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Predicting Zombie Firms Among Global Companies After COVID-19 Using Explainable Artificial Intelligence

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Abstract

This study develops a global predictive model to identify zombie firms that have emerged in the post-COVID-19 era, integrating high-performing machine learning algorithms with explainable artificial intelligence (XAI) techniques. Using firm-level financial data from 25,981 listed companies across multiple countries between 2020 and 2023, we compare 11 machine learning algorithms and identify CatBoost as the most effective model in terms of accuracy and F1 score. To address the model's black-box nature, we employ SHAP and LIME to enhance interpretability, enabling both global and firm-specific analyses. The results reveal that net profit margin, SG&A-to-sales ratio, asset turnover ratios, and ROE are key indicators of zombie firms status. This dual approach of combining predictive accuracy with interpretability provides theoretical and practical insights into financial distress, aligning with core principles of corporate finance. The study offers actionable implications for policymakers and investors, suggesting differentiated support strategies based on firm characteristics and financial inefficiencies. Our findings highlight the importance of transparent, data-driven tools in managing systemic risk in the evolving global economic landscape.

Keywords: Zombie Firms, Machine Learning, Explainable Artificial Intelligence (XAI), CatBoost, SHAP, LIME, Financial Distress

1. INTRODUCTION

The COVID-19 pandemic has reignited global concerns about the prevalence and persistence of so-called "zombie firms"—companies that continue to operate despite being unable to generate sufficient profits to service their debt obligations. These firms distort resource allocation, crowd out productive investment, and ultimately undermine economic resilience (Caballero et al., 2008; Acharya et al., 2020). Recent studies suggest that the share of zombie firms has increased significantly in both advanced and emerging economies since the onset of the pandemic. According to Banerjee and Hofmann (2022), the average share of zombie firms in advanced economies rose from 4% in 2000 to nearly 15% by 2021, posing a growing threat to post-pandemic recovery.

Traditional approaches such as Altman's Z-score (1968), Ohlson's O-score (1980), and Merton's structural credit risk model (1974) provided foundational tools for distress prediction. Yet these frameworks share common limitations, including linearity assumptions, reliance on a narrow set of financial ratios, and restricted generalizability across markets and industries. As a result, their applicability to the complex and nonlinear dynamics of post-pandemic global firms remains limited (Peek & Rosengren, 2005; McGowan et al., 2018; Song et al., 2021).

In response to these limitations, this study develops a globally applicable model for predicting zombie firms using machine learning (ML) and explainable artificial intelligence (XAI) techniques. Leveraging a comprehensive panel dataset of 25,981 listed firms from 2020 to 2023 across more than 30 countries, we evaluate 11 classification algorithms to assess their performance in identifying zombie firms. Among these, CatBoost—a gradient boosting

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model—emerges as the most effective, outperforming both traditional models and other ensemble methods across accuracy, precision, recall, and F1 metrics.

However, while ML models offer superior predictive power, their opaque, "black-box" nature limits interpretability, which is critical for adoption in policy, regulatory, and managerial contexts (Barredo Arrieta et al., 2020). To address this, we incorporate SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to explain the inner workings of our best-performing model.

Our SHAP-based global analysis reveals that net profit margin, SG&A-to-sales ratio, gross profit margin, return on equity, log of revenue, operating income growth rate, net income growth rate, total capital turnover, and debt-to-equity ratio are the most influential features in predicting zombie firms. SHAP summary plots demonstrate that firms with high SG&A ratios or low profit margins are more likely to be classified as zombies. Local SHAP analysis further illustrates how combinations of these features affect predictions at the firm level.

Similarly, LIME results reinforce the central role of net profit margin and SG&A-to-sales ratio in both global and local contexts. For example, firms with net profit margins of –26.62% and gross profit margins of –1.31% were more likely to be identified as zombie firms, consistent with thresholds identified in the SHAP analysis. This dual-method XAI approach enables transparent interpretation of model outputs, bridging the gap between technical modeling and practical decision-making.

This study contributes to the literature in several ways. First, it is among the first to construct a globally generalized prediction model for zombie firms in the post-pandemic period using large-scale international data. Second, by integrating SHAP and LIME, we enhance the explainability of high-performance ML models, thereby improving their practical relevance. Third, we identify key financial indicators—such as profitability margins and cost structure ratios—that consistently drive zombie status across firms and countries. Finally, this study establishes a foundation for future research that incorporates macroeconomic, institutional, and sectoral heterogeneity into predictive frameworks for financial distress.

The remainder of this paper is structured as follows. Section 2 reviews the prior literature on zombie firm identification and the application of AI and XAI techniques in financial distress prediction. Section 3 describes the dataset, variable definitions, and empirical methodology. Section 4 presents the prediction results of various AI models, followed by the interpretation of model outcomes using SHAP and LIME. Section 5 concludes the paper with key findings, policy implications, and suggestions for future research.

2. LITERATURE REVIEW

2.1 Definition and Macroeconomic Relevance of Zombie Firms

Zombie firms are broadly defined as companies that cannot generate sufficient operating income to cover interest payments over an extended period—commonly identified by an interest coverage ratio (EBIT/Interest Expense) below 1 for three consecutive years (Banerjee & Hofmann, 2018). These firms survive not through profitability, but by relying on ongoing external financing or debt refinancing.

The macroeconomic implications of zombie firms are substantial. Their persistent presence distorts the allocation of capital, crowds out more productive firms, and suppresses overall economic dynamism. Caballero et al. (2008) document how the survival of unproductive firms in Japan during the 1990s—fueled by lenient bank lending—undermined economic recovery and structural adjustment. Building on this work, Banerjee and Hofmann (2022) report a steady rise in the share of zombie firms among OECD countries—from 4% in the mid-1980s to over 15% by 2017—highlighting the systemic risks they pose to long-term economic growth and productivity.

These firms act as a drag on aggregate productivity and may increase financial fragility by concentrating credit risk in unviable firms. Their survival is often attributed to prolonged periods of low interest rates, ineffective insolvency regimes, and the unwillingness of banks to recognize losses on non-performing loans.

2.2 Traditional Models of Corporate Distress Prediction

Foundational studies in financial distress prediction have primarily relied on statistical models. Beaver (1966) emphasizes liquidity, profitability, and leverage as core predictors of failure. Altman's Z-score (1968), using Multiple Discriminant Analysis, combines five key financial ratios into a single metric to assess bankruptcy risk. Ohlson (1980) develops the O-score using logistic regression, providing a probabilistic estimate of default.

