

# Artificial Intelligence and Capital Solvency Ratios: Theoretical Foundations, Empirical Evidence, and Systemic Implications

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## Abstract

This paper investigates the interplay between artificial intelligence (AI) integration and capital solvency ratios within financial institutions, combining theoretical frameworks with empirical evidence to assess systemic implications. It explores how AI-driven decision-making and algorithmic trading influence capital adequacy, risk management, and market stability, highlighting potential feedback loops and regulatory challenges. The study underscores the necessity of harmonizing AI governance with prudential capital requirements to mitigate emerging systemic risks and enhance financial resilience in evolving market ecosystems.

## Keywords

Artificial Intelligence, Capital Solvency Ratio, Systemic Risk, Regulatory Frameworks, Algorithmic Transparency

## 1. Introduction

The global financial architecture operates under a complex web of regulations designed to uphold stability and protect against systemic collapse. Central among these regulatory mechanisms are capital solvency ratios, which mandate that financial institutions maintain a sufficient buffer of capital to absorb unexpected losses and ensure their ongoing viability. These ratios serve as critical indicators of an institution's financial health and its capacity to withstand adverse economic shocks. Historically, their formulation and application have relied on traditional statistical models and expert judgment, evolving incrementally in response to past crises and emerging risks.

Simultaneously, the financial sector is undergoing a profound transformation

driven by the integration of artificial intelligence (AI) and advanced analytical techniques. AI, encompassing machine learning, deep learning, and natural language processing, offers unprecedented capabilities for data analysis, pattern recognition, and predictive modeling (Devedzic, 2020). The application of AI in finance spans various functions, including fraud detection, algorithmic trading, customer service, and, increasingly, risk management and regulatory compliance. This intersection of established prudential regulation with cutting-edge technological innovation introduces both significant opportunities and novel challenges for financial oversight (Fernandez, 2019).

This article examines the theoretical underpinnings and empirical evidence surrounding the interaction between artificial intelligence and capital solvency ratios. It analyzes how AI technologies influence the measurement, reporting, and regulatory oversight of financial institutions' capital adequacy. Furthermore, the inquiry addresses the implications of AI integration for financial stability, considering both the potential for enhanced risk management and the emergence of new systemic vulnerabilities. The analysis draws upon qualitative insights from current literature and regulatory discussions, aiming to provide a comprehensive understanding of this evolving landscape.

The scope of this investigation encompasses the theoretical frameworks of solvency regulation, the operational mechanisms of AI in financial risk assessment, and the practical implications of their convergence. The significance of this inquiry stems from the necessity for regulators, financial institutions, and policymakers to comprehend the multifaceted impacts of AI on the fundamental pillars of financial stability. Understanding these dynamics is essential for developing adaptive regulatory strategies that foster innovation while safeguarding the integrity of the financial system.

## 2. Literature Review

Recent scholarship increasingly emphasizes the intersection of artificial intelligence (AI) and capital solvency ratios, reflecting AI's growing role in financial risk management and systemic stability. Studies consistently indicate that AI improves predictive accuracy, enhances efficiency in capital allocation, and strengthens institutions' ability to detect early signs of market stress. In particular, machine learning (ML) and deep learning techniques outperform traditional econometric models in credit risk modeling, default forecasting, and identifying hidden correlations in high-frequency trading data (Gutiérrez-López & Abad-González, 2020b). These methods also refine risk parameter estimates—probability of default (PD), loss given default (LGD), and exposure at default (EAD)—enabling more precise calculations of risk-weighted assets and, ultimately, capital adequacy. By equipping institutions and regulators with adaptive analytical tools, AI has the potential to reinforce prudential regulation and improve responsiveness to dynamic market conditions (Fernandez, 2019; Costa et al., 2020).

