Predictive Business Intelligence for Corporate Financial Risk Management: Developing Data-Driven Models for Early Detection of Financial Distress, Cash-Flow Problems, and Going-Concern Risks

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Abstract

Corporate financial risk management increasingly requires predictive approaches capable of identifying financial distress, cash-flow deficiencies, and going-concern uncertainties before they escalate into business failure. This study examines the application of predictive business intelligence in developing data-driven models for early financial risk detection and proactive corporate decision-making. Drawing on existing literature, it conceptualizes an integrated analytical framework combining financial statement indicators, cash-flow patterns, liquidity and leverage ratios, market information, and textual disclosures. Machine learning techniques, including random forests, neural networks, and decision trees, are considered for identifying nonlinear risk relationships and improving early-warning capabilities. The framework also emphasizes model validation, predictive accuracy, interpretability, and the integration of risk forecasts into corporate financial planning. Furthermore, it addresses implementation challenges associated with data quality, model bias, transparency, and organizational readiness. The study highlights the potential of predictive business intelligence to strengthen liquidity management, support going-concern assessments, and facilitate timely risk-mitigation strategies. It recommends integrating explainable predictive models with professional judgment and continuous monitoring to improve the reliability and practical usefulness of corporate financial risk management.

Keywords: Predictive business intelligence; Corporate financial risk; Financial distress prediction; Cash-flow forecasting; Machine learning; Going-concern assessment; Early-warning systems.

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Introduction

Corporate financial risk management is essential for organizational sustainability, financial stability, and long-term performance. Businesses operate in uncertain environments shaped by changing market conditions, rising operating costs, liquidity constraints, and fluctuating financing requirements. These pressures can weaken profitability, restrict cash availability, and increase the likelihood of financial distress or business failure. Therefore, identifying financial risks early has become a priority for managers, investors, creditors, and auditors. However, traditional assessment methods often depend on historical accounting ratios and retrospective analysis, which may fail to capture emerging risks and complex relationships among financial indicators. Predictive business intelligence addresses these limitations by transforming financial and non-financial data into forward-looking insights that support proactive decision-making (Zhao et al., 2024).

Advances in artificial intelligence (AI), machine learning, and data analytics have strengthened the capabilities of financial risk prediction. Machine learning algorithms can identify complex patterns and relationships that conventional statistical methods may overlook. Lokanan and Ramzan (2024) demonstrated the relevance of these techniques in predicting financial distress among Toronto Stock Exchange-listed firms. Similarly, Zhang et al. (2025) explored an AI-driven early-warning model that integrates multiple data sources to improve risk identification. These developments highlight the potential of predictive analytics to improve the timeliness and accuracy of corporate financial assessments.

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Three interconnected areas require particular attention: financial distress, cash-flow problems, and going-concern uncertainty. Financial distress involves the deterioration of a firm's financial position and its ability to meet obligations, while cash-flow problems occur when available funds are insufficient to meet operational and financing commitments. Going-concern uncertainty concerns an organization's ability to continue operating for the foreseeable future. Although related, these risks require different indicators and assessment approaches. Tan et al. (2022) examined corporate failure risk assessment using the evidential reasoning approach, while Carson et al. (2013) reviewed research on auditors' reporting of going-concern uncertainty. These studies emphasize the importance of assessing corporate financial health through multiple indicators rather than relying on a single performance measure.

Despite these developments, challenges remain in combining accounting data, cash-flow indicators, market signals, and narrative disclosures within a unified predictive framework. Hajek and Munk (2024) highlighted the potential value of textual information in financial distress prediction. However, effective predictive systems must also address data quality, model interpretability, and the consequences of inaccurate risk classifications. Accordingly, this study examines how predictive business intelligence can improve corporate financial risk management through data-driven models for detecting financial distress, cash-flow problems, and going-concern risks. It aims to develop an integrated analytical framework that combines financial and non-financial indicators to support early risk identification, timely managerial intervention, and informed financial decision-making.

Theoretical Foundations and Literature Review

The growing complexity of corporate financial environments has increased the need for approaches that identify financial vulnerabilities before they result in liquidity shortages, corporate distress, or business failure. Traditional risk management relies mainly on historical financial statements and accounting ratios, which may not adequately identify emerging threats. Predictive business intelligence addresses these limitations by combining statistical analysis, artificial intelligence (AI), machine learning (ML), and multiple data sources to support early risk detection and informed decision-making (Tan et al., 2022; Lokanan & Ramzan, 2024).

