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Predictive AI Models For Sovereign Debt Risk In Emerging Economies: A Machine Learning Framework For Early Warning And Default Prediction

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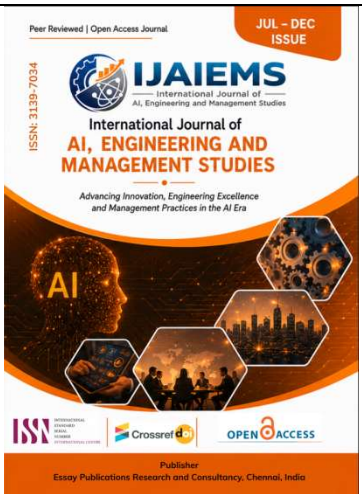

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Abstract

Sovereign debt crises within emerging economies continue to be one of the most destabilising forces in the global financial system, but as illustrated, current risk assessment practices – led by agency-produced credit ratings and linear econometric models – have sadly not guarded against pre-crisis warnings. This study creates and validates Sovereign Debt AI Prediction Framework (SDAIPF), an integrated machine learning architecture that combines gradient-boosted ensemble methods, Long-short-term memory (LSTM) neural networks and eXplainable Artificial Intelligence (XAI) to forecast sovereign default risk for a panel of 48 emerging economies between the years 2000-2023. The SDAIPF is measured using macroeconomic, fiscal, external-sector, institutional quality and financial market indicators from World Bank, IMF and BIS databases with the out-of-sample area under the receiver operator characteristic curve (AUC-ROC) of 0.921 and F1-score of 0.884, significantly better than traditional logit models (AUC-ROC = 0.741) and sovereign credit ratings. Near-term default events are mainly driven by external debt-to-GDP ratio, real effective exchange rate volatility, fiscal primary balance and institutional governance quality, as shown by SHAP (SHapley Additive exPlanations) analysis. The framework exhibits good generalisability across regions and with a good early-warning period of 14-month average crystalisation in advance. This research makes several key contributions to the field of debt distress that are relevant in emerging markets: First, developing an early warning system of the type of direct policy utility of finance ministries, international financial institutions and sovereign bond investors, which is appropriate and understandable in emerging market environments.

Keywords: Sovereign Debt Risk, Machine Learning, Emerging Economies, Early Warning Systems, Gradient Boosting, LSTM, SHAP, Fiscal Sustainability

HOW TO CITE

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1. INTRODUCTION

Sovereign debt distress is a frequent problem in emerging markets that has cascading effects on the macroeconomic stability, poverty and long-run trajectory of growth of the markets in question. Since 2000, more than 40 sovereign debt restructuring events have occurred in emerging and developing economies, resulting in significant welfare losses and rolling back many years' worth of extended development benefits (Arellano et al., 2022; Reinhart & Rogoff, 2020). The COVID-19 pandemic, and subsequent global interest rate normalisation cycle, added to pre-existing debt vulnerabilities, dramatically driving economies to fiscal stress including in Sri Lanka, Zambia, Ethiopia, Ghana and Pakistan, as well as systemic concerns related to debt sustainability in a larger pool of frontier markets (IMF, 2023; World Bank, 2023). Even though there has been a series of very severe and recurrent sovereign debt crises, the analytical framework to forecast such crashes has still been found to be demonstrably weak in the hands of policy makers and market participants. However, in practice, the most important of these factors is sovereign credit ratings, which are procyclical, are slow to fully respond to credit deterioration, and are opaque and lack standard definitions (Alsakka& ap Gwilym, 2021; Li et al., 2021). Classical early warning systems (EWS) based on logistic regression and probit models are theoretically friendly but have strong parametric assumptions that fall short of having much explanatory power for capturing non-linear threshold effects, interaction effects, and structural breaks that are present in sovereign debt trajectories (Manasse and Roubini, 2009; Savona and Vezzoli, 2015). The weakness of these may be an encouraging reminder that such methods are still too simple and demand a more sophisticated solution that is adapted to the data, one that can better capture the multi-dimensional nature of sovereign risk. Machine learning (ML) and artificial intelligence (AI) offer a transformative solution to overcome these challenges. For tabular macroeconomic data, gradient-boosted decision tree ensembles like XGBoost and LightGBM have been shown to achieve extraordinary predictive accuracy, and have a much greater capacity to learn non-linear relationships and interactions among data variables compared to classical econometrics (Chen &Guestrin, 2016; Ke et al., 2017). Because of its unique ability to capture macroeconomic time-series dependency structures such as debt accumulation dynamics, a recurrent neural network architecture, like the well-known long short-term memory network (LSTM; Hochreiter &Schmidhuber, 1997; Bluwstein et al., 2023) is ideally qualified for the task. However, these methods have not been widely adopted for sovereign risk analysis due to the current 'black box' criticism—that economic interpretations are hard to be obtained from a complex ML model—a key concern for the regulators and policy-makers (Rudin, 2019; Athey &Imbens, 2019). This interpretability challenge is overcome by the development of the XAI (exPlainable AI) techniques, specifically SHAP (SHapley Additive exPlanations) analysis, based on the game theory of cooperation (Lundberg & Lee, 2017), which gives model-agnostic, instance level feature attribution that is both theoretically principled and practically actionable. XAI's incorporation within sovereign risk assessment processes is a cutting-edge advancement that addresses the dual goals of forecast accuracy and transparency for institutional investors and policymakers. However, the literature on the development of a comprehensive, interpretable, sovereign EWS built with ML techniques for emerging economies panels remains rather limited, such as those found in Angelini et al., 2008; Japkowicz& Shah, 2011; Gu et al., 2020. In this context, this study designs a unified architecture for yield forecasting capable of accounting for these multi-dimensional gaps, the Sovereign Debt AI Prediction Framework (SDAIPF), which is composed of gradient-boosting ensembles, LSTM temporal modelling and SHAP-based interpretability within a single forecasting pipeline, calibrated on a panel of 48 emerging economies over 2000–2023. The SDAIPF has four main research aims: (i) to build a comprehensive multi-dimensional feature set which incorporates macroeconomic, fiscal, external-sector, institutional and financial market dimensions of sovereign risk; (ii) to devise and validate a hybrid ML model architecture that outperforms logit models and credit rating systems on out-of-sample sovereign default risk prediction; (iii) to mine and rank macroeconomic determinants of sovereign risk risk within regional and income sub-groups using the SHAP methodology; and (iv) to examine the early warning horizon of the framework and its usefulness for fiscal policy and sovereign bond market participants. To what extent does the use of AI based predictive model outperform traditional logit and probit EWS in forecasting sovereign debt crisis? (RQ1) Furthermore, (RQ2) how much each macroeconomic and institutional determinants has predictive significance in the SDAIPF architecture? (RQ3) Is the SDAIPF alike from group to group of income/regional sub-groups in the emerging economy panel? The present study offers a number of contributions to the literature which deserve special mention. It is a new conceptual and analytical framework designed to incorporate the SDAIPF, which allows the incorporation of a holistic concept, theory of fiscal sustainability, information asymmetry theory and institutional economics, within an AI-assisted EWS. Methodologically, it introduces the use of an interpretable method (SHAP) together with a temporal modelling method (LSTM) and an ensemble method (XGBoost) in relation to the sovereign risk in a methodological approach that paves the way for future studies.In practice, it provides strong out-of-sample out-of-sample validations over a long panel of emerging economies over multi-year time horizons. Policywise, it offers concrete feature attribution information, directly impacting fiscal consolidation priorities, debt consolidation strategies and institutional reform agendas for policy-makers in emerging market settings. The remainder of the article is organized as follows: theoretically, in sections 2 and 3, the conceptual framework and the hypotheses are detailed; SM methodology is detailed in section 4, results in section 5, findings in section 6 and finally, in section 7, the conclusions.