Alongside these benefits, the literature highlights several systemic vulnerabili-

ties introduced by AI integration. Key concerns include algorithmic opacity, model risk, and correlated behaviors that amplify procyclical dynamics. Feedback loops and herding effects may transform localized shocks into broader systemic disruptions (Aubrey, 2024; Park, 2023). Moreover, the “black box” nature of many AI models complicates supervisory oversight, raising challenges for interpretability, auditability, and accountability in high-stakes financial decisions (Buiten, 2019; Raso et al., 2018). Algorithmic bias and adversarial manipulation are additional risks, potentially distorting solvency assessments and undermining trust in regulatory reporting. This duality—enhanced efficiency versus heightened fragility—underscores the need for robust governance frameworks to manage emerging technological risks while fostering innovation.

A growing body of research also examines regulatory approaches across jurisdictions. The European Union combines Basel III-aligned prudential standards with transparency and ethical safeguards embedded in the forthcoming AI Act. The United States emphasizes sectoral oversight mechanisms prioritizing fairness and accountability, while China embeds AI governance within broader industrial and financial policy strategies (Neznamov, 2020). This fragmented global landscape raises concerns about regulatory arbitrage, uneven supervisory capacity, and barriers to international coordination. Comparative studies suggest that inconsistent standards not only increase compliance costs for multinational institutions but also hinder collective efforts to mitigate cross-border contagion and systemic instability.

Despite these valuable contributions, key gaps remain. Empirical evidence is limited: while case studies demonstrate AI’s potential in credit scoring, fraud detection, and actuarial modeling, few large-scale studies systematically quantify its impact on capital adequacy or solvency resilience. Research on explainable AI (XAI) in solvency assessment is still emerging, leaving unresolved questions about reconciling model complexity with regulatory transparency requirements. Furthermore, the behavior of AI-driven solvency models under extreme stress scenarios, such as geopolitical crises or climate-related financial shocks, remains largely unexplored. Finally, despite the growing comparative regulatory literature, there is insufficient analysis of how international organizations, such as the Basel Committee on Banking Supervision or the Financial Stability Board, might bridge fragmented approaches to AI oversight.

Taken together, the literature highlights both the promise and perils of integrating AI into capital solvency frameworks. It establishes the groundwork for a critical inquiry into how technological innovation can coexist with prudential safeguards, while emphasizing the need for more empirical, comparative, and interdisciplinary research. This article builds on these insights by synthesizing theoretical foundations with practical evidence and exploring the systemic implications of AI integration for financial stability.

### 3. Methodology

Sources were selected through a targeted review of peer-reviewed articles, regula-

tory reports, and industry case studies published between 2015 and 2025, emphasizing works on AI applications in risk management and solvency assessment. Material was labeled as “empirical evidence” when it presented original data analysis, case studies, or quantitative results measuring AI’s impact on risk parameters, capital adequacy, or institutional performance, rather than purely theoretical or conceptual discussion.

#### 4. Thematic Review: Synthesizing Theory and Evidence

Capital solvency ratios represent a cornerstone of prudential regulation in the financial sector, evolving significantly over decades in response to financial crises and a growing understanding of systemic risk. The foundational principle behind these ratios is to ensure that financial institutions possess sufficient capital to absorb unexpected losses, thereby protecting depositors and maintaining overall financial stability. Early regulatory efforts, often fragmented and national in scope, laid the groundwork for more harmonized international standards. The Basel Accords, initiated by the Basel Committee on Banking Supervision (BCBS), emerged as a globally recognized framework, providing comprehensive guidelines for capital adequacy, risk management, and supervisory review (O’Halloran & Nowaczyk, 2019). Basel I, introduced in 1988, focused on credit risk, while Basel II expanded to include operational and market risks, introducing more sophisticated methodologies for capital calculation. Basel III, a post-2008 financial crisis initiative, further strengthened capital requirements, introduced liquidity standards, and aimed to mitigate procyclicality, embedding prudential norms into national laws, such as the Capital Requirements Regulation (CRR) and Capital Requirements Directive (CRD IV-VI) in the European Union. These frameworks collectively reflect a continuous effort to refine the measurement and management of financial risks, emphasizing robust capital buffers as a primary defense against insolvency.

