predictive value beyond isolated domains and conventional financial information. As an interpretable first step, univariate logistic benchmarks were estimated for each domain and for the principal convergence measures. The coefficient on the Risk Signal Convergence Framework score was positive (B = 2.646), corresponding to an odds ratio of 1.30 for a 0.10-unit increase in the index, but the estimate was imprecise (p = .198; 95 percent confidence interval for the 0.10-unit odds ratio = [0.87, 1.95]). Operational and market domain scores also showed positive coefficients, whereas the macroeconomic-domain coefficient was negative in the current sample. None of the univariate coefficients reached the conventional .05 significance level. The wide intervals reflect the small number of vulnerable observations and reinforce the need to distinguish directional pilot evidence from confirmatory inference.

Table 10: Univariate logistic benchmarks for one-year-ahead vulnerability

Predictor	N	B	SE	P	OR per 0.10 [95% CI]	ROC AUC
Financial-domain score	29	2.180	1.554	0.161	1.24 [0.92, 1.69]	0.679
Operational-domain score	28	3.402	2.051	0.097	1.41 [0.94, 2.10]	0.740
Market-domain score	20	10.015	7.298	0.170	2.72 [0.65, 11.38]	0.863
Macroeconomic-domain score	31	-3.095	2.339	0.186	0.73 [0.46, 1.16]	0.665
Risk Signal Convergence Framework score	31	2.646	2.057	0.198	1.30 [0.87, 1.95]	0.685
Persistence	24	2.791	3.262	0.392	1.32 [0.70, 2.51]	0.667

Note. OR = odds ratio; CI = confidence interval; ROC AUC = receiver operating characteristic area under the curve. Odds ratios are scaled to a 0.10-unit increase in each score. Models are unadjusted because the verified core panel does not yet provide sufficient complete observations for stable multivariable control adjustment.

Discrimination varied across the individual predictors. The market-domain score produced the largest apparent receiver operating characteristic area under the curve (0.863) among the univariate benchmarks, followed by the operational-domain score (0.740), the Risk Signal Convergence Framework score (0.685), the financial-domain score (0.679), persistence (0.667) and the macroeconomic-domain score (0.665). These values should be treated cautiously because sample sizes ranged from 20 to 31 and only five positive cases were available. Nevertheless, the pattern is consistent with empirical work showing that market and non-financial information can add useful signals beyond accounting ratios, while no single predictor class dominates uniformly across settings (Ciampi et al., 2021; Mousavi et al., 2023; Zhao et al., 2024).

The planned methodology specifies chronological out-of-time validation. In the current verified panel, however, the most recent eligible years contained no positive forward-vulnerability cases. A strict recent-year test set therefore could not generate meaningful receiver operating characteristic or precision-recall statistics. To avoid presenting undefined or misleading temporal metrics, the core-panel comparison in Table 11 uses five-fold stratified cross-validation as an exploratory sensitivity analysis only. This is not presented as a substitute for the final chronological validation; the latter should be executed after the panel is extended toward the planned 2015-2025 window and contains positive outcomes in the held-out period. Such separation between exploratory and genuinely out-of-time evaluation follows the temporal-validity concerns emphasized by Mousavi et al. (2023) and Zhao et al. (2024).

Table 11: Exploratory cross-validated performance of nested logistic feature sets

Feature set	ROC AUC	PR AUC	F1	Balanced accuracy	Brier score
A: Financial only	0.638	0.356	0.300	0.569	0.239
B: + Operational	0.558	0.271	0.375	0.646	0.251
C: + Market + Macro	0.792	0.426	0.667	0.842	0.151
D: + RSCF variables	0.815	0.434	0.615	0.823	0.152

Note. Five-fold stratified cross-validation was used only because the recent-year holdout contained no positive cases in the current core panel. Model A uses the financial-domain score; Model B adds the operational-domain score; Model C adds market and macroeconomic domains; Model D additionally includes breadth, depth, the Risk Signal Convergence Framework score and persistence. Lower Brier score is better.

