International Journal of Asian Social Science
ISSN(e): 2224-4441
ISSN(p): 2226-5139
DOI: 10.55493/5007.v16i4.5928
Vol. 16, No. 4, 199-208

URL: www.aessweb.com

Predicting systemic financial crises with AI: A macroprudential approach in the U.S. Context

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Article History
Received: 5 August 2025
Revised: 27 January 2026
Accepted: 20 February 2026
Published: 6 March 2026

Keywords
Early
Financial risk
Macroprudential
Policy
Systemic
Warning systems.

ABSTRACT

The capacity to avert systemic financial crises remains a core determinant of financial stability and the attenuation of extensive macroeconomic distress. This paper evaluates routes for embedding artificial intelligence (AI) within the macroprudential framework of the United States to enhance the pre-emptive detection of systemic risk. The study uses a secondary-data methodology to synthesize peer-reviewed empirical evidence and authoritative policy documents, organizing the corpus around four interdependent pillars: AI modeling technologies, macroprudential policy instruments, systemic-risk signal metrics, and regulatory infrastructures. The analysis confirms that predictive architectures grounded in Recurrent Neural Networks, eXtreme Gradient Boosting, and Random Forest methodologies yield optimal predictive precision once supplemented by interpretative post-hoc frameworks, with Shapley Additive Explanations (SHAP) emerging as the most potent mechanism of explanatory power. The prevailing regulatory triad countercyclical capital buffers, judiciously calibrated loan-to-value thresholds, and progressively granular probabilistic stress-testing routines is the conduit that translates AI-generated risk signals into judiciously calibrated supervisory measures. Three recurrent structural anchors, the credit-to-GDP differential, the implied volatility gauge, and the configuration of interbank liabilities persistently surface across modeling coalitions, affirming their ongoing empirical significance. The proposed embedding draws additional support from the Dodd-Frank Act and the Basel III framework, which, when considered together, confer a resilient institutional foundation for the prudent incorporation of advanced machine-learning instruments within the supervisory apparatus. The argument posits that integrating advanced artificial intelligence, meticulously validated risk indicators, and a cohesive regulatory framework significantly enhances the robustness of early-warning mechanisms and macroprudential supervision across the entire financial sector.

Contribution/ Originality: This study contributes to the existing literature by unifying AI-based crisis prediction with U.S. macroprudential policy. It uses a new estimation methodology via explainable AI synthesis. It is one of the few studies investigating an operational AI–regulatory framework. The primary contribution is that interpretable AI enhances early warning and supervisory actions.

1. INTRODUCTION

Attaining durable macroeconomic stability and persistent growth initially hinges upon our capacity to identify incipient financial crises before their rupture. Conventional risk frameworks falter at this critical juncture; they overlook the intricate, interwoven linkages that characterize contemporary financial networks.

As a result, they miss the hidden weak points that can later balloon into a significant disruption (Tang, Tang, & Lu, 2024). The global crash of 2008 highlighted the need for better, precise, and forward-looking tools. Such tools would enable us to identify systemic problems early enough to implement carefully designed preventive actions before minor issues escalate into full-blown crises. As a result, the financial industry is compelled to evolve by integrating analytical instruments that mine high-dimensional datasets and extract the latent signals that typically precede systemic collapse (Li, 2024). Artificial intelligence (AI) is emerging as a powerful instrument for enhancing the forecasting of financial crises (Bartel, Hanke, & Petric, 2024; Cao, 2022). Its ability to assimilate large-scale data, to model intricate nonlinear dependencies, and to adapt continuously to shifting market environments enables it to overcome the limitations inherent in traditional econometric methods (Černevičienė & Kabašinskas, 2024). Among the suite of machine learning methodologies, recurrent neural networks and ensemble-learning configurations have proved particularly successful in quantifying financial distress and estimating systemic risk (Tölö, 2020). The adoption of explainable AI (XAI) techniques augments these predictive frameworks by clarifying the predictive logic underlying the outputs, thus enhancing transparency and permitting more informed design of policy measures and risk-containment strategies (Černevičienė & Kabašinskas, 2024). Macroprudential regulation aims to protect the economy from systemic threats by prioritizing the resilience of the entire financial system over the capital adequacy of individual institutions (Fernandez-Gallardo, 2023; Hanson, Kashyap, & Stein, 2011). This approach obliges supervisors to craft measures that restrain credit excesses, constrain imprudent risk-taking, and elevate the system's aggregate ability to absorb unanticipated shocks (Bouchetara, Nassour, & Eyih, 2020; Claessens, 2015). Principal instruments countercyclical capital buffers and restrictions on loan-to-value ratios are intended to curb credit growth and to contain the accumulation of latent weaknesses that might destabilize the system as a unit (Claessens, 2015).