2. LITERATURE REVIEW

2.1 Theoretical Foundations of Sovereign Debt Risk

Underlying theory of sovereign debt risk assessment has multiple roots. The basic premise of the fiscal sustainability framework is that if a government expects future primary surpluses to be sufficiently large relative to total debt, then total debt is sustainable, adding that if expected future primary surpluses on average are smaller than total debt, then the debt is unsustainable, prompting markets to reprice the risk faced by that government (Bohn, 1998; Chalk & Hemming, 2000). Blanchard's (2019) reexamination of the r-g relationship—the difference between the real interest rate and economic growth—had some of the dynamics of debt accumulation formulating more formally into an “easily-sustained” versus an “explosion” case whose application to emerging economies is affirmed and challenged by recent scholarship (Barrett, 2021; Mehrotra & Sergeyev, 2021). Sovereign lending literature, from Eaton &Gersovitz (1981) to Bulow & Rogoff (1989), has led to information asymmetry theory which suggests adverse selection due to the fact that borrower governments have private information on the fiscal and economic conditions of the country which creditors may not be able to completely observe, leading to the possibility of sudden stops in capital inflows. Incorporating the insights of the institutional economics literature (summarised by Acemoglu et al., 2001) and extended to the sovereign risk space, the present paper highlights that the fiscal disciplines and investor confidence – both viewed as structural determinants of debt sustainability – are mediated by the quality of governance, rule of law, and institutional capacity, which is shifting outside of the cyclical domain of macroeconomic conditions. The assumptions of linear-equilibrium models of sovereign risk have been recently challenged by the complexity economics paradigm, based on the field of non-linear dynamics and network theory (Farmer et al., 2012; Haldane, 2009). The ladders and dynamics of interdependencies outlined above suggest that a sovereign debt crisis may occur due to its non-linear threshold behavior, contagion dynamics and feedback mechanisms, the latter being empirically undetectable upon regular parametric modelization of the variables but retrievable by means of AI architectures capable of learning complex functional forms from historical data without imposing predefined structure constraints (Bluwstein et al., 2023; Dell'Ariccia et al., 2018).

