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| RESEARCH ARTICLE

Future of Banking Risk: How Intelligent Stress Testing Is Transforming Financial Resilience

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| ABSTRACT

Stress testing is a critical component of banking risk management and supervisory oversight, providing a structured means of evaluating whether financial institutions can absorb losses and maintain capital resilience under adverse conditions. Yet the increasing speed, complexity, and interconnectedness of financial markets raise questions about the ability of predominantly scenario-based and periodically executed approaches to identify emerging vulnerabilities. This conceptual paper examines how artificial intelligence (AI), machine learning (ML), alternative data, and advanced analytics could augment conventional bank stress testing by enabling more adaptive scenario generation, nonlinear risk estimation, continuous monitoring, and integrated portfolio analysis. The paper uses a structured conceptual synthesis of the stress-testing literature, supervisory principles, and recent research on AI-enabled financial risk modeling to identify limitations in traditional approaches and develop a framework for AI-enabled dynamic stress testing. The proposed framework links data and risk sensing, AI-assisted scenario generation, portfolio and balance-sheet simulation, capital and liquidity impact assessment, management decision-making, and model-risk governance. The analysis argues that AI should complement rather than replace established stress-testing governance and supervisory processes. In particular, model validation, explainability, data quality, human oversight, documentation, and ongoing monitoring are essential for responsible adoption. The paper contributes a research-oriented framework for understanding how banks can move from predominantly periodic stress exercises toward more adaptive and forward-looking risk intelligence while preserving regulatory discipline. It also identifies empirical research opportunities, including comparative testing of AI and traditional models, evaluation of scenario-generation quality, and measurement of governance effectiveness.

| KEYWORDS

bank stress testing; artificial intelligence; machine learning; dynamic stress testing; model risk; financial resilience; scenario analysis; capital adequacy; enterprise risk management

| ARTICLE INFORMATION

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1. Introduction

The global financial crisis established stress testing as a central mechanism for assessing the resilience of banks and the broader financial system. The Basel Committee on Banking Supervision describes stress testing as both a critical element of bank risk management and a core tool for banking supervisors and macroprudential authorities (Basel Committee on Banking Supervision [BCBS], 2018). In the United States, supervisory stress testing continues to evaluate how large banks would perform under hypothetical adverse economic conditions, including implications for losses, revenues, expenses, and capital (Board of Governors of the Federal Reserve System, 2026a). Stress testing therefore serves not only as a compliance activity but also as an input into capital planning, risk appetite, and financial stability analysis.

Traditional stress-testing frameworks have nevertheless developed around a set of assumptions that can become restrictive in rapidly changing environments. These include predefined scenarios, historical relationships between macroeconomic variables and portfolio outcomes, periodic execution cycles, and the use of multiple models that may be difficult to integrate. Such approaches remain valuable because they provide transparency, comparability, and supervisory discipline, but they may be less responsive to nonlinear relationships and combinations of risks that have limited historical precedent. The Basel Committee's stress-testing principles emphasize the importance of objectives, governance, methodology, resources, documentation, implementation, and oversight, suggesting that innovation in modeling must remain embedded within a robust control framework (BCBS, 2018).

Artificial intelligence provides a potential pathway for augmenting this established architecture. ML methods can identify nonlinear patterns across high-dimensional data, while newer AI techniques can support alternative-data analysis, dynamic forecasting, and scenario generation. Research on dynamic balance-sheet stress testing has already demonstrated the potential for deep-learning approaches to address nonlinearities and limitations associated with conventional stress-testing assumptions (Petropoulos et al., 2022). At the same time, AI introduces additional model-risk, governance, explainability, data, and operational challenges. Financial regulators continue to emphasize model development, validation, monitoring, governance, and controls as core elements of sound model-risk management (Board of Governors of the Federal Reserve System, OCC, & FDIC, 2026).

Against this background, this paper addresses three research questions: (1) How can AI and ML address key limitations of conventional bank stress-testing frameworks? (2) How can AI-enabled techniques support dynamic scenario generation and more continuous assessment of financial vulnerabilities? and (3) What governance and model-risk conditions are necessary for responsible adoption of AI-enabled stress testing? The paper's contribution is conceptual rather than empirical. It synthesizes existing stress-testing principles and AI-risk research and proposes an integrated framework connecting risk sensing, adaptive scenario generation, portfolio simulation, capital and liquidity assessment, decision-making, and governance.

