

Review Article

Interdisciplinary Perspectives on Financial Risk: Integrating Economics, Mathematics, and AI for Smarter Investments

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A B S T R A C T

Financial risk management has undergone a profound transformation by integrating insights from economics, mathematics, statistics, and artificial intelligence (AI). While traditional risk assessment techniques, such as Value-at-Risk (VaR), scenario analysis, and stochastic modeling, provide foundational tools for quantifying financial risk, they often fall short in capturing the complex, nonlinear, and dynamic behaviors of modern financial markets. Increasingly, financial institutions operate in environments characterized by high-frequency trading, large-scale data flows, and rapidly shifting market conditions, which require more adaptive, real-time, and data-driven decision-making frameworks. Interdisciplinary approaches that combine economic theory, quantitative modeling, and AI-based analytics offer a more holistic understanding of risk, enabling improved forecasting, anomaly detection, and scenario planning. The integration of machine learning, deep learning, and reinforcement learning techniques allows for the modeling of intricate relationships among market variables, investor behavior, and systemic risk factors, while also supporting dynamic portfolio optimization and automated risk mitigation strategies. This review systematically examines the theoretical foundations, quantitative methodologies, and practical applications of AI in financial risk management, emphasizing how these tools enhance prediction accuracy, portfolio performance, and operational resilience. It also evaluates empirical evidence and case studies demonstrating the effectiveness of AI-augmented approaches in credit, market, liquidity, and operational risk domains. Furthermore, the paper discusses implementation challenges, regulatory considerations, and governance issues, as well as emerging trends and future research directions aimed at building robust, adaptive, and explainable risk management systems.

Keywords: Financial risk, Artificial intelligence, Quantitative finance, Interdisciplinary approaches, Investment strategies

Introduction

Financial markets are inherently complex and uncertain, shaped by a multitude of factors including macroeconomic

conditions, investor sentiment, technological innovations, and geopolitical events. Traditional financial models, such as Value-at-Risk (VaR), Capital Asset Pricing Model

(CAPM), and Black-Scholes option pricing, rely heavily on assumptions of rational behavior, normally distributed returns, and market efficiency.¹ While these models have provided foundational insights, historical financial crises—including the 2008 global financial meltdown—have exposed their limitations, particularly in capturing nonlinear interactions, extreme events, and behavioral anomalies.^{2,3} These shortcomings have motivated the adoption of interdisciplinary approaches that integrate the analytical rigor of economics and mathematics with the computational power of artificial intelligence (AI). Economics offers the theoretical foundation for understanding market dynamics, asset pricing mechanisms, investor incentives, and systemic interactions.⁴ Mathematical and statistical techniques provide the necessary tools to quantify uncertainty, model volatility, estimate correlations, and simulate complex market scenarios.⁵ AI, particularly machine learning, deep learning, and reinforcement learning, enables the extraction of subtle patterns from large, high-dimensional datasets, supports real-time risk monitoring, and allows for predictive analytics that can anticipate market shifts before they materialize.^{6–8} By combining these disciplines, financial institutions can develop adaptive, data-driven, and resilient risk management frameworks. Integrating AI with economic theory and quantitative models not only enhances portfolio optimization and risk assessment but also facilitates more informed investment decision-making under uncertainty. This review explores the synergistic potential of these approaches, examining theoretical frameworks, quantitative methodologies, AI applications, and empirical evidence, while also addressing implementation challenges, regulatory considerations, and future research directions. The goal is to provide a comprehensive perspective on how interdisciplinary methods can strengthen financial risk management, improve decision-making, and foster

more robust, adaptive strategies in increasingly complex financial markets.

Theoretical Foundations

The theoretical foundations of financial risk management are grounded in economics, mathematics, and statistics, which provide the framework for understanding market behavior, asset pricing, and uncertainty.

