Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 4, Issue 4, 2026

THE ROLE OF ARTIFICIAL INTELLIGENCE IN PREDICTING FINANCIAL CRISES: A MACHINE LEARNING APPROACH

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Keywords
Artificial Intelligence, Machine Learning, Financial Crises, Early Warnings, Financial Stability, Qualitative Study

Article History
Received on 29 March, 2026
Accepted on 17 April, 2026
Published on 19 April, 2026

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Abstract
Financial crises continue to be one of the most disorienting phenomena in the global economy due to the harm they cause to the banking systems, decrease production, high unemployment rates, and decline in confidence of investors. The recent developments in artificial intelligence (AI) and machine learning (ML) have increased the capacity of researchers and policymakers to identify early warning signals of financial instability. This qualitative research paper discusses the role of AI in predicting financial crises by reviewing and thematically analyzing the recent scholarly and institutional literature. The research concludes that machine learning models tend to be more effective in the crisis prediction compared to traditional econometric models since nonlinear relations and high-dimensional interaction and hidden patterns in macro-financial signals are more likely to be represented by machine learning models. Concurrently, there are significant issues of interpretability, data quality, model bias, and predictive versus causal gap. The paper concludes that AI is not supposed to replace traditional financial surveillance but enhance the existing early warnings measures using interpretable, transparent, and policy-relevant modeling frameworks.

Introduction

Financial crises have already shown that the instability of the economy can arise within a short period and cross-border effects with the most terrible social and institutional implications. Banking collapses, sovereign debt distress and currency crises tend to develop out of the buildup of weaknesses like a booming credit expansion, an asset price bubble and over leveraging. Due to these dangers, governments, central banks, and international institutions have pumped a lot of money in early warning systems that help in detecting crisis conditions prior to their full realization (Laeven & Valencia, 2018; Chen and Svirydzenka, 2021).

The role of artificial intelligence has taken on a greater significance in this respect since the occurrence of financial crisis is seldom a linear issue. Conventional statistical techniques, as informative as they are, might fail to identify multi-faceted relationships between macroeconomic, banking, market and network variables. Machine learning models are able to work with large amounts of structured and unstructured data and discover nonlinear patterns that could lead to systemic stress. According to recent research by the BIS, ECB, IMF, and peer-reviewed journals, machine learning models can outperform the current logistic regression models in out-of-sample prediction in most crisis-prediction problems (Bluwstein et al., 2021; Calice et al., 2020; Candelon et al., 2020).

This article explores how AI is used to forecast financial crises through a qualitative research design. It does not need to estimate a new model, instead, it synthesizes key themes in the recent literature on machine learning-based early warning systems. The objectives of the paper are to provide answers to three questions: How does AI improve financial crisis prediction? Which machine learning techniques are the most widely used? What are the policy issues and restrictions that impact their application? The importance of these questions is that a high predictive accuracy is not enough when financial authorities are unable to interpret, trust, or operationalize the outputs of the model in practice (Aikman et al., 2023; Tiffin, 2019).

Research Objectives

This study has the following objectives:

1. To investigate how AI and machine learning can be used in predicting financial crisis.
2. To find out the primary machine learning techniques that are employed in early warning systems.
3. To examine the pros and cons of AI-based crisis prediction models.
4. To examine the policy relevance of AI in financial surveillance and management of financial stability.

Research Methodology

The research takes a qualitative literature review method. The research is based on thematic analysis of academic papers and institutional reports focused on AI, machine learning, and financial crisis prediction. The chosen literature consists of IMF, BIS, ECB, and peer-reviewed journals that discuss systemic banking crises, macro-financial early warning signals, and machine learning forecasting models. The qualitative design is suitable as the aim of the study is to interpret, compare, and synthesize the existing knowledge of the use of AI in this area rather than to develop a new statistical model (Aikman et al., 2023; Bluwstein et al., 2021).

The literature was sorted into common themes using thematic analysis: predictive benefits of machine learning, typical sources and indicators of data, interpretability of the model, and challenge of implementation. By doing so, the study can assess both the technical performance and the institutional relevance of AI to financial oversight, in general. The literature demonstrates that predicting a crisis does not solely rely on the accuracy of the algorithms, but also on transparency, regulators, and policymakers usability (Crisanto et al., 2024; IMF, 2024).

Literature Review

Early Warning Systems and Financial Crises.

The value of early warning signs in financial crises has not been a new concept in the literature. Among the most frequently cited variables with a future crisis episode are financial overheating, high growth rate in credit, housing and equity price boom, poor lending standards, and increasing debt burdens. Chen and Svirydzenka (2021) discovered that the early warning indicators have the potential to give signals as far as five years ahead, but the best indicators can be different among developed and developing economies. Their analysis indicates that equity prices and the output gap are more informative in mature markets and equity prices, property prices, and the credit gap are more informative in emerging markets.