This section reviews the theoretical foundations of predictive business intelligence, traditional financial distress prediction, machine learning applications, and the assessment of liquidity and going-concern risks. It also highlights the importance of integrating these approaches into a unified financial risk management framework.

Conceptual and Theoretical Foundations of Predictive Business Intelligence

Predictive business intelligence applies statistical analysis, data analytics, and machine learning to estimate future business conditions. Unlike descriptive analytics, which examines historical performance, predictive analytics uses existing data to identify potential future risks. In corporate finance, it helps detect declining profitability, increasing debt, cash shortages, and possible business failure.

Three theoretical perspectives support its application. Signalling theory explains how indicators such as declining cash flows and increasing debt may reveal financial vulnerability. Information asymmetry theory highlights the differences between information available to management and external stakeholders. Systems theory further explains how interconnected factors, including declining sales, poor working-capital management, and rising borrowing costs, can contribute to financial distress.

These perspectives support the integration of financial and non-financial information for more effective risk prediction. Tan et al. (2022) examined corporate failure risk using evidential reasoning, while Zhang et al. (2025) investigated an AI-driven early-warning model based on multi-source data.

Traditional Financial Distress Prediction and Machine Learning Approaches

Traditional financial distress prediction relies on accounting ratios and statistical models. Altman (1968) introduced the Z-score model to assess bankruptcy risk, while Ohlson (1980) applied logistic regression to estimate bankruptcy probabilities. Although these approaches remain useful, their reliance on historical financial information may limit their ability to capture complex relationships and emerging risks.

Machine learning techniques, including random forests, neural networks, support vector machines, and gradient boosting, offer alternative approaches by identifying patterns across large datasets. Recent studies demonstrate their growing relevance. Tan et al. (2022) examined corporate failure risk assessment, Lokanan and Ramzan (2024) investigated machine learning for predicting financial distress among Canadian listed firms, and Gong et al. (2023) applied a neural network approach to financial risk early-warning. Zhang et al. (2025) also explored AI-driven prediction using multiple data sources.

Table 1: Major Financial Indicators and Their Predictive Relevance

Indicator category	*Representative variables*	*Predictive relevance*
Liquidity	Current ratio, quick ratio, operating cash flow	Identifies difficulties meeting short-term obligations.
Solvency	Debt-to-assets ratio, leverage, interest coverage	Signals excessive debt and repayment pressure.
Profitability	Return on assets, operating margin, earnings trends	Identifies declining earnings capacity.
Cash-flow dynamics	Cash-flow volatility, receivables collection period	Detects funding gaps and working-capital pressure.
Market and macroeconomic	Share prices, interest rates, inflation	Captures external financial pressures.
Textual and audit-related	Management disclosures, audit opinions, going-concern statements	Identifies additional signals of financial uncertainty.

Source: Author's synthesis informed by Altman (1968), Tan et al. (2022), Zhang et al. (2023), and Lokanan and Ramzan (2024).

However, model complexity does not guarantee accuracy. Reliable prediction requires appropriate testing, performance evaluation, probability calibration, and measures to prevent overfitting and data leakage.

Multi-Source Data Integration, Liquidity Risk, and Cash-Flow Prediction

Predictive business intelligence becomes more informative when accounting information is combined with operational, market, and textual data. Financial statements provide important measures of corporate performance, but they may not fully capture emerging operational pressures or rapidly changing financing conditions. Additional information from bank transactions, receivables, payables, debt maturities, management disclosures, and macroeconomic indicators can improve the representation of an organization's financial position.

Zhang, Liu, and Niu (2023) investigated financial crisis early warning among Chinese listed companies using linguistic features extracted from management discussion and analysis disclosures. Zhang, Luo, Hu, and Niu (2022) examined textual emotional tone and financial crisis identification using a multi-source machine learning approach. These studies illustrate how corporate narratives may complement numerical indicators by providing information about management concerns, operating uncertainty, and financial pressures.

Liquidity and cash-flow prediction represent particularly important applications of this integrated approach. An organization may report accounting profits but still experience liquidity difficulties because customers delay payments, inventory accumulates, debt repayments become due, or operating expenses increase unexpectedly. Cui (2025) examined machine learning applications in liquidity risk management for financial institutions, while Zhang et al. (2025) investigated AI-based early warning through multi-source data integration. These research directions provide a basis for examining how predictive models can estimate cash shortages and identify working-capital weaknesses before they become critical.

