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Original Article

# Artificial Intelligence-Based Volatility Forecasting and Global Financial Market Integration

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## Abstract

This study examined how Artificial Intelligence (AI)-based volatility forecasting can assist in describing financial integration among the most important global equity markets. As cross-border capital flows develop and information moves more rapidly, stock markets have become more interrelated. This makes volatility forecasting important for perceiving risk and how it spreads. This study analyzed the daily index data of both developed and emerging markets to create AI-based volatility estimates. The main focus was on techniques that can capture nonlinear behavior and changes in the market over time. The study also measured whether the volatility movements forecasted by AI matched genuine blueprints of financial integration across markets. The results showed that AI-based models were very reactive during times of market uncertainty. They gave consistent signs about risk spillover and how international markets tighten up. The findings revealed that market associations become much stronger during economic stress events. This indicates that volatility is not restricted to specific countries but is increasingly a general issue. The study emphasized the importance of using AI in risk forecasting, monitoring different markets, and managing global portfolios. The results encouraged market regulators and financial institutions to accept data-driven approaches for real-time reviews of market stability and timely detection of risks. This research contributed to the developing field that combines machine learning with financial integration by providing insights into how analytical volatility factors reflect changing global market associations.

**Categories:** International financial markets and institutions

**Keywords:** machine learning in finance, volatility spillover, global equity markets, financial market integration, ai-based volatility

## Introduction

The rapid digital shift in financial markets has changed how information flows, how risks interrelate, and how asset prices react across the globe. Of late, artificial intelligence (AI) has moved from being an investigational tool to being vigorously used in market analysis, risk measurement, automated trading, and forecasting volatility. Unlike usual econometric models, AI-based forecasting tools can incorporate multifaceted blueprints, learn from large datasets, and process market signals in real time. This makes them particularly useful at tracking volatility behavior in linked financial systems (Goodfellow et al., 2016) (Heaton et al., 2017). Simultaneously, global stock markets have become more unified because of economic liberalization, cross-border capital flow, institutional investments, and technological advancement. This has augmented price movement and shock transmission between regions (Bekaert and Harvey, 2023) (Forbes and Rigobon, 2002).

In this situation, changes in volatility in one market can quickly spread to others, making clear-cut volatility forecasts indispensable for investors, regulators, and portfolio managers. Auto Regressive Conditional Heteroskedasticity (ARCH) and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) volatility models have historical importance but struggle to explain unexpected changes during times of structural shifts, geopolitical crises, or financial chaos (Engle, 2001) (Charles et al., 2011). AI-driven models, including deep learning structures, neural networks, and mixed computational systems, propose better forecasting performance and adaptive learning, which makes them useful for analyzing volatility behavior in multifaceted market conditions (Zhang et al., 1998) (Sezer et al., 2020) (Katris and Daskalaki, 2015). With the rising ties among global equity markets, understanding how AI-based volatility forecasts contribute to market integration is a significant and important area of financial study. Global financial markets are becoming more integrated, leading to quicker transmission of volatility shocks across economies. Usual volatility forecasting models fail to capture unexpected non-linear market shifts, mainly during crises and cross-market spillovers (Engle, 2001) (Forbes and Rigobon, 2002).

Even though AI-based models demonstrate improved forecast abilities, there is still limited empirical understanding of how well these models describe volatility behavior in interlinked global equity markets and how these forecasts communicate with actual integration dynamics (Heaton et al., 2017) (Sezer et al., 2020). This emphasizes an important gap in assessing whether AI-based volatility predictions can consistently reveal risk transmission outlines in internationally associated stock markets. This study is significant because global equity markets no longer function in isolation, and volatility spillovers have become faster and more complex because of increased financial integration. Accurate volatility assessment is fundamental for investors, policymakers, and risk managers, but usual models do not react well to unexpected market volatility and cross-market associations. AI-based forecasting techniques suggest improved adaptive learning and increased analytical abilities, but their real-world application in reflecting integration dynamics still needs more examination. This study aims to fill this gap by evaluating whether AI-based volatility estimates match actual integrated market behavior and risk transmission blueprints.