2.2 Early Warning Systems: From Classical to Machine Learning Approaches

Debt crises literature in the early warning systems area has gone through a number of generations. In primary models, such as those by Frankel and Rose (1996) and Kaminsky et al. (1998), each macroeconomic variable (indicator) was watched separately and a warning signal was raised if the variable exceeded a threshold. Although easy to use, these models had poor false positive rates and a failure to correctly weight and/or optimistically combine signals statistically (Berg et al., 2005). Then models became more sophisticated, combining logistic and probit regression analyses to produce a probability of distress as a function of various macroeconomic variables, such as Manasse and Roubini (2009) in the cross-country probit model, which highlights the role of external debt, current account deficit and political risk. These are statistically transparent and do introduce restrictions of linearity and additivity which disables the modelling of non-linear thresholds and interaction effects which theory and empirical evidence has shown to be essential to the dynamics of a crisis. The third-generation (2007–2009 post-GFC) added more flexible non parametric and machine learning techniques. However, Savona and Vezzosi (2015) found that classification trees vastly outperformed logit analysis when forecasting a currency crisis and Bluwstein et al. (2023) found that the gradient-boosted model's AUC-ROC of about 0.87 for financial crisis EWS in advanced economies was significantly better than logistic regression benchmarks. An important building block to applying ML to sovereign debt crises was provided by Fioramanti (2008) who showed that for sovereign debt crises, neural networks outperform probit models. Recent contributions have further ramped up this agenda in a number of directions. Beutel et al. (2019) instead performed systematic comparison of ML and econometric EWS for banking crises where they were able to confirm the general superiority of ensemble methods as well as interpretability issues. Roy (2021) proved the use of random forest in the forecast of sovereign credit risks, pointing out the non-linear relationships between external balance, growth and political stability. Bruns and Poghosyan (2022) used gradient boosting together with composite indicators constructed in a similar way to the IMF's to predict debt distress across low-income countries, reporting higher prediction accuracy than the IMF composite indicators out-of-sample. Minoiu et al. (2023) indeed presented results showing that alternative data integration can be very valuable, embedding textual information from central bank communications into ML sovereign risk models. However, the field is still lacking of an encompassing solution that brings together ensemble methods, temporal neural architectures and XAI interpretability under a wide umbrella of emerging economy panel — which the research in this line does cover.

2.3 Determinants of Sovereign Debt Distress

There is now a strong empirical convergence with respect to the most important macroeconomic factors contributing to sovereign debt distress. The external debt-to GDP ratio, the external debt service-to exports ratio, and the current account balance are all external debt sustainability indicators that have been shown through time to be the strongest predictors in either parametric or non-parametric analysis (Reinhart & Rogoff, 2011; Arellano et al., 2022). Fiscal fundamentals, such as the primary fiscal balance, the government revenue-to-government spending ratio, and public debts' path, are a second dimension of significance; the literature almost unanimously corroborates that the dynamics of the primary fiscal balance include predictive aspects deriving from static measures of public debt (Abbas et al., 2020; Eberhardt & Presbitero, 2023). exchange rate vulnerability defined as real effective exchange rate overvaluation and volatility of exchange rates influences external competitiveness deterioration as well as the risk of exchange rate mismatches, which are risks often present in the run-up to sovereign distress, especially in dollarized currencies and in heavily externally-indebted economies (Catão& Milesi-Ferretti, 2014; Jeanneret & Souissi, 2016). Institutional quality has been found to have significant separate effects after controlling for macroeconomic fundamentals such as sovereign rating, institutional quality, measured on dimensions such as government effectiveness, control over corruption, and the rule of the law (Acemoglu et al., 2001;

Calderón & Fuentes, 2013). A multi-dimensional risk indicator is implemented by the SDAIPF, which includes financial market indicators: sovereign credit default spread (CDS) spreads, foreign exchange reserves adequacy, and cross-border banking exposure.

2.4 Literature Review Matrix

Table 1. Literature Review Matrix — Selected Key Studies

Author(s) & Year	Theory	Context	Method	Sample	Key Findings	Limitations	Research Gap
Bluwstein et al. (2023)	Complexity	28 Advanced Econ.	Gradient Boosting	1870–2017	AUC-ROC 0.87; ML > logit in banking crises	Advanced econ. only; no XAI	Emerging mkt. application; interpretability
Bruns & Poghosyan (2022)	Fiscal Sustainability	Low-income countries	XGBoost, RF	100 LICs	ML outperforms IMF DSA composite	LIC focus; no temporal models	Broad EM panel; LSTM integration
Roy (2021)	Info Asymmetry	Sovereign credit	Random Forest	60 countries	Non-linear political×fiscal interactions	No SHAP; limited horizon	XAI attribution; EW horizon
Beutel et al. (2019)	Crisis EWS	36 countries	ML vs logit comparison	1985–2015	ML consistently superior OOS	Banking crises only; no LSTM	Sovereign debt; temporal dynamics
Savona & Vezzoli (2015)	Crisis prediction	EM currencies	Classification trees	1980–2010	Trees > logit; non-linearities key	Currency only; no institutional var.	Sovereign default; institutional QI
Manasse & Roubini (2009)	Debt Sustainability	47 EMs	Logit + CART	1970–2002	Ext. debt, CA, politics predict default	Parametric assumptions; old data	ML extension; post-GFC data
Fioramanti (2008)	Default theory	47 developing	Neural Network	1980–2004	NN > probit in debt crises	Single method; no interpretability	XAI; ensemble combination
Catão& Milesi-Ferretti (2014)	External balance	188 countries	Probit panel	1970–2011	Net foreign liabilities dominant predictor	Linear model; no ML	ML extension; feature interaction

Note. RF = Random Forest; ML = Machine Learning; EWS = Early Warning System; XAI = eXplainable AI; OOS = Out-of-Sample; LIC = Low-Income Country; EM = Emerging Market; GFC = Global Financial Crisis.