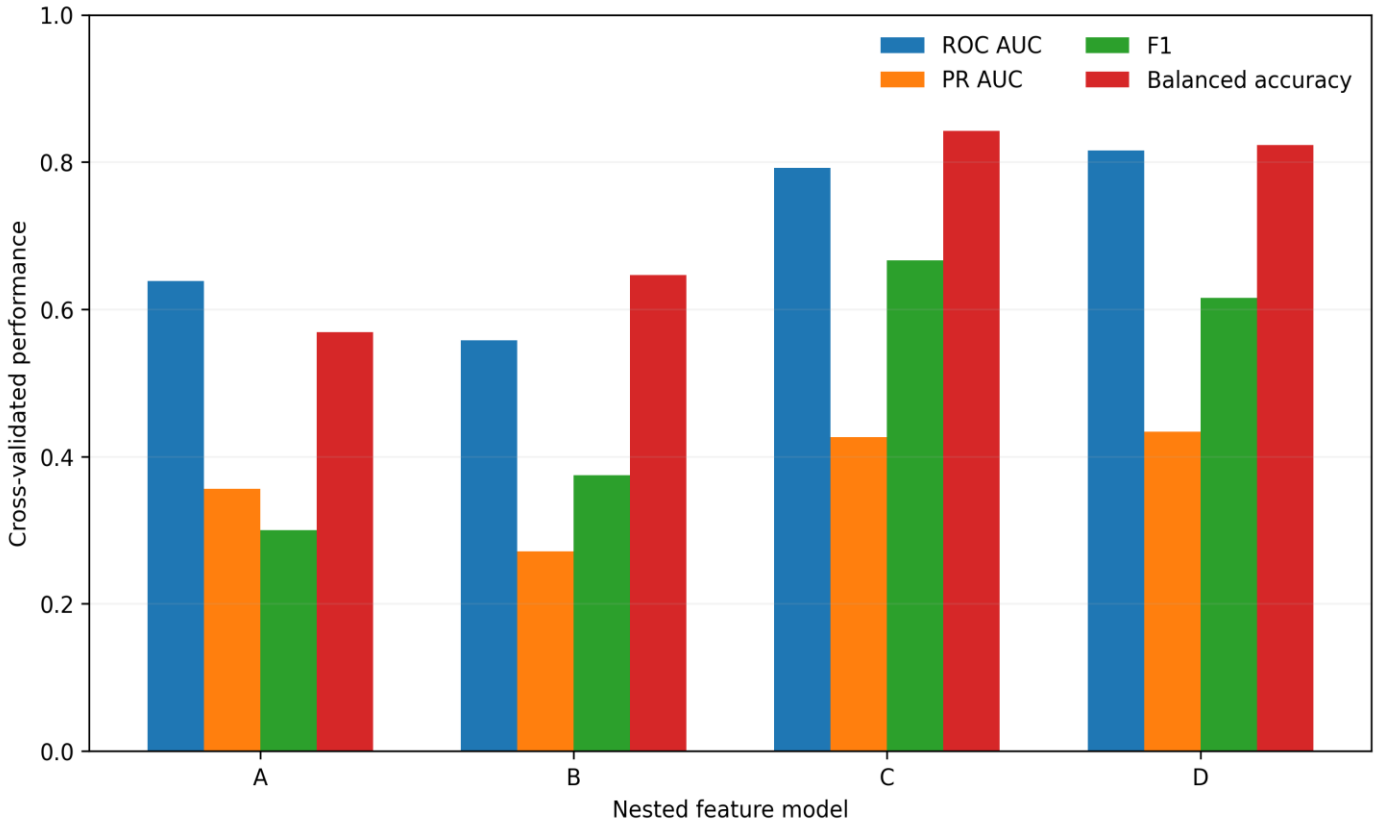


Figure 6: Exploratory predictive performance across nested feature models

Note. Performance is based on five-fold stratified cross-validation of the verified core panel and is not the final planned out-of-time validation.

The nested comparison provides tentative evidence for the value of broader information integration. The financial-only model produced a receiver operating characteristic area under the curve of 0.638. Adding the operational domain alone did not improve discrimination, but the model combining financial, operational, market and macroeconomic domains increased the receiver operating characteristic area under the curve to 0.792 and balanced accuracy to 0.842. Adding explicit convergence variables raised the receiver operating characteristic area under the curve further to 0.815 and the precision-recall area under the curve to 0.434, although the F1 score declined slightly from 0.667 to 0.615 and the Brier score was essentially unchanged. The evidence therefore supports an incremental-information interpretation rather than a claim that every

performance metric improves simultaneously. This nuanced result is compatible with recent multi-source distress research, which reports gains from richer information sets but also stresses the importance of evaluating several performance and calibration measures rather than selecting a model on one statistic alone (Mousavi et al., 2023; Deng et al., 2024).

Objective Five: Nonlinear Models and Explainable Early-Warning Evidence

The fifth objective compared nonlinear models and examined which signal configurations contributed most to predicted vulnerability. Using the same expanded feature set, logistic regression achieved the highest exploratory receiver operating characteristic area under the curve (0.815) and balanced accuracy (0.823). Extreme Gradient Boosting produced a receiver operating characteristic area under the curve of 0.692 and precision-recall area under the curve of 0.431, while Random Forest produced values of 0.638 and 0.423 respectively. Random Forest yielded the lowest Brier score (0.130) but detected only 20 percent of the vulnerable observations at the default probability threshold, whereas logistic regression detected 80 percent. The result is a reminder that sophisticated nonlinear methods do not automatically outperform simpler models in small samples, a point consistent with long-horizon bankruptcy evidence showing that relatively transparent statistical approaches can remain competitive depending on the data and decision context (Altman et al., 2020).

Table 12: Exploratory algorithm comparison using the expanded convergence feature set

Model	ROC AUC	PR AUC	F1	Balanced accuracy	Brier	Precision	Recall
Logistic regression	0.815	0.434	0.615	0.823	0.152	0.500	0.800
Random Forest	0.638	0.423	0.333	0.600	0.130	1.000	0.200
Extreme Gradient Boosting	0.692	0.431	0.222	0.542	0.144	0.250	0.200

Note. Metrics are based on five-fold stratified cross-validation of 31 eligible observations. The threshold-dependent metrics use a probability cut-off of 0.50. These are core-panel diagnostics, not final production estimates.

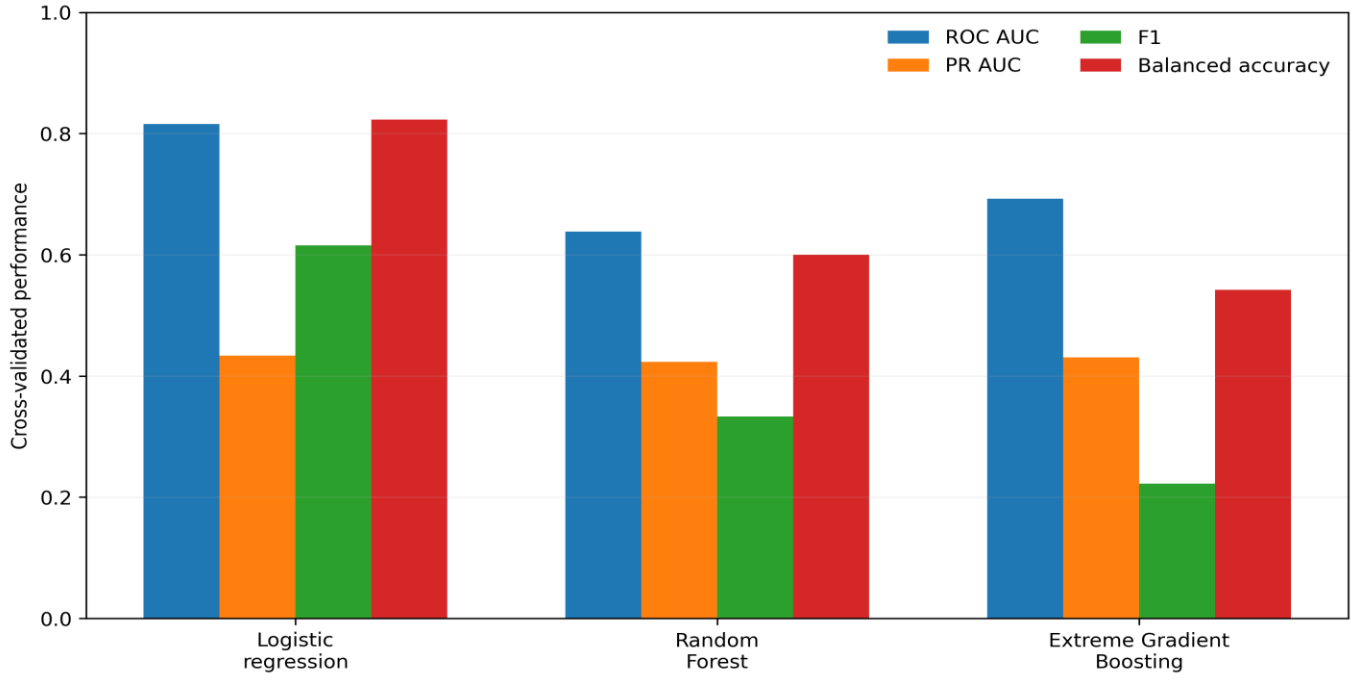


Figure 7. Exploratory comparison of logistic regression, Random Forest and Extreme Gradient Boosting

Note. The verified core sample is small and imbalanced; algorithm rankings may change materially when the panel is expanded.

