REVISTA INVECOM
ISSN en línea: 2739-0063

Evaluating the resilience of AI-based predictive models in the context of economic crises: a systematic review

Evaluación de la resiliencia de modelos predictivos basados en IA en contextos de crisis económicas: una revisión sistemática

Received: 28/05/2025 - **Accepted:** 12/10/2025

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Abstract

In a context of growing economic uncertainty, understanding how crises impact the resilience of artificial intelligence (AI)-based predictive models is fundamental. This article aims to comprehensively assess the effect of various economic crises on the effectiveness and adaptability of these models. To this end, a systematic review of 29 articles indexed in Scopus and published between 2020 and 2025 was conducted. The selection of studies considered strict inclusion criteria, prioritizing peer-reviewed research that addressed issues related to financial, health, and social crises, discarding those that did not meet these requirements. The results reveal that models that incorporate macroeconomic and contextual variables present greater robustness and accuracy, standing out for their ability to adapt to highly volatile scenarios. Furthermore, it was identified that the resilience of these models depends not only on their technical soundness but also on their sensitivity to changes in the economic environment. Together, these findings offer a deeper understanding of the mechanisms that strengthen predictive stability during crises, proposing a path for the development of more adaptive and resilient AI models capable of more accurately anticipating the effects of future economic shocks.

Keywords: economic crises, artificial intelligence, resilience.

Resumen

En un contexto de creciente incertidumbre económica, comprender cómo las crisis impactan la resiliencia de los modelos predictivos basados en inteligencia artificial (IA) es fundamental. Este artículo tiene como objetivo evaluar de forma integral el efecto de diversas crisis económicas en la efectividad y adaptabilidad de estos modelos. Para ello, se realizó una revisión sistemática de 29 artículos indexados en Scopus, publicados entre 2020 y 2025. La selección de estudios consideró criterios estrictos de inclusión, priorizando investigaciones revisadas por pares que abordaran problemáticas vinculadas a crisis financieras, sanitarias y sociales, descartando aquellos que no cumplían con dichos requisitos. Los resultados revelan que los modelos que incorporan variables

macroeconómicas y contextuales presentan mayor robustez y precisión, destacándose por su capacidad para adaptarse a escenarios de alta volatilidad. Además, se identificó que la resiliencia de estos modelos depende no solo de su solidez técnica, sino también de su sensibilidad ante cambios en los entornos económicos. En conjunto, estos hallazgos ofrecen una comprensión más profunda de los mecanismos que fortalecen la estabilidad predictiva durante crisis, proponiendo un camino para el desarrollo de modelos de IA más adaptativos y resilientes, capaces de anticipar con mayor precisión los efectos de futuras perturbaciones económicas.

Palabras clave: crisis económicas, inteligencia artificial, resiliencia.

Introduction

Artificial intelligence (AI) has profoundly transformed the landscape of economic forecasting by providing advanced tools for analyzing and anticipating market fluctuations. However, the effectiveness of AI-based predictive models faces particularly complex challenges in contexts of economic crises, where macroeconomic variables undergo abrupt changes. Therefore, it is crucial to study how the specific characteristics of these crises affect the resilience of such models, aiming to enhance their adaptability and accuracy. In scenarios of high volatility, algorithms and methodologies must be adjusted to ensure reliable estimates, as highlighted by recent studies (Amamou et al., 2024).

One of the primary challenges of applying AI in economic forecasting during crises lies in the nonlinear interdependence among variables, which increases complexity and elevates the margin of error in predictions (Amamou et al., 2024). This situation underscores the importance of investigating how the sudden onset or prolongation of a crisis conditions the adaptability of models. In this regard, literature indicates that crises not only distort traditional economic indicators but also introduce additional factors, such as investors' risk perceptions (Addisu & Bang, 2022).

Moreover, it has been suggested that combining machine learning techniques with macroeconomic approaches can offer novel perspectives for assessing the resilience of predictive models in critical situations (Amamou et al., 2024). However, a significant gap remains in the research concerning a systematic approach that articulates different types of crises and analyzes the efficacy of AI models in each case.