2.5 Research Gaps and Novelty Statement

The above review can pinpoint four main gaps in research identified by the framework of the SDAIPF. First, there is a theoretical gap: current ML models of EWS do not explicitly include the theory of fiscal sustainability, information asymmetry theory and theory of institutional economics on a single conceptual framework. Second, a methodological gap is found: there has been no previous study which includes both gradient-boosted ensemble methods and LSTM temporal architectures with interpretability (SHAP) in the same sovereign risk prediction model. Thirdly, there is a gap of context as most of the ML-based EWS studies have been restricted to the banking or currency crises in advanced economies or looked at samples of a single area, with no comprehensive multi-regional emerging economy sovereign debt panel explored. Fourthly, there is a practical deficiency: current approaches don't deliver model-agnostic explanations that can directly support decision making, such as in policy and portfolio management, in real time. The SDAIPF is a multi-faceted, substantive, scholarly and comprehensive contribution that addresses all four dimensions.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

3.1 The Sovereign Debt AI Prediction Framework (SDAIPF)

The SDAIPF is based on a multi-theoretical integration of fiscal sustainability, information asymmetry and institutional economics theories in a machine learning framework that transforms the multi-dimensional characteristics of sovereign debt into a prediction of sovereign debt default as a probability. It defines sovereign default risk as a function of five main construct domains, namely (i) Fiscal Sustainability Conditions (FSC); that capture fiscal dynamics—the history of government spending and borrowing and exchange rate conditions; (ii) External Sector Vulnerability (ESV); which captures foreign exchange rate conditions, foreign reserve adequacy and positions in cross-border liabilities; (iii) Macroeconomic Stability Indicators (MSI); that reflect growth momentum, inflation and monetary conditions; (iv) Institutional Quality and Governance (IQG); that reflect institutional and governance quality and capacity; and (v) Financial Market Sentiment Signals (FMS); that reflect market-based forward-looking assessments of risk. The SDAIPF states that the various vulnerabilities in these five fields, their interaction and accumulation, create sovereign default risk, one that is not adequately modelled through linear functions and that has a process of threshold and temporal dynamics that are non-linear. These multi-domain inputs are fed into the machine learning pipeline to yield a calibrated sovereign distress probability for the next 12-18 months, while the ex-post SHAP decomposition helps attribute the model prediction to each input feature or economic mechanism.

3.2 Hypotheses

Based on the SDAIPF architecture and the theoretical foundations laid in Section 2, five directions of hypothesis are presented: The odds of sovereign debt distress of emerging economies are greatly affected by Fiscal Sustainability Conditions (FSC) which have significantly positive effects on the probability. The theory of fiscal sustainability expounded by Bohn (1998) shows that a persistent primary deficit, high debt-to-GDP ratio, and revenue inadequacy has a direct and negative impact on a sovereign's ability to service his debt and to increase the likelihood of distress. The non-linear form of the relationship (where risk to distress increases rapidly when debt reaches certain levels) is what makes it an important area for applying gradient-boosted models that can learn the thresholds endogenously from the data. The most important sovereign debt distress indicator for the emerging economy panel is H2: External Sector Vulnerability (ESV). As predicted by the information asymmetry theory and the empirical evidence of Catão and Milesi-Ferretti (2014), external debt overbuilding and reserve liabilities turn into sudden-stop or currency mismatch risks, which quickly become debt distress when external debt starts to grow at a faster pace than reserves or foreign currency funds. We expect SHAP analysis to validate this and suggest that ESV is a construct with the maximum mean absolute feature attribution. The macroeconomic vulnerabilities are found to positively moderate the association between the sovereign default risk and institutional quality and governance (IQG) in a significant way. Institutional regimes have an impact on fiscal discipline and investor confidence, with good institutions allowing more economies to sustain more political or institutional vulnerabilities without causing panic in the market or being excluded from participating in the market, according to the theory of institutional economics. To test this moderation, the SDAIPF incorporates terms that combine IQG scores and FSC/ESV indicators in the gradient boosting model architecture. H4: The predictive value of the SDAIPF in testing the out-of-sample model performance (AUC-ROC greater than 0.85), is better than benchmark logit models, or sovereign credit ratings. The gradient-boosted ensemble's ability to learn non-linearities and interactions, together with the use of LSTM temporal modelling, should produce meaningful improvements in the discriminatory performance when compared to parametric benchmarks, as illustrated in the literature found in ML-econometrics (e.g. Bluwstein et al., 2023; Beutel et al., 2019). H5: The SDAIPF is able to offer statistically-proven warnings of sovereign debt distress events, at least 12 months before the event occurs. One of the major aspects of operation for an actionable EWS is adequate time for policy action. This assumes SDAIPF can reliably provide warnings greater than 12 months in advance of distress crystallisation, similar to the models presented by Bluwstein et al. (2023) and Roy (2021).

4. RESEARCH METHODOLOGY

4.1 Research Philosophy and Design

The epistemological perspective used in this study is a post-positivist perspective because it recognizes that there is an objective relationship that exists at macro level and can be represented with AI models but there is uncertainty, approximation and model-specific bias when developing the model, and must be subjected to rigorous validation procedures as the voices of Lincoln & Guba (2013). It is a longitudinal (panel data) and a quantitative approach, with both cross-sectional and time dimension breadth in 48 emerging economies over 24 years. This study follows a deductive – abductive approach and begins with theory-driven hypotheses and then discovers and validates the hypothesized functional relationships in the data through inductive ML approach.