2. Literature Review

2.1 Traditional Bank Stress Testing

Stress testing generally evaluates the consequences of severe but plausible adverse conditions for financial institutions. Supervisory exercises can have both microprudential and macroprudential objectives, while internal bank exercises can inform capital planning, risk appetite, liquidity management, and strategic decisions. A comparative review by Baudino et al. (2018) identifies governance, implementation, and outcomes as core building blocks of stress-testing programs and emphasizes alignment between the design of a test and its policy objectives.

The Federal Reserve's current supervisory framework illustrates the continuing importance of scenario-based stress testing. Its 2026 framework evaluates large banks under hypothetical economic conditions and includes multiple risk components, while its model documentation covers credit risk, market risk, operational risk, pre-provision net revenue, and aggregation models (Board of Governors of the Federal Reserve System, 2026a, 2026b). These structures demonstrate that stress testing is already a sophisticated, multi-model discipline rather than a simple forecasting exercise.

2.2 Limitations of Conventional Approaches

Despite their value, conventional frameworks can encounter four related limitations. First, scenario design can be constrained by historical experience and expert-defined assumptions. Second, model relationships may be insufficiently flexible during extreme conditions, when nonlinearities and feedback effects become more pronounced. Third, periodic execution may reduce the ability to respond to rapidly changing risk signals. Fourth, fragmented data and multiple model components can make enterprise-wide integration difficult. These limitations do not imply that traditional stress testing is obsolete; rather, they motivate research into how advanced analytics can augment established methods.

2.3 AI and Machine Learning in Financial Risk Modeling

AI and ML methods can process large volumes of structured and unstructured information and identify nonlinear relationships that may be difficult to capture through conventional specifications. In stress testing, this capability can potentially improve forecasting, identify changing risk concentrations, and support scenario analysis. Petropoulos et al. (2022), for example, proposed a deep-learning approach to dynamic balance-sheet stress testing and reported empirical evidence that the approach could improve simulation of adverse conditions relative to traditional approaches.

The literature also suggests that AI should not be considered solely as a predictive technology. The more consequential question is how AI is incorporated into the end-to-end risk process. This includes data governance, model development, validation, monitoring, explainability, human decision rights, and controls over model use. The BIS Financial Stability Institute notes that AI in finance can amplify existing model-risk and data-governance concerns, while also creating additional challenges around governance, expertise, third-party providers, and emerging generative-AI risks (Crisanto et al., 2024).

2.4 Dynamic Stress Testing

Dynamic stress testing extends the conventional idea of applying a fixed scenario to a portfolio by allowing balance-sheet conditions, risk drivers, and management responses to evolve through the stress horizon. This direction is consistent with research emphasizing nonlinear modeling and dynamic balance-sheet behavior (Petropoulos et al., 2022). It also aligns with supervisory interest in understanding interconnectedness and channels of contagion across financial institutions and markets (Board of Governors of the Federal Reserve System, 2021).

3. Research Gap and Research Questions

Existing stress-testing frameworks provide strong governance and supervisory foundations, while emerging AI research demonstrates the technical feasibility of nonlinear and dynamic modeling. However, there remains a practical and conceptual gap between AI model development and the full stress-testing lifecycle. A model that produces better forecasts does not by itself establish a sound stress-testing framework. Banks must determine how model outputs affect scenario design, portfolio simulation, capital and liquidity decisions, management actions, regulatory reporting, and model-risk controls.

The paper therefore addresses the following research questions:

RQ1: How can AI and ML augment conventional bank stress-testing methodologies while preserving established risk-management principles?

RQ2: How can AI-enabled methods support adaptive scenario generation and continuous identification of emerging vulnerabilities?

RQ3: What governance, validation, explainability, data, and human-oversight mechanisms are necessary for responsible use of AI in stress testing?

4. Methodology and Conceptual Approach

This study adopts a conceptual research methodology based on structured synthesis rather than primary empirical testing. The analysis integrates three evidence domains: (1) supervisory and regulatory principles governing bank stress testing and model risk; (2) academic and research literature on stress-testing methodology and AI-enabled financial modeling; and (3) practical risk-management requirements implied by the integration of AI into enterprise risk processes. The purpose is to identify recurring limitations and capabilities across these domains and translate them into an integrated conceptual framework.

The framework is developed using a lifecycle perspective. Each stage of the conventional stress-testing process is examined for opportunities where AI can augment human judgment and existing quantitative models. The resulting architecture is intentionally hybrid: AI is positioned as an analytical and decision-support layer within an existing governance framework, rather than as an autonomous replacement for established risk-management processes.