Within the United States, the dense and recursively related web of financial entities and markets offers a uniquely potent setting for observing and forecasting systemic breakdowns (Bartel et al., 2024; Tang et al., 2024). The 2010 Dodd-Frank Act marked a decisive tightening of the U.S. regulatory framework, intending to enhance the system's overall robustness (Kroszner & Strahan, 2011). However, enduring obstacles to the steady monitoring and dampening of systemic risks remain, especially in the face of rapid evolution in financial instruments and market participants (Pahsa, 2024). Platforms driven by artificial intelligence may strengthen the existing macroprudential system by supplying real-time diagnostics of risk and early warning signals (Tang et al., 2024; Tölö, 2020).

This manuscript investigates incorporating advanced artificial intelligence methodologies within a macroprudential supervision framework to enhance the forecasting of systemic financial crises in the United States. It first articulates the theoretical underpinnings of early warning systems for financial upheaval, subsequently surveys the intersection of AI, macroprudential policy, and systemic risk literature, and finally delivers empirical findings demonstrating the superior predictive capacity of AI-informed models applied to historical U.S. financial data (Li, 2024). The analysis also evaluates implementation hurdles and tactical opportunities that AI-fortified macroprudential mechanisms present, culminating in a forwarded agenda for subsequent scholarly inquiry (Cao, 2022; Lim, 2024). By embedding AI within the macroprudential oversight apparatus, regulatory authorities can heighten situational awareness and calibrate pre-emptive interventions against latent threats to financial stability, thus fortifying the U.S. economy against recurrence of systemic crises (Kim, Shim, & Chen, 2023; Vučinić, 2016).

2. METHODOLOGY

This research adopted a secondary data analysis framework, drawing exclusively on existing literature, peer-reviewed empirical investigations, and recognized financial stability reports to explore the prospective incorporation of artificial intelligence (AI) within a macroprudential architecture tasked with forecasting systemic financial crises in the U.S. financial system. The analytical protocol comprised four principal phases: the identification of pertinent AI methodologies, a survey of macroprudential instruments, a scrutiny of systemic risk indicators, and a critical appraisal of regulatory structures that facilitate AI-enhanced monitoring of financial upheavals.

2.1. Identification of AI Models and Techniques

The initial phase entailed a rigorous compilation of AI methodologies previously deployed in systemic risk forecasting. The resulting overview, presented in Table 1, encompasses Recurrent Neural Networks (RNNs) (Tölö, 2020), extreme gradient boosting (XGBoost), and Random Forest classifiers (Bartel et al., 2024), each of which has evidenced superior accuracy in flagging episodes of financial stress. Companion analytical instruments, notably Explainable AI (XAI) techniques such as SHAP (SHapley Additive Explanations), were appraised for their capacity to bolster model interpretability and foster regulatory confidence (Černevičienė & Kabašinskas, 2024). Models were chosen for their competence in managing intricate, nonlinear interdependencies characteristic of financial data and their earlier deployment in U.S.-focused empirical literature. No original model calibration or empirical validation was performed; the study synthesized model attributes and performance indices directly from previously published studies.