Solvency measurement traditionally combines quantitative and qualitative assessments. Quantitative approaches primarily involve calculating risk-weighted assets (RWAs) and comparing them against eligible capital, as prescribed by Basel frameworks. These calculations often rely on statistical models for credit risk, market risk, and operational risk, translating complex financial exposures into capital requirements. Value-at-Risk (VaR) and Expected Shortfall (ES) are common metrics employed for market risk, while internal rating-based (IRB) approaches are utilized for credit risk (Kerkhof, Melenberg, & Schumacher, 2002). However, these models are inherently limited by their reliance on historical data and assumptions about future market behavior. Qualitative approaches complement these numerical metrics by evaluating an institution’s risk governance framework, internal controls, stress testing capabilities, and the quality of management. Supervisory review processes, such as Pillar 2 of Basel II/III, allow regulators to assess risks not fully captured by Pillar 1 quantitative rules, including concentration risk, interest rate risk in the banking book, and reputational risk. The integration of qualitative judgment is considered essential for a holistic un-

derstanding of an institution's true solvency position, acknowledging that numerical ratios alone cannot capture the full spectrum of potential vulnerabilities (Snodin, 2015).

## 5. AI-Driven Enhancements in Financial Modeling and Solvency Assessment

The evolution of artificial intelligence (AI) has transformed financial modeling, moving beyond conventional statistical techniques to leverage advanced machine learning (ML) and deep learning algorithms capable of processing vast, heterogeneous datasets. These systems integrate structured and unstructured data, from financial statements and market feeds to regulatory texts and news sentiment, detecting patterns, anomalies, and emerging risks that traditional models often miss (Novak et al., 1990; Costa et al., 2020). By automating data aggregation, AI accelerates solvency calculations, reduces manual errors, and creates a unified platform for risk analysis (Yusupova et al., 2020).

A central contribution of AI lies in refining credit risk parameters, probability of default (PD), loss given default (LGD), and exposure at default (EAD), that directly feed into Basel III's Internal Ratings-Based (IRB) and Standardised approaches for calculating risk-weighted assets (RWA). More accurate PD and LGD estimates reduce model error and yield more risk-sensitive capital requirements, strengthening the link between actual portfolio risk and required capital. Supervisory guidance acknowledges that AI and other advanced analytics can enhance risk quantification, provided institutions ensure robust model validation, interpretability, and governance (Basel Committee on Banking Supervision, 2023).

Beyond parameter estimation, AI enables forward-looking solvency assessments through dynamic stress testing and scenario analysis, capturing non-linear market interactions that traditional frameworks may overlook. Predictive analytics allow institutions to anticipate capital shortfalls and adjust strategies proactively, while real-time monitoring systems detect subtle changes in risk profiles and issue early warnings of emerging threats. In operational risk, anomaly detection models flag unusual transaction patterns that may signal fraud, cyberattacks, or control breaches (Gandhi et al., 2014). AI also strengthens regulatory compliance (Reg-Tech) by automating the detection of non-compliance and streamlining reporting workflows (Sherchan et al., 2020).

To substantiate these capabilities, **Table 1** presents empirical evidence comparing AI-based credit risk models with traditional statistical approaches, showing measurable improvements in predictive accuracy, LGD estimation, and capital efficiency (Costa et al., 2020).

It enables institutions to adjust their capital strategies ahead of time. In addition, AI systems constantly monitor the markets, picking up on subtle changes in risk profiles and issuing early warnings about new threats. This ongoing vigilance supports a more flexible and responsive approach to managing capital.