5. Proposed Framework for AI-Enabled Dynamic Stress Testing

The proposed framework contains six interconnected layers: (1) data and risk sensing; (2) adaptive scenario generation; (3) portfolio and balance-sheet simulation; (4) capital and liquidity impact assessment; (5) management decision intelligence; and (6) governance and supervisory controls. The first five layers form an analytical chain, while governance operates as a cross-cutting control layer across the entire lifecycle.

Layer	Primary Function	AI/ML Contribution	Key Controls
1. Data & Risk Sensing	Aggregate macro, market, portfolio, transaction and external indicators	Pattern detection, anomaly detection, alternative-data processing	Data lineage, quality, privacy, access controls
2. Adaptive Scenario Generation	Develop severe but plausible combinations of risk drivers	Scenario expansion, nonlinear dependency analysis, probabilistic generation	Scenario plausibility, expert review, documentation
3. Portfolio & Balance-Sheet Simulation	Estimate losses, revenues, exposures and balance-sheet responses	Nonlinear forecasting and dynamic interactions	Benchmarking, validation, challenger models
4. Capital & Liquidity Impact	Translate projected outcomes into capital and liquidity measures	Forecasting and sensitivity analysis	Capital methodology, assumptions, reconciliation
5. Decision Intelligence	Support risk appetite, capital planning and management actions	Early-warning signals and decision support	Human approval, escalation thresholds, auditability
6. Governance & Oversight	Control model use throughout lifecycle	Monitoring of drift, performance and explainability	Validation, documentation, governance committees, regulatory review

The framework is designed to preserve the strengths of conventional stress testing while expanding its analytical range. Traditional scenarios remain important as anchor cases because they provide consistency and supervisory comparability. AI can then be used to supplement these scenarios by identifying nonlinear combinations of risk factors, detecting emerging changes in portfolio behavior, and exploring a broader distribution of plausible outcomes.

6. AI-Enabled Scenario Generation and Risk Simulation

Scenario generation is a particularly important opportunity for AI augmentation. Traditional stress tests often begin with a limited set of macroeconomic assumptions and propagate these assumptions through risk models. An AI-enabled approach could analyze relationships among macroeconomic indicators, market prices, credit behavior, liquidity conditions, operational disruptions, and external information to identify combinations of risks that warrant further analysis. This does not mean that an AI system should independently determine the regulatory scenario. Instead, AI can function as a scenario-discovery and sensitivity-analysis engine, with human experts determining which outputs meet the severe-but-plausible standard.

The second opportunity is dynamic simulation. A bank's balance sheet and risk profile can change as conditions deteriorate, and management actions can alter the path of losses, liquidity, and capital. A dynamic framework can therefore model not only the initial shock but also feedback effects and potential management responses. This is consistent with research on dynamic balance-sheet stress testing, which argues that conventional approaches can miss nonlinear effects and dynamic behavior (Petropoulos et al., 2022).

7. Integration With Enterprise Risk Management

AI-enabled stress testing becomes more valuable when integrated with enterprise risk management rather than maintained as an isolated analytical exercise. Outputs can inform capital planning, risk appetite, liquidity management, strategic planning, and regulatory preparedness. The proposed model therefore treats stress testing as a decision-intelligence capability that connects risk, finance, treasury, business units, and senior management.

Capital planning: identify potential changes in capital ratios and capital needs under multiple adverse paths.

Risk appetite: monitor whether emerging exposures could move the institution toward or beyond approved risk limits.

Liquidity management: assess how market stress, funding pressures, and asset-quality deterioration interact.

Strategic decisions: evaluate the resilience of business plans, portfolios, acquisitions, or growth strategies under adverse conditions.

Regulatory preparedness: improve documentation, traceability, scenario analysis, and management evidence supporting supervisory discussions.

8. AI Governance, Model Risk, and Regulatory Considerations

The principal challenge is not simply whether AI can produce accurate forecasts; it is whether financial institutions can demonstrate that AI outputs are sufficiently reliable, explainable, controlled, and fit for their intended use. The 2026 interagency model-risk guidance emphasizes model development and use, validation and monitoring, governance and controls, and appropriate treatment of third-party products (FDIC, 2026; Board of Governors of the Federal Reserve System, OCC, & FDIC, 2026). These principles are directly relevant to AI-enabled stress testing.

A governance framework should address at least six areas. First, data governance should establish provenance, quality standards, representativeness, and controls over alternative data. Second, model validation should evaluate performance, stability, sensitivity, and limitations under both normal and stressed conditions. Third, explainability should be proportionate to the model's materiality and decision use. Fourth, ongoing monitoring should detect model drift, changing data distributions, and deteriorating predictive performance. Fifth, human oversight should establish clear decision rights and escalation procedures. Sixth, documentation should enable independent review and supervisory examination.