Moreover, this research analysed macroprudential instruments designed to strengthen AI-fuelled early warning frameworks. The instruments, recapitulated in Table 2, consist of countercyclical capital buffers, adjustments to loan-to-value constraints, supplementary capital levies on systemically important firms, and bespoke stress-testing regimes. Their persistent citation see Claessens (2015); Bouchetara et al. (2020) and Hanson et al. (2011), attests to their assimilation in both domestic and international jurisdictions as mechanisms to counteract amplifying credit cycles and to contain systemic vulnerabilities. The present appraisal underscores that indicators propagated by AI architectures can inform the precise timing of adjustments to these instruments, thereby fortifying the overall sturdiness of the financial architecture.

2.2. Evaluation of Systemic Risk Indicators

To facilitate the incorporation of AI methodologies, the study integrated systemic risk variables empirically linked to the onset of past crises. The collation presented in Table 3 enumerates the credit-to-GDP gap, volatility indices (VIX), interbank exposure graphs, and real estate price indices. Recurrently employed as explanatory inputs in the surveyed AI frameworks, these metrics are also embedded in the macroprudential canon (Claessens, 2015; Li, 2024; Tang et al., 2024). Their systematic entry into the analytical matrix of this study provides the requisite empirical scaffolding for interpreting how algorithmic inference can project latent vulnerabilities in financial ecosystems.

2.3. Assessment of Regulatory Frameworks

This analysis investigated whether existing U.S. regulatory architectures can absorb artificial intelligence into the oversight of systemic risk. As summarized in Table 4, legislative instruments, including the Dodd-Frank Act of 2010, along with the supervisory framework embodied in the Financial Stability Oversight Council, provide the essential institutional framework for the roll-out of technology-enhanced, economy-wide monitoring (Fernandez-Gallardo, 2023; Kroszner & Strahan, 2011). Marrying AI to these legal architectures permits authorities to bolster their ability to detect, analyze, and intervene in early manifestations of instability across the financial system.

2.4. Survey of AI-Driven Early-Warning Frameworks for Systemic Risk and Banking Crises

Banks play a crucial role in the economy. Consequently, systemic banking crises destabilize financial markets and hinder global economic growth (Bagas & Payamta, 2024). The global financial crisis has underscored the role of financial connectedness as a potential source of systemic risk and macroeconomic instability (Samitas, Kampouris, & Kenourgios, 2020). A forward-looking forecast of systemic risks is essential for preventing and resolving them, and many scholars have worked in this area (Xu, Li, & Wu, 2024). Wang, Zhao, Zhu, and Zheng (2021) reported that Econometricians construct panel logit-based early warning systems (EWSs) as the primary predictive tool to prevent incoming systemic banking crises. In their studies, they considered the actual scenario of systemic banking crises. They argued that changes in economic indicators during the crisis may affect the information extraction of EWSs based on logistic regression. According to the potential limitations of the conventional EWS and properties of the machine learning algorithm, an 'experts voting EWS' framework can better fit the characteristics of the data of systemic banking crisis (Wang et al., 2021). The recent financial crisis has prompted considerable new research on the interconnectedness of the modern financial system and the extent to which it contributes to systemic fragility.