In this context, the resilience of AI-supported predictive models has become a critical area, especially in light of crises that directly affect financial markets. Analyzing how the particularities of these crises impact model effectiveness is essential for understanding their adaptability and improving their performance under adverse conditions. In recent years, several studies have contributed relevant advancements in this field, strengthening the development of more resilient AI models in economics.

A notable contribution is from Kyriakou et al. (2023), who designed a methodology to anticipate the resilience of firms during critical episodes. By utilizing historical government data, their study optimized economic stimulus programs and highlighted the role of AI in identifying vulnerable organizations. Complementarily, Evgrafova et al. (2023) explored corporate resilience during the COVID-19 pandemic, demonstrating that corporate social responsibility enhances organizations' capacity to withstand systemic shocks, implying that predictive models should integrate qualitative variables.

On another front, Wang and Li (2022) analyzed the determinants of regional economic resilience, revealing that the impact of crises varies significantly according to geographic and structural contexts. This finding underscores the necessity for models to incorporate regional factors to more accurately anticipate outcomes in different economic environments.

Collectively, these studies deepen our understanding of how crises condition the efficacy of AI models and provide a solid foundation for future research aimed at developing strategies that integrate both macroeconomic and qualitative variables.

Nevertheless, important gaps persist in the literature. For instance, Puli et al. (2024) conducted an analysis of machine learning techniques for predicting banking crises in India, emphasizing the need to adapt models to the particularities of the local financial system. However, they did not address how different types of crises affect the efficacy of these models, indicating a continued deficit in understanding this relationship.

Similarly, Iuga and Mihalciuc (2020) noted that 21st-century crises have had devastating effects on economic growth, raising doubts about the current capacity of models to anticipate and respond to such events. Reier and Garay (2021) discussed the role of digital transformation and AI in business during crises, although they warned about the limited exploration of how to specifically optimize them in the face of financial crises.

These gaps justify conducting studies that thoroughly examine the relationship between crisis characteristics and the resilience of AI-based predictive models. Therefore, the purpose of this article is to analyze

how factors such as the severity, duration, and nature of economic events affect the efficacy of these models, guiding the development of more robust and adaptable methodological proposals.

Methodology

The PRISMA 2020 method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was applied to ensure transparency and traceability in the review process. The following research questions were posed: What specific characteristics of economic crises are most relevant to the resilience of AI-based predictive models? How have these AI models responded to different types of economic crises in previous studies? What methodologies have been employed to evaluate the effectiveness of predictive models in critical contexts?

The literature search was conducted between January and March 2024, consulting the Scopus, Web of Science (WoS), SciELO, and Latindex databases. Peer-reviewed publications in English and Spanish from the period 2019-2024 were considered. Boolean operators were employed with combinations of keywords such as: ("predictive model resilience" AND "artificial intelligence" AND "economic crisis") OR ("AI-based prediction" AND "financial resilience") OR ("machine learning models" AND "crisis forecasting") NOT ("non-economic applications" OR "education" OR "medicine only").

The results were exported to Mendeley, where an automatic and manual review was conducted to eliminate duplicates. Selection was carried out in several stages: reviewing titles and abstracts, excluding irrelevant studies or those lacking methodological rigor, and evaluating full texts according to inclusion and exclusion criteria (see Table 1).

Articles with empirical, methodological, or mixed approaches that evaluated the resilience or performance of AI predictive models in contexts of economic, financial, health, or geopolitical crises were prioritized.

Table 1
Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Peer-reviewed articles on economic crises and AI	Studies on non-economic applications of AI
Research with quantitative or qualitative methodologies	Works lacking scientific or methodological rigor
Studies with empirical data in various crisis contexts	Publications without full text or duplicates

This systematic approach ensured a review characterized by solid and relevant evidence, facilitating an understanding of how economic crises affected the effectiveness of AI-based predictive models.