Structural models, such as the Merton (1974) framework, treat equity as a call option and define default as the point at which asset values fall below debt obligations. This model and its extensions, such as the KMV-Merton approach (Bharath & Shumway, 2008), use market data to compute the likelihood of default through the concept of Distance-to-Default.

While widely used, traditional models face several limitations. They rely on historical financial statements, assume linearity, and are often unable to account for firm-specific qualitative factors or changing macroeconomic conditions. Moreover, they tend to underperform in periods of market disruption, such as during financial crises or pandemics, highlighting the need for more adaptive methods.

2.3 Machine Learning and Deep Learning Models in Distress Prediction

In response to the limitations of classical models, researchers have increasingly turned to artificial intelligence (AI) techniques. Early studies demonstrate that Artificial Neural Networks (ANNs) outperform traditional methods such as Multiple Discriminant Analysis (Odom & Sharda, 1990). Subsequent research shows that Support Vector Machines (Shin & Lee, 2005), Decision Trees, Random Forests (Kim & Ahn, 2016), and K-Nearest Neighbors (Lee et al., 2020) offer improved predictive accuracy.

Ensemble learning methods such as bagging and boosting further enhance model performance (Min, 2014; Kim, 2009). Deep learning architectures—RNN, LSTM, CNN—have shown exceptional results when dealing with large, nonlinear datasets (Hosaka, 2019; Vochozka, 2020; Jo et al., 2021), making them highly relevant for default prediction in dynamic financial environments.

2.4 Machine Learning and Deep Learning Models in Distress Prediction

Despite their predictive accuracy, AI models are often criticized for their "black-box" nature, which limits transparency and practical usability—especially in regulated sectors like finance. To address this, Explainable Artificial Intelligence (XAI) methods have emerged. LIME (Ribeiro et al., 2016) and SHAP (Lundberg & Lee, 2017) allow for post-hoc interpretation of AI model predictions by quantifying the contribution of each input variable.

In financial applications, XAI enhances model interpretability in areas such as credit scoring, loan approval, and risk forecasting (Bae, 2023). Park et al. (2023) apply integrated gradients to explain default predictions from deep learning models, offering insights into how model decisions align with financial theory and regulatory expectations.

While prior studies have highlighted the practical importance of interpretability in regulatory compliance and risk monitoring, the theoretical contribution of XAI extends further. XAI provides a mechanism by which machine learning outputs can be systematically integrated into established frameworks of financial decision making.

Specifically, global explanations such as SHAP feature importance reveal the aggregate determinants of zombie status, including profitability shortfalls, excessive operating costs, and low asset utilization, which align with classical theories on agency costs of free cash flow (Jensen, 1986), inefficient resource allocation (Barney, 1991), and financing frictions (Myers & Majluf, 1984). At the same time, local explanations generated by LIME or SHAP supply firm level diagnostics that enable heterogeneous responses across companies, thereby supporting decision making under asymmetric information and heterogeneous risk exposures. In this sense, XAI does not merely enhance the transparency of predictive models but also operationalizes theoretical constructs by assigning interpretable contributions to specific financial mechanisms. This dual role, linking global systemic patterns with firm level heterogeneity, positions XAI as a distinctive bridge between predictive analytics and theory consistent governance frameworks in corporate finance.

2.5 The Importance of Global Perspective in Zombie Firm Research

Although a substantial body of research on zombie firms has been conducted in country-specific contexts—such as Japan (Caballero et al., 2008), Korea (Kim & Choi, 2017), and China—there remains a critical gap in understanding the global characteristics and drivers of zombie firm persistence. The COVID-19 pandemic introduced a profound and asymmetric shock to the global economy, revealing structural vulnerabilities that vary significantly across regions, industries, and financial systems. This heterogeneity underscores the need for a comprehensive, cross-country approach to studying zombie firm dynamics.

The importance of a global perspective becomes particularly evident when considered through the lens of three core theoretical mechanisms frequently cited in the literature and employed in our XAI-based interpretive analysis: resource misallocation, information asymmetry, and financial resilience.

First, zombie firms are closely linked to the issue of resource misallocation. Inconsistent policy responses and varying capital market efficiencies across countries influence how financial resources are allocated between viable and non-viable firms. A global framework enables comparative analysis of how institutional settings exacerbate or mitigate the crowding-out effects of zombie firms on more productive enterprises.

Second, the prevalence of information asymmetry in capital markets varies depending on governance quality and transparency standards across jurisdictions. By analyzing firms across multiple countries, this study provides insight into how opaque financial structures and limited disclosure practices affect the predictability and detectability of zombie firms—challenges that can be addressed using explainable AI models like SHAP and LIME.

Third, a global analysis enhances our understanding of financial resilience—how quickly and effectively firms recover from economic disruptions. Zombie firm prevalence is often an indicator of underlying fragility in the corporate sector. Understanding cross-country differences in financial resilience helps policymakers design more effective strategies to contain systemic risk and promote long-term economic stability.

This study contributes to the literature by applying state-of-the-art AI and XAI techniques to a unique global dataset of over 25,000 listed companies spanning from 2020 to 2023. Unlike prior research confined to domestic samples, our approach reveals universal patterns as well as regional idiosyncrasies in zombie firm behavior, thereby offering a more generalizable model for both academic and policy applications in the post-COVID-19 economic landscape.

3. THEORETICAL BACKGROUND

3.1 Concept of Explainable AI

To promote the broader utilization of AI, it is essential that users are capable of retrospectively understanding and evaluating the rationale behind AI-generated decisions. Explainable Artificial Intelligence (XAI) aims to make the outputs of complex, often opaque AI models interpretable to humans by offering explanations in a comprehensible form (Gunning, 2016). By revealing the underlying logic of AI decisions, XAI not only supports human users in identifying and rectifying erroneous outputs, but also facilitates iterative improvements to AI models themselves (Adadi & Berrada, 2018).

While certain conventional models, such as logistic regression, naturally offer interpretability by design, they often fall short in terms of predictive performance. This highlights the trade-off between model interpretability and performance, where more sophisticated models typically offer better accuracy but reduced transparency (Gunning, 2016). As a result, recent research has increasingly emphasized the development of XAI techniques that can preserve the predictive power of complex algorithms while making their outputs understandable to human users (Adadi & Berrada, 2018). Such advancements play a crucial role in enhancing the transparency and trustworthiness of AI systems, particularly in high-stakes domains like finance.

3.2 Explainable AI: LIME

One of the core principles of Explainable Artificial Intelligence (XAI) is identifying how individual input variables contribute to a model's prediction. Among the various approaches to achieving this, the use of a surrogate model is particularly common. A surrogate model refers to the process of approximating a complex, often opaque AI model with a simpler, interpretable model that users can understand. Models such as linear regression or decision trees are typically used in this role due to their straightforward structure and interpretability. This allows users to gain insights into the behavior of the original model by interpreting the output of the surrogate model.