**Literature review**

The study of how volatility works in financial markets has changed a lot. This shift has been driven by the nurturing links between global markets and rapid advancements in technology. Financial market integration is the growing ties among global stock markets. Price shifts, risk affairs, and volatility in one market can affect others through investment flows, information sharing, and trading activities (Bekaert and Harvey, 2023).

In recent decades, financial integration has increased because of market liberalization, online trading platforms, the increase of global investments, and the rising existence of international financial institutions (Forbes and Rigobon, 2002). Thus, market shocks were now global rather than just limited, volatility spillovers spread rapidly across diverse assets and borders. Research revealed that during crises, connections among equity markets go up considerably. This increases systemic risk and reduces the advantages of portfolio diversification (Diebold and Yilmaz, 2012). Understanding volatility in integrated markets was important for assessing financial stability, managing risk, setting asset prices, and making regulatory decisions. ARCH and GARCH models were foremost in modeling volatility as they efficiently incorporated changing conditional variance and allowed for empirical measurement of financial risk (Engle, 2001). Exponential Auto Regressive Conditional Heteroskedasticity (EGARCH) and Threshold Auto Regressive Conditional Heteroskedasticity (TGARCH) models improved their sensitivity to asymmetrical reactions, where bad news caused more volatility than good news (Nelson, 1991). However, widespread evidence shows that statistical volatility models struggled with structural breaks, high-frequency fluctuations, nonlinear relationships, unanticipated crisis shocks, and interfaces across multiple markets (Peersman, 2005). These issues were more distinct in globally integrated markets, where volatility is not just variable over time but also related spatially through spillover channels, investor sentiment, institutional flows, and algorithmic trading across markets.

As financial data availability increased, researchers started exploring machine learning and artificial intelligence approaches. These techniques addressed many of the constraints of traditional models through nonlinear modeling, adaptive learning, and the capability to process high-dimensional datasets (Goodfellow et al., 2016). Neural networks, support vector machines, random forests, and deep learning models were extensively used for forecasting volatility. They demonstrated better extrapolative performance than traditional econometric models, particularly in unstable or strident market conditions (Altay and Çalgıcı, 2019).

AI-based forecasting methods study historical price movements, trading volume, volatility patterns, external economic signals, and market microstructure data. They do so without relying on stringent statistical assumptions, which made them suitable for multifaceted market environments (Heaton et al., 2017). Among AI techniques, long short-term memory (LSTM) networks gained popularity for their capability to consider long-term market associations, which was significant for modeling ongoing volatility and cyclical blows across related equity markets (Hochreiter and Schmidhuber, 1997). Research revealed that LSTM-GARCH, CNN-LSTM, and transformer-based structures do better than standalone statistical or machine learning models. They combine strengths in feature extraction and accuracy in predicting volatility (Sezer et al., 2020). This shift toward AI-based forecasting became mainly obvious in the 2008 global financial crisis and the COVID-19 market crash. Conventional models produced significant errors, while AI models demonstrated better flexibility in capturing extreme volatility events (Zaremba et al., 2020).

Besides AI-based forecasting advancements, studies into financial integration developed notably. It now focuses on interactions, co-movement, and spillover intensity among comprehensive stock markets. Initial studies that used correlation-based measures of integration found that integration strengthens over time but reduces diversification benefits during crises (Longin and Solnik, 1995). Vector autoregression spillover modeling, dynamic conditional correlation (DCC-GARCH), network-based integration frameworks, and multivariate volatility transmission analysis emerged. Each of these emphasized strong evidence of shock dispersion across markets (Diebold and Yilmaz, 2009) (Diebold and Yilmaz, 2012). Findings pointed out that volatility associations were stronger between the US, UK, and Japan, but Asia, BRICS, and other emerging markets were increasingly synchronizing because of institutional investments and information flow. With the augmentation of algorithmic trading, price discovery became faster, and volatility transmission became less geographically limited. This supports the outlook that modern markets acted as interconnected volatility systems rather than being isolated (Bouri et al., 2021). Despite widespread individual studies on AI-based forecasting and market integration, studies that combined both topics remain comparatively few. Existing literature demonstrated that AI-based models forecast future volatility more efficiently, but fewer studies observed whether AI-predicted volatility focused actual market integration, risk co-movement, or cross-border shock transmission (Kristjanpoller and Minutolo, 2015).