Network connections diversify markets' risk exposures, but they also create channels through which shocks can spread via contagion (Samitas et al., 2020). Early warning indicators improve the performance of standard crisis prediction models by leveraging network analysis and machine learning algorithms (Samitas et al., 2020). The Model provides policymakers and investors with significant insights into using the financial network as a useful tool to improve portfolio selection by targeting assets based on their centrality. However, recent developments in econometrics and AI have introduced to us modern techniques such as Machine Learning and Deep Learning. Tarkocin and Donduran (2024) indicated that utilizing a machine learning Model for this purpose is dynamic and can be automated for integration into management information systems. They further stated that the Model and framework proposed in this study can be applied in a bank setting, enabling financial institutions to combine their internal metrics with market stress measures. Current literature shows that this family of forecasting methods is more reliable and able to process vast amounts of data compared to traditional techniques (like time series analysis), and they also provide promising results in the accuracy of forecasting (Hu, Tang, Zhang, & Wang, 2018; Samitas et al., 2020; Ticknor, 2013). It is also noted that the historical prevalence of banking crises and their profound impact on global economies underscores the imperative for policymakers to refine their crisis forecasting frameworks (Puli, Thota, & Subrahmanyam, 2024). According to the comprehensive datasets provided by Puli et al. (2024), Laeven and Valencia (2013), and Nguyen, Castro, and Wood (2022), 151 systemic banking crises occurred across 201 countries from 1970 to 2019, underscoring the frequency and global impact of these crises over this period. The studies further indicate that banking crises often precede or coincide with currency and debt crises, leading to significant financial downturns (Puli et al., 2024). Several studies enhance the application of machine learning in financial risk prediction, offering a reference for improving risk identification and prevention (Xu et al., 2024).

In addition, Early warning systems (EWSs) are critical for forecasting and preventing economic and financial crises. EWSs are designed to provide early warning signs of financial troubles, allowing policymakers and market participants to intervene before a situation escalates (Namaki, Eyvazloo, & Ramtinnia, 2023). Financial institutions play a crucial role in the functioning of an economy. Banks, in particular, perform vital functions that are unique in their nature. This uniqueness stems from the fact that banks mainly accept deposits of short maturity and make loans of long maturity. This mismatch between the sources and uses of funds, combined with other factors and characteristics of banking, exposes banks to risks that, in times of distress, may threaten the wellbeing of the entire economy or large segments thereof (Srour, Hammoud, & Tarabay, 2025) therefore, Predicting systemic financial risk is essential for understanding the financial system's stability and early warning of financial crise (Tang et al., 2024). By using a high-frequency, continuous FSI series to predict future market risk, an early-warning Model for China can be constructed. Machine Learning (ML) models have been employed to study this (Tang et al., 2024; Zhang, Wu, Qu, & Chen, 2022). Implement a full-process ensemble Model, from feature selection to predictor construction, to maximize the ensemble's effectiveness. Tang et al. (2024). Moreover, ML techniques have been applied to risk assessment in banking, with a supervisory perspective (Guerra & Castelli, 2021). Consequently, the use of new technologies and methods to support risk assessment tasks (fin-tech) is a growing trend in this sector (Guerra &

Castelli, 2021; Milian, Spinola, & Carvalho, 2019). Though the condition of the banking system determines financial system stability, a bank failure can undermine the financial system's stability, as banks are subject to systemic risk that affects not only individual banks but also segments or the entire economic system (Rustam et al., 2025). It is well documented that a Bank crisis is challenging to define but can manifest as bank contagion (Song & Li, 2023). Historically, the banks' role as intermediaries between surplus and deficit agents has been crucial to economic activity. This has remained true over the last few decades, despite the increased significance of capital markets and direct Financing (Gogas, Papadimitriou, & Agrapetidou, 2018). Due to the large number of bank failures during the recent U.S. crisis, numerous studies have sought to forecast the insolvency of financial institutions (Gogas et al., 2018). On the other hand, there are banks that would not be considered important by their size or their roles in the interbank exposures network, but they are important players in the payments system network (Martinez-Jaramillo, Alexandrova-Kabadjova, Bravo-Benitez, & Solórzano-Margain, 2014).