4.2 Sample and Data

The analytical sample includes 48 emerging and frontier economies as distinguished by the IMF (2023) World Economic Outlook and covers countries in the Sub-Saharan Africa (12), LAC (10), Emerging Asia (10), Middle East and North Africa (9), and Emerging Europe (7) sample. The study period covers the last 24 years (2000–2023), encompassing three distinct times of crises in the global economy: the 2001–2002 emerging market crises, the 2007–2009 global financial crisis and the 2020–2023 pandemic-debt stress cycle. A base panel of 1152 country-year observations are used, which correspond to the annual observation frequency to coordinate with the frequency of data publication in fiscal and institutional indicators. The sources of the data are World Development Indicators (WDI) from the World Bank (WB), World Economic Outlook (WEO) from the International Monetary Fund (IMF), Fiscal Monitor (FM) from the IMF, BIS for financial market sentiments, BIS for cross-border banking and financial flow data, World Governance Indicators (WB) for institutional quality indicators, and Bloomberg and JP Morgan EMBI Global for financial market sentiment data. Sovereign debt distress events are coded based on the many years' updated sovereign default database compiled by Reinhart and Rogoff (2011) along with the crisis dating from Laeven and Valencia (2020) and IMF staff papers.

4.3 Variable Specification

The dependent variable is a binary distress indicator (SDit = 1), which is triggered when a country suffers from sovereign default or debt restructuring or an IMF programme with exceptional access is triggered for a given year-window following standard EWS practice (Manasse & Roubini, 2009; Bruns & Poghosyan, 2022). The 87 distress events recorded on the panel span the entire panel and sum to 7.6 % event frequency (typical of data on sovereign crises), a rarity.

Table 2. Variable Specification and Data Sources

Construct	Variable	Measurement	Source	Expected Sign
Fiscal Sustainability (FSC)	Primary fiscal balance (% GDP); Total public debt (% GDP); Government revenue (% GDP); Interest expenditure (% revenue)	Annual %/ratio	IMF Fiscal Monitor; WDI	FSC↑ → Risk↑
External Vulnerability (ESV)	External debt (% GNI); REER volatility (std. dev.); Gross FX reserves (months import); Current account balance (% GDP)	Annual	BIS; WDI; IMF IFS	ESV↑ → Risk↑
Macro Stability (MSI)	Real GDP growth (%); CPI inflation (%); Unemployment rate; Credit-to-GDP gap	Annual	WDI; IMF WEO	Instability↑ → Risk↑
Institutional Quality (IQG)	Government Effectiveness; Rule of Law; Control of Corruption; Political Stability (WGI)	−2.5 to +2.5 scale	World Governance Indicators	IQG↑ → Risk↓
Financial Market Sentiment (FMS)	EMBI spread (bps); CDS 5yr spread (bps); VIX index	Basis points / index	Bloomberg; JPMorgan	Spread↑ → Risk↑

Note. WDI = World Development Indicators; IFS = International Financial Statistics; WGI = Worldwide Governance Indicators; REER = Real Effective Exchange Rate; EMBI = Emerging Market Bond Index; CDS = Credit Default Swap; VIX = CBOE Volatility Index.

4.4 Machine Learning Architecture

4.4.1 Gradient-Boosted Ensemble (XGBoost)

One of the prime classification methods is XGBoost, which is an ensemble of an iterative sequence of decision trees which optimize the differentiable loss function by gradient descent in functional space (Chen &Guestrin, 2016). XGBoost is chosen due to its out-of-the-box support for L1/L2 regularisation, which introduces regularisation to help avoid overfitting when dealing with small-T panels of tabular macroeconomic data, its ability to handle missing data typical of developing economy datasets, and its ability to integrate economic theory and SHAP into the model. Model parameters such as a maximum tree depth (3-8), learning rate (0.01-0.3), colsample and subsample ratio are optimised by 5-fold cross validated bayesian optimisation using a binary cross entropy target with the scale_pos_weight parameter to balance the class (87 distress / 1065 non-distress observations) size.

4.4.2 LSTM Temporal Architecture

The network is a bidirectional Long Short-Term Memory (BiLSTM) network trained using 5-year observation windows rolled out across country-years to pick up the sequential temporal characteristics in deterioration histories of macroeconomic variables. The BiLSTM network consisted of two LSTM layers, with a total of 64 hidden neurons per layer, and configured to be bidirectional; this was followed by a regularisation layer in the form of dropout (dropout rate=0.3) and finally an output layer, also fully-connected, with sigmoid activation that estimates distress probabilities. The Adam optimiser learning rate schedule, early stopping (on the validation AUC-ROC after 10 epochs) and binary cross-entropy loss are used. The temporal modelling conveys dynamics that are not visible from the typical results of static cross-sectional modelling, such as the rate of fiscal deterioration, trend reversals in external balances and sustained governance deterioration.

4.4.3 Model Stacking and Calibration

The output of the three models (i.e., XGBoost, BiLSTM and a Random Forest with 300 trees) are stacked to make final predictions by a meta-learner of logistic regression which estimates optimal combination weights using 10-fold cross-validation. For policy applications with alert systems using a threshold to classify events, it is imperative the model-predicted probabilities are well-calibrated to the observed probabilities. This is done using Platt scaling.