There are two main types of surrogate model analysis: global and local. Global surrogate analysis approximates the entire behavior of the original model by using all available input data. This approach is useful for understanding the overall importance of features across the dataset but may suffer from overfitting or loss of nuance due to its broad scope. In contrast, local surrogate analysis focuses on interpreting individual predictions by approximating the model only around specific data points. This method can offer more precise and context-specific insights, especially when the goal is to understand how a model behaves in particular situations.

A widely adopted local analysis technique is LIME (Local Interpretable Model-agnostic Explanations). LIME enables users to evaluate the contribution of input features to a model's prediction without requiring any assumptions about the structure or type of the original AI model. Essentially, it creates a simple, interpretable model that mimics the behavior of the complex model near a specific data instance. By doing so, it provides human-readable explanations for otherwise opaque predictions.

In applying this method, LIME generates a set of perturbed samples near the instance of interest and observes how the black-box model responds to each variation. It then uses these responses to train a simple, interpretable model—typically using feature selection methods such as LASSO—that approximates the complex model's behavior in that local region. The result is an interpretable representation that reveals which features were most influential for a particular prediction, offering transparency and actionable insight into complex machine learning systems.

3.3 Explainable AI: SHAP

SHAP (SHapley Additive exPlanation) is a widely used method in the field of explainable artificial intelligence (XAI) that builds on the concept of Shapley values from cooperative game theory, originally introduced by economist Lloyd Shapley (Shapley, 1953). Developed by Lundberg and Lee (2017), SHAP provides a unified framework for interpreting the contribution of each input feature to the prediction outcome of a complex AI model. It does so by translating the prediction process into an additive format that reflects how each variable influences the final output.

At its core, the Shapley value quantifies the marginal contribution of a particular variable by comparing predictions with and without that variable across all possible combinations of inputs. In other words, it calculates how much a prediction would change if a specific feature were removed from the input data. This value represents the fair contribution of each feature to the model's decision, taking into account all possible interactions with other features.

Lundberg and Lee propose that any feature attribution method intended to explain model behavior should satisfy three key properties: local accuracy, missingness, and consistency. The key properties of SHAP include local accuracy, missingness, and consistency. Local accuracy ensures that the sum of all feature contributions, along with a baseline value, matches the actual prediction generated by the AI model for a specific data point. This guarantees that the explanation is faithful to the model's behavior in that local context. Missingness indicates that if a feature is absent from the input data, it should not influence the prediction. In practical terms, this means that features not present (or not relevant) in a specific instance are assigned zero contribution. Consistency refers to the logical requirement that if a model becomes more reliant on a particular feature, the attributed importance of that feature should increase accordingly. Conversely, if the model becomes less dependent on the feature, its importance should decrease.

These properties ensure that SHAP produces explanations that are not only intuitive but also aligned with the behavior of the underlying model. To generate these explanations, SHAP evaluates the prediction outcomes across many different combinations of input features. By doing so, it produces a breakdown of the final prediction into a baseline value and a series of additive contributions from each feature.

For instance, when a prediction is made using a dataset with four input variables, SHAP decomposes the total prediction into individual contributions from each variable, showing which features pushed the prediction higher or lower. This breakdown can be visualized graphically, with positive contributions typically marked in one color (e.g., blue) and negative contributions in another (e.g., red), helping users to quickly grasp how and why a specific decision was made.

In the context of financial distress or zombie firm prediction, SHAP is particularly powerful. It allows researchers and practitioners to identify not only which firms are likely to fall into distress, but also which specific financial indicators or features (such as profitability, debt ratios, or asset turnover) were most influential in that classification. This level of transparency is essential for building trust in AI models and for making actionable decisions based on their outputs.

In this study, LIME and SHAP are employed as explainable artificial intelligence (XAI) techniques to facilitate local and global interpretability, respectively. These methods are applied to interpret the predictions generated by machine learning and deep learning models, which are typically regarded as black-box models due to their lack of transparency. By leveraging XAI, we aim to uncover the distinguishing characteristics of zombie firms, whose prevalence has increased in the aftermath of the COVID-19 pandemic, and to identify the key features that contribute to accurate prediction. The primary contribution of this study lies not in comparing the determinants of zombie firms before and after the pandemic, but in addressing the interpretability limitations of conventional AI models. By incorporating explainable methods, this research enhances the transparency and practical utility of predictive modeling in the context of financial distress.

3.4 XAI and Theoretical Implications for Financial Decision Making

The integration of explainable artificial intelligence (XAI) into financial prediction models offers theoretical contributions that extend beyond the pursuit of predictive accuracy. In particular, SHAP and LIME provide structured interpretability that bridges the gap between firm level indicators of financial distress and the systemic frameworks emphasized in corporate finance theory. SHAP, by producing global measures of feature importance, identifies consistent drivers of zombie status across firms and industries. This global perspective complements theoretical arguments on agency costs of free cash flow (Jensen, 1986), inefficient resource allocation (Barney, 1991), and systemic financial fragility by highlighting the aggregate determinants of distress.

LIME, in contrast, generates localized explanations that emphasize the firm specific attributes shaping predicted outcomes. This local perspective aligns with theories of asymmetric information and heterogeneous financing constraints, which posit that financial distress manifests differently depending on managerial discretion and firm level characteristics. By making these distinctions visible, XAI provides a theoretically grounded tool for examining how micro level heterogeneity translates into macro level vulnerabilities.

Taken together, SHAP and LIME operationalize the dual role of XAI as both a predictive and explanatory framework. Their complementary functions connect aggregate theoretical insights with firm specific diagnostics, thereby enhancing the conceptual foundations of financial distress analysis. This dual interpretability positions XAI as a distinctive mechanism for informing governance mechanisms and policy interventions that require simultaneous attention to systemic stability and firm level resilience.

4. DATA AND METHOD

4.1 Data Collection and Sample Selection

This study investigates zombie firm prediction using firm-level financial data collected from the Compustat Capital IQ Global and North America databases. The sample period spans from 2020 to 2023, covering the post-COVID-19 era in which zombie firm risk has become increasingly prominent across global markets.

The initial dataset includes 25,981 publicly listed firms across multiple countries, resulting in a total of 163,583 firm-year observations. To ensure comparability and remove structural outliers, we exclude financial firms (defined by two-digit SIC codes 60–69) and firms in regulated industries such as utilities (SIC code 49), following common practice in financial distress prediction studies.