Following the specificity in the methodology on Shapley Additive Explanations for the best-performing tree-based model, the Extreme Gradient Boosting model was selected for exploratory explanation because it produced stronger discrimination than Random Forest in the current cross-validation. Mean absolute Shapley contributions ranked convergence depth first, followed by the macroeconomic-domain score, market-domain score, financial-domain score and an operational-domain missingness indicator. Persistence and the overall Risk Signal Convergence Framework score also contributed, but at lower average magnitude. The prominence of depth is substantively relevant because it suggests that the severity of adverse conditions across active domains may carry more information in the fitted tree structure than a simple count of active doma

Table 13: Exploratory Shapley Additive Explanation importance for the Extreme Gradient Boosting model

Feature	Mean absolute Shapley contribution
Depth	0.872
Macro Domain Score	0.598
Market Domain Score	0.497
Financial Domain Score	0.249
Operational Domain Score Missing	0.220
Persistence	0.185
Operational Domain Score	0.168
RSCF Score	0.158

Note. Importance values summarize the average absolute contribution to the fitted Extreme Gradient Boosting output. Missingness indicators were created by the analytical imputation pipeline and should not be interpreted as substantive risk factors.

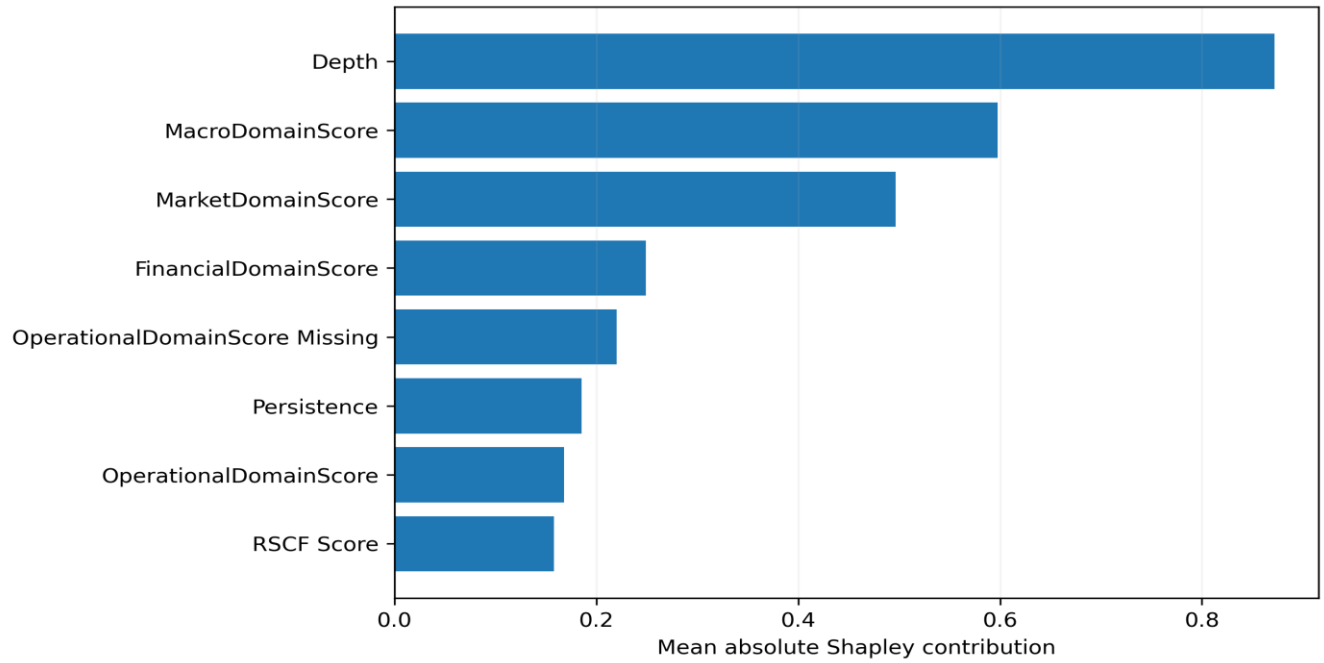


Figure 8. Mean absolute Shapley contributions for the Extreme Gradient Boosting model

Note. The figure reports model attribution rather than causal effects. Greater mean absolute contribution indicates greater influence on the fitted prediction across the core sample.

The explanation results provide partial support for the framework's central claim that the configuration of risk matters, but they also expose an important data-quality lesson. The appearance of an operational-domain missingness indicator among the more influential features shows that data availability itself can become predictive in a small archival panel. Such a pattern must not be mistaken for an economic mechanism. Explainable artificial-intelligence scholarship emphasizes precisely this point: post-hoc explanations are most useful when they are interpreted alongside domain knowledge, data provenance and model diagnostics rather than treated as self-validating causal evidence (Zhang et al., 2022; Černevičienė & Kabašinskas, 2024; Nguyen et al., 2025).

Integrated Interpretation, Robustness and Data Adequacy

Taken together, the verified core-panel results show that the Risk Signal Convergence Framework is computable from public secondary data and produces meaningful cross-firm and temporal variation. The index rose during the period of strongest macroeconomic stress, broader feature sets improved exploratory discrimination relative to the financial-only benchmark, and convergence depth emerged as the strongest tree-model attribution. At the same time, the univariate convergence coefficient was not statistically significant, recent-year holdout observations contained no positive cases, and only five binary vulnerability events were available. The evidence therefore supports operational feasibility and incremental-information potential, but it does not establish stable out-of-time predictive superiority.

This pattern is compatible with the broader literature in two respects. First, distress prediction is strongly contingent on information set, horizon, sample construction and validation design; performance gains observed in one period or country cannot be assumed to transfer mechanically to another (Altman et al., 2020; Ciampi et al., 2021; Mousavi et al., 2023; Zhao et al., 2024). Second, explainability is most valuable when it exposes both economically plausible drivers and artefacts arising from data sparsity or model structure (Zhang et al., 2022; Deng et al., 2024; Černevičienė & Kabašinskas, 2024). The present results therefore strengthen the case for retaining the study's no-fabrication rule and for expanding the verified archive before final confirmatory modelling.