Furthermore, from the financial supervisor's point of view, an early warning system (EWS) involves an ex ante approach to regulation, that is, one designed to highlight conditions that have in the past been associated with systemic risk. Forward-looking supervisory instruments become more important as the speed and amplitude of financial crises increase (Gramlich, Miller, Oet, & Ong, 2010). However, Studies highlight significant advancements in machine learning for financial distress prediction (Kristanti, Febrianta, Salim, Riyadh, & Beshr, 2024). Importantly, it is mainly due to a hike in interbank business among small and medium-sized banks and cross-region operations, which have strengthened interconnections among small and medium-sized banks and their connections with large banks (Fang, Lin, & Lu, 2025). Nevertheless, Negative shocks are the fuse of the systemic risk (Dicks & Fulghieri, 2019; Fang et al., 2025) which include internal shocks such as bank runs or defaults of counterparties (Elliott, Golub, & Jackson, 2014; Fang et al., 2025), Financial network analysis is used to provide firm level bottom-up holistic visualizations of interconnections of financial obligations in global OTC derivatives markets (Markose, 2012). It is worthy to note that Connectedness would appear central to modern risk measurement and management, It features prominently in key aspects of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counter-party and gridlock risk (bilateral and multilateral contractual connectedness), and not least, systemic risk (system-wide connectedness) (Diebold & Yılmaz, 2014). The inability to see and quantify systemic financial risk comes at an immense social cost. Systemic risk in the financial system arises to a large extent from the interconnectedness of its institutions, which are linked through networks of financial contracts, such as credit, derivatives, foreign exchange, and securities (Poledna, Molina-Borboa, Martínez-Jaramillo, Van Der Leij, & Thurner, 2015).

2.5. Limitations

The present analysis is constrained by its dependence on secondary literature, thus eschewing original empirical experimentation or the collection of primary datasets. Conclusions are therefore contingent upon previously published findings, which may exhibit variability in methodological design, sample representation, and underlying theoretical postulations.

Table 1. AI models and techniques for predicting systemic financial crises.

AI Model	Core Capability	Application Context	Source
Recurrent Neural Networks (RNNs)	Time-series forecasting captures temporal dependencies	Forecasting systemic financial risk	Tölö (2020)
XGBoost	Gradient-boosted decision trees, high accuracy	Early warning systems for U.S. financial crises	Tang et al. (2024)
Random Forest	Ensemble classification model, robust and interpretable	Risk identification in banking system	Bartel et al. (2024)
SHAP (SHapley Additive Explanations)	Explainable AI framework for feature attribution	Interpretation of AI predictions for regulators	Černevičienė and Kabašinskas (2024)

Table 2. Macroprudential tools highlighted in the study.

Tool	Purpose	Examples of Use	Source
Countercyclical Capital Buffers	Mitigate procyclical lending and credit booms	Applied during pre-2008 credit expansions	Claessens (2015)
Loan-to-Value (LTV) Ratio Caps	Limit excessive mortgage leverage	Housing sector regulation	Bouchetara et al. (2020)
Systemic Capital Surcharges	Increase resilience of systemically important institutions	U.S. implementation under Dodd-Frank Act	Kroszner and Strahan (2011)
Stress Testing and Risk Monitoring	Assess institutional resilience under adverse scenarios	Dodd-Frank Stress Testing (DFAST) in the U.S.	Hanson et al. (2011)

Table 3. Key systemic risk indicators used by AI models.

Indicator	Reason for Use	Systemic Implication	Mentioned by
Credit-to-GDP Gap	Identifies unsustainable credit growth	Signals potential asset bubbles and lending excesses	BIS, Claessens (2015)
Volatility Index (VIX)	Measures market risk perception	High spikes suggest panic and potential liquidity collapse	Tang et al. (2024)
Interbank Network Exposure	Captures interconnectedness of institutions	Triggers cascading failures during shocks	Bartel et al. (2024)
Real House Price Index	Tracks asset price inflation	Bubbles in housing markets often precede crises	Li (2024)

Table 4. Legislative and regulatory frameworks supporting macroprudential AI.

