Author Interview: Financial Risk Management Modeling [AI] with Sachin Dave

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By Mike Rizk, Director, The Paper House Publishing

BERKELEY HEIGHTS, NJ, UNITED STATES, October 1, 2025 /EINPresswire.com/ -- Introduction
Sachin Dave, Associate Vice President at Barclays Bank PLC, is a leader in risk management, Basel/CCAR frameworks, and AI-driven modeling, blending finance, machine learning, and tech innovation in global banking.

1. What inspired you to write Financial Risk Management Modeling [AI] and how does your professional journey shape the book's perspective?

> Financial risk management is not about avoiding uncertainty—it's about mastering it. With intelligent modeling and AI, we turn volatility into foresight and resilience."
>
> *Sachin Dave*

Over two decades in financial risk management, I've worked across market risk, counterparty credit risk, and enterprise-scale technology solutions. I noticed that risk modeling was often either too theoretical or disconnected from regulatory and technology realities. My aim was to bridge this gap—combining quantitative rigor with my experience in Basel frameworks, CCAR stress testing, and capital modeling—while showing how AI and modern data architectures can redefine risk management. The book reflects that blend of theory, regulation, and applied machine learning.

2. How do you conceptualize financial risk, and what frameworks do you find most effective for modeling it?
I view risk as the probability of adverse financial outcomes across classes such as market, credit,

liquidity, operational, systemic, and regulatory. Risk is best seen as a property of loss distributions, not a single number. Modeling choices matter: GBM may capture normal price regimes, but fat tails and volatility clustering require GARCH or jump processes. VaR methods—historical, variance-covariance, Monte Carlo—all offer trade-offs, while extreme value theory provides more realism in the tails. I also emphasize PCA for yield curve risk, copulas for credit portfolios, and regime-based correlation modeling to reflect how stress conditions undermine diversification.

3. Basel frameworks and regulatory stress testing continue to evolve. What are the most important shifts practitioners should be aware of?
One major shift is the move from Value-at-Risk to Expected Shortfall under FRTB, as regulators seek to capture not just the probability but the severity of losses. Risk-factor eligibility rules mean banks must now hold additional capital for non-modellable factors, creating a direct link between data quality and capital requirements. Stress testing has matured into a governance exercise where P&L attribution, sensitivity analysis, and back testing play a decisive role in model approval. Basel IV's output floor—ensuring model-based RWAs remain at least 72.5% of standardized levels—limits arbitrage and forces firms to balance supervisory stress testing with their internal economic capital models. This helps address procyclicality, where capital needs rise sharply during downturns.

4. Machine learning is increasingly applied to risk management. Which models and use cases have proven most valuable in your experience?
Machine learning models are highly effective when applied carefully. Random Forests and gradient boosting methods perform well for credit risk and probability of default estimation because they capture nonlinearities and handle class imbalance. Support Vector Machines can define stress boundaries, distinguishing between "safe" and "breach" zones under shocks. Neural networks, particularly LSTMs, capture time dependencies in volatility, while Transformers extend this to cross-asset relationships. Reinforcement learning shows promise for dynamic hedging strategies that adjust to evolving markets. However, adoption must be cautious: adversarial inputs and data drift can undermine reliability. Explain ability tools such as SHAP are essential to ensure transparency and compliance with supervisory expectations.

5. Advanced statistical tools like Bayesian methods, HMMs, and clustering are featured in your book. How do they strengthen risk modeling in practice?
Bayesian networks allow us to model conditional dependencies among risk factors, which is invaluable for scenario propagation under uncertainty. Hidden Markov Models and clustering approaches help identify regime shifts in volatility and liquidity, which inform stress scenarios and hedging decisions. Bootstrapping methods provide confidence intervals around VaR estimates, giving a probabilistic view of model reliability. Cointegration techniques help construct stable hedges that persist through regime changes. These tools add realism to stress testing by acknowledging non-stationary volatility, contagion channels, and complex interdependencies that traditional models often miss.

6. Can you share examples of how banks can integrate AI into their existing risk data architecture and overcome data or parameter limitations?
Integration starts with the data pipeline: diverse inputs feed into a centralized lake, which supports risk engines that calculate VaR, ES, and stress metrics before reporting to dashboards and regulatory systems. AI enhances this pipeline by improving scenario generation, parameter calibration, and real-time monitoring. Where historical data is limited, hybrid approaches that combine Monte Carlo simulation with machine learning predictors help fill gaps. Benchmarking AI outputs against traditional models using error metrics and back testing ensures reliability before results are embedded in official reporting. This staged approach allows banks to adopt innovation without sacrificing control.

7. Model risk is a recurring concern. How should organizations balance innovation with validation and explain ability requirements?
Model risk comes from both incorrect structures and uncertain parameters. Organizations should adopt SR 11-7 style validation, which includes challenger models, sensitivity analysis, out-of-sample testing, and strong governance. Documentation and transparency remain essential. While deep learning models may deliver performance gains, their opacity requires pairing with monitoring systems and explain ability tools such as SHAP. A culture of model accountability is critical: innovation must be matched with equally rigorous validation practices. This ensures stakeholders—from regulators to boards—can trust results, even when advanced AI techniques are applied.

8. Looking ahead, how do you see AI, blockchain, and even quantum computing shaping the future of risk management and regulatory design?
AI will continue to expand its role in real-time monitoring and stress scenario design, merging prescribed shocks with ML-driven simulations. Blockchain adds entirely new dimensions of risk, from smart contract vulnerabilities to decentralized liquidity shocks, which risk frameworks must now incorporate. Quantum computing, while still experimental, offers the potential to accelerate high-dimensional Monte Carlo simulations at the core of risk measurement. Together, these technologies will push banks and regulators toward more adaptive, transparent, and technology-driven systems for safeguarding financial stability. The challenge will be to harness these innovations responsibly without losing the rigor and discipline that define effective risk management.

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