One of the most popular databases of systemic banking crises is offered by Laeven and Valencia (2018) that includes 151 crisis episodes that took place between 1970 and 2017. This has made their work fundamental since the prediction models of crisis demand historically proven crisis labels to determine the common patterns that precede a crisis. This database has aided researchers to compare machine learning techniques with conventional econometric in different countries and over time. It also substantiates the fact that crises are linked to high losses of output and high spending on fiscal costs, which emphasize the importance of enhancing predictive systems (Laeven and Valencia, 2018).

Artificial Intelligence and Machine Learning in Crisis Prediction

Crisis prediction AI is generally based on the supervised machine learning techniques and classifies historical macro-financial indicators as either crisis or non-crisis. Machine learning algorithms are better at nonlinearities, interaction between variables and high-dimensional data compared to conventional models. Research has been accumulating to demonstrate that random forests, support vector machines, neural networks, recurrent neural networks, and ensemble techniques, among others, can perform better than traditional logistic regression in out-of-sample prediction tasks (Alqaralleh et al., 2024; Bluwstein et al., 2021; Candelon et al., 2020).

As an illustration, Bluwstein et al. (2021) demonstrate that; in regard to financial crisis prediction, nonlinear machine learning models are stronger compared to logistic regression based on macro-financial data of 17 countries in a long historical context. Other economic drivers found in their work include credit growth and the yield curve, indicating that machine learning does not need to be black-box in the right combination with suitable interpretive methods. In the same vein, BIS studies show that by integrating multiple models, it is possible to forecast systemic financial crises several years in advance with better signal-noise ratios, providing a better foundation upon which early policy action can be taken (Bluwstein et al., 2021; Candelon et al., 2020).

The approach is extended to network analysis and temporal modeling by other studies. Calice et al. (2020) demonstrate that machine learning and structured financial network indicators can enhance the early warning system by infusing the contagion risk. The use of recurrent neural network models to take advantage of sequential information in macro-financial time series has also been demonstrated to detect evolving vulnerabilities prior to the onset of a crisis (Calice et al., 2020; Candelon et al., 2020).

Findings and Discussion

1. AI Enhances Pattern Recognition in Multifaceted Financial Systems.

One of the key topics of the literature is that AI is better at predicting the crisis since the financial system is very interconnected and nonlinear. Conventional econometric models usually assume fixed functional forms and thus they can overlook threshold effects or patterns of interaction between variables like credit growth, leverage, asset prices and the term structure of interest rates. These relationships can be identified more effectively using machine learning models based on the data itself, particularly in the case of varying risk environment over time (Bluwstein et al., 2021; Alqaralleh et al., 2024).

This is particularly necessary as the accumulation of crisis is mostly slow, covert, and multidimensional. It is hardly possible to predict a crisis by only one variable. Rather, risks arise due to aggregations of macroeconomic imbalances and market vulnerabilities. Machine learning algorithms have the flexibility of weighting such combinations than the traditional methods, enhancing sensitivity and forecasting range. This is well supported by BIS results that ensemble systems can forecast crises up to three years in advance (Candelon et al., 2020).

2. Machine Learning tends to perform better than the conventional models.

A second key observation is that machine learning tends to be superior to the logistic regression and other traditional econometric models in out-of-sample analyses. There is no evidence that all AI models are necessarily better but it does point to nonlinear models often giving lower false-signal rates and greater predictive power in cases where the data are rich enough. It is especially the case when the dynamics of the crisis are associated with interactions that are hard to define analytically (Alqaralleh et al., 2024; Bluwstein et al., 2021).

The literature however reveals model comparison to be interpreted with caution. The optimal model is not necessarily the one that has the highest statistical score in policy environments. Regulators need to consider precision, recall, false alarms, interpretability, and timeliness. A very precise model which is unable to explain why it has sent a warning can be not easy to apply in macroprudential policy. This is the reason why the newer literature is starting to focus more on interpretable machine learning, as opposed to pure prediction (Aikman et al., 2023; Tiffin, 2019).

3. Interpretability is a Continuing Issue.

Even though AI has a high predictive potential, one of its biggest drawbacks is its interpretability. Most policymakers would require more than a probability score; they require knowledge of the mechanisms of the signal. When the model fails to determine the factors that are causing the alarm, then it is more difficult to formulate specific interventions like tightening of macroprudential regulation, changing capital buffers or enhancing supervisory scrutiny. IMF studies on surrogate data models deal with this directly, by suggesting approaches that maintain predictive power but enhance interpretability of large-scale crisis models (Aikman et al., 2023).