Economic Theory

Economic principles explain the mechanisms of supply and demand, investor incentives, market equilibrium, and the behavior of financial agents. Classical theories, such as the Efficient Market Hypothesis (EMH) and Capital Asset Pricing Model (CAPM), assume rational decision-making and are fundamental in shaping risk assessment and portfolio management frameworks. Behavioral economics further extends these foundations by accounting for cognitive biases, heuristics, and emotional influences that deviate from strict rationality.¹²

Mathematical and Statistical Models

Mathematics and statistics provide tools to quantify and model risk, including probability theory, stochastic calculus, time series analysis, and multivariate statistics. These techniques underpin traditional risk measures such as Value-at-Risk (VaR), Conditional VaR, and option pricing models, enabling institutions to estimate potential losses, volatility, and correlations across assets.¹³

Integration with Decision Theory

Decision theory connects economic and statistical foundations by offering frameworks for optimal decision-making under uncertainty, including expected utility theory, risk aversion modeling, and multi-criteria optimization. These models guide the allocation of capital, hedging strategies, and dynamic portfolio adjustments.¹⁴

Table 1. Key Economic and Mathematical Approaches to Financial Risk

Approach	Description	Applications in Risk Management
Capital Asset Pricing Model (CAPM)	Measures expected return relative to market risk	Portfolio optimization, risk-adjusted returns
Arbitrage Pricing Theory (APT)	Multi-factor asset pricing based on economic factors	Factor-based portfolio construction
Stochastic Differential Equations	Models asset price evolution and volatility	Option pricing, dynamic hedging
Value-at-Risk (VaR) & CVaR	Quantifies potential losses under given confidence intervals	Regulatory compliance, risk monitoring
Mean-Variance Optimization	Balances expected return against portfolio variance	Risk-adjusted asset allocation

Limitations and Extensions

While traditional models provide a structured approach, they often assume linear relationships, normal distributions, and rational actors, which may not hold during market stress or crises. This has motivated the integration of computational methods, AI, and behavioral insights to capture nonlinearities, adapt to high-frequency data, and account for real-world investor behavior.

Artificial Intelligence in Financial Risk

Artificial intelligence (AI) has transformed financial risk management by enabling dynamic, data-driven, and predictive approaches beyond traditional statistical models. AI techniques, including machine learning (ML), deep learning, and reinforcement learning, allow institutions to process large-scale, high-frequency, and unstructured data, uncover hidden patterns, and improve forecasting accuracy for risk assessment.

Machine Learning Applications

Machine learning (ML) algorithms, including Random Forests, Gradient Boosting, Support Vector Machines (SVM), and Neural Networks, are widely applied in finance to enhance predictive accuracy and decision-making.^{6,15} These models are capable of handling large, high-dimensional datasets, uncovering complex nonlinear relationships, and adapting to evolving market conditions.

Key applications include:

- Credit risk assessment: ML models analyze borrower behavior, transaction history, and alternative data sources to predict defaults and optimize lending decisions.¹⁶
- Market volatility prediction: Advanced algorithms forecast price movements and volatility patterns, supporting portfolio management, hedging, and risk mitigation strategies.¹⁷
- Fraud detection and anomaly identification: ML techniques detect irregular transactions and suspicious

patterns in real-time, enhancing operational and cybersecurity risk management.¹⁸

Deep Learning and Big Data

Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are increasingly applied in finance to extract insights from high-frequency trading data and unstructured sources, including news articles, social media posts, and financial reports.^{19,20} These models excel at capturing complex, nonlinear patterns and temporal dependencies, enabling more accurate market trend forecasting, sentiment analysis, and anomaly detection.

By integrating big data analytics with deep learning, financial institutions can process massive datasets in real-time, detect emerging risks, and generate predictive signals that enhance portfolio optimization, trading strategies, and risk monitoring. This combination allows for more adaptive and data-driven decision-making in fast-moving and information-rich financial markets.

Reinforcement Learning in Investment Strategies

Reinforcement learning (RL) has emerged as a powerful tool for dynamic portfolio management, where agents learn optimal investment strategies by interacting with simulated or real market environments.²¹ By combining AI with stochastic control theory, RL models continuously adapt to evolving market conditions, learning from both rewards (gains) and penalties (losses) to optimize long-term returns.

Applications include asset allocation, algorithmic trading, and risk-adjusted portfolio optimization, where RL agents can explore multiple strategies, respond to volatility, and adjust positions in real-time. This approach enables adaptive, data-driven decision-making that outperforms static models in complex, uncertain, and high-frequency markets.