Among the total sample, 13,877 firm-year observations are classified as zombie firms, while the remaining 149,706 are considered non-zombie. This indicates that approximately 8.5% of the firms in the global sample exhibit persistent financial weakness as defined by zombie firm criteria.

4.2 Definition of Dependent and Explanatory Variable

The dependent variable, Zombie_Firm, is a binary indicator that equals 1 if a firm's interest coverage ratio (ICR), calculated as EBIT divided by interest expense, remains below 1 for three consecutive years. Otherwise, the value is 0. This classification rule is widely used in previous research to identify zombie firms and is particularly suitable for panel data covering multiple years.

The explanatory variables include core financial ratios reflecting a firm's growth, profitability, activity, and stability—dimensions that are central to Altman's (1968) Z-score model for financial distress prediction. While the current preliminary analysis focuses primarily on firm-level accounting variables, we also plan to incorporate macroeconomic indicators and country-level institutional characteristics in subsequent stages of the analysis to reflect cross-national heterogeneity in corporate distress dynamics. The list of variables used in this preliminary analysis is summarized in Table 1.

Table 1. Firm characteristic variables used.

Category	Variable Name	Description
Growth	Total asset growth rate	(Total assets – Prior-term total assets)/Prior-term total assets × 100
	Current asset growth rate	(Current assets – Prior-term current assets)/Prior-term current assets × 100
	Sales growth rate	(Current period sales - Prior period sales)/Prior period sales ×100
	Net income growth rate	(Current period net income - Prior period net income)/Prior period net income ×100
	Operating income growth rate	(Current period operating income - Prior period operating income)/Prior period operating income ×100
Profitability	Net profit margin	Net profit/Revenue × 100
	Gross profit margin	Gross profit/Revenue × 100
	Return on equity	Net income/Shareholder's equity × 100
Activity	Accounts receivable turnover ratio	Sales/Accounts receivable
	Inventory turnover ratio	Cost of sales/inventory assets
	Total capital turnover ratio	Sales/Total capital
	Tangible asset turnover ratio	Sales/Total assets
	Ratio of cost of sales to sales	Cost of sales/Sales ×100
	Ratio of selling, general, and administrative costs (SG&A) to sales	SG&A/Sales ×100
Stability	Debt-to-equity ratio	Debt/Shareholder's equity × 100
	Current ratio	current assets/current liabilities ×100
	Equity to total asset ratio	Equity/Total asset ×100
	Quick ratio	Quick assets/current liabilities ×100
	Fixed assets to net worth ratio	Fixed assets/Total equity ×100
	Net working capital ratio	Net working capital/total equity ×100
	Leverage level	(Current and non-current loans + bonds)/total equity ×100
	Cash ratio	Cash and cash equivalents/Current liabilities ×100
Firm Size	Ln(sales)	Natural log value of sales
	Ln(total assets)	Natural log value of total assets

4.3 Model Training, Test Procedure, and Data Balancing

To evaluate the predictive performance of our models in identifying zombie firms across global markets, we randomly split the dataset into a training set (70%) and a test set (30%), following standard protocols for supervised learning (Kuhn et al., 2013). The training set is used for model estimation and hyperparameter tuning, while the test set is reserved exclusively for evaluating generalization performance on unseen data.

Due to the inherent class imbalance—only 8.5% of firm-year observations in our dataset are classified as zombie firms—we apply the Synthetic Minority Oversampling Technique (SMOTE) to the training set. SMOTE creates synthetic samples for the minority class using a K-nearest neighbors algorithm, thereby improving model sensitivity and reducing bias toward the majority class (Song et al., 2021). Importantly, the test set retains the original class distribution, as recommended by Zhou (2013), to reflect real-world conditions and avoid inflated performance estimates.

To improve model reliability and feature consistency, we implement a structured preprocessing pipeline. First, we compute pairwise correlations and exclude highly correlated variables (correlation > 0.8). We also examine variance inflation factors (VIFs) to detect multicollinearity and apply recursive feature elimination (RFE) using a tree-based estimator to retain the most predictive variables. All observations with missing values are excluded from the final analysis, ensuring that the models are trained and evaluated on complete data without the use of imputation techniques.

For feature scaling, we adopt a model-specific strategy. Tree-based models such as CatBoost, LightGBM, and Random Forest do not require normalization. However, for linear models like logistic regression and LDA, we apply z-score standardization to ensure numerical stability and interpretability of coefficients.

For each machine learning model, we conduct hyperparameter tuning using grid search within the training set, following best practices outlined in Kuhn et al. (2013). For the CatBoost model, we tune parameters such as learning rate, tree depth, and number of iterations. Final model performance is assessed on the untouched test set using four key classification metrics: accuracy, precision, recall, and F1 score.

To further mitigate overfitting, we incorporated a five-fold cross-validation procedure within the training phase, ensuring that model performance was not overly dependent on a particular data split. For tree-based models, including CatBoost, early stopping criteria were employed during hyperparameter tuning to prevent excessive iterations from fitting noise in the training data. In addition, robustness checks were conducted by altering random seeds and minority-class sampling ratios, which yielded highly consistent rankings of algorithmic performance. These measures enhance the credibility of the reported results by demonstrating that the predictive advantages of CatBoost are not driven by overfitting or sample-specific artifacts.

4.4 Model Specifications

To identify the most effective predictive framework for detecting zombie firms in a global context, we evaluate the performance of 11 machine learning algorithms commonly used in financial distress classification tasks. These models represent a combination of traditional statistical techniques, tree-based ensemble methods, and neural networks.

In this study, we classify the applied prediction models into three main categories. First, traditional statistical models include Logistic Regression (LR), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN), which have been widely used in early financial distress prediction research. Second, tree-based ensemble methods consist of Decision Tree (DT), Random Forest (RF), AdaBoost, XGBoost, LightGBM, and CatBoost. These models are particularly effective in capturing non-linear relationships and interactions among variables. Third, other machine learning techniques such as Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) are employed for their ability to model complex patterns in high-dimensional data.

These models are trained using the SMOTE-balanced training dataset and evaluated using the original (unbalanced) test set to reflect real-world class distributions. Model performance is assessed using standard classification metrics, including Accuracy, Precision, Recall, and F1 Score.

Among the tested models, CatBoost demonstrates the highest overall prediction accuracy and balanced performance across all evaluation metrics. Consequently, we adopt the CatBoost model as our final classifier. To interpret the model's decision logic and understand the key features influencing zombie firm classification, we apply explainable AI techniques—LIME for local interpretability and SHAP for global feature attribution.