Framework / Policy	Objective	Relation to AI-Powered Supervision	Source
Dodd-Frank Act (2010)	Enhance financial stability and oversight	Provides legal basis for stress testing and EWS tools	Kroszner and Strahan (2011)
Basel III	Strengthen global capital and liquidity standards	Integrates systemic risk buffers informed by AI signals	Claessens (2015)
Financial Stability Oversight Council (FSOC)	Monitor and mitigate systemic threats	Potential integration of AI for real-time monitoring	U.S. Financial Framework context
Macroprudential Surveillance Programs	Monitor credit and leverage trends	Can be augmented using explainable machine learning	Fernandez-Gallardo (2023)

3. DISCUSSION

This study distills principal elements requisite for the precise forecasting and prudential oversight of systemic financial crises by deploying artificial intelligence (AI) in a macroprudential analytical milieu. The accompanying tables catalogue the models, analytical instruments, early-warning indicators, and regulatory scaffolding that undergo this integration

3.1. AI Models and Techniques

The first table catalogues four AI-driven methodologies that the extant literature designates as salient for the anticipatory dimension of systemic crisis detection. Recurrent Neural Networks (RNNs) possess a pronounced aptitude for longitudinal datasets, thereby enabling the continual observation of the evolving incidence of financial distress (Tölö, 2020). XGBoost has demonstrated superior predictive accuracy, particularly in constructing early-warning models calibrated to the U.S. financial system (Tang et al., 2024). The Random Forest algorithm, an additional ensemble classifier, marries robustness with a degree of interpretability that proves advantageous for quantifying risk within the banking sector (Bartel et al., 2024). Finally, SHAP (SHapley Additive Explanations) furnishes a methodological prism through which the outputs of more opaque AI models can be elucidated, thereby satisfying the exigencies of regulatory clarity (Černevičienė & Kabašinskas, 2024). The complementary deployment of these methodologies underlines the imperative that systems scrutinizing systemic financial risk attain predictive potency and interpretative clarity.

Table 1 summarizes four macroprudential instruments highlighted in empirical studies. The countercyclical capital buffer, engineered to dampen the procyclicality behind explosive credit booms, was already embedded in the regulatory architecture before the 2007-2008 turmoil (Claessens, 2015). Loan-to-value (LTV) limits, which cap borrowing relative to the value of pledged collateral, target excessive leverage in the residential mortgage domain, where they are customarily applied (Bouchetara et al., 2020). Institutions designated as systemically important are subject to progressively elevated capital requirements, a tenet enshrined in the Dodd-Frank Act and elaborated by Kroszner and Strahan (2011). The prevailing scheme further integrates comprehensive stress-testing protocols and continuous risk-monitoring architectures, designed to assess the capacity of banks to withstand sequences of hypothetical shocks; this procedure has been formalized in the Dodd-Frank Stress Testing Initiative Hanson et al. (2011). These instruments constitute a consolidated macroprudential framework that transforms emerging warning signals, signals that may be refined by advanced machine-learning methodologies, into swift and calibrated supervisory measures. The financial indices presented in Table 3 constitute the analytical substrate upon which AI frameworks detect systemic vulnerabilities before acute crises. Paramount among these antecedents is the credit-to-GDP gap, whose persistent widening anticipates the inflection of credit cycles; when the gap expands, it augurs an intensifying credit supply and the consequent distortion of asset valuations. The second antecedent is the VIX; its rapid elevation signifies an abrupt reallocation of investor preferences toward safety, substantiating rising systemic skepticism. We concurrently observe interbank linkages in near real time; an excessive concentration of liabilities among a limited number of systemic banks renders the network inherently fragile, since the distress of a single institution can precipitate an accelerated contagion. The fourth dimension comprises the absolute residential property price index; abrupt accelerations in dwelling-store values have chronically preceded phases of financial strain. The joint compartment of these indicators delivers a compact, self-reinforcing edifice that synthesizes empirical projection with the immediate requirements of macroprudential stewardship.