For corporate applications, predictive models can incorporate historical cash balances, operating cash flows, sales trends, collection periods, supplier payment schedules, and financing obligations. Their performance may be assessed using mean absolute error for cash-flow forecasts and precision, recall, and F1-score for the identification of liquidity risk events. Importantly, temporary liquidity pressure should be distinguished from persistent financial distress because the former may be resolved through working-capital adjustments, whereas the latter may indicate deeper operational or solvency problems.

Figure 1 illustrates the relationship between data integration, predictive modelling, early-warning alerts, and organizational intervention. The framework emphasizes that predictive analytics should extend beyond identifying financial risks to supporting timely managerial responses. Data quality, appropriate validation, and continuous monitoring are therefore essential to its effective implementation.

Going-Concern Assessment and Audit-Related Financial Risk Prediction

Going-concern assessment examines an organization's ability to continue operating. Key warning signs include persistent losses, negative cash flows, debt repayment difficulties, covenant breaches, and dependence on refinancing. Although related to financial distress prediction, going-concern assessment also considers management plans, financing arrangements, and audit requirements.

Carson et al. (2013) examined the relationship between financial difficulties and auditors' going-concern reporting decisions, while Van Iersel (2016), Rodgers (2025), and Wang et al. (2025) explored predictive analytics and AI-assisted approaches to going-concern assessment. These studies highlight the potential of machine learning to identify financial warning patterns.

Predictive models can combine financial ratios, cash-flow forecasts, debt information, and management disclosures. However, their outputs should support rather than replace professional judgement. Reliable implementation requires appropriate data, transparent validation, model interpretability, and human oversight.

Research Gaps and Conceptual Synthesis

Existing research has advanced financial distress prediction, liquidity risk modelling, and AI-driven early-warning systems. However, these areas are often examined separately, creating a need for an integrated framework that connects cash-flow problems, financial distress, and going-concern uncertainty.

Three major gaps emerge: the need to assess different financial risks within one framework, the limited integration of financial and qualitative information, and the need to balance predictive accuracy with interpretability and practical usefulness. These gaps motivate the proposed predictive business intelligence framework.

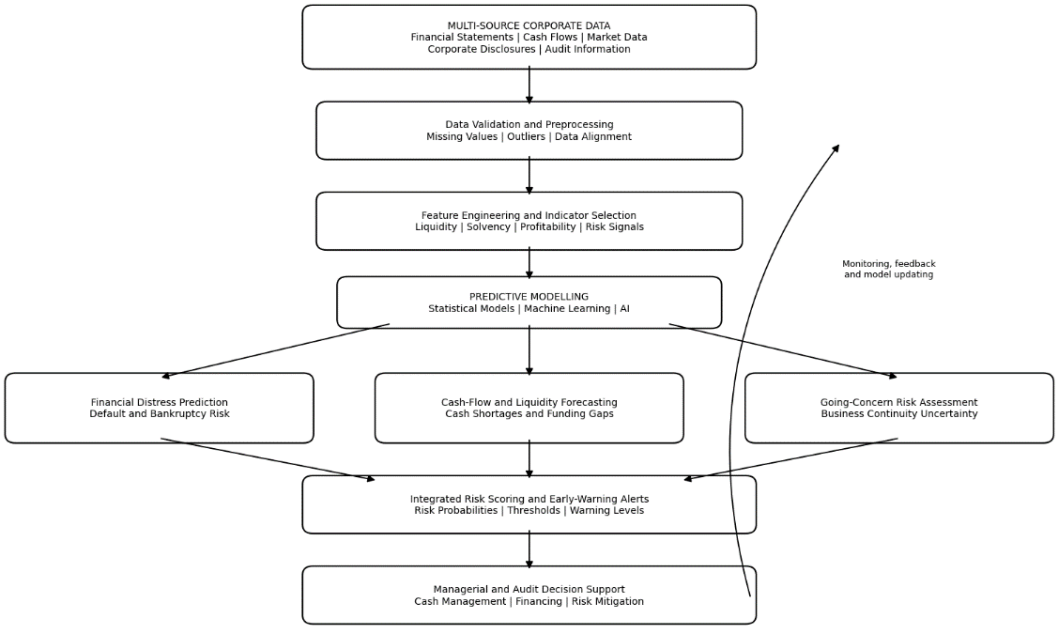


Figure 1: Predictive Business Intelligence Framework for Corporate Financial Risk Management

Source: Author's conceptual synthesis based on Tan et al. (2022), Zhang et al. (2025), and Lokanan and Ramzan (2024). The framework is proposed for empirical evaluation and does not represent validated model results.