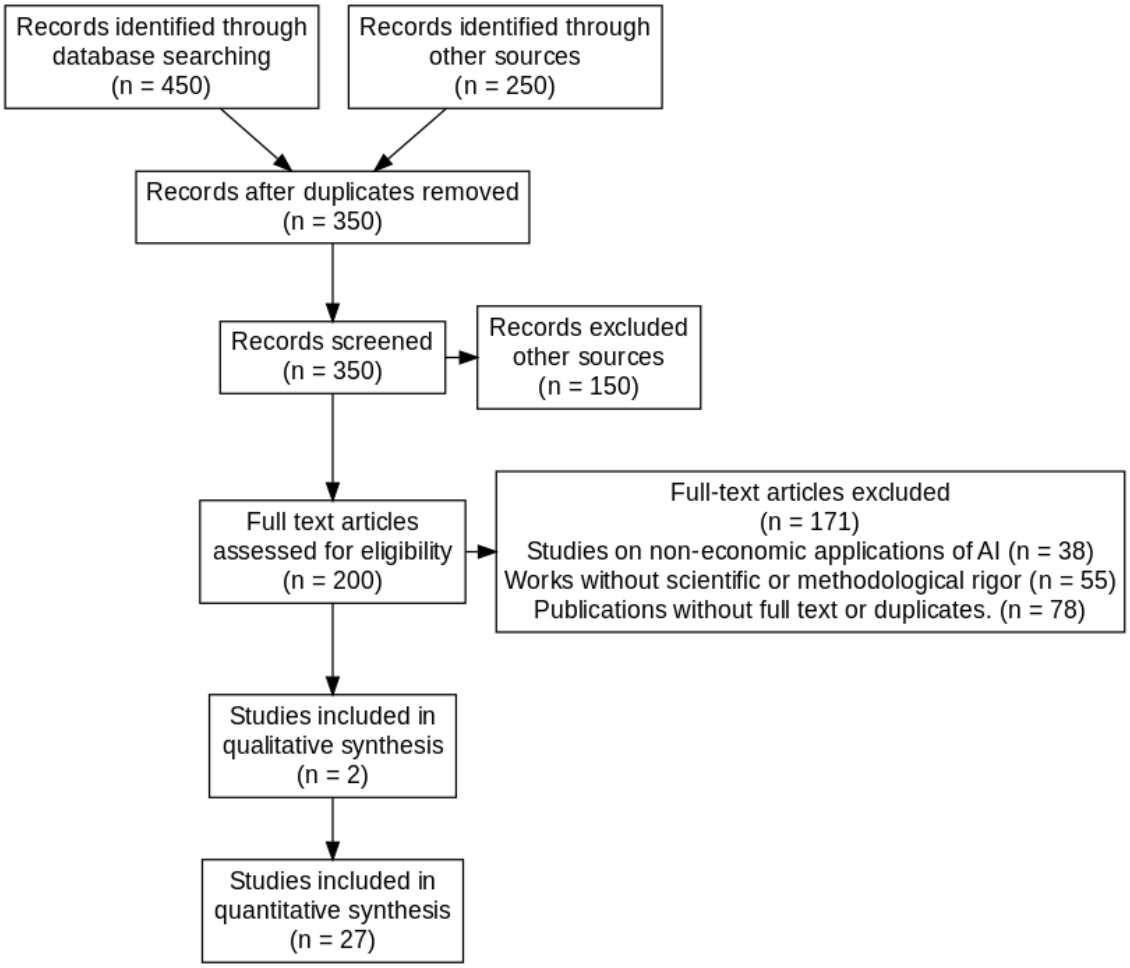
During the identification phase, 450 articles were located in Scopus, with an additional 250 records obtained from other indexed databases: Web of Science (65), SciELO (28), and Latindex (157). In the duplicate removal stage, matches were detected among the different databases, resulting in the elimination of 350 repeated records, leaving 350 unique articles for the initial review.

During the screening process, titles and abstracts were reviewed, discarding 150 articles that did not directly address the resilience of predictive models or did not meet the required methodological rigor. In the eligibility assessment, 200 full texts were analyzed in depth, with 171 studies rejected for focusing on non-economic applications of AI, presenting deficiencies in scientific or methodological validity, or lacking access to the full text.