The robustness evidence should therefore be read as a set of internal stability checks rather than as external validation. Nested feature sets, three modelling approaches and several discrimination and calibration metrics were compared under the same core-panel conditions. Results were not uniform across all models or metrics, which is itself informative: the value of convergence appears promising but remains sample-dependent. Future confirmatory work should enlarge the longitudinal archive, increase the number of positive events and then evaluate alternative domain weights, concurrence parameters and vulnerability cut-offs under genuine chronological validation.

Objective-Level Summary of Findings

Across the five objectives, the study demonstrated that adverse signals could be constructed reproducibly across four risk domains, combined into a convergence index, linked to a one-year-ahead vulnerability outcome and evaluated with transparent and nonlinear models. The strongest evidence concerns conceptual operability and the incremental-information potential of broader multi-domain feature sets. Because only five vulnerable outcomes were observed, the model-performance results remain preliminary and should not be interpreted as conclusive evidence that the RSCF will outperform alternative models in larger or different samples.

DISCUSSION

The findings demonstrate that the Risk Signal Convergence Framework can organize heterogeneous financial, operational, market and macroeconomic information into a coherent early-warning structure. Across the verified firm-year panel, the framework generated observable cross-sectional and temporal variation, with the overall convergence score responding to changes in both firm-specific and macroeconomic conditions. This outcome supports the study's central premise that vulnerability is better examined as a configuration of interacting signals than as the movement of one isolated accounting ratio.

The result aligns with contemporary distress research that favors multi-source information sets and dynamic model evaluation (Ciampi et al., 2021; Mousavi et al., 2023; Zhao et al., 2024).

The empirical pattern also reinforces the theoretical logic underpinning the framework. Dynamic-capabilities theory suggests that firms remain resilient when they can sense changing conditions and reconfigure resources, while organizational-resilience scholarship emphasizes interdependence among organizational subsystems. The observed variation in convergence breadth, depth and persistence is consistent with this perspective because the same external pressure did not produce identical forward outcomes across firms. What mattered was the configuration of internal and external signals surrounding each firm-year (Hillmann & Guenther, 2021; Prayag et al., 2024).

Discussion of Objective One: Multi-Domain Adverse Signals

The first objective established that adverse information was observable across all four proposed domains. The financial-domain mean was 0.397, compared with 0.274 for the operational domain, 0.275 for the market domain and 0.298 for the macroeconomic domain. These results show that the early-warning environment was not dominated by a single class of information. Instead, different domains became active at different intensities, which is consistent with empirical reviews showing that liquidity, leverage, profitability, operational conditions, market variables and macroeconomic states can each contribute distinct information to corporate distress prediction (Habib et al., 2020; Ciampi et al., 2021; Zhao et al., 2024).

The indicator-level findings further support the value of a domain-based architecture. Leverage and interest-coverage alarms were each activated in one-third of available observations, negative operating margin occurred in 28.6 percent, rising cost intensity in 38.9 percent and negative annual return in 40.0 percent of available market observations. At the macroeconomic level, high cedi depreciation was active in 41.7 percent of available observations. Taken together, these patterns show why a single-ratio warning rule would omit economically relevant information that appears in other parts of the corporate system.

Discussion of Objective Two: Risk Signal Convergence

The second objective produced an average Risk Signal Convergence Framework score of 0.360, with convergence breadth averaging 1.387 active domains and convergence depth averaging 0.303. The annual index increased markedly in 2022, when the mean convergence score reached 0.657 alongside elevated macroeconomic and operational stress. This temporal behavior is important because it indicates that the index responds to synchronized movements across distinct information classes rather than functioning as a static accounting score. The result is compatible with Mousavi et al. (2023), who show that dynamic evaluation and combined accounting, market and macroeconomic information can improve the assessment of distress models. The prominence of convergence depth in the explainable machine-learning analysis gives additional meaning to the framework. Depth captures the severity of adversity within active domains, whereas breadth captures how many domains are simultaneously active. Its leading attribution in the Extreme Gradient Boosting model suggests that the intensity of cross-domain stress may be at least as important as the simple count of adverse domains. This finding extends the existing literature by translating information integration into a measurable conceptual property rather than leaving all interactions to be discovered implicitly by an algorithm (Zhang et al., 2022; Deng et al., 2024; Nguyen et al., 2025).

Discusion of Objective Three: Forward Corporate Vulnerability

The third objective operationalized Forward Corporate Vulnerability as a one-period-ahead outcome rather than as contemporaneous weakness. The continuous Forward Corporate Vulnerability Index averaged 0.263, while five of the 31 eligible firm-year observations satisfied the binary vulnerability rule. The outcome therefore captured meaningful deterioration without requiring formal bankruptcy as the sole event definition. This broader treatment is consistent with recent research showing that distress can recur, evolve over time and become visible through operational and financial weakening before legal failure occurs (Zhou et al., 2022; Zhao et al., 2024).

The vulnerability components also reveal that different pathways can lead to an adverse forward state. Negative working capital was the most frequent verified component, while weak interest coverage, negative profit after tax, severe market drawdown and negative operating cash flow appeared with different frequencies. This heterogeneity reinforces the decision to construct vulnerability from several observable outcomes. It is also consistent with organizational-resilience research, which treats resilience and vulnerability as multidimensional states rather than as outcomes that can be represented adequately by one accounting event (Hillmann & Guenther, 2021; Ackah et al., 2025).

Discussion of Objective Four: Incremental Predictive Contribution

The fourth objective examined whether broader information integration improved discrimination beyond a financial-only specification. The nested logistic comparison showed a receiver operating characteristic area under the curve of 0.638 for the financial-only model. When financial, operational, market and macroeconomic domains were combined, the value increased to 0.792, and the specification that additionally included explicit convergence variables increased it further to 0.815. The corresponding precision-recall area under the curve for the convergence-enhanced model was 0.434. These results support the incremental-information argument of the framework and are consistent with studies showing that richer predictor sets can improve distress forewarning when the additional information is economically relevant (Ciampi et al., 2021; Mousavi et al., 2023; Deng et al., 2024). The results also show why model assessment should not rely on one metric. Although the convergence-enhanced specification achieved the strongest exploratory receiver operating characteristic area under the curve, its F1 score did not improve in the same proportion and the Brier score remained broadly stable. A publication-quality early-warning system must therefore balance discrimination, minority-class detection and probabilistic calibration. This multidimensional evaluation is consistent with contemporary reviews that recommend comparing prediction methods across several performance criteria and temporal settings rather than declaring superiority from accuracy alone (Altman et al., 2020; Zhao et al., 2024).