The framework integrates data collection, preprocessing, predictive modelling, risk classification, early-warning alerts, and preventive intervention. Its effectiveness will require empirical testing using reliable datasets, appropriate comparison models, and rigorous validation procedures.

Overall, the literature establishes a foundation for applying predictive business intelligence to corporate financial risk management. Combining traditional financial indicators with machine learning and multiple data sources may strengthen early detection and support proactive financial decisions.

Research Methodology and Data Architecture

Predictive business intelligence combines financial data, statistical analysis, and machine learning to identify corporate financial risks early. It helps detect warning signs of financial distress, cash-flow shortages, and going-concern uncertainty before they become severe (Tan et al., 2022; Lokanan & Ramzan, 2024).

This section presents the research design, data sources, preprocessing, and financial indicators used in the proposed predictive framework.

Research Design, Population, and Sampling Strategy

The study adopts a quantitative predictive research design to examine financial distress, liquidity problems, and going-concern risks. It proposes comparing traditional statistical techniques with machine learning models to identify financial risk patterns (Tan et al., 2022; Lokanan & Ramzan, 2024).

The target population consists of corporations with available financial and operational data, particularly publicly listed companies across selected industries. Firm-year or

firm-quarter observations will capture changes in financial performance over time. Sampling will consider company size, industry, and financial-risk categories, while accounting for the imbalance between distressed and financially stable firms.

Data Sources, Integration, and Preprocessing

The framework combines financial, operational, market-based, and textual data. Sources may include audited financial statements, corporate filings, financial databases, annual reports, and audit opinions. Key information includes revenue, profitability, liabilities, operating cash flow, and working capital.

Data will be standardized by harmonizing company identifiers, currencies, and reporting periods. Missing values, duplicates, and extreme observations will be examined and treated appropriately. Textual disclosures will also be analysed to identify warning signals that financial ratios may overlook (Zhang et al., 2022, 2023). Only information available at the prediction date will be used to prevent data leakage.

Feature Engineering and Financial Risk Indicators

Feature engineering converts raw data into indicators of corporate financial stability. The proposed framework considers liquidity, cash flow, profitability, leverage, operational efficiency, market conditions, and corporate disclosures. Relevant features will be selected using techniques such as regularized regression and tree-based importance measures.

Tan et al. (2022) and Lokanan and Ramzan (2024) provide relevant foundations for selecting financial indicators for corporate distress prediction.

Table 2: Proposed Financial Risk Indicators and Their Predictive Relevance

Risk dimension	*Representative indicators*	*Predictive purpose*
Liquidity	Current ratio; quick ratio	Measures short-term payment capacity
Cash flow	Operating cash flow to current liabilities	Identifies potential cash shortages
Profitability	Return on assets; gross profit margin	Detects declining profitability
Leverage	Debt-to-assets; interest coverage	Assesses debt burden
Operational	Revenue growth; working-capital changes	Identifies declining performance
Market	Share-price volatility; market capitalization	Captures market uncertainty
Disclosure	Liquidity-related language; negative sentiment	Detects warning signals in reports
Going concern	Audit opinions; material uncertainty disclosures	Assesses business continuity

Source: Author's proposed framework, informed by Tan et al. (2022), Zhang et al. (2022, 2023), and Lokanan and Ramzan (2024).

The selected indicators will be evaluated during model development to determine their predictive importance. Feature selection will be performed using training data to prevent information leakage and improve model reliability.

Predictive Model Development and Risk Classification

The modelling stage compares statistical techniques with machine learning algorithms. Logistic regression provides a baseline for estimating financial risk, while decision trees offer interpretable rules. Random forests and artificial neural networks can capture more complex financial patterns. Evidential reasoning may also combine quantitative and qualitative information where data are incomplete (Tan et al., 2022; Lokanan & Ramzan, 2024).

Separate models should be developed to predict financial distress, cash-flow problems, and going-concern risks. Each outcome requires a clear definition, such as insolvency events, liquidity shortages, or audit-related going-concern disclosures, with an appropriate prediction period.