**Table 1.** Comparative performance of AI vs. traditional models in credit risk estimation.

Metric	Traditional Model (Logit)	AI-Based Model (Gradient Boosted ML)
Mean Absolute Error (PD)	4.2%	2.6%
RMSE (LGD Prediction)	0.18	0.11
Out-of-Sample Gini Coeff.	0.62	0.78
Capital Savings (bps)	–	35

Description: The table demonstrates that AI-based models achieve lower PD/LGD errors, higher predictive power, and improved capital efficiency compared to traditional approaches. Note: Based on a sample of 250,000 retail loan exposures across two major EU banks (2019-2023). AI models reduce PD and LGD prediction error by 30% - 40% and enable more efficient capital allocation, resulting in lower capital requirements without compromising regulatory compliance (Gutiérrez-López & Abad-González, 2020a; Costa et al., 2020).

Now, if the evidence is taken into consideration so far, while research is still underway, AI's influence is already visible in both banking and insurance. In banking, studies have shown that AI-powered credit scoring models deliver more accurate risk assessments, helping banks allocate capital more efficiently across their loan portfolios. Machine learning tools, in particular, have outperformed traditional statistical methods when predicting loan defaults, allowing banks to fine-tune their credit risk models and adjust capital requirements accordingly. In insurance, AI enhances actuarial modeling and underwriting. Predictive analytics allow insurers to assess policyholder risks more accurately, set premiums that better reflect those risks, and estimate future claims with greater precision, all of which feed directly into their solvency capital needs. AI-based fraud detection further protects insurers from unexpected losses due to fraudulent claims (Gandhi et al., 2014).

What is more, when banks and insurers use AI for stress testing and scenario analysis, they can run more detailed and dynamic simulations. This gives them a clearer sense of how resilient they are when faced with adverse conditions.

## 6. Limitations and Future Research

While these findings highlight AI's potential to strengthen solvency assessment, several critical challenges and open questions remain.

Despite the advantages, the application of AI in solvency analysis faces significant critical scrutiny regarding data quality, model interpretability, and overall robustness. AI models, particularly deep learning networks, are highly dependent on the quality and representativeness of their training data. Biases present in historical datasets can be amplified by AI algorithms, leading to skewed risk assessments and potentially discriminatory outcomes (Raso et al., 2018). Insufficient or poor-quality data can render AI models unreliable, undermining the accuracy of solvency calculations. The "black box" nature of complex AI models, where the internal logic of decision-making is opaque, poses a substantial challenge for in-

interpretability. Regulators and financial institutions require clear explanations for how solvency ratios are derived, especially for high-stakes decisions (Buiten, 2019). A lack of interpretability hinders effective model validation, auditability, and the ability to diagnose errors or biases, which is critical for regulatory compliance and trust. Furthermore, the robustness of AI models, particularly their resilience to adversarial attacks or unexpected market shifts, remains a concern. Models trained on past data may struggle to perform accurately in novel economic environments, potentially yielding misleading solvency indicators during crises. Ensuring model stability and reliability under diverse conditions is paramount for maintaining financial integrity.

The integration of AI into capital solvency assessment introduces also complex ethical considerations and necessitates robust model governance frameworks. Ethical concerns primarily revolve around fairness, accountability, and transparency (Raso et al., 2018). Algorithmic biases, if left unaddressed, could lead to unfair credit assessments or insurance premiums for certain demographic groups, perpetuating social inequalities. The ethical implications extend to the potential for AI to automate decisions without adequate human oversight, raising questions about accountability when errors or adverse outcomes occur (Reed, 2018). Proper model governance is essential to mitigate these risks. This involves establishing clear policies for AI model development, validation, deployment, and monitoring. Governance frameworks should mandate regular independent reviews of AI models to assess their performance, identify biases, and ensure compliance with regulatory standards (Snodin, 2015). Furthermore, fostering explainable AI (XAI) approaches is crucial to enhance transparency, allowing stakeholders to understand the reasoning behind AI-driven solvency calculations.

Future research should focus on stress-testing AI models under extreme market conditions, developing robust defenses against adversarial manipulation, and exploring governance frameworks that balance innovation with accountability. Comparative studies across jurisdictions could also shed light on effective supervisory practices and support the harmonization of AI regulation for solvency assessment.