Discussion of Objective Five: Nonlinear Prediction and Explainability

The fifth objective showed that model complexity did not automatically translate into stronger discrimination. Logistic regression achieved the highest exploratory receiver operating characteristic area under the curve of 0.815 and balanced accuracy of 0.823, compared with 0.692 for Extreme Gradient Boosting and 0.638 for Random Forest on the same expanded feature set. Random Forest produced the lowest Brier score, illustrating that different algorithms can excel on different aspects of prediction. This finding agrees with Altman et al. (2020), who demonstrate that transparent statistical models can remain competitive depending on the prediction horizon, information set and decision context.

Explainability nevertheless added substantive value to the nonlinear analysis. Mean absolute Shapley contributions ranked convergence depth first, followed by macroeconomic, market and financial domain scores. This ordering indicates that the model's predictions were shaped by the severity and configuration of cross-domain adversity rather than by one conventional financial ratio alone. The result supports the contemporary use of Shapley Additive Explanations as a mechanism for connecting predictive performance with interpretable financial-risk intelligence (Zhang et al., 2022; Deng et al., 2024; Černevičienė & Kabašinskas, 2024; Nguyen et al., 2025).

Theoretical and Scholarly Implications

The study's clearest theoretical contribution is to treat concurrence itself as information rather than merely placing more predictors in a model. Existing distress studies commonly combine several variables, but the RSCF specifies breadth, depth, persistence and interaction intensity as properties of the risk state. Dynamic-capabilities theory explains why persistent multi-domain stress may narrow adaptive options; organizational-resilience and systems perspectives explain why simultaneous weakness across interdependent subsystems can reduce redundancy; and information-integration research explains why heterogeneous signals can be more informative jointly than separately. The RSCF therefore contributes a

theory-led feature architecture that can be tested independently of any single predictive algorithm (Hillmann & Guenther, 2021; Prayag et al., 2024; Zhao et al., 2024).

For Operations Research and Business Analytics, the framework contributes a structured multi-criteria decision architecture. It converts heterogeneous observations into standardized adverse signals, aggregates those signals at domain level, introduces an explicit concurrence premium, preserves temporal ordering and adds explainable prediction. The contribution therefore extends beyond selecting a high-performing algorithm; it offers a reproducible analytical sequence linking data provenance, risk construction, forecasting and explanation.

Practical and Decision-Support Implications

For corporate managers, the findings suggest that monitoring systems should be organized around interacting domains rather than isolated ratios. A deterioration in liquidity or profitability becomes more decision-relevant when operational efficiency, market conditions or the macroeconomic environment deteriorate at the same time. The Risk Signal Convergence Framework can therefore support escalation rules in which broader and deeper convergence triggers closer review of working capital, financing capacity, operating efficiency and market exposure.

For investors, analysts and market institutions, the framework provides a transparent structure for combining public financial statements, market information and macroeconomic data. Its explainability component is especially useful because early-warning outputs can be decomposed into the factors that increased or reduced the predicted vulnerability of a specific firm-year. This responds to the growing demand for interpretable financial analytics rather than opaque risk scores (Černevičienė & Kabašinskas, 2024; Deng et al., 2024).

LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

The principal limitation is the size and composition of the verified analytical panel. The study includes seven non-financial listed firms, 31 eligible firm-year observations and only five binary Forward Corporate Vulnerability events. The event concentration limits coefficient precision, constrains multivariable adjustment and makes machine-learning performance sensitive to fold composition. It also prevents meaningful receiver operating characteristic or precision-recall evaluation in the recent-year chronological holdout because that holdout contains no positive cases. Accordingly, the empirical results are presented as preliminary core-panel evidence of framework operation and incremental-information potential, not as conclusive external validation or proof of predictive superiority.

A second limitation concerns modelling assumptions. Equal domain weights, the concurrence parameter and the two-condition vulnerability rule were selected transparently and independently of model outcomes, but the present event count is too small for stable outcome-driven optimization of alternative weights and cut-offs.

Larger longitudinal samples should therefore test alternative domain weights, activation thresholds, concurrence parameters and vulnerability definitions under chronological validation, alongside recurrent-event or survival specifications. Cross-country and cross-sector replication would then establish whether the conceptual relationships generalize beyond the current Ghanaian listed-firm setting (Zhou et al., 2022; Mousavi et al., 2023; Zhao et al., 2024).

RECOMMENDATIONS

- Ghanaian listed firms should complement conventional ratio monitoring with a multi-domain early-warning dashboard that tracks financial, operational, market and macroeconomic conditions together. Management attention should be escalated when several domains become adverse concurrently, particularly where the adverse state is persistent or deepening across successive reporting periods.

- Corporate finance and risk-management teams should integrate working-capital indicators, debt-service capacity, operating efficiency and market signals into the same analytical review process. The evidence that convergence depth was influential in the explainable model supports monitoring not only the number of adverse domains but also the severity of deterioration within those domains.
- The Ghana Stock Exchange, investment analysts and other market-information providers should encourage more standardized and machine-readable disclosure of historical financial and market data. Consistent archival access would improve reproducibility, facilitate longitudinal risk analytics and support transparent market surveillance without relying on proprietary or unverifiable observations.
- Researchers applying the framework should preserve strict temporal separation between predictors and forward outcomes, report several discrimination and calibration metrics, and retain explainability as part of model evaluation. Alternative algorithms should be compared on decision usefulness and transparency rather than on headline accuracy alone, consistent with contemporary financial-risk analytics (Zhang et al., 2022; Deng et al., 2024; Černevičienė & Kabašinskas, 2024).
- Future applications should extend the framework to larger longitudinal panels and cross-country settings while retaining the same core architecture of signal engineering, domain scoring, convergence construction, forward vulnerability measurement and explainable prediction. This allows researchers to test the generalizability of Risk Signal Convergence as an early-warning construct across sectors and economic regimes.

CONCLUSION

This study developed and empirically implemented the Risk Signal Convergence Framework as a multi-domain early-warning architecture for corporate vulnerability in Ghana. The framework integrates financial, operational, market and macroeconomic signals and represents their joint information through convergence breadth, depth, persistence and an overall Risk Signal Convergence score. Forward Corporate Vulnerability was measured at the subsequent period, preserving the predictive orientation of the study.