4.5 Evaluation Metrics

We apply the 11 machine learning models selected for this study to predict zombie firm status in the test dataset and compare the predicted outcomes with the actual classifications. As summarized in Table 2, we evaluate model performance using four widely accepted classification metrics: Accuracy, Precision, Recall, and F1 Score. These metrics are calculated based on the confusion matrix, which compares the predicted probability of zombie status (ranging from 0 to 1) with a predefined classification threshold.

In the context of the confusion matrix, a true positive (TP) occurs when the model correctly predicts a firm as a zombie firm and the firm is indeed a zombie firm in reality. A false negative (FN) arises when the model incorrectly classifies a zombie firm as a non-zombie firm, thus failing to detect a truly distressed company. A false positive (FP) refers to the case where the model predicts a firm to be a zombie firm, but it is actually a healthy, non-zombie firm. Lastly, a true negative (TN) occurs when the model correctly identifies a non-zombie firm as such.

By comparing these prediction outcomes against actual zombie firm status, we assess the classification performance of each model and identify the most reliable approach for large-scale zombie firm detection in the post-COVID-19 global context.

Table 2. Evaluation Metrics: Confusion Matrix.

Actual \ Predicted	**True (Positive)**	**False (Negative)**
True (Positive)	True Positive (TP)	False Negative (FN)
False (Negative)	False Positive (FP)	True Negative (TN)

To compare the performance of the prediction models, we employ four evaluation metrics: accuracy, precision, recall, and F1 score. These metrics are commonly used in classification tasks and are summarized along with their formulas in Table 3.

Accuracy measures the proportion of all correct predictions—both zombie firms and non-zombie firms—out of the total number of observations. Precision is defined as the proportion of correctly predicted zombie firms among all firms that the model identified as zombie firms. Recall captures the proportion of actual zombie firms that were correctly identified by the model, reflecting the model's ability to detect distressed firms. F1 score is the harmonic mean of precision and recall, and a higher F1 score indicates a better balance between the model's ability to identify zombie firms and its accuracy in doing so.

Table 3. Evaluation Metrics and Formulas.

Evaluation Metric	**Formula**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 Score	$\frac{2(\text{Recall} \times Precision)}{(\text{Recall} + Precision)}$

5. MAIN RESULTS

5.1 Prediction for zombie firms

To evaluate the predictive accuracy and robustness of different machine learning approaches in identifying zombie firms, we apply 11 classification models to the global firm-year dataset. All models are trained and tested on the same sample, allowing for a consistent performance comparison. Evaluation is based on four standard classification metrics: accuracy, precision, recall, and F1 score.

As shown in Table 4, the CatBoost model achieves the highest overall performance, with an accuracy of 0.96 and an F1 score of 0.812. This reflects a well-balanced trade-off between precision and recall, which is particularly important in detecting zombie firms—where minimizing false negatives is critical. In contrast, traditional models such as logistic regression and linear discriminant analysis (LDA) perform substantially worse, especially in recall and F1 score, suggesting that they struggle to capture the complex, nonlinear patterns underlying financial distress.

CatBoost outperforms other state-of-the-art tree-based ensemble models, including XGBoost and LightGBM. Its advantage lies in its native support for categorical variables, efficient handling of missing data, and built-in regularization techniques that prevent overfitting. While ensemble methods such as Random Forest and AdaBoost also yield competitive results, they exhibit relatively lower recall scores, reducing their effectiveness in identifying financially distressed firms.

Based on this comprehensive evaluation, we select CatBoost as the final model for subsequent interpretation and policy implication analysis. The model's predictive superiority provides a strong empirical foundation; however, like most ensemble learning models, CatBoost lacks interpretability. This motivates the integration of explainable artificial intelligence (XAI) methods in the next section to uncover the underlying rationale behind its predictions.

LIME (Local Interpretable Model-agnostic Explanations) approximates the model's behavior in the vicinity of a specific prediction by building an interpretable surrogate model, thereby enabling the identification of feature contributions at the individual observation level. SHAP (SHapley Additive exPlanations), based on cooperative game theory, quantifies the marginal contribution of each feature by comparing model outputs with and without the feature in question. This approach enables consistent global feature ranking and explains the relationship between inputs and outputs more robustly.

Notably, the XAI analysis in this study is conducted on the original test data without applying SMOTE, to preserve the natural distribution of zombie and non-zombie firms. This ensures that the interpretability results reflect realistic scenarios and are not biased by synthetic oversampling techniques.

Moreover, the superiority of CatBoost was confirmed through additional validation exercises. Five-fold cross-validation produced performance metrics highly consistent with those obtained from the original train–test split, suggesting that the results are not dependent on a particular data partition. Robustness checks conducted with alternative random seeds and varying class rebalancing ratios yielded similar rankings of model performance, further mitigating concerns of overfitting. These findings collectively indicate that CatBoost's predictive advantage reflects genuine model generalizability rather than sample-specific artifacts.

Table 4. Comparison of evaluation metrics by model.

Model	Accuracy	Precision	Recall	F1 Score
CatBoost	0.96	0.75	0.68	0.72
LightGBM	0.95	0.73	0.67	0.70
XGBoost	0.95	0.74	0.66	0.69
Decision Tree	0.95	0.71	0.67	0.69
RandomForest	0.95	0.76	0.63	0.69
MLP	0.95	0.73	0.53	0.61
SVM	0.95	0.78	0.50	0.61
AdaBoost	0.94	0.71	0.51	0.59
LDA	0.94	0.71	0.40	0.51
KNN	0.94	0.76	0.36	0.49
Logistic Regression	0.94	0.75	0.32	0.45

5.2 Feature Attribution Analysis Through LIME

To enhance the interpretability of the CatBoost model's predictions, we employed the Local Interpretable Model-Agnostic Explanations (LIME) technique. This model-agnostic approach enables both global and local interpretability by approximating the behavior of complex models through locally linear surrogate models.

We first conducted a global analysis to examine the average contribution of each explanatory variable to the classification of zombie firms across the entire dataset. The results, presented in Fig. 1, show the average feature importance computed over all firms in the sample. The most influential predictor was net profit margin, particularly when it was less than or equal to 0.89, which consistently contributed to the model's classification of firms as zombies. These finding highlights that persistently low profitability is a defining characteristic of financially distressed firms. The second most important variable was the ratio of SG&A to sales, where values exceeding 8 percent were strongly associated with zombie status. Other significant variables included the total capital turnover ratio, tangible asset turnover ratio, gross profit margin, and return on equity, all of which provide insight into the firm's operational efficiency and financial structure. Taken together, these global patterns confirm that inefficient cost structures and weak profitability are systemic drivers of zombie status, as emphasized in Fig. 1, and they provide valuable signals for policymakers seeking to identify industry-wide vulnerabilities and implement early warning systems.