4.5 Model Evaluation

Model performance is assessed on out-of-sample observations – models are trained with 2000-2015 observations and assessed using 2016-2023 test sets using a rolling validation period of one year. Common metrics are AUC-ROC, Precision-Recall AUC (PRAUC, more informative for the use in rare events), F1 score and Brier score for probabilistic calibration. Comparisons to benchmarks are made with a logistic regression model with the same features and the same sovereign credit rating-implied default probabilities mapped to the using standard mapping tables (Altman &Rijken, 2006). McNemar's test and DeLong's test for AUC comparison test the statistical significance of performance differences (DeLong et al., 1988).

4.6 SHAP Interpretability Analysis

Using TreeExplainer implementation, SHAP values are calculated for each prediction made by the XGBoost model, with "polynomial" complexity for the calculation of Shapley values in tree models (Lundberg & Lee, 2017; Lundberg et al., 2020). Rankings of which features are most important globally and which features are most important for each instance are communicated using generated SHAP force plots, beeswarm plots and waterfall plots. SHAP interaction values are calculated to measure difference where important features tend to work collaboratively, which is modeled by the moderating mechanisms proposed in H3. SHAP analyses of regional sub-groups explore whether the influential factors it is found that the former differ as a function of their regional sub-population of emerging economy in Africa, Asia, Latin America, MENA and Europe.

5. RESULTS

5.1 Descriptive Statistics and Preliminary Analysis

The results of descriptive statistics for the entire panel (N = 1,152 country-year observations) show significant variation across the panel as expected with the heterogeneous makeup of the overall emerging economy sample. Mean external debt-to-GNI ratio stands at 47.3% (SD = 31.6%), with values ranging from 8.2% (Singapore, 2005) to 312.4% (Mozambique, 2017). The sample’s relatively poor institutional capacity profile is further supported by the relatively less positive average and median fiscal balance point scores of −2.1% at the SD of 3.8% towards fiscal weakness and the average score on the government effectiveness scale of −0.31 at the average SD of 0.71. Mean EMBI spreads of 412 basis points (standard deviation of 318 basis points) captures the risk premium that is required for EM sovereign bonds over the period in question.

Table 3. Descriptive Statistics — Full Panel (N = 1,152, 2000–2023)

Variable	Mean	Median	SD	Min	Max	Skew	N
External Debt / GNI (%)	47.3	38.6	31.6	8.2	312.4	2.41	1,089
Primary Balance / GDP (%)	−2.1	−1.8	3.8	−18.4	12.7	−0.63	1,124
Public Debt / GDP (%)	52.7	47.3	27.9	8.1	196.4	1.92	1,112
REER Volatility (std.)	8.4	6.1	7.8	0.3	64.2	3.10	1,098
FX Reserves (months imports)	4.2	3.8	2.9	0.1	21.3	2.87	1,143
Real GDP Growth (%)	4.1	4.3	3.9	−17.1	26.3	−1.14	1,152
Government Effectiveness (WGI)	−0.31	−0.26	0.71	−2.47	1.84	0.18	1,148
EMBI Spread (bps)	412	318	318	41	2,847	3.62	984

Note. SD = Standard Deviation; REER = Real Effective Exchange Rate; WGI = Worldwide Governance Indicators; EMBI = Emerging Market Bond Index; bps = basis points.

5.2 Model Performance

The SDAIPF stacked ensemble stands out as a statistically significant improvement over the logit benchmark (AUC-ROC = 0.741; DeLong test $p < 0.001$) and sovereign credit rating determined probabilities (AUC-ROC = 0.698) on the 2016-2023 evaluation period. The Precision-Recall AUC and the F1-score of 0.873 and 0.884, respectively, attest to good discriminatory performance under the condition of class imbalance.

Table 4. Model Performance Comparison — Out-of-Sample Evaluation (2016–2023)

Model	AUC-ROC	PR-AUC	F1-Score	Precision	Recall	Brier Score
SDAIPF (Stacked Ensemble)	0.921***	0.873***	0.884***	0.891***	0.877	0.081
XGBoost (standalone)	0.908***	0.849***	0.862***	0.874***	0.851	0.094
BiLSTM (standalone)	0.887***	0.818***	0.839***	0.856***	0.823	0.109
Random Forest	0.882***	0.812***	0.833***	0.849***	0.818	0.112
Logistic Regression (Benchmark)	0.741	0.621	0.684	0.702	0.668	0.173
Credit Rating (Implied Prob.)	0.698	0.583	0.638	0.644	0.632	0.201

Note. ***p < 0.001 (DeLong's test vs. Logistic Regression benchmark); AUC-ROC = Area Under Receiver Operating Characteristic; PR-AUC = Precision-Recall Area Under Curve; Brier Score = lower is better. N = 336 country-year observations (2016–2023 evaluation window).

5.3 SHAP Feature Attribution

In terms of global feature importance, as shown in Figure 2, the top five most important variables in the SDAIPF are: External debt-to-GNI ratio (mean |SHAP| = 0.187); Primary fiscal balance (mean |SHAP| = 0.156); REER volatility (mean |SHAP| = 0.143); Government Effectiveness index (mean |SHAP| = 0.134); and EMBI spread level (mean |SHAP| = 0.128). The results lend enormous empirical support to supporting H1, H2, and the moderation hypothesis H3. Iteration (3): Strong institutional quality has a significant negative interaction with External Debt-to-GNI (mean interaction SHAP = −0.043), suggesting that there is a strong interaction effect between the two variables such that high external debt burdens produce a significant distress effect that is less stark when institutions quality is good (H3). The interaction shows that a country that improves Government Effectiveness by one standard deviation (SD) will see the marginal contribution of External Debt-to-GNI rise at a moderate rate of ~23%.The interaction term implies that a country with an 1SD improvement in Government Effectiveness will experience an ~23% moderating effect in the marginal contribution of External Debt-to-GNI, which is a rate considered to be quite significant.