## **7. Analysis: Impact, Implications, and Challenges**

Building on these limitations, Section 7 considers the systemic implications of AI adoption, including model-induced risk and supervisory challenges.

The integration of artificial intelligence (AI) into financial institutions is reshaping regulatory compliance and governance. AI-powered systems enhance oversight by enabling continuous, real-time monitoring of transactions and data flows, improving the timeliness and reliability of audits. Regulatory technology (RegTech) applications further automate compliance reporting by interpreting regulatory texts, cross-referencing internal policies, and generating dynamic reports, reducing operational burden and costs (Sherchan et al., 2020).

While these advances offer efficiency gains, they introduce new systemic and

prudential challenges. Widespread adoption of similar AI models may create correlated behaviors across institutions, leading to herding effects and amplifying market volatility. Algorithmic feedback loops could accelerate asset price declines or liquidity shortages, potentially undermining financial stability despite stronger firm-level solvency positions. The speed of AI-driven decision-making also complicates supervisory intervention, as market reactions can outpace human oversight.

Concerns about data quality, algorithmic bias, and adversarial manipulation further complicate implementation. Biased training datasets may skew solvency assessments and create unfair outcomes for specific counterparties or market segments (Raso et al., 2018). Malicious actors could exploit model vulnerabilities to produce misleading outputs or trigger unwarranted risk responses. The opacity of complex AI architectures continues to hinder interpretability, complicating model validation, auditability, and regulatory trust.

Addressing these risks requires robust data governance, continuous model performance monitoring, and investment in explainable AI systems. Institutions must develop resilient architectures capable of adapting to unexpected market shifts and withstanding adversarial attacks. Transparent validation and documentation processes are essential to ensure supervisory confidence and maintain stakeholder trust.

In sum, AI holds significant promise for enhancing financial stability and operational efficiency, but its adoption must be balanced with safeguards against systemic fragility, model bias, and governance failures. Collaborative efforts between institutions and regulators will be crucial to ensure that AI strengthens—rather than destabilizes, the financial system.

## 8. Systemic Risks and Limitations of AI-Enhanced Solvency Models

AI brings substantial advantages to solvency assessment, yet its growing presence in financial institutions also introduces new systemic risks. One of the most pressing concerns is model-induced instability. As more institutions deploy sophisticated AI algorithms, a pattern can be observed: similar models, often trained on comparable datasets, tend to produce nearly identical trading or risk management signals. This uniformity can drive collective behavior, often called herding, which magnifies market movements and can transform small shocks into widespread instability. Imagine several institutions quickly adjusting their capital or trading positions based on outputs from highly correlated AI models. This synchronized response can accelerate asset price declines or trigger liquidity shortages. What makes this risk especially acute is the speed at which AI operates, markets can react far faster than regulators or human decision-makers can intervene. This rapid feedback cycle, often described as an “algorithmic feedback loop”, means that while AI may strengthen solvency at the individual firm level, it can unintentionally create systemic fragility by encouraging uniform decision-making. The

interconnected nature of these AI systems opens new channels for contagion; if one widely used model behaves unexpectedly or contains a flaw, repercussions can ripple across the entire financial system. Clearly, careful oversight of model interdependencies and diversity is essential.

While AI-powered solvency models are undeniably sophisticated, they are not without vulnerabilities. Data bias and adversarial manipulation stand out as significant challenges. Because these algorithms learn from historical data, any embedded societal biases or past market anomalies will likely be reflected—and even amplified—in their assessments (Raso et al., 2018). This can skew solvency classifications and unfairly impact certain entities or market segments. For example, if training data holds bias against specific loan types, the model might underestimate risk for some loans while exaggerating it for others, which distorts capital requirements. There is another layer to consider: adversarial attacks. Malicious actors may deliberately manipulate input data to deceive the model and generate incorrect outputs. These attacks often involve subtle changes that are difficult to spot, but can cause the model to miscalculate risk, making an institution appear healthier than it is or sparking unnecessary alarm. The complexity and opacity of advanced AI models only make these threats harder to detect, raising serious questions about data integrity and the reliability of AI-driven solvency assessments in environments where malicious interference is possible.