This difficulty also relates to the larger difference between prediction and causation. Tiffin (2019) believes that machine learning would be extremely effective in predicting, but prediction does not determine the reasons behind a crisis. This difference is important, as policy must be causal. Officials must not only be aware that the risk is increasing, but what is causing it and what intervention will probably decrease it. Hence, AI might be utilized in financial stability best as a supplement to theoretically informed and institutionally based study instead of its replacement (Tiffin, 2019).

4. Data Quality and Data Governance Form Model Reliability.

The next significant observation is that data quality, coverage, and consistency are critical factors to the success of AI. Crisis datasets are usually small owing to the fact that the occurrence of systemic crises is relatively uncommon. This causes imbalance in the classes thereby complicating the learning of algorithms using a few positive cases. There also may be variations in cross-country data in terms of quality, definition, and reporting standards. Even sophisticated machine learning models can generate unreliable signals when the data are incomplete or not harmonized properly (Laeven and Valencia, 2018; Alqaralleh et al., 2024).

Governance matters are also critical. The BIS observes that the generalization of AI in finance has financial stability consequences in that the generalization will lead to more reliance on common models, common data sources, and common decision structures among institutions. Within this framework, AI has the potential to stabilize markets by enhancing information processing but may also destabilize them in case a large number of actors react to risk simultaneously (BIS, 2024; Zigrand et al., 2025).

5. AI is not supposed to override Human and Institutional Judgment, but to assist it.

The last theme is that AI ought to be incorporated into more extensive financial surveillance frameworks as opposed to being applied as an independent decision maker. Financial crises are social, political and institutional, as well as statistical. Models can send warnings, but it requires human experts to analyze structural changes, policy context and market behavior that may not be completely reflected by historical data. Supervisory experience, theoretical reasoning, and institutional trust are also crucial to convert predictions into policy decisions (IMF, 2024; Crisanto et al., 2024).

That is why, the most promising solution seems to be a hybrid one: integrate machine learning with traditional indicators, stress testing, expert judgment and explainability tools. This would retain predictive benefits of AI but minimize the risks of black-box reliance and misinterpretation of policies. This moderate opinion is well justified in the literature.

Table 1: ***Summary of Key Studies on AI and Financial Crisis Prediction***

Author(s) / Year	Focus of Study	Method / Approach	Main Finding
Laeven & Valencia (2018)	Global systemic banking crises database	Historical crisis database	Identified 151 systemic banking crises from 1970–2017; provides a core foundation for crisis prediction research.
Chen & Svirydzenka (2021)	Early warning indicators of banking crises	Macro-financial early warning analysis	Financial overheating indicators can signal crises several years in advance; useful variables differ across country groups.
Candelon et al. (2020)	Systemic financial crisis prediction	Ensemble ML models	A mix of models predicts systemic crises up to three years ahead with better signal-to-noise ratios.
Bluwstein et al. (2021)	Financial crisis prediction with ML	Nonlinear ML vs. logistic regression	Nonlinear ML models outperform logistic regression in many out-of-sample settings and highlight key drivers such as credit growth and yield curves.
Calice et al. (2020)	Financial crisis early warning	Network analysis + ML	Combining contagion indicators with ML improves crisis-warning capability.
Aikman et al. (2023)	Interpretability of crisis models	Surrogate data models	Interpretability is essential for policy use; simplified structures can make large-scale ML models more understandable.
Alqaralleh et al. (2024)	Comparative evaluation of crisis prediction models	Logistic regression, k-NN, RF, Extra Trees, SVM, ANN	ML methods show strong potential for early crisis detection relative to conventional approaches.
Crisanto et al. (2024)	Regulation of AI in finance	Policy and governance review	AI in finance requires stronger governance, risk management, and supervisory frameworks.

Conclusion

This qualitative research study demonstrates that artificial intelligence has proved useful in predicting financial crises and especially by machine learning-based early warning systems. The literature is in agreement that AI can be used to enhance crisis prediction with nonlinearities, interactions, and hidden vulnerabilities in large macro-financial data. Machine learning models tend to be more predictive with earlier identification of systemic risk than traditional econometric models (Bluwstein et al., 2021; Candelon et al., 2020; Alqaralleh et al., 2024).

Simultaneously, the study concludes that the strength of predictions is not sufficient. The issues of interpretability, data quality, data governance, and prediction versus causation are still a priority. Financial regulators and policymakers can be assisted by AI systems, although these must be utilized alongside expert judgment, transparent analytical models, and well-established macroprudential instruments. Practically speaking, hybrid systems that can be both flexible like AI and accountable and relevant to policy like interpretable financial analysis are likely to form the future of crisis predicting (Aikman et al., 2023; Tiffin, 2019; Crisanto et al., 2024).

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