Table 2.AI Applications in Financial Risk Management

AI Technique	Description	Use Case in Finance
Machine Learning (ML)	Supervised and unsupervised learning models	Credit scoring, fraud detection, volatility prediction
Deep Learning (DL)	Neural networks for complex pattern recognition	Sentiment analysis, high-frequency trading
Reinforcement Learning (RL)	Learning optimal strategies via reward-driven simulation	Dynamic portfolio management
Natural Language Processing (NLP)	Analyzing textual data for insights	News sentiment analysis, market signal extraction

Interdisciplinary Integration

Interdisciplinary integration in financial risk management combines economics, mathematics, statistics, and artificial intelligence (AI) to create more robust, adaptive, and data-driven strategies. Each discipline contributes unique strengths.

- Economics provides theoretical foundations for understanding market behavior, asset pricing, and investor incentives.
- Mathematics and statistics offer quantitative tools for modeling uncertainty, volatility, correlations, and extreme events.
- AI and machine learning enable the analysis of high-dimensional, high-frequency, and unstructured data, uncovering patterns that traditional models may miss.

By integrating these fields, financial institutions can develop hybrid frameworks that improve predictive accuracy, optimize portfolios, and enhance risk assessment across credit, market, liquidity, and operational domains. This approach also supports adaptive decision-making, allowing strategies to adjust dynamically to evolving market conditions, behavioral patterns, and systemic risks.

Combining Economics, Math, and AI

Interdisciplinary risk models integrate.

- Economic insights: Macro factors, behavioral biases, market microstructure
- Mathematical models: Stochastic processes, copulas, optimization
- AI analytics: Pattern recognition, predictive modeling, automated decision-making.²²
- This combination improves prediction accuracy, portfolio resilience, and proactive risk management.

Applications in Portfolio Management

The integration of quantitative methods, behavioral insights, and AI has significantly enhanced portfolio management.

Financial institutions now leverage machine learning and deep learning algorithms to optimize asset allocation, forecast returns, and manage risk dynamically. These models can process large volumes of market, economic, and alternative data, enabling more precise portfolio diversification, volatility control, and risk-adjusted performance optimization.

Behavioral finance insights also inform portfolio strategies by accounting for investor biases, sentiment, and herd behavior, helping managers anticipate market overreactions and correct for systematic errors in decision-making. Additionally, reinforcement learning techniques allow portfolios to adapt in real-time to changing market conditions, optimizing allocation through trial-and-error learning while considering risk constraints and reward objectives.

Risk-Adjusted Portfolio Optimization

AI-enhanced optimization integrates predictive signals with classical mean-variance or risk parity methods. This allows portfolios to adapt dynamically to evolving market conditions and investor risk preferences.^{14,21}

Hedging and Derivative Strategies

Interdisciplinary approaches improve hedging using derivatives, particularly under complex market scenarios or tail events. ML models can predict correlations and volatilities that traditional models might underestimate.^{6,17}

Real-Time Risk Monitoring

Big data and AI enable continuous monitoring of portfolio exposure, market events, and investor sentiment, enhancing proactive risk mitigation.^{19,20}

Empirical Evidence and Case Studies

Empirical studies and case analyses provide concrete evidence of how interdisciplinary and AI-driven approaches improve financial risk management. For example, machine learning models have been shown to predict credit defaults more accurately than traditional logistic regression models,

Table 3.Example Framework

Component	Role in Risk Management	Techniques Applied
Economic Theory	Market drivers, investor incentives	CAPM, APT, behavioral finance
Mathematical Models	Quantification, volatility, correlation	VaR, CVaR, SDEs, optimization
Artificial Intelligence	Real-time analytics, prediction, adaptive strategies	ML, DL, RL

Table 4.Interdisciplinary Integration for Smarter Investments

Component	Role in Risk Management	Techniques Applied
Economic Theory	Market drivers, behavioral biases	CAPM, APT, Behavioral Economics
Mathematical Models	Quantification of risk, optimization	SDEs, VaR, CVaR, Portfolio Optimization
Artificial Intelligence	Real-time analytics, predictive modeling	ML, DL, RL

while deep learning techniques have successfully forecast market volatility and detect anomalies in high-frequency trading data.

Case studies from banks, hedge funds, and asset management firms demonstrate the practical benefits of AI-enhanced portfolio management, such as improved risk-adjusted returns, dynamic asset allocation, and real-time monitoring of operational and market risks. Additionally, research integrating behavioral finance highlights how accounting for investor biases can prevent systematic errors and enhance decision-making during market stress.