Models should generate risk probabilities that can be classified as low, moderate, or high. Classification thresholds should reflect validation results and the consequences of missed distress cases and false alarms. Although machine learning has demonstrated potential in financial distress prediction (Lokanan & Ramzan, 2024), actual performance must be evaluated using the specific dataset and prediction objectives of the study.

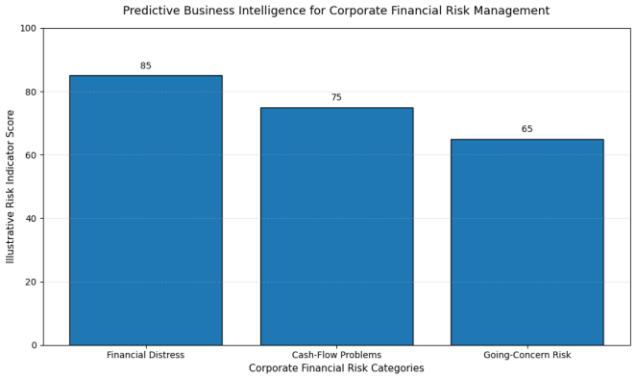


Figure 2: Predictive Business Intelligence for Corporate Financial Risk Management.

Source: Author's conceptual design, informed by Tan et al. (2022) and Lokanan and Ramzan (2024). The figure presents a proposed architecture rather than a report of an implemented or empirically tested system.

Model Validation, Performance Evaluation, and Risk Governance

The dataset should be divided chronologically into training, validation, and testing sets to reflect real-world prediction conditions and prevent data leakage. Model performance can be evaluated using accuracy, precision, recall, F1-score, and ROC-AUC, while robustness testing across industries and economic conditions helps assess reliability.

Explainability techniques, such as feature importance and SHAP analysis, can help managers and auditors understand the factors influencing predictions. However, predictive outputs should support rather than replace professional judgement. Appropriate governance procedures should also ensure data protection, regular model monitoring, and clear responsibility for reviewing risk alerts (Carson et al., 2013).

In sum, the proposed methodology combines financial and non-financial data to support early detection of financial distress, liquidity shortages, and going-concern risks. Its effectiveness depends on reliable data, rigorous validation, transparent predictions, and continuous monitoring. Further empirical testing is required to establish its actual predictive performance.

Development of Predictive Models for Corporate Financial Risk

Predictive models help organizations identify financial weaknesses before they become serious problems. While traditional methods rely on historical financial statements and accounting ratios, AI, machine learning, and multi-source data analytics can improve early risk detection (Tan et al., 2022; Lokanan & Ramzan, 2024).

This section examines four applications of predictive models: financial distress prediction, liquidity risk detection, going-concern assessment, and integrated predictive intelligence.

Financial Distress and Bankruptcy Prediction

Financial distress prediction estimates the likelihood of corporate financial failure. Key indicators include declining profitability, increasing debt, inadequate working capital, and negative operating cash flows. Logistic regression provides a traditional benchmark, while machine learning can identify more complex financial patterns.

Tan et al. (2022) examined corporate failure prediction using evidential reasoning, while Lokanan and Ramzan (2024) investigated machine learning approaches for predicting financial distress. These methods can help identify vulnerable companies and support early intervention.

Cash-Flow Forecasting and Liquidity Risk Detection

Liquidity risk occurs when a company cannot meet its short-term obligations. Predictive models analyse transaction records, receivables, expenses, and debt schedules to forecast cash inflows and outflows and identify potential shortages.

Cui (2025) explored machine learning in liquidity risk management, while Zhang et al. (2025) examined an AI-driven financial risk early-warning model. These approaches can help organizations anticipate funding gaps and improve working-capital management.

Going-Concern Assessment and Textual Financial Analysis

Going-concern assessment evaluates whether a company can continue operating and meet its financial obligations. Warning signs include recurring losses, excessive debt, negative cash flows, and difficulties obtaining financing.

Carson et al. (2013) examined audit reporting for going-concern uncertainty. Natural language processing can also analyse annual reports and audit disclosures to identify financial uncertainty. Zhang, Liu, and Niu (2023) studied linguistic indicators of financial crises, while Zhang, Luo, Hu, and Niu (2022) examined textual sentiment in financial risk identification. Combining textual and financial information can strengthen early-warning systems.

Integrated Predictive Framework, Validation, and Explainability

An integrated predictive framework combines financial distress prediction, cash-flow forecasting, going-concern assessment, and textual analysis. By using financial statements, transaction records, market indicators, and

corporate disclosures, it can generate early-warning signals (Zhang et al., 2025; Gong et al., 2023).