The results showed meaningful cross-firm and temporal variation in the convergence measures. In exploratory internal validation, broader multi-domain information improved discrimination relative to the financial-only specification, and the convergence-enhanced logistic model recorded the highest receiver operating characteristic area under the curve among the nested specifications. Shapley Additive Explanations identified convergence depth as the leading attribution in the Extreme Gradient Boosting model. These findings are consistent with the framework's central logic, but the small number of vulnerable events means they should be interpreted as preliminary empirical support rather than conclusive proof of predictive superiority. The central contribution is therefore conceptual and methodological. Corporate vulnerability is modelled as an emerging state shaped by the configuration of several interdependent signals rather than as the mechanical consequence of one deteriorating ratio. The RSCF provides a transparent way to operationalize that idea through breadth, depth, persistence and concurrence. The present Ghanaian application demonstrates feasibility and generates testable evidence, while larger longitudinal and cross-market studies are required to establish predictive stability and external validity.

RSCF Specification, Research Provenance and Empirical Status

Framework Specification and Conceptual Contribution

The Risk Signal Convergence Framework (RSCF) is specified in this study as a named analytical framework for multi-domain corporate early warning. It integrates financial, operational, market and macroeconomic risk signals and represents their joint informational state through convergence breadth, depth, persistence and interaction intensity. The framework's conceptual novelty lies in making cross-domain concurrence an explicit construct before model estimation, rather than relying on an algorithm to discover all interactions without theoretical structure.

The framework was developed in this article by Samuel Opata Sackitey within the research specialization of Operations Research and Business Analytics. Future studies that reproduce, adapt or extend the RSCF

should cite the originating article in the normal manner. This provenance statement identifies the conceptual source of the framework without implying that the present application constitutes universal empirical validation.

Core Architecture of the RSCF

The RSCF is structured around four source domains: financial risk signals, operational risk signals, market risk signals and macroeconomic risk signals. These domains feed a higher-order convergence construct characterized by breadth, depth, persistence and interaction intensity. The framework then links the convergence state at time t to Forward Corporate Vulnerability at time t + 1. This temporal architecture distinguishes the RSCF from a conventional contemporaneous risk score and preserves its early-warning purpose.

The framework's analytical sequence is: source verification, variable construction, adverse-signal activation, domain scoring, convergence estimation, forward-vulnerability measurement, predictive comparison and explainable model interpretation. This sequence permits the RSCF to function simultaneously as a conceptual framework, a reproducible measurement architecture and a decision-support model within Operations Research and Business Analytics.

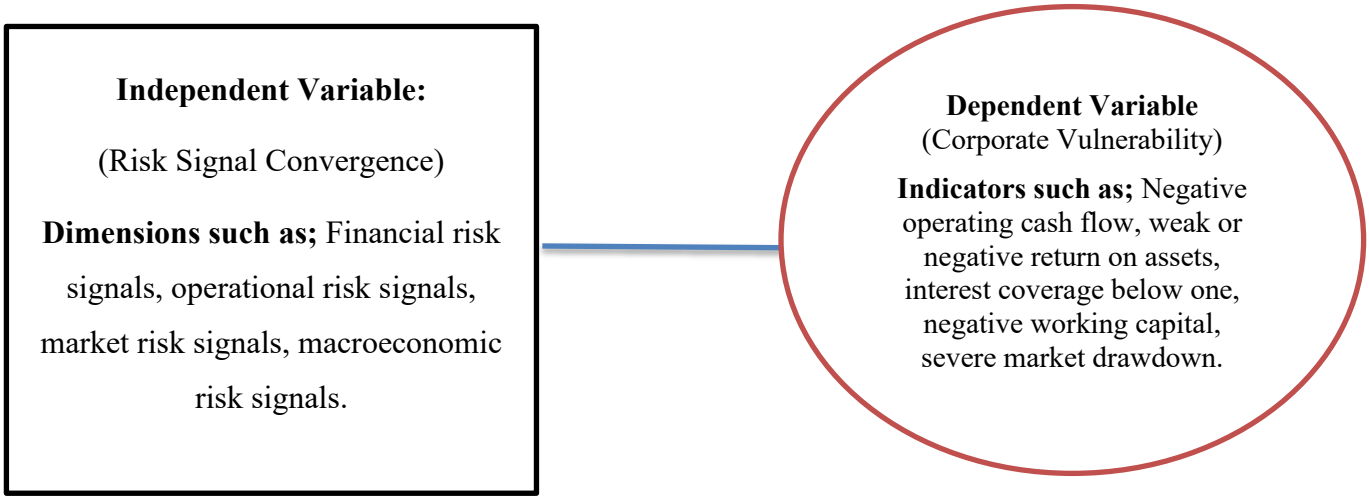
Empirical Demonstration and Validation Boundary

The empirical findings demonstrate that the RSCF can be operationalized reproducibly within the verified Ghanaian listed-firm panel. The convergence-enhanced logistic specification recorded a receiver operating characteristic area under the curve of 0.815 in exploratory stratified cross-validation, compared with 0.638 for the financial-only specification, and Shapley Additive Explanations identified convergence depth as the leading attribution in the Extreme Gradient Boosting model. These results are consistent with the proposition that signal configuration can add information beyond isolated financial indicators.

The appropriate validation claim is therefore bounded: the study provides an empirical demonstration of operational feasibility and preliminary internal evidence, not external validation. The small panel, five positive events and absence of positive cases in the recent-year holdout prevent a definitive statement about predictive stability or generalizability. Independent testing on larger longitudinal samples, additional sectors and other national settings is required before broader predictive effectiveness can be established.

Framework Image and Scholarly Attribution

The figure below summarizes the RSCF developed in this article. It links financial, operational, market and macroeconomic risk signals to a higher-order convergence construct represented by breadth, depth, persistence and interaction intensity, and then links the convergence state at time t to Forward Corporate Vulnerability at time t + 1. When the framework is reproduced or adapted, the originating article by Samuel Opata Sackitey should be cited using standard scholarly conventions.