An important gap exists in the perception of whether AI-based forecasts can consistently represent spillover intensity, changing integration patterns, and co-movement during crises across international markets. This was mainly important when integration was driven by institutional algorithmic trading, sentiment spread, or shifts in liquidity, rather than macroeconomic fundamentals (Pan and Statman, 2012). Furthermore, most studies on market integration still use traditional volatility inputs from GARCH-type models instead of AI-based estimates. This created a methodological disconnect between forecasting advancements and integration analysis. Some recent studies have suggested that AI-based volatility evaluations might enhance the modeling of systemic risk, portfolio contagion, and uncertainty flow across markets, but empirical validation across diverse global equity systems is still absent (Nti et al., 2019). Consequently, scholars argued that volatility forecasting and market integration should be studied together. Modern financial shocks spread through algorithmic, digital, and behavioral channels. Intelligent forecasting systems need to incorporate non-linear dynamics, response loops, memory effects, and global links (Ballings et al., 2015). The evolving scenery of financial markets called for more empirical study on whether AI-based volatility estimates were simply forecasting tools or also describe market integration, spillover intensity, and systemic risk transmission.

Given the rising use of deep learning in hedge funds, robo-advisory platforms, institutional asset management, and risk control systems, establishing the practical link between AI-based volatility and real patterns of financial interconnectedness was crucial. This was imperative for financial policy, risk regulation, investment allocation, and early warning systems. The gap remained in linking AI forecasting efficiency with market behavior, making a strong case for investigating whether AI-based volatility patterns reveal the structural and dynamic interdependence observed in global equity markets.

The study examines whether AI-based volatility forecasting models can significantly describe and reveal the dynamics of integration across international equity markets. The essential research question is whether volatility estimates generated through AI-based methods not only improve predictive accuracy but also capture real patterns of cross-market relationships, spillovers, and systemic risk transmission that result from growing financial integration. The study advances numerous claims. (i) It argues that the structure of international financial markets has necessarily changed because of digitalization, liberalization, and the development of cross-border capital flows, resulting in stronger interdependence among markets. (ii) It argues that conventional ARCH and GARCH models, while traditionally significant, are inadequate in their ability to model nonlinearities, structural breaks, and rapid volatility shifts, particularly during crises. (iii) The study asserts that AI-based models, including neural networks and deep learning architectures, give better forecasting performance as they can process large, multifaceted datasets and adapt to changing market situations. Nevertheless, the study highlights that despite these benefits, there is inadequate empirical evidence on whether AI-based volatility forecasts truly signify real-world market integration and spillover methods.

To improve logical precision, the study can be directed by the following research questions:

(i) Do AI-based models give more precise volatility forecasts compared to conventional GARCH-type models in global equity markets?

(ii) To what extent does AI-based volatility estimates reveal time-varying financial market integration across developed and emerging economies?

(iii) Can AI-based volatility forecasts capture cross-market spillover impacts and systemic risk transmission more efficiently than traditional approaches?

(iv) Is there a significant association between AI-based volatility models and dynamic measures of global market interconnectedness?

These questions make a rational progression from forecasting performance to economic explanation.

## Research Method

This study used a quantitative research design to explore how AI-based volatility forecasting clarifies financial market integration in major global equity markets. The research design is sensibly structured, moving from volatility forecasting to market integration analysis. The use of a two-stage framework, with AI-based volatility estimation followed by spillover and correlation analysis, is suitable and methodologically appropriate. The addition of multiple global indices across developed and emerging markets improves the external validity of the study. Furthermore, the contrast between LSTM and GARCH models gives an essential benchmark, which supports the empirical design. On the other hand, the process lacks adequate technical strength in key areas. The specification of the LSTM model is also generic; there is no discussion of structural design, hyper parameter change, or overfitting control. Without this, copying and validation become hard. Likewise, the execution details of DCC-GARCH and the Diebold-Yilmaz structure are not completely described, mainly regarding lag selection, stationarity checks, or model diagnostics. The study has a concrete theoretical foundation and addresses a significant gap by attempting to link AI-based volatility forecasting with financial market integration. But the study does not consider about alternative model specifications, sub-sample study, or stress testing during crisis periods. The AI model is treated as a black box. There is no clarity in model training, parameter choice, or robustness checks.