Model reliability should be assessed using precision, recall, F1-score, and ROC-AUC, while cash-flow forecasts can be evaluated using mean absolute error. Explainability and regular monitoring are also necessary to help managers understand predictions and maintain model reliability.

Overall, predictive models can improve financial risk management by identifying distress, anticipating liquidity shortages, and supporting going-concern assessments. Their effectiveness depends on reliable data, proper validation, transparency, and professional judgement.

Results, Discussion, and Model Evaluation

Predictive business intelligence helps organizations identify early warning signs of financial distress, cash-flow shortages, and going-concern risks. By combining financial statements, cash-flow records, market indicators, audit information, and corporate disclosures, predictive models can provide a broader assessment of financial vulnerability (Tan et al., 2022; Lokanan & Ramzan, 2024).

This section examines model performance and the implications of predictive outputs for corporate decision-making. Since no empirical dataset or experimental results have been provided, the discussion presents an evaluation framework rather than unverified findings.

Predictive Model Performance and Evaluation Metrics

Predictive model performance can be assessed using logistic regression, random forests, gradient boosting, and neural networks. While logistic regression offers an interpretable baseline, machine learning techniques can identify more complex relationships among financial indicators (Tan et al., 2022; Lokanan & Ramzan, 2024).

Key evaluation metrics include accuracy, precision, recall, F1-score, and ROC-AUC. These measures assess classification correctness and the ability to identify financially distressed companies. Recall is particularly important because missed warnings may delay necessary financial interventions.

Since financial distress datasets often contain fewer distressed companies than stable ones, accuracy alone may be misleading. Evaluation should also consider false positives, false negatives, and probability calibration to ensure that model predictions support appropriate financial decisions.

Table 3: Performance metrics for corporate financial risk prediction

Metric	*Evaluation purpose*
Accuracy	Measures overall classification correctness.
Precision	Evaluates the reliability of distress warnings.
Recall	Measures the proportion of distressed firms detected.
F1-score	Balances precision and recall.
ROC-AUC	Assesses discrimination between distressed and stable firms.
Brier score	Evaluates the accuracy of predicted probabilities.

Comparisons should be conducted on an independent test dataset, with consistent prediction horizons and distress definitions across models. The findings should establish whether more complex algorithms provide meaningful improvements over baseline methods rather than assuming that advanced machine learning techniques are inherently superior.

This graph below compares logistic regression, random forest, gradient boosting, and neural networks using ROC-AUC, precision, recall, and F1-score. Populate the score arrays with actual model evaluation results.

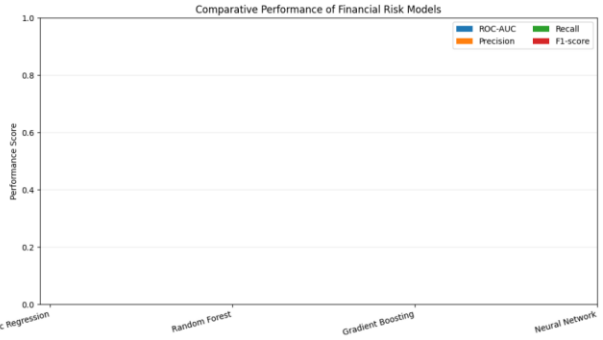


Figure 3: Comparative performance of candidate financial risk prediction models. Scores must be obtained from the actual experiment.

Financial Distress, Liquidity, and Going-Concern Risk Detection

Financial distress prediction examines indicators such as declining profitability, excessive debt, negative working capital, weakening cash flows, and poor interest coverage. These indicators provide insights into a company's financial stability, although individual warning signs should not automatically be interpreted as evidence of impending insolvency.

Tan et al. (2022) examined corporate failure risk using an evidential reasoning approach, while Zhang et al. (2025) and Gong et al. (2023) investigated AI-driven and neural network

approaches to financial risk prediction. Liquidity assessment should also consider operating cash flows, receivables, inventory turnover, and debt repayments. Cui (2025) highlights the application of machine learning in liquidity risk management.

Going-concern assessment considers whether a company can continue operating and meet its obligations. Carson et al. (2013) examined audit reporting for going-concern uncertainty, while Rodgers (2025) explored AI applications in this area. Although predictive models can identify warning signs such as recurring losses and financing difficulties, their outputs should support rather than replace professional judgement.