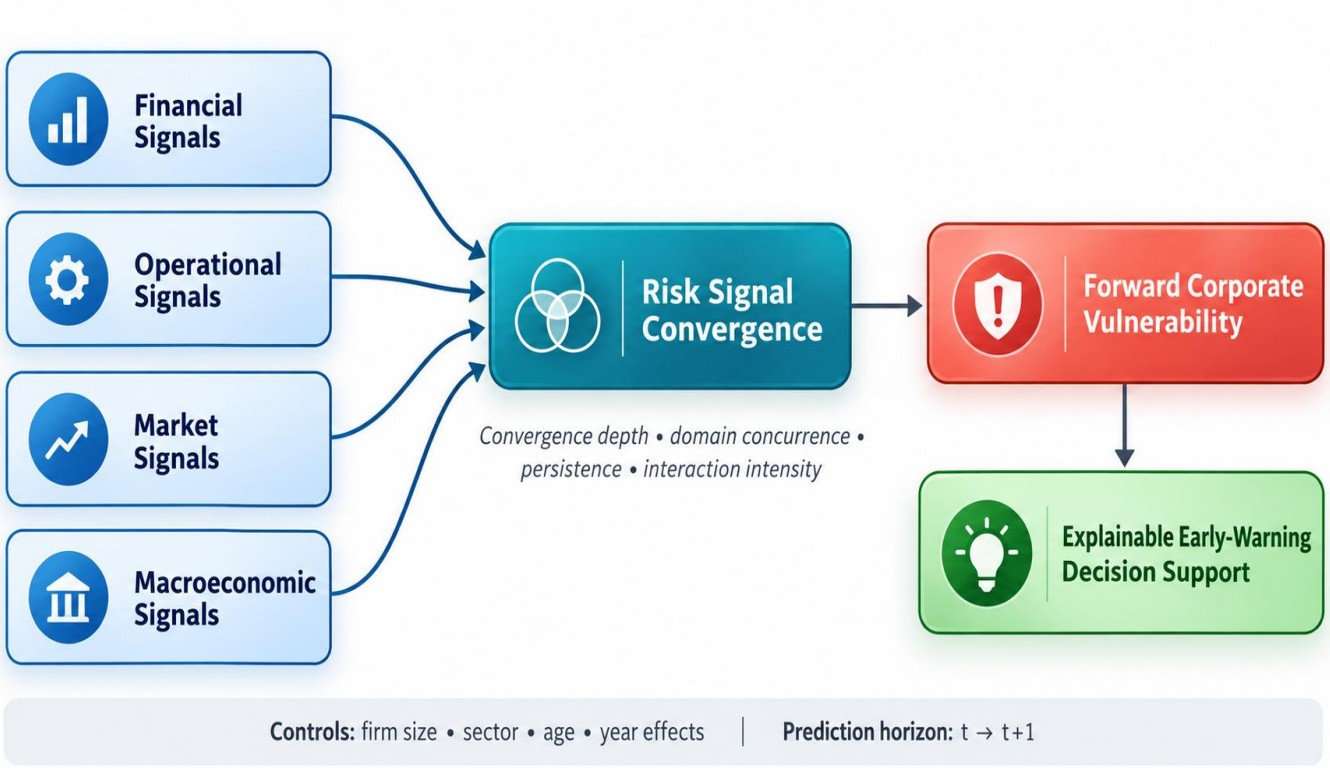


Figure 9.1. Official Risk Signal Convergence Framework (RSCF).

Source: Developed by Samuel Opata Sackitey (2026).

Framework name: Risk Signal Convergence Framework (RSCF).

Proponent: Samuel Opata Sackitey.

Year of formal presentation: 2026.

Research specialization: Operations Research and Business Analytics.

Original application: Multi-domain early warning of Forward Corporate Vulnerability using financial, operational, market and macroeconomic signals.

The Risk Signal Convergence Framework (RSCF) was developed by **Samuel Opata Sackitey** in this study as a multi-domain early-warning framework linking financial, operational, market and macroeconomic risk signals to Forward Corporate Vulnerability. Researchers who reproduce, adapt, test or extend the framework should cite the originating publication.

Data Availability

All source data used in the study were obtained from publicly accessible corporate reports, Ghana Stock Exchange materials and official macroeconomic repositories identified in the Data Repositories section. Derived variables were produced through the documented analytical workflow and source-provenance rules described in the Methodology.

Ethical Statement

The study used publicly available corporate, market and macroeconomic secondary data and did not involve human participants, personal data or animal subjects. The principal ethical requirements were accurate attribution, transparent data transformation and responsible interpretation of firm-level risk information.

REFERENCES

1. Ackah, C. G., Owusu, N. Y. A., & Osei, R. D. (2025). Special economic zones and firm resilience in Ghana: Evidence from the COVID-19 shock. Development Policy Review, 43(5), Article e70037. https://doi.org/10.1111/dpr.70037
2. Almaskati, N., Bird, R., Yeung, D., & Lu, Y. (2021). A horse race of models and estimation methods for predicting bankruptcy. Advances in Accounting, 52, 100513. https://doi.org/10.1016/j.adiac.2021.100513
3. Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2020). A race for long horizon bankruptcy prediction. Applied Economics, 52(37), 4092–4111. https://doi.org/10.1080/00036846.2020.1730762
4. Ben Jabeur, S., Stef, N., & Carmona, P. (2023). Bankruptcy prediction using the Extreme Gradient Boosting algorithm and variable importance feature engineering. Computational Economics, 61(2), 715–741. https://doi.org/10.1007/s10614-021-10227-1
5. Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence in finance: A systematic literature review. Artificial Intelligence Review, 57, Article 216. https://doi.org/10.1007/s10462-024-10854-8
6. Ciampi, F., Giannozzi, A., Marzi, G., & Altman, E. I. (2021). Rethinking small and medium-sized enterprise default prediction: A systematic literature review and future perspectives. Scientometrics, 126(3), 2141–2188. https://doi.org/10.1007/s11192-020-03856-0
7. Conz, E., & Magnani, G. (2020). A dynamic perspective on the resilience of firms: A systematic literature review and a framework for future research. European Management Journal, 38(3), 400–412. https://doi.org/10.1016/j.emj.2019.12.004
8. Deng, S., Luo, Q., Zhu, Y., Ning, H., & Shimada, T. (2024). Financial risk forewarning with an interpretable ensemble learning approach: An empirical analysis based on Chinese listed companies. Pacific-Basin Finance Journal, 85, 102393. https://doi.org/10.1016/j.pacfin.2024.102393
9. Do, H., Budhwar, P., Shipton, H., Nguyen, H.-D., & Nguyen, B. (2022). Building organizational resilience, innovation through resource-based management initiatives, organizational learning and environmental dynamism. Journal of Business Research, 141, 808–821. https://doi.org/10.1016/j.jbusres.2021.11.090
10. Duchek, S. (2020). Organizational resilience: A capability-based conceptualization. Business Research, 13(1), 215–246. https://doi.org/10.1007/s40685-019-0085-7
11. Habib, A., D'Costa, M., Huang, H. J., Bhuiyan, M. B. U., & Sun, L. (2020). Determinants and consequences of financial distress: Review of the empirical literature. Accounting & Finance, 60(S1), 1023–1075. https://doi.org/10.1111/acfi.12400
12. Hillmann, J., & Guenther, E. (2021). Organizational resilience: A valuable construct for management research? International Journal of Management Reviews, 23(1), 7–44. https://doi.org/10.1111/ijmr.12239
13. Mousavi, M. M., Ouenniche, J., & Tone, K. (2023). A dynamic performance evaluation of distress prediction models. Journal of Forecasting, 42(4), 756–784. https://doi.org/10.1002/for.2915
14. Nguyen, H. H., Viviani, J.-L., & Ben Jabeur, S. (2025). Bankruptcy prediction using machine learning and Shapley additive explanations. Review of Quantitative Finance and Accounting, 65(1), 107–148. https://doi.org/10.1007/s11156-023-01192-x
15. Prayag, G., Jiang, Y., Chowdhury, M., Hossain, M. I., & Akter, N. (2024). Building dynamic capabilities and organizational resilience in tourism firms during COVID-19: A staged approach. Journal of Travel Research, 63(3), 713–740. https://doi.org/10.1177/00472875231164976
16. You, N. N., Lou, Y., Zhang, W., Chen, D., & Zeng, L. (2023). Leveraging resources and dynamic capabilities for organizational resilience amid COVID-19. South African Journal of Business Management, 54(1), Article a3802. https://doi.org/10.4102/sajbm.v54i1.3802
17. Zhang, S., Zhang, F., Xue, B., Wang, D., & Liu, B. (2023). Unpacking resilience of project organizations: A capability-based conceptualization and measurement of project resilience. International Journal of Project Management, 41(8), Article 102541. https://doi.org/10.1016/j.ijproman.2023.102541