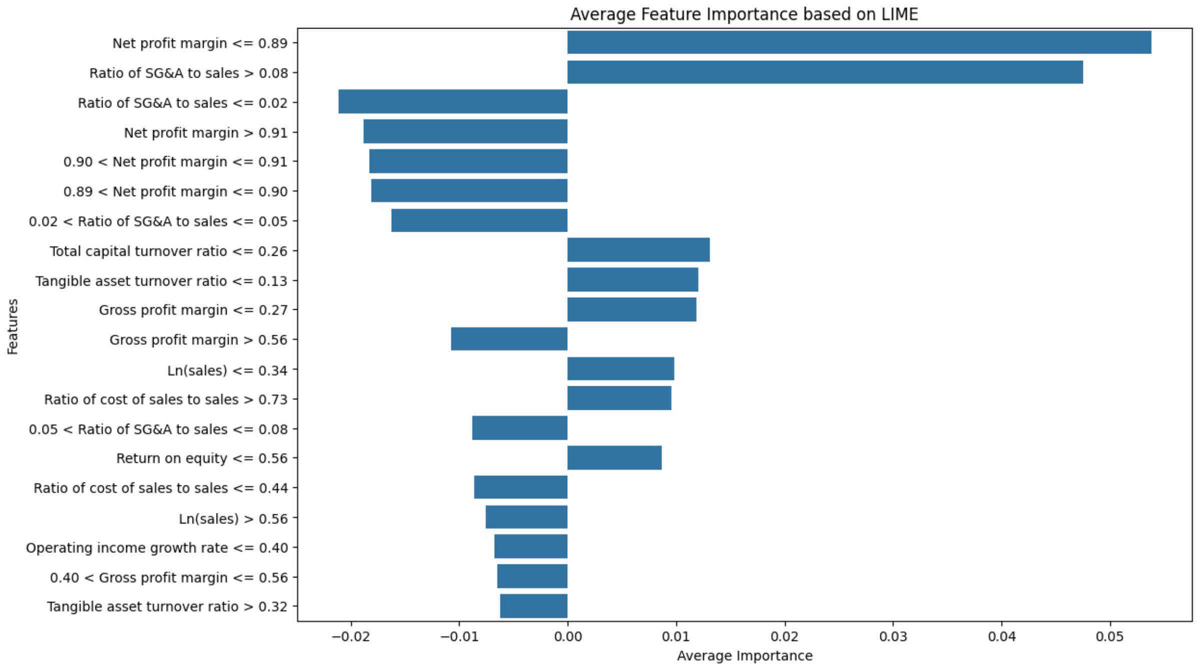

Fig. 1. Global analysis results based on LIME

Note: The figure presents the average contribution of each variable to the classification of zombie firms across all firms. Net profit margin and SG&A-to-sales ratio are the most influential predictors of zombie status. Specifically, firms with net profit margin below 0.89% and SG&A ratios above 8% are more likely to be classified as zombie firms, highlighting the role of cost inefficiency and low profitability. These global patterns suggest that persistent unprofitability and high operating costs represent systemic vulnerabilities, underscoring the need for policymakers to monitor these indicators as early warning signals of financial fragility at the industry and economy-wide levels.

Next, we performed a local analysis to examine the specific features that contributed to the classification of a particular firm as a zombie. As shown in Fig. 2, the CatBoost model predicted this firm as a zombie with high confidence, and LIME identified the key variables that influenced this decision.

The most decisive factor was again the net profit margin, which was less than or equal to 0.89 for this firm. In addition, the ratio of SG&A to sales above 8%, total capital turnover ratio below 0.26, and tangible asset turnover ratio below 0.13 further reinforced the model's prediction of zombie status. These variables are highlighted in green, indicating their positive contribution to the zombie classification. Conversely, variables such as gross profit margin greater than 56% and total asset growth rate exceeding 0.56 contributed negatively to the zombie classification (shown in red), slightly offsetting the final prediction.

Taken together, the LIME results underscore the importance of distinguishing between global and local interpretations. While the global analysis reveals recurring financial patterns that characterize zombie firms across the dataset, thereby informing industry-wide monitoring and macroprudential policy design, the local analysis provides firm-specific diagnostics that pinpoint the precise drivers of distress at the individual level. This dual perspective highlights the complementary value of explainable AI methods in financial research, as they simultaneously support systemic risk surveillance and regulatory guidelines at the macro level, and targeted restructuring and firm-level interventions at the micro level.