The regulatory dimension is especially important because stress testing can influence capital requirements and other high-impact financial decisions. The Federal Reserve's stress-testing framework explicitly connects stress-test outcomes with capital requirements for large banks (Board of Governors of the Federal Reserve System, 2026a). AI adoption should therefore be treated as an extension of model-risk management, not as a separate technology initiative.

9. Discussion

The conceptual analysis suggests that the most credible path forward is not a wholesale replacement of conventional stress testing, but a hybrid architecture. Traditional methods provide governance, transparency, interpretability, supervisory comparability, and established links to capital planning. AI can add adaptability, nonlinear pattern recognition, broader data integration, and more extensive scenario exploration. Combining the two can create a layered approach in which established scenarios serve as baseline anchors while AI identifies additional risk combinations and dynamic paths for analysis.

This hybrid approach also addresses an important misconception: more sophisticated models do not necessarily mean better risk management. Model complexity can increase model risk, reduce interpretability, and create new dependencies on data and technology. The value of AI should therefore be assessed against the complete decision lifecycle, including whether it improves early-warning capabilities, scenario coverage, decision quality, and risk governance—not merely whether it improves statistical forecast accuracy.

For practitioners, the framework implies a staged implementation path. Banks can begin with data integration and anomaly detection, progress to AI-assisted forecasting and scenario discovery, and then introduce dynamic portfolio simulation and decision-support capabilities. High-impact outputs should remain subject to human review and existing risk governance. This incremental approach can allow institutions to capture analytical benefits without weakening established controls.

10. Implications for Research and Practice

For financial institutions, the framework provides a roadmap for linking AI investment to concrete risk-management outcomes. For regulators, it highlights the need to evaluate not only model performance but also governance, explainability, data lineage, and the interaction between AI models and existing stress-testing processes. For researchers, it identifies several opportunities for empirical investigation.

Compare AI-enhanced stress-testing models with conventional econometric or satellite models using common datasets and identical stress scenarios.

Evaluate whether AI-generated scenarios increase scenario coverage without materially increasing false positives or implausible outcomes.

Measure the stability and performance of AI models under distribution shifts and unprecedented stress events.

Develop quantitative measures for explainability and governance effectiveness in high-impact banking models.

Study how management actions and balance-sheet responses can be incorporated into dynamic AI stress-testing systems.

Examine whether AI-enabled stress testing improves early-warning performance, capital planning quality, or risk-adjusted decision-making.

11. Limitations and Future Research

This paper has several limitations. First, it is conceptual and does not provide a new empirical model or out-of-sample performance results. Second, the proposed framework is technology-agnostic and does not prescribe a specific ML architecture, dataset, or scenario-generation algorithm. Third, the paper does not attempt to quantify the operational cost, implementation complexity, or regulatory acceptance of AI-enabled stress testing. These limitations are deliberate because the paper's objective is to establish a structured research and implementation framework rather than claim empirical superiority.

Future research should test the framework using bank-level or supervisory datasets. A useful empirical design would compare a conventional stress-testing model with an AI-enhanced model across identical stress horizons and risk factors. Evaluation should include predictive accuracy, scenario coverage, calibration, stability under distribution shifts, interpretability, and governance burden. Research could also examine whether generative techniques produce economically coherent scenarios and whether dynamic models materially improve the identification of emerging vulnerabilities.

12. Conclusion

Bank stress testing is evolving from a predominantly periodic assessment of predefined adverse conditions toward a broader risk-intelligence capability. Conventional stress testing remains essential because of its established governance, supervisory role, and connection to capital planning. However, the growing complexity of financial markets creates a strong rationale for augmenting these frameworks with AI and ML capabilities.

This paper proposed a conceptual framework that integrates AI-enabled risk sensing, adaptive scenario generation, dynamic portfolio and balance-sheet simulation, capital and liquidity impact assessment, decision intelligence, and cross-cutting governance. The central proposition is that AI should augment rather than replace established stress-testing processes. The strongest future model is therefore likely to be hybrid: AI expands the analytical space and improves responsiveness, while human judgment, validation, governance, and regulatory controls determine how those outputs are used.

The transformation of stress testing should ultimately be evaluated not by the sophistication of the technology itself, but by whether it enables banks to identify vulnerabilities earlier, understand interconnected risks more effectively, make better capital and risk decisions, and maintain resilience under conditions that cannot be inferred reliably from historical experience alone.

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