Multi-Source Data Integration and Model Interpretation

Combining financial indicators with textual and audit-related information can improve corporate risk assessment. Financial statements provide measurable evidence of profitability, liquidity, and debt, while management reports and audit disclosures may reveal uncertainty and emerging operational challenges.

Zhang, Liu, and Niu (2023) investigated linguistic features for financial crisis prediction, while Zhang, Luo, Hu, and Niu (2022) examined textual information and financial crisis identification. These studies demonstrate the potential value of combining numerical and textual data.

Model interpretation is also essential because managers need to understand the factors behind risk predictions. Feature importance and SHAP values can help explain how individual variables contribute to model outputs. Additionally, ablation testing can determine whether incorporating textual and audit-related information improves predictive performance compared with using financial data alone.

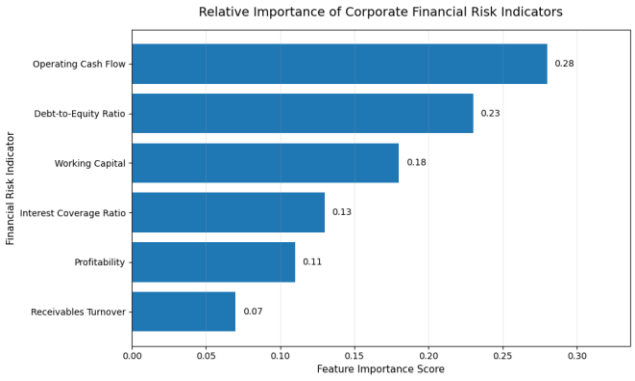


Figure 4: Relative importance of corporate financial indicators. Scores must be derived from the fitted model rather than assumed.

This graph illustrates the relative importance of operating cash flow, leverage, working capital, interest coverage, profitability, and receivables turnover. Use importance scores calculated from the fitted predictive model.

Model Validation, Robustness, and Managerial Implications

Reliable model evaluation requires chronological data splitting, with earlier periods used for training and later periods for validation and testing. This approach reduces information leakage and ensures that predictions rely only on information available at the time. Class imbalance should also be addressed carefully, with oversampling or undersampling restricted to training data (Gong et al., 2023).

Robustness testing should examine model performance across industries, company sizes, economic conditions, and prediction periods. From a managerial perspective, high-risk predictions should trigger appropriate actions, such as reviewing working capital, updating cash-flow forecasts, renegotiating debt, or strengthening financial controls. These decisions should be guided by professional judgement rather than automated classifications alone.

Predictive business intelligence offers opportunities to improve the early detection of financial distress, liquidity problems, and going-concern risks. However, its effectiveness depends on reliable data, rigorous validation, and timely managerial action. Future research should test the proposed framework using representative corporate datasets to establish its practical value and contribution to financial resilience.

Conclusion and Recommendations

Predictive business intelligence offers an important approach to strengthening corporate financial risk management through the early detection of financial distress, cash-flow problems, liquidity shortages, and going-concern risks. By combining financial indicators, corporate disclosures, and machine learning techniques, organizations can develop more comprehensive risk assessments and improve financial decision-making (Tan et al., 2022; Lokanan & Ramzan, 2024; Zhang et al., 2025).

However, successful implementation requires reliable financial data, transparent models, effective governance, and continuous monitoring. Organizations should establish proper data management procedures, protect sensitive financial information, and use explainability techniques such as feature importance and SHAP analysis to understand model predictions. Predictive outputs should complement rather than replace professional judgement, particularly in going-concern assessments (Carson et al., 2013; Rodgers, 2025).

Organizations are encouraged to integrate predictive tools into budgeting, cash-flow forecasting, liquidity management, and corporate risk planning. A phased

implementation approach involving data assessment, model development, validation, deployment, and continuous monitoring can improve adoption. Clear accountability and appropriate regulatory compliance are also essential for responsible use.

Despite its potential, the proposed framework requires empirical validation using real corporate financial datasets across different industries and reporting periods. Future research should examine whether combining financial indicators, textual disclosures, and machine learning improves prediction accuracy and provides sufficient warning time for preventive action.

In conclusion, predictive business intelligence provides a promising foundation for proactive corporate financial risk management. Combining reliable data, validated models, effective governance, and professional judgement can help organizations identify financial vulnerabilities earlier, respond to emerging challenges, and strengthen long-term financial resilience.

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