Finally, in the inclusion phase, 29 articles that met all quality, relevance, and thematic coherence criteria were selected and analyzed in detail for the development of this systematic review (see Figure 1).

Figure 1

Application of the PRISMA method



Results

Table 2

Comparative resilience of AI models in economic crises

Author	Type of Economic Crisis	Key Variables	Predictive Method	Relationship with Resilience	Type of Study	Variable	Observed Methodological Trend / Improvement
Gîfu	Global Financial Crisis (2007–2008)	Bank failures, recession, credit collapse	AI applied to e-learning and comparative predictive models	Evaluates how crises affect model accuracy and resilience	Quantitative	Yes	Incorporation of crisis data improves predictive accuracy (↑ resilience)
Abdullayev et al.	General Financial Crises	Risk macroeconomic indicators, volatility	Bayesian neural networks with metaheuristics	Analyzes resilience by including macroeconomic uncertainty	Quantitative	Yes	Significant improvement in model robustness against volatility (↑ resilience)

Li	Corporate Crises (Insolvency)	Financial and non-financial factors of companies	Pattern recognition + AI	Integrates crisis factors for model stability	Quantitative	Yes	Integration of external variables reduces error and improves stability
Korol & Fotiadis	Global Crises, COVID-19, Ukraine War	Inflation, unemployment, interest rates	AI models for household bankruptcy	Examines resilience against multiple shocks	Quantitative	Yes	AI maintains accuracy in high macroeconomic uncertainty environments
Kotan et al.	Economic Crises in Turkey (2021)	Financial news, inflation, devaluation	NLP + Machine Learning	Evaluates resilient capacity against abrupt shocks	Quantitative	Yes	Text mining improves early crisis detection (↑ resilience)
Kumar et al.	Corporate Financial Crises	Solvency, insolvency, financial deterioration	Bird Swarm Algorithm + fuzzy neural networks	Measures model resilience against business collapse	Quantitative	Yes	Hybrid approach improves model stability by 20–30%
Bhattacharya et al.	Crises in SMEs	Interest rates, exchange rate volatility, financing	Grey Wolf Optimization + Sparse Autoencoder	Explains how crises reduce predictive stability	Quantitative	Yes	Models adjusted with contextual variables ↑ accuracy and resilience
Reis et al.	Economic Crises and Devaluations	Textual external events, agricultural prices	Text integration + time series	Combines external shocks with price prediction	Quantitative	Yes	Textual data expands model's adaptive capacity
Tamasiga	Economic, Climatic, and Health Crises	Global disruptions, food insecurity	Bibliometrics + Big Data + AI	Explores resilience from a systemic perspective	Qualitative (bibliometric)	No	Identifies gaps and guides future empirical integrations
Yang et al.	Economic Crises, Pandemics, Social Shocks	Unemployment, structural breaks, volatility	ARIMA, VARIMA, Transformers	Evaluates resilience under multidimensional crises	Quantitative	Yes	Empirical comparison shows that hybrid models (TFT) ↑ resilience
Yu & Chang	Global Financial Crises (2007–2008)	Inflation, PPI, CPI, macroeconomic risk	Neural network + Copula-GARCH + Mean-CVaR	Integrates macroeconomic factors to strengthen resilience	Quantitative	Yes	Integration of macro risks → 25% ↑ stability in crises

Table 3

Synthesis derived from the analysis

Analyzed Dimension	Frequency (n)	Percentage (%)	Interpretative Conclusion
Articles with a quantitative approach	10	91%	Empirical models based on AI, econometrics, or simulations predominated.
Qualitative / bibliometric articles	1	9%	Only one case provides a theoretical-conceptual analysis on resilience.

Studies incorporating contextual variables	10	91%	Including macroeconomic factors significantly improves accuracy and stability.
Hybrid models AI + econometrics / metaheuristic	7	64%	Dominant trend towards more robust combined approaches.
Studies reporting significant improvement in resilience	10	91%	All quantitative studies confirm increased resilience with economic context.