Empirical studies confirm that integrating interdisciplinary approaches enhances predictive performance and reduces tail risk exposure compared to single-discipline models^{6,16,19}

Challenges and Limitations

Despite the significant advances in AI, machine learning, and interdisciplinary approaches, financial risk management faces several challenges and limitations.

- **Data Quality and Availability:** Accurate modeling depends on large, high-quality datasets, yet missing, biased, or unstructured data can compromise predictions and decision-making.⁶
- **Model Interpretability:** Complex AI and deep learning models often function as “black boxes,” making it difficult to explain predictions to regulators, stakeholders, and decision-makers.⁸
- **Overfitting and Model Risk:** Advanced algorithms can overfit historical data, leading to poor out-of-sample performance and potential misestimation of risk.¹⁷
- **Behavioral and Systemic Factors:** Models may fail to fully capture investor behavior, market psychology, or systemic shocks, particularly during extreme events.
- **Regulatory and Ethical Constraints:** Compliance with financial regulations, ethical considerations, and governance standards is critical, but rapidly evolving AI applications may outpace regulatory frameworks.²²
- **Implementation Costs and Complexity:** Integrating interdisciplinary and AI-driven systems requires substantial investment in technology, expertise, and infrastructure, which may limit adoption, especially for smaller institutions.

Emerging Trends

Financial risk management is increasingly shaped by advanced AI, big data analytics, and behavioral insights, driving the development of more adaptive and resilient frameworks. Emerging trends include the adoption of explainable AI (XAI) to ensure model transparency and regulatory compliance, the integration of alternative data sources such as social media and transaction data to enhance predictive accuracy, and the implementation of real-time

risk monitoring using high-frequency data. Hybrid modeling approaches that combine classical quantitative methods with machine learning and behavioral insights are gaining prominence, while reinforcement learning enables dynamic portfolio optimization and adaptive decision-making. Additionally, there is a growing focus on sustainable and ESG risk assessment, incorporating environmental, social, and governance factors into AI-driven risk models to capture broader systemic risks. Collectively, these trends highlight a shift toward data-rich, transparent, and intelligent risk management strategies that can respond dynamically to complex and rapidly changing financial markets.

- **Explainable AI (XAI):** Making ML models interpretable for regulators and investors.²⁰
- **Hybrid AI-Mathematical Models:** Combining ML with stochastic or optimization models for robust risk assessment.²²
- **Alternative Data Integration:** Using satellite data, social media, and news for predictive risk modeling.¹⁹
- **Interdisciplinary Risk Labs:** Collaborative environments for testing AI, economic, and mathematical models in real-time.²²

Conclusion

The integration of economics, mathematics, and artificial intelligence (AI) represents a transformative approach to modern financial risk management, combining theoretical rigor, quantitative modeling, and data-driven adaptability. By leveraging economic principles, institutions can better understand market dynamics, investor behavior, and incentive structures, while mathematical and statistical techniques provide robust frameworks for modeling uncertainty, volatility, and correlations. AI, particularly machine learning, deep learning, and reinforcement learning, enhances predictive accuracy, supports dynamic portfolio optimization, and enables real-time monitoring of credit, market, liquidity, and operational risks. Interdisciplinary models facilitate adaptive decision-making, allowing financial institutions to respond effectively to complex, high-frequency, and rapidly evolving market conditions. They also support the incorporation of behavioral insights and alternative data sources, improving risk assessment and investment strategies. However, challenges remain, including data quality and availability, model interpretability, computational complexity, regulatory compliance, and ethical considerations. Addressing these limitations is crucial to ensure transparency, reliability, and resilience in AI-driven risk management frameworks. Future research should focus on the development of hybrid AI-mathematical models, integration of explainable AI (XAI) to improve interpretability and regulatory compliance, and enhanced cross-disciplinary collaboration to combine economic theory, computational techniques, and behavioral

finance insights. Such efforts will further optimize risk-adjusted returns, strengthen adaptive investment strategies, and enhance the resilience of financial systems against both systemic and behavioral risks. Ultimately, the convergence of these disciplines offers a holistic, robust, and forward-looking approach to navigating the complexities of contemporary financial markets.

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