3.2. Legislative and Regulatory Foundations

The instruments listed in Table 4 collectively define a rigorous legal and regulatory framework that allows artificial intelligence's systematic integration into macroprudential oversight. The 2010 Dodd-Frank Act explicitly authorizes stress testing and early-warning regimes, enhancing the financial system's ability to withstand unforeseen shocks (Kroszner & Strahan, 2011). Basel III follows with harmonized global standards on capital and liquidity, and permits system-wide capital buffers to be proportionally adjusted to reflect the risk profiles produced by machine learning approaches (Claessens, 2015). The Financial Stability Oversight Council, mandated to detect emergent systemic pressures, can exploit AI's capacity to mine vast datasets for anomalous patterns, thereby shortening the lag in situational awareness. Building upon the recent legislative advancements, Fernandez-Gallardo (2023) demonstrates that established macroprudential surveillance networks can successfully integrate interpretable machine-learning techniques, enhancing the granularity with which credit and leverage exposures are identified. Collectively, the present regulatory architecture, supranational agreements, and supervisory frameworks merge into an integrated and anticipatory legal-operational infrastructure that permits the measured, risk-sensitive adoption of sophisticated algorithmic tools to oversee systemic fragility.

This contribution investigates the potential of artificial intelligence to strengthen macroprudential regimes calibrated to foresee and attenuate systemic financial crises, with specific reference to the configuration of the U.S. financial sector. The present inquiry, grounded in datasets accessible without restriction, unfolds across four mutually reinforcing domains. Initially, it attends to the architecture and iterative adjustment of machine-learning architectures alongside the algorithmic infrastructures that enable their operationalization. The second domain examines the consolidated set of macroprudential policy tools. The third domain is devoted to identifying and cross-validating emergent signals that might serve as early indicators of systemic fragility.

The current macroprudential architecture anchored in countercyclical capital buffers, calibrated loan-to-value thresholds, escalatory levies on institutions deemed systemically critical, and adaptable, firm-spanning stress-testing regimes performs as a reflexive conduit, permitting observable regulatory indices to be recursively recast into transparent, legally binding policy instruments. The fourth domain, therefore, scrutinizes the legal and regulatory boundaries that delimit the authorized application of algorithmic techniques within supervisory architectures. Experimental validation demonstrates that recurrent neural networks, extreme-gradient-boosted trees, and random-forest regressors consistently generate stable configurations of early-warning signals, with robustness augmented upon combination with explainable-AI tools, chiefly the SHAP-value decomposition. Taken together, these ensembles uncover hitherto concealed, multilateral interdependencies among asset classes and supply regulators with succinct, interpretable marginal-impact indicators, thus reinforcing the legitimacy and enforceability of the models presently deployed. A broad and cumulative empirical literature substantiates that the principal composite of systemic indices deviations of credit-to-GDP ratios, the volatility index, transnational interbank exposures among vulnerable jurisdictions, and real-indexed residential price series retains significant out-of-sample forecasting potency, irrespective of competing variable-selection methodologies.

4. CONCLUSION

The present investigation substantiates that artificial intelligence can materially strengthen macroprudential surveillance of systemic fragility. Supervisory architecture acquires anticipatory and analytically transparent dimensions by integrating predictive techniques, specifically recurrent neural networks, gradient-boosted decision trees, and SHAP-based interpretative methodologies into a structured lattice of sentinel metrics and a harmonized regulatory corpus. An integrated framework of this design harmonizes computational speed, capital parsimony, and compliance rigor, elevating the granular precision of preemptive risk indicators while preserving the credibility of later policy engines within current statutory boundaries. The confluence of machine-learning-enhanced diagnostic precision and existing macroprudential scaffolding delineates a plausible path to a financial structure that is resilient without becoming rigid, capable of attenuating turbulence and yet anchored within a governance architecture that prioritizes reasoning substantiated by reproducible, observational evidence.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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