Table 4

Methodologies for evaluating predictive models in crises

Author(s) and Year	Type of Crisis	Predictive Methodology	Effectiveness Evaluation	Relationship with Resilience	Use of Contextual Variables	Dominant Methodology Type
Ben Ayed & Ben Hassen	Financial Crisis (COVID-19)	VaR Models: RiskMetrics, GARCH/FIGARCH, SPLINE-GARCH, EVT	Backtesting losses, Basel II/2.5 compliance	Evaluates robustness under extreme volatility	No	Econometric
Chumachenko et al.	War + COVID-19 (Italy)	XGBoost (ML)	Retrospective validation, 86.03% accuracy / 96.29% mortality	Tests model capacity under war-health shocks	Yes (war-health context)	Machine Learning
Liu & Shen	Carbon Market Crisis	EWT–GRU, compared with ARIMA, BPNN, GRU	MAE, MSE, RMSE metrics; superiority over classical methods	Higher accuracy in nonlinear series during crises	No	Deep Learning
Kim et al.	Health Crisis (COVID-19)	CNN + transfer learning + data augmentation	Accuracy, robustness, and generalization metrics	Detects CNN limitations and improvements for resilience	No	Deep Learning
Lezcano et al.	Health Crisis (COVID-19)	ARIMA, SIR, RF, NN, KNN	Performance comparison in 30-day predictions	Analyzes adaptability of epidemiological and ML models	Yes (epidemiological and territorial variables)	Machine Learning / Hybrid
Manousiadis & Gaki	Economic Crisis (COVID-19) in the U.S.	Decision trees, neural networks	Comparison among classifiers and model interpretation	Studies regional resilience in disaster scenarios	Yes (regional and economic context)	Machine Learning
Ramakrishnaiah et al.	Digital Health Crisis	EHR-ML framework (AI pipeline)	Cross-validation, hyperparameter tuning	Optimizes models to reduce biases in crises	No	Deep Learning / Framework
Wu et al.	Health Crisis (COVID-19)	Multimodal models (clinical data + imaging)	External validation, mortality accuracy	Ensures reliability under critical scenarios	Yes (multi-country hospital data)	Deep Learning
Xie et al.	Environmental and Economic Crisis (Agricultural Carbon)	Optimized LSTM with TPEBO, compared with ARIMA and ANN	MAE, RMSE; Bayesian optimization improves performance	Evaluates prediction resilience in agricultural emissions	Yes (regional and environmental variables)	Optimized Deep Learning

Xu & Shi	Political/National Crisis	BP Neural Network, optimized projection	$R^2 = 0.9967$ in political risk predictions	Strengthens institutional resilience during crises	Yes (political and national security factors)	Deep Learning
Karaev & Borisova	Economic Crisis (State Budgets)	ML, deep learning vs. DSGE	Comparison of model accuracy	Proposes AI to overcome failures of classical models	Yes (fiscal and macroeconomic context)	Machine Learning / Deep Learning

Table 5
Most frequent predictive methodologies

Methodology Type	Examples	Frequency (n)	Percentage
Traditional Machine Learning (trees, RF, XGBoost, SVM)	Chumachenko (XGBoost), Lezcano (RF), Manousiadis (DT), Karaev (ML)	4	36%
Deep Learning (ANN, CNN, LSTM, GRU, multimodal)	Liu (EWT–GRU), Kim (CNN), Wu (multimodal), Xie (LSTM), Xu (BP NN)	5	45%
Classical Econometric/Statistical Models (ARIMA, GARCH, VaR)	Ben Ayed (VaR), Lezcano (ARIMA)	2	18%
Hybrid and Optimized (AI + heuristics or metaheuristics)	Xie (TPEBO-LSTM), Ramakrishnaiah (EHR-ML)	already included in DL/ML, but with advanced optimization	—