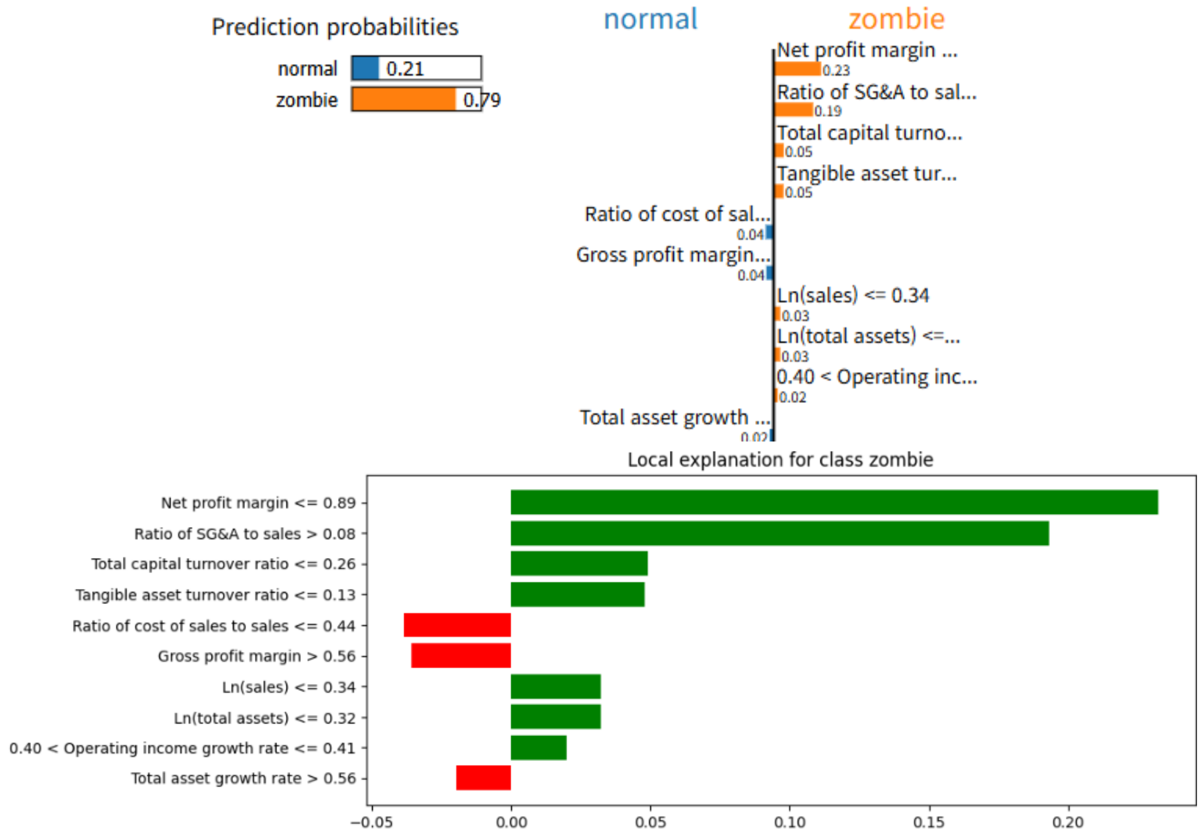

Fig. 2. Local analysis results based on LIME

Note: This figure illustrates how individual variables affected the prediction of a specific firm being classified as a zombie. Key factors such as a net profit margin below 0.89 percent and a high SG&A-to-sales ratio positively influenced the zombie classification (green bars), while high gross profit margin and asset growth partially offset this effect (red bars). The model assigns a high confidence score to the zombie label based on this combination. Beyond its descriptive function, the figure highlights how local explanations can support firm-level diagnostics, enabling managers, regulators, and policymakers to identify the precise financial weaknesses driving distress. This localized interpretability provides a practical basis for designing targeted restructuring strategies and firm-specific support policies, thereby complementing the broader systemic insights obtained from global analyses.

5.3 Feature Attribution Analysis Through SHAP

To interpret the internal logic of the CatBoost model, which was identified as the best performing model in our analysis, we apply SHAP, an explainable artificial intelligence technique that quantifies the contribution of each input feature to the model's output. A global analysis is first conducted using SHAP to examine which variables most significantly affect the prediction of zombie firms across the entire dataset. As shown in Figure 3, the summary plot presents the top ten features ranked by their average absolute SHAP values. The most influential variable is net profit margin, followed by the ratio of selling, general, and administrative expenses to sales, tangible asset turnover ratio, gross profit margin, return on equity, and net income growth rate. Additional important variables include the ratio of cost of sales to sales, operating income growth rate, the logarithm of sales, and total capital turnover ratio.

In this plot, each dot represents a firm, with its color indicating the feature value where red corresponds to high values and blue corresponds to low values. The horizontal axis shows the SHAP value, or the impact of each variable on the model's prediction. For example, lower net profit margins, which appear in blue, tend to have negative SHAP values, thereby increasing the probability that the firm is classified as a zombie firm. Conversely, higher selling, general, and administrative expense ratios, which appear in red, tend to display positive SHAP values, similarly raising the likelihood of zombie classification. Taken together, the global SHAP analysis presented in Figure 3 highlights systematic inefficiencies in cost structures and weaknesses in profitability that recur across firms and industries. This evidence enhances the interpretability of model outputs while providing practical insights for policymakers. Specifically, the recurring patterns revealed in this analysis offer robust signals for the development of macroprudential surveillance mechanisms and the design of industry wide early warning systems.

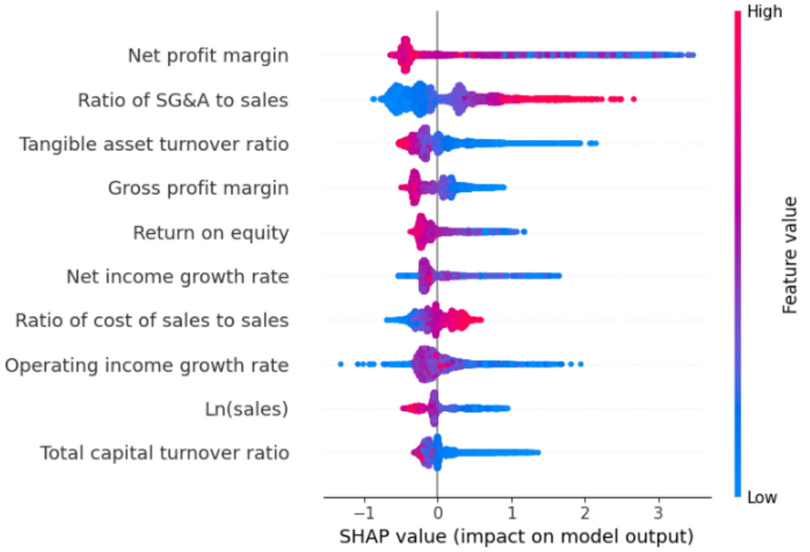

Fig. 3. Global analysis results (summary plot) based on SHAP

Note: The SHAP values indicate that net profit margin, SG&A-to-sales ratio, tangible asset turnover, and gross profit margin are the most influential features in predicting zombie firms. Red dots represent high feature values, and blue dots indicate low values. For example, low net profit margins and high SG&A ratios consistently shift predictions toward the zombie classification, reflecting cost inefficiencies and underperformance. Beyond identifying statistical associations, this figure highlights systemic vulnerabilities that recur across firms and industries, underscoring the value of SHAP in informing macroprudential surveillance and academic debates on financial distress. By translating complex model outputs into clear patterns of profitability and efficiency, the analysis provides policymakers with robust signals for early warning systems and regulators with empirical grounding for sector-wide monitoring.

Next, a local analysis is performed to explain why the model predicts a specific firm as a zombie firm. Fig. 4 shows the SHAP local explanation plot for a particular sample. The base value of –4.345 corresponds to the expected log-odds of the model's output for a random firm. The final prediction (f(x) = 1.35) is obtained by summing the SHAP values of individual features, which are then converted into a probability score indicating the likelihood of zombie firm classification. In this case, the net profit margin (–0.6278), SG&A-to-sales ratio (0.2516), tangible asset turnover ratio (0.06839), and total capital turnover ratio (0.1718) strongly contribute to the classification as a zombie firm, while the gross profit margin (0.6963) slightly offsets this effect.