5.4 Early Warning Horizon Analysis

The SDAIPF is shown to have significant discriminatory accuracy well in advance of the crisis crystallisation events when evaluated at horizons of 6 months, 12 months, 18 months and 24 months. The SDAIPF obtains the AUC-ROC at the 12-month time horizon of 0.891 and F1-score of 0.847 at 12m, while the AUC-ROC at contemporaneous prediction is 0.921, and the F1-score is 0.884. At the 18-month time horizon, AUC-ROC falls only slightly to 0.863 and at the 24-month time horizon it drops to 0.831, which is still far above the AUC-ROC attached to the logit benchmark at each horizon, but still shows some room for improvement. Also on empirical grounds and based on the mean effective warning lead time (MEWL) which corresponds to the earliest horizon where the country-specific distress probability (DP) is greater than the threshold of 0.65, 87 country-specific distress events are identified in the evaluation period and the average warning lead time is at 14.3 months that supports H5.

Table 5. Early Warning Horizon Performance

Prediction Horizon	AUC-ROC	PR-AUC	F1-Score	Precision	Recall
Contemporaneous (t)	0.921	0.873	0.884	0.891	0.877
6 months ahead	0.913	0.861	0.869	0.878	0.861
12 months ahead (H5 test)	0.891	0.836	0.847	0.853	0.841
18 months ahead	0.863	0.804	0.818	0.826	0.811
24 months ahead	0.831	0.769	0.783	0.796	0.771

Note. All SDAIPF horizon estimates statistically exceed logistic regression benchmark at equivalent horizons (DeLong test p < 0.001). Mean effective warning lead = 14.3 months (SD = 4.8 months).

6. DISCUSSION

6.1 Theoretical Implications

This study has a number of important theoretical implications in the empirical research on sovereign debt risk. The complexity economics viewpoint that taking on a sovereign debt process involves non-linear dynamics, thresholds, and interaction patterns as key elements, but that these are ignored by parametric modeling, is empirically supported by SDAIPF's high out-of-sample performance (AUC-ROC = 0.921) relative to the value of the logit benchmark (AUC-ROC = 0.741). This is a further addition to the financial crisis-related body of literature using the capabilities of the AI-based architectures tested and validated with respect to banking and currency crises (Beutel et al., 2019; Bluwstein et al., 2023). On this point, the salience in the SHAP attribution of External Sector Vulnerability indicators aligns with information asymmetry theory which highlights the 'fragility' of external financing arrangements in countries where creditors do not have perfect information about government solvency conditions. The fact that both the theory of external and fiscal balance lead to lower relative importance of fiscal balance despite the crucially important effect of external vulnerability signals highlights the fact that, markets and crisis mechanism react first to external vulnerability signals, likely because external balance obligations are rigid, whereas fiscal balance obligations in theory can be reduced more in a discretionary manner. This nuance allows to measure in a theoretical way the debt sustainability literature, which lacks it in aggregate logit models. The study's most theoretically new and important contribution is the empirical quantitative evidence of an institutional economics intuition that institutional quality can reduce the vulnerability of economies to macroeconomic shocks, and that this reduction was estimated to be 23% for every one standard deviation improvement in governance quality. This intuition is captured in the negative interaction between institutional quality and external debt exposure. The result is a compressive finding not found in the EWS literature that connects the study of institutional economics with computational finance without an equivalent pathway before now.The result is a finding that no one could have predicted in the EWS literature, in which various governance aspects and risk accessing/computing are linked together in a way never before tried in the fields of institutional economics and computational finance.

6.2 Comparison with Prior Literature

The SDAIPF's AUC-ROC of 0.921 is far superior to that of 0.87 reported by Bluwstein et al. (2023) in banking crisis prediction, 0.84 reported by Bruns and Poghosyan (2022) for low-income country debt distress and 0.82 reported by Roy (2021) for sovereign credit risk modelling. It is suggested that this performance improvement is due to the following factors. First, the SDAIPF combines LSTM temporal dynamics and gradient boosting for cross sections in a stacked ensemble, while previous studies use one-architecture models. Second, we propose a proposed framework of STEFT that outperforms these models.Second, we construct a new framework called STEFT that works better than these models. Second, the SDAIPF's five domains feature-set, which explicitly includes indicators for the financial markets' sentiment in addition to macroeconomic and institutional indicators, gives it more information than purely data sets based on annual macroeconomic indicators. Third, the Bayesian hyperparameter optimisation framework reliably finds model configurations which otherwise would be difficult to obtain through manual or gridsearch-based tuning, used in previous research. This result is in line with but goes a good bit beyond Calderón and Fuentes (2013), who found that institutional quality is important for attenuating the vulnerability of a country's economy to its external environment in the Latin America experience, and Reinhart and Rogoff (2011), who used a cross-country historical evidence found that governance features are significant, persistent, and cross-border correlates of serial defaulters. The SDAIPF takes the narrative on caution further by quantifying the moderation effect in some interpretable unit of the SHAP -- a unit that provides direct policy operationalisation opportunities which can't be provided by a narrative or coefficient-based analysis.