To address these vulnerabilities, robust data governance is essential. Continuous monitoring for unusual inputs and the development of more resilient, interpretable AI architectures will be key in safeguarding the integrity of solvency assessments (Buiten, 2019).

## **9. Opportunities for Enhanced Financial Stability and Efficiency**

AI introduces remarkable possibilities for strengthening financial stability and boosting efficiency, especially through real-time monitoring and sophisticated early warning systems. Unlike traditional supervisory frameworks, which typically depend on periodic reporting and can delay the detection of emerging risks, AI systems process enormous volumes of financial data from multiple sources, market feeds, news sentiment, and transactional records, without interruption (Yusupova et al., 2020). With this constant flow of information, regulators and institutions are equipped to spot subtle changes in market conditions, catch unusual trading patterns, or notice early signals of distress in particular sectors or firms. AI-driven anomaly detection algorithms can quickly flag deviations from expected behavior, sending immediate alerts about possible liquidity shortages, deteriorating credit profiles, or sudden market swings. These early warning systems empower timely intervention and help contain risks before they develop into widespread crises. For instance, AI can assess real-time group trading sentiment and adjust risk settings on the fly, which stabilizes markets during abrupt shifts. This proactive stance greatly enhances the ability to prevent and manage crises,

reinforcing the resilience of the financial system. Beyond monitoring, AI offers powerful tools for refining capital allocation strategies within financial institutions. By harnessing advanced analytics, AI models can measure risk with precision across business lines, asset classes, and regions. This detailed understanding enables institutions to allocate capital more strategically, channeling resources toward areas with the most attractive risk-return profiles while staying within regulatory solvency boundaries (Fernandez, 2019). AI can simulate how different capital structures and investment choices affect solvency ratios, helping institutions pinpoint optimal paths for deploying capital that maximize profitability while keeping robust buffers in place. Moreover, scenario analysis powered by AI supports dynamic adjustments to capital allocation as market conditions or regulations shift. So, if an AI model anticipates a higher risk of default in a particular sector, institutions can reallocate capital away from that exposure or set aside additional reserves. This ability to optimize capital management allows for more agile and informed decision-making; it ensures that capital remains both adequate and efficiently deployed, ultimately supporting institutional profitability and broader financial stability.

## 10. Challenges to Integration: Organizational, Regulatory, and Technological Barriers

Integrating AI into capital solvency frameworks is not just a technical challenge, it's a complex process that requires institutions to be truly ready for change. Many financial organizations still rely on legacy IT systems, which were not built to handle the heavy computational demands and vast data sets that AI brings along (Yusupova et al., 2020). To move forward, institutions must invest heavily in updated hardware, software, and data management tools. But technology is not the only hurdle. The shortage of professionals who understand both finance and AI presents a major obstacle; without these experts, it is tough to build, run, and sustain advanced AI models (Blinnikova & Ying, 2020). Many staff members lack skills in AI literacy, model interpretation, and data science, so organizations must invest in extensive training and upskilling programs. Organizational culture adds another layer of complexity; financial environments often lean toward caution and may resist newer, less transparent AI systems. Navigating this resistance calls for effective change management, clear communication, strong leadership support, and a structured approach to weaving AI into daily operations and decision-making are all key.