These SHAP based interpretations offer several advantages. In the global analysis, stakeholders can identify the relative importance of financial variables affecting zombie firm predictions, something that traditional statistical models such as logistic regression are often unable to visualize effectively. At the same time, the local analysis provides firm specific rationales for classification decisions, ensuring transparency and accountability in financial policy and risk management contexts. Taken together, the SHAP results underscore the complementary value of global and local perspectives. The global analysis informs regulators and policymakers by revealing systemic determinants of zombie status, while the local analysis enables precise diagnosis of firm level weaknesses and supports the design of targeted restructuring strategies, managerial responses, and creditor negotiations. By integrating these two dimensions, SHAP contributes not only to a macro level understanding of financial distress but also to micro level tools for intervention, thereby enhancing the practical utility of explainable artificial intelligence in financial decision making.

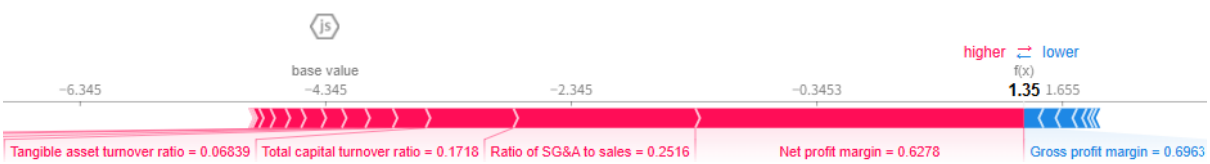

Fig. 4. Local analysis results based on SHAP

Note: The base value represents the expected model output, and the final prediction is determined by summing the SHAP values of each feature. In this case, a negative net profit margin and high selling, general, and administrative expenses are the primary contributors to the zombie classification, while a strong gross profit margin slightly reduces the prediction score. This firm is ultimately classified as a zombie due to the dominance of negative financial indicators. Beyond illustrating the mechanics of local SHAP explanations, the figure demonstrates how firm specific weaknesses can be diagnosed with precision. Such localized interpretability is particularly valuable for managers, regulators, and policymakers, as it enables the identification of concrete financial drivers of distress and informs targeted restructuring strategies and individualized policy interventions.

5.4 Interpretation of Results Using Explainable Artificial Intelligence

The post-hoc interpretation using explainable artificial intelligence techniques—SHAP and LIME—yields both statistically and theoretically meaningful insights into the financial characteristics of zombie firms. Importantly, these findings are not only empirically robust but also aligned with foundational theories in corporate finance.

First, Jensen's (1986) Free Cash Flow Theory posits that managers with control over abundant internal resources but limited profitable investment opportunities may engage in wasteful spending, exacerbating agency problems. SHAP and LIME consistently show that firms with high selling, general, and administrative (SG&A) expenses relative to sales—as well as high cost-of-sales ratios—are more likely to be classified as zombie firms. This reflects inefficient internal cost structures and supports the notion that unmonitored internal funds may be misallocated, consistent with Jensen's hypothesis.

Second, the low tangible asset turnover and return on equity (ROE) observed among zombie firms align with the Resource-Based View (Barney, 1991), which suggests that sustainable firm performance hinges on the effective deployment of both tangible and intangible assets. In both SHAP and LIME analyses, these variables emerge as critical contributors to zombie classification, indicating structural weaknesses in converting resources into competitive advantage.

Third, Myers and Majluf's (1984) theory of financial constraints offers a theoretical explanation for the observed stagnation in earnings growth. Our SHAP-based global analysis shows that firms with persistently low growth in net income and operating income are more likely to be categorized as zombies, suggesting limited access to external financing and underinvestment, consistent with the pecking order theory and capital market frictions.

Together, these results demonstrate that SHAP and LIME are not merely technical tools for feature attribution, but also serve as mechanisms for linking data-driven predictions to well-established economic theories. The ability to map financial indicators to theoretical constructs significantly enhances the interpretability and academic value of AI-based distress models.

6. CONCLUSION

This study contributes to the literature on corporate financial distress by developing a global post-pandemic model to predict zombie firms using state-of-the-art machine learning algorithms combined with explainable artificial intelligence (XAI) techniques. Leveraging a large-scale dataset of 25,981 listed firms across multiple countries from 2020 to 2023, we evaluate the predictive performance of 11 classification models and select CatBoost as the final model due to its superior accuracy and balanced performance. Given the inherent opacity of black-box models, we further apply SHAP and LIME to enhance interpretability at both the global and firm levels.

Our findings underscore the critical role of profitability, internal cost efficiency, and asset utilization in identifying zombie firms. Net profit margin consistently emerges as the most influential factor, followed by SG&A-to-sales ratio, gross profit margin, ROE, and various turnover ratios. These financial indicators not only exhibit strong predictive power but also align closely with foundational theories in corporate finance.

Specifically, SHAP and LIME results reveal patterns that support Jensen's (1986) Free Cash Flow Theory, as zombie firms typically display inefficient internal cost structures that suggest agency problems stemming from excess internal funds. Additionally, low asset turnover and depressed ROE reflect the resource mismanagement posited by Barney's (1991) Resource-Based View, while stagnation in earnings growth aligns with Myers and Majluf's (1984) theory of financial constraints. These connections demonstrate that XAI tools serve not only as interpretive mechanisms but also as bridges linking data-driven models with theoretical constructs.

From a policy perspective, the study offers actionable insights. Small and medium-sized enterprises (SMEs) exhibiting temporary cash flow difficulties may benefit from targeted liquidity support, whereas persistently inefficient firms with structural weaknesses should be subject to strategic restructuring. Policymakers should consider differentiated intervention frameworks based on firm-level financial signals revealed by interpretable AI models. Enhancing profitability, streamlining cost structures, and reducing leverage are essential strategies for mitigating systemic risk in the post-COVID global economy.

Beyond its empirical contributions, this study provides both methodological and theoretical advancements. While prior research has primarily focused on enhancing prediction accuracy, our integration of explainable AI empirically operationalizes economic theory within machine learning models. This dual contribution—improving both predictive precision and theoretical interpretability—marks a significant step forward in applying AI to corporate finance research.

Nevertheless, this study has several limitations. First, while our dataset is global in scope, the model does not explicitly control for cross-country heterogeneity such as differences in fiscal stimulus, interest rate policies, or institutional settings. Second, the analysis does not distinguish across industries, despite sectoral variation in financial structure and operating risk. Third, macroeconomic and policy-level variables (e.g., inflation, subsidies, or governance quality) are excluded from the current modeling framework. These limitations may affect the generalizability of the results in certain regional or industrial contexts. Future research could extend our framework by incorporating country- and industry-level features, decomposing SHAP values across subsamples, and examining how macroeconomic shocks interact with firm-level vulnerabilities in driving zombie firm dynamics.

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