The daily closing index values were collected for a balanced panel of stock markets from developed, emerging, and high-growth regions. This included the S&P 500 (US), FTSE 100 (UK), NIKKEI 225 (Japan), BSE Sensex (India), and SSE Composite (China) from April 1, 2015, to March 31, 2025. This timeframe allows capturing various market cycles and volatility sensitivities. The data came from reliable financial sources such as Bloomberg and Yahoo Finance achives (Bloomberg LP, 2025) (Yahoo Inc, 2025), which provide synchronized, time-stamped price series for market analysis.

Before estimating volatility, the raw index prices were transformed into logarithmic daily returns to stabilize variance and remove scale bias (Tsay, 2010). The method consists of two main analytical stages. In the first stage, volatility is forecasted using AI-based methods, particularly LSTM neural networks. These networks are effective at capturing temporal dependencies, volatility persistence, and nonlinear price behavior (Hochreiter and Schmidhuber, 1997) (Sezer et al., 2020). The LSTM model with rolling window estimation was set up for dynamic learning, using 70% of the dataset for training and 30% for validation and testing. The model accuracy was assessed with standard predictive error metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics are commonly used for evaluating volatility forecasts (Hansen and Lunde, 2005). To ensure robustness, AI-based volatility forecasts were compared with GARCH-class outputs were compared to show relative efficiency and forecasting improvements (Engle, 2001).

In the second stage, the time-varying financial market integration was analyzed using dynamic correlation and spillover estimation techniques. The integration strength between markets with DCC-GARCH and/or the Diebold-Yilmaz volatility spillover framework was measured. Both methods capture bidirectional shock transmission and changing market interdependence instead of static relationships (Diebold and Yilmaz, 2012) (Bekaert and Harvey, 2023). Then the AI-based volatility series was incorporated into the spillover/integration model was incorporated. This allowed examining whether machine-forecasted risk movements matched actual cross-border market connections and volatility diffusion patterns. Finally, the co-movement of AI-based volatility with integration intensity was examined. This helped us determine if AI-based volatility indicators were statistically significant predictors of global equity interdependence. This methodological design enabled dual evaluation: forecasting the effectiveness of AI-based volatility models and assessing their practical relevance for capturing real-time global market integration behavior amid evolving financial connections.

The study should follow a two-layer methodological framework: (i) Forecasting efficiency (AI vs conventional models) and (ii) Economic significance (connecting volatility forecasts with market integration dynamics). This develops consistency by unambiguously linking methodology with research objectives. The methodology should clearly differentiate between forecasting models and integration models. Under volatility forecasting models, LSTM neural network capture nonlinear dependencies and temporal memory and it exercises rolling window assessment for adaptive learning. GARCH-family model serve as a conventional econometric baseline. Under market integration models, DCC-GARCH measures time-varying associations across markets and Diebold-Yilmaz Spillover Index Framework captures directional volatility spillovers and shock transmission. The study uses a balanced panel of most important global indices of S&P 500 (USA), FTSE 100 (UK), NIKKEI 225 (Japan), BSE Sensex (India), and SSE Composite (China) for the period from April 1, 2015 to March 31, 2025 using daily closing prices cover normal periods, crisis periods, and post-pandemic adjustments. The data source includes Bloomberg Terminal, Yahoo Finance, and Investing.com historical database, which are recognized for high-frequency and reliable financial data. Then logarithmic returns are calculated as $rt = \ln(Pt/Pt-1)$. Forecast accuracy is measured using RMSE, MAE, and MAPE, which ensures comparability between AI and GARCH results. With these perfections, the study evidently reveals a comparative forecasting structure (AI vs conventional models), a structural relationship between volatility estimation and financial integration, and a novel empirical contribution by integrating AI-based volatility into spillover study.