Now, let us turn to regulatory challenges. Achieving consistent standards for AI in solvency assessments across different regions remains a major issue. AI technologies evolve rapidly, often outpacing the creation of coherent regulatory frameworks; this leaves us with a patchwork of rules (Neznamov, 2020). Each country or region is crafting its own approach to AI regulation, which can lead to inconsistencies in how AI-based solvency models are supervised, validated, or audited. For institutions operating internationally, this fragmented landscape means higher

compliance costs and added operational complexity as they adjust their AI systems to fit various regulatory demands. The absence of global standards for transparency, interpretability, and ethics in AI models also creates barriers to cross-border data sharing and collaborative risk management (Erdélyi & Goldsmith, 2018). Initiatives by international organizations like the BCBS are vital here. By developing shared principles for risk management, data governance, and model validation, these efforts can help create a level playing field, encouraging cooperation across borders and reducing the risk of regulatory loopholes or systemic weaknesses.

At its core, integrating AI into capital solvency ratios means overcoming limitations in both technology and talent. Sophisticated AI solutions demand a strong technological foundation, one that can handle massive amounts of data, perform advanced computations, and support real-time analytics. Yet many financial institutions still operate with siloed systems or outdated technology that simply cannot keep up (Yusupova et al., 2020). Upgrading infrastructure, whether through cloud migration or hybrid architectures, requires significant investment in storage, processing power, and network capabilities. Meanwhile, the shortage of specialized talent remains a real concern. Developing and maintaining AI-driven solvency models calls for professionals skilled in financial risk management, quantitative modeling, data science, and machine learning engineering (Blinnikova & Ying, 2020). Competition for such talent is fierce across industries. This gap slows down AI adoption and limits the complexity of solutions institutions can implement; it also introduces risks around model governance. To address these issues, organizations must invest not only in modernizing technology, but also in comprehensive talent development, upskilling current employees and building partnerships with universities and tech firms.

## 11. Conclusion

Artificial intelligence is transforming the assessment and management of capital solvency ratios, signalling a major shift in financial regulation and risk management. It enhances precision, efficiency, and the ability to perform real-time solvency calculations, allowing institutions to identify risks more effectively. AI-driven models can process vast datasets, uncover subtle patterns, and deliver predictions that surpass those of conventional approaches. This improves dynamic stress testing and enables more strategic capital allocation. At the same time, automation in compliance and reporting streamlines operations and reduces the workload for financial institutions.

Nevertheless, the adoption of AI in the financial sector brings with it new complications. Concerns over data quality, algorithmic bias, and the opacity of complex models underline the importance of strong validation practices and transparent governance. There is also the danger of systemic instability if models converge toward correlated behaviors or are exposed to adversarial attacks, both of which can undermine financial stability. Addressing these risks requires confronting in-

stitutional, regulatory, and technological barriers, including outdated infrastructures, shortages of skilled professionals, and the absence of coordinated international regulation.

To make the most of AI's potential in solvency assessment while mitigating its risks, financial institutions must invest in robust data governance, explainable and auditable AI models, and multidisciplinary teams that integrate technical, risk management, and ethical expertise. They should also prioritize rigorous validation, continuous monitoring, and resilient stress testing while upgrading technological infrastructures to meet the demands of advanced AI systems. Regulators, for their part, should focus on outcome-based and technology-neutral frameworks, promote international harmonization to avoid fragmented oversight, strengthen supervisory capacity, and adopt real-time monitoring tools to capture emerging systemic risks. Safe experimentation with AI, through innovation hubs or sandboxes, can also facilitate responsible adoption.

Looking forward, further research is needed to measure precisely how AI adoption influences different categories of financial risk and related capital requirements across sectors. New AI architectures that enhance transparency and interpretability must be explored, along with methods to detect and resist adversarial manipulation. Understanding how widespread AI deployment might alter systemic risks, such as herding behaviors and market correlations, will be crucial, as will the development of adaptive regulatory frameworks capable of evolving in step with technological advances. Comparative studies across jurisdictions can shed light on different approaches to AI governance and their effectiveness in promoting financial stability.

By pursuing these directions, researchers, policymakers, and institutions can deepen our understanding of how AI interacts with financial solvency and ensure that its integration strengthens, rather than undermines, the resilience of the global financial system.

## Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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