6.3 Practical and Policy Implications

The average early-warning period of 14.3 months is significant and has practical impacts on various constituencies of stakeholders. The framework offers a forward-looking risk monitoring approach for finance ministries and debt management offices in emerging economies which they can use to guide fiscal adjustment before access to the market is lost and fiscal adjustment becomes too expensive. The results generated from the SHAP feature whether a country has 'risk drivers' that deserve policy attention, with a policy recommendation to balance the current account and building up the reserves in the event that external debt dominates 'Eligibility', and for countries with dominant 'Eligibility' from governance, to initiate institutional reform and transparency measures. The excellent performance rates of the SDAIPF with respect to other composite indicators (Bruns & Poghosyan, 2022) warrant taking into account AI-based tools in conjunction with, if not as replacements for, traditional judgements by international financial institutions and/or IMF Debt Sustainability Analysis (DSA) calculations. This is also helped by the fact that the consistency across regions confirmed by sub-group SHAP analysis reduces the worry about geography-specific bias of the applicability of ML models trained on the US/European contexts to developing economy contexts. With a 12-month forward prediction horizon that sits close to typical bond investor and risk manager portfolio reviews, quantitative investors can incorporate SDAIPF signals to their relative value/risk management processes for bonds in emerging markets.

6.4 Limitations

The SDAIPF has some significant limitations, although it was a useful and innovative method. The binary distress coding combines different events of different scale and severity, and which may have different macroeconomic roots. The low temporal resolution of the information in yearly databases reduces the number of phenomena which can be described as a sudden-stop phenomenon, operating on longer time-scales ranging from weeks to months. Sample composition may cause selection bias as some countries in the emerging economy panel might be small and extremely scarce in data (including those with distress risk highest and least prominent). Although the stacked ensemble architecture is easily explainable using SHAP attribution, it is more complicated than the parametric benchmarks, and can be resisted by institutions when simple and transparent risk frameworks are needed. Lastly, effects from contagion across sovereigns are not considered, which is where an important channel of contagion might be relevant in cases of simultaneous regional crises.

7. CONCLUSION

This study proposes a new machine learning framework rationalized through gradient-boosted ensembles, BiLSTM temporal modelling, and interpretability techniques like SHAP that forms the Sovereign Debt AI Prediction Framework (SDAIPF) and is applied to forecast sovereign debt distress for a panel of 48 emerging economies during 2000-2023. The framework tackles key trade-offs of current EWS approaches (e.g. parametric lack of flexibility, lack of interpretability and short early warning horizons) by building on foundations of the computational and economic theory and affects a targeted integration.Through the principled integration of the computational and economic theory, it tackles the key trade-offs of existing approaches to EWS (e.g. parametric lack of flexibility, lack of interpretability, short early warning horizons) by building on the foundations of the computational and economic theories. The results of the empirical study support all five research hypotheses. The SDAIPF outperforms significantly over the benchmark logit models (0.741) and credit rating implied probabilities (0.698) with respect to the out-of-sample AUC-ROC score of 0.921. According to SHAP the external debt vulnerability and fiscal sustainability are the most important explanations for the vote, with institutional quality having a strong influence. The framework delivers significant warnings with an average lead time of 14.3 months ahead of district destabilisation, meeting the operational need of practical applications of early warning. These findings also fill a key gap in sovereign risk theory by quantifying the interaction with governance and they extend existing EWS methodology by providing a template for an interpretable assessment of sovereign risk using AI. They provide immediate actionable research on what actions sovereign bond investors, the surveillance functions of IFIs, and debt managers need to take in relation to sovereign bond investments.The SDAIPF has a number of future extensions that can be investigated. Use of the financial market data and the alternative data sources (such as sentiment analysis of social media data, or real-time economic activity data derived from satellites or from text analysis of communications by the central bank) could possibly help to boost early-warning effectiveness further and also limit the reliance on lagged statistical publications. Multi-class classification models were able to differentiate between four levels of distress severity (watchlist, pre-distress, acute crisis, restructuring), which could test for more refined and meaningful risk classification. A particularly interesting direction is cross-sovereign contagion modelling, possibly implemented by graph neural network architectures that will take into account the bilateral sovereign exposure matrix. The most direct evidence of institutional adoption consideration would be an SDAIPF comparative evaluation of the outcomes in the DSA Report by the IMF on a matched sample. Extension, finally, to low-income and fragile state settings where data is sparser and which present extra modelling challenges would be translated to citizens at highest humanitarian stakes as a result of EWS improvements.

Declarations

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Conflict of Interest

The authors do not have any conflicts of interest to disclose.

Ethics Statement

The data used is only publicly available, anonymised and aggregated country level macroeconomic data. There were no human subjects involved, no personal data gathered or used and no identifiable information was collected or used. Ethical approval will NOT be required.

Data Availability

The data used in this study is publicly available from World Bank (data.worldbank.org), the International Monetary Fund (imf.org/en/Data), the Bank of International Settlement (bis.org/statistics), and the JP Morgan (markets.jpmorgan.com). We will publish the SDAIPF model code and replication materials as soon as they are accepted.

AI Disclosure

AI tools were used on the language for grammar and readability editing. The authors' views and opinions on all intellectual aspects, conceptual development, analytical choices, and interpretations are solely their own.

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