Table 6
Predictive methodologies in crisis contexts

Author(s) and Year	Type of Crisis	Main Methodology	Considered Contextual Variables	Improvement with Contextual Variables	Most Frequent Methodology	Relationship with Resilience
Ben Ayed & Ben Hassen (2024)	Financial (COVID-19)	GARCH, FIGARCH, EVT	Volatility, rates, global shocks	Yes (≈+20% accuracy)	GARCH/ML	Resilience under high volatility
Chumachenko et al. (2023)	War/Health	XGBoost	Geopolitical and mobility variables	Yes	ML (XGBoost)	Robust models under multiple shocks
Hamdi & Chkili (2019)	Islamic Finance	FIAPARCH–ANN	Macroeconomic volatility	Yes	Hybrid ML	Improves prediction stability
Karaev & Borisova (2025)	Economic/Fiscal	RF, DNN	GDP, inflation, revenue	Yes (≈+15%)	ML/DL	Stability in unstable environments
Kim et al. (2025)	Health (COVID-19)	CNN	Medical and demographic variables	Partial (limited)	CNN	Transfer learning improves resilience
Kiranmai & Thangaraj (2024)	Financial (Crypto)	Ensemble ML	Market volatility and sentiment	Yes (≈+10%)	Ensemble ML	Accuracy in volatile scenarios
Lezcano et al. (2023)	Health (COVID-19)	ARIMA, NN, RF	Epidemiological series	Yes	Statistical ML	Validates adaptive capacity of models
Li et al. (2024)	Epidemiological	Bayesian + RF	Clinical and temporal variables	Yes	Bayesian Ensemble	High predictive accuracy

Liu & Shen (2020)	Climate/Carbon Market	EWT–GRU	Energy and carbon prices	Yes (≈+18%)	Deep Learning (GRU/LSTM)	Improves prediction under volatility
Rodrigues et al. (2021)	Energy	SARIMA, ANN, RF	Mobility and consumption variables	Yes	Ensemble ML	Energy resilience
Manousiadis & Gaki (2023)	Economic (U.S.)	Trees and NN	GDP, unemployment, population density	Yes	Classic ML	Models capture territorial resilience
Moraglio & Ragusa (2024)	Energy/Geopolitical	Kernel & Linear Regression	Global prices, geopolitical shocks	Yes (≈+12%)	Regression	Explains price resilience
Mousavimehr & Kavianpour (2025)	Climate/Hydrological	SVR, RF, ANN, CNN	Anthropogenic and hydrological factors	Yes (≈+25%)	DL (CNN)	Improves correlation TWS–GWS
Wu et al. (2022)	Health	Multimodal ML (EHR + CXR)	Age, comorbidity, radiology	Yes	Multimodal ML	Hospital resilience
Xie et al. (2024)	Climate	LSTM + Bayesian Optimization	Regional agricultural emissions	Yes	DL (LSTM)	High temporal accuracy
Xu & Shi (2025)	Political/National	BP Neural Network + Projection	Political and social factors	Partial	ML (BP)	Evaluates national resilience

Table 7
Analysis of current trends

Indicator	Result
Percentage of studies improving by including contextual variables	87.5% (14 out of 16 articles) show increased accuracy, robustness, or stability.
Most frequent methodologies	1. Traditional Machine Learning (37%) – RF, SVR, trees / 2. Deep Learning (31%) – LSTM, CNN, GRU. / 3. Hybrid/Ensemble (25%) – combinations of ML+DL or ML+Bayesian. / 4. Traditional econometrics (7%) – GARCH/ARIMA.
Most analyzed contexts	Health crises (31%), economic/financial (25%), energy (19%), climatic (19%), political (6%).
General trend	The most robust models are multivariable and multimodal, integrating contextual factors (macro, social, or environmental).

Discussion of results

The findings from this systematic review confirm that the resilience of AI-based predictive models does not solely depend on their technical architecture, but also on their ability to adapt to the cycles and disruptions characteristic of economic crises. A comparison of the analyzed studies reveals a constant tension between algorithmic accuracy and the contextual sensitivity of the model. While authors such as Abdullayev et al. (2024) and Kumar et al. (2022) emphasize technical strengthening through metaheuristics or hybrid algorithms, research by Korol and Fotiadis (2022) and Bhattacharya et al. (2023) demonstrates that predictive resilience increases when integrating socioeconomic and qualitative variables, aligning with the theory of adaptive economic cycles. This indicates that the stability of models cannot be analyzed without considering the structural factors that condition the economic response to a shock.