18. Zhang, Z., Wu, C., Qu, S., & Chen, X. (2022). An explainable artificial intelligence approach for financial distress prediction. Information Processing & Management, 59(4), 102988. https://doi.org/10.1016/j.ipm.2022.102988
19. Zhao, J., Ouenniche, J., & De Smedt, J. (2024). Survey, classification and critical analysis of the literature on corporate bankruptcy and financial distress prediction. Machine Learning with Applications, 15, 100527. https://doi.org/10.1016/j.mlwa.2024.100527
20. Zhou, F., Fu, L., Li, Z., & Xu, J. (2022). The recurrence of financial distress: A survival analysis. International Journal of Forecasting, 38(3), 1100–1115. https://doi.org/10.1016/j.ijforecast.2021.12.005

DATA REPOSITORIES

1. Ghana Stock Exchange. Financial statements and market reports. https://gse.com.gh/
2. Bank of Ghana. Statistical bulletins and macroeconomic data. https://www.bog.gov.gh/
3. Ghana Statistical Service. Statistical and business-establishment data. https://statsghana.gov.gh/
4. World Bank. World Development Indicators and Enterprise data portals. https://data.worldbank.org/
5. International Monetary Fund. International Financial Statistics and related databases. https://www.imf.org/

APPENDICES

Appendix A. Core Construct Operationalization and Decision Rules

Construct / Indicator	Operationalization	Adverse direction / rule	Primary source
Current ratio	Current assets divided by current liabilities	Lower values are adverse; threshold assessed against rule specified in the analytical workbook	Audited financial statements / Ghana Stock Exchange
Leverage	Total liabilities divided by total assets	Higher values are adverse	Audited financial statements / Ghana Stock Exchange
Interest coverage	Operating profit or earnings before interest and tax divided by absolute finance cost	Below one is adverse	Audited financial statements
Return on assets	Profit after tax divided by average total assets	Negative or materially weak values are adverse	Audited financial statements
Asset turnover	Revenue divided by average total assets	Decline is adverse	Audited financial statements
Operating margin	Operating profit divided by revenue	Negative or declining values are adverse	Audited financial statements
Annual market return	Year-end price relative to previous year-end price	Negative return is adverse	Ghana Stock Exchange market data
Macroeconomic conditions	Inflation, cedi depreciation, policy rate and real Gross Domestic Product growth	Higher inflation, depreciation and rates, or weak growth are adverse	Bank of Ghana / World Bank
Risk Signal Convergence	Weighted domain scores plus concurrence premium	Higher score indicates greater convergence	Derived
Forward Corporate Vulnerability	One-year-ahead composite of adverse observable outcomes	More simultaneous adverse outcomes indicate greater vulnerability	Derived from firm-year and market data

Note. The appendix summarizes the principal operational rules used in the verified analytical workbook. Detailed equations remain in the Methodology section.

Appendix B. Data Provenance and Reproducibility Sources

Source	Data contribution	Study use
Ghana Stock Exchange	Factbooks, financial statements, market reports and listed-company information	Firm accounting, market-price and sample-frame variables
Bank of Ghana	Exchange-rate and monetary-policy series	Macroeconomic risk indicators
World Bank World Development Indicators	Inflation and real Gross Domestic Product growth	Macroeconomic risk indicators
Issuer annual reports	Audited financial statements and notes	Verification of firm-level accounting values
Analytical workbook	Formula-driven ratios, adverse signals, domain scores, convergence measures and forward outcomes	Reproducible transformation and analysis pipeline

Note. Only values traceable to a documented public source or transparent calculation were retained in the research data architecture.

Appendix C. Analytical Workflow and Model Evaluation

Stage	Procedure	Output
1. Data acquisition	Collect audited firm, market and macroeconomic records	Traceable firm-year source file
2. Harmonization	Align fiscal years, currencies, signs and reporting definitions	Consistent analytical panel
3. Signal engineering	Construct ratios and adverse-state indicators	Financial, operational, market and macroeconomic signals
4. Convergence construction	Aggregate domain scores; calculate breadth, depth and persistence	Risk Signal Convergence Framework variables
5. Forward outcome construction	Measure observable vulnerability at time t + 1	Forward Corporate Vulnerability Index and binary state
6. Predictive analysis	Estimate logistic regression, Random Forest and Extreme Gradient Boosting	Comparative model predictions
7. Evaluation	Assess receiver operating characteristic area under the curve, precision-recall area under the curve, F1, balanced accuracy and Brier score	Discrimination and calibration evidence
8. Explainability	Apply Shapley Additive Explanations to the selected tree model	Global and firm-year feature attribution

Note. The workflow is consistent with the study's longitudinal early-warning logic: predictor information is formed at time t and evaluated against Forward Corporate Vulnerability at time t + 1.