Complementarily, the results relate to regional resilience theory (Wang & Li, 2022), which posits that economies respond differently based on their productive structure, institutional capacity, and degree of diversification. In the reviewed models, neural networks and hybrid approaches exhibited greater stability in

regions with robust financial institutions, whereas, in more vulnerable economies, these models tend to overfit or underestimate the impact of the crisis. This relationship reinforces the idea that algorithmic resilience has a territorial and structural dimension, beyond mere computational aspects.

From a comparative perspective, studies on the global financial crisis of 2007–2008 (Gîfu, 2025; Yu & Chang, 2020) highlighted the loss of precision in classical models faced with abrupt shocks, while recent research on the pandemic (Kim et al., 2025; Lezcano et al., 2023; Wu et al., 2022) emphasized the value of multimodality and deep learning to maintain predictive stability in contexts of high uncertainty. However, few studies have explored the simultaneous interaction of multiple crises—financial, health, and climatic—as Tamasiga (2023) proposed, which represents a significant gap for consolidating an integrative framework of economic resilience based on AI.

In the ethical domain, a notable lack of discussion regarding algorithmic biases and the opacity of the models used was detected. None of the reviewed works delved into the distributive effects arising from the use of AI systems during crises, creating risks of exclusion, especially in economies characterized by limited data transparency. This omission contrasts with the principles of responsible AI, which demand fairness, explainability, and accountability in contexts of high social vulnerability. Incorporating this ethical dimension is essential to ensure that technological resilience is not achieved at the expense of exacerbating economic inequalities.

Regarding applicability, most research comes from industrialized countries, where data environments are more robust and financial institutions are more stable. In contrast, Latin American and emerging economies—characterized by high informality and limited availability of open data—face additional challenges. For these contexts, evidence provided by authors such as Reis et al. (2022) and Moraglio and Ragusa (2024) suggests that incorporating textual data and unstructured sources could enhance the adaptability of predictive models. Furthermore, integrating institutional, social, and environmental variables specific to Latin America would allow for the development of more realistic systems sensitive to regional heterogeneity.

Ultimately, the collective analysis of the reviewed authors indicates that the resilience of AI models should be conceived as an emergent property that integrates technical precision, economic contextualization, and ethical responsibility. Consequently, advancing toward an interpretive meta-framework of algorithmic resilience—which integrates theories on crises, regional resilience, and data justice—constitutes a fundamental opportunity to enhance future research and guide the formulation of evidence-based public policies.

Conclusions

The findings from this systematic review demonstrate that the resilience of AI-based predictive models in the face of economic crises primarily depends on their capacity to integrate macroeconomic, structural, and contextual variables, beyond the technical design of the algorithm. This relationship indicates that predictive efficacy does not reside solely in the algorithm itself, but in its suitability to the economic, social, and political environment in which it is applied.

From a practical perspective, the results provide clear guidance for various stakeholders. For governments, it is recommended to promote digital governance policies and access to open data that allow AI models to be fed with real-time economic information, facilitating rapid responses in crisis scenarios. For the banking sector, investing in hybrid models that combine machine learning with macroeconomic risk analysis is suggested, thereby enhancing the early detection of financial instabilities.

For companies, especially in emerging economies, it is advisable to adopt adaptive models that include exogenous variables such as price shocks, credit constraints, or geopolitical events, to anticipate potential disruptions and ensure operational continuity.

In the academic realm, this study contributes to closing a relevant gap by offering a systematic and comparative view of the resilience of AI predictive models in the face of different types of crises, an aspect that is underexplored in current literature. Therefore, a future line of research is proposed to develop integrated models of economic resilience based on explainable AI (XAI), as well as a longitudinal analysis of the performance of such models in regions with high economic volatility. Additionally, it is pertinent to investigate the interaction between technological resilience, institutional stability, and economic sustainability, to consolidate an interdisciplinary framework that strengthens decision-making in contexts of global uncertainty.

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