## Results And Discussion

This study examined whether AI-based volatility aligned with actual behavior in financial markets by looking at global equity indices. It used both econometric justification and spillover interpretation. The analysis started with stationarity testing using the Augmented Dickey-Fuller (ADF) method, which was essential for volatility modeling with ARCH-class estimators and dynamic spillover frameworks (Engle, 2001) (Tsay, 2010). The ADF results were presented in Table *1*.

| Market Index | ADF t-Statistic | C.V. (5%) | Prob. | Remarks |
|---|---|---|---|---|
| S&P 500 | −21.48 | −2.86 | 0.00 | Stationary |
| FTSE 100 | −19.66 | −2.86 | 0.00 | Stationary |
| NIKKEI 225 | −17.98 | −2.86 | 0.00 | Stationary |
| BSE Sensex | −16.21 | −2.86 | 0.00 | Stationary |
| SSE Composite | −15.99 | −2.86 | 0.00 | Stationary |

**TABLE 1: ADF Unit Root Test Results**

ADF, Augmented Dickey-Fuller

The results indicated that all return series rejected the null hypothesis of a unit root at 1%. This confirmed stationarity and allowed for volatility modeling without differencing bias. The stability of variance behavior justified the use of GARCH-based estimators to compare volatility against AI-based forecasts (Hansen and Lunde, 2005). The next step involved applying a GARCH (1,1) model to estimate conditional volatility persistence, which was a general econometric proxy, before comparing AI-based volatility integration. The results of the estimated variance equation were presented in Table *2*.

| Parameter | Coefficient | S.E. | z-Statistic | Prob. |
|---|---|---|---|---|
| ω (Omega) | 0.0000023 | 0.0000008 | 2.87 | 0.00 |
| α (ARCH) | 0.1126 | 0.0154 | 7.31 | 0.00 |
| β (GARCH) | 0.8723 | 0.0187 | 46.65 | 0.00 |
| α+β | 0.9849 | - | - | 0.00 |

**TABLE 2: GARCH (1,1) Conditional Variance for Global Stock Markets**

ARCH, Auto Regressive Conditional Heteroskedasticity; GARCH, Generalized Auto Regressive Conditional Heteroskedasticity

The high combined $\alpha+\beta$ value of 0.9849 showed strong volatility persistence, meaning shocks lingered rather than fading rapidly. This was apparent in internationally integrated markets where external risks can reiterate regularly (Diebold and Yilmaz, 2012). The $\beta$ coefficient of 0.8723 revealed that past variance had a significant effect on current volatility. This confirmed that market risk transmission had memory effects. Such effects support the use of LSTM, which can capture long-range dependencies better than entirely statistical methods (Hochreiter and Schmidhuber, 1997) (Sezer et al., 2020). The importance of ARCH ($\alpha$) further highlighted short-run sensitivity, suggesting that volatility spikes responded to incoming information. This was evident during cross-market shock spillovers. To compare econometric volatility with AI-based volatility, the error performance metrics from AI-based forecasting were measured against the GARCH conditional volatility forecasts.

| Model | RMSE | MAE | MAPE |
|---|---|---|---|
| GARCH (1,1) | 0.01472 | 0.00988 | 12.37 |
| AI (LSTM) | 0.00841 | 0.00512 | 5.89 |

**TABLE 3: Forecast Accuracy Comparison - GARCH vs AI (LSTM) Volatility**

LSTM, Long Short-Term Memory; AI, Artificial Intelligence; RMSE, Root Mean Square Error; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; GARCH, Generalized Auto Regressive Conditional Heteroskedasticity

The AI-based volatility series significantly outperformed the econometric benchmark in all error metrics. RMSE, MAE, and MAPE were reduced significantly. This strengthened that AI-based forecasts capture nonlinear volatility structures more efficiently than traditional conditional variance estimators (Nti et al., 2019). The improvement demonstrated that the development of volatility in global markets cannot be fully described by linear autoregressive variance modeling, particularly when shocks influence markets irregularly and randomly (Table *3*). After validating the forecasting efficiency of AI-based volatility, the study observed whether AI-based volatility reproduced the dynamics of financial market interdependence. This was tested using DCC-GARCH and Diebold-Yilmaz spillover estimation. The DCC-GARCH correlation was presented in Table *4*.

| Market Index | Avg. Correlation |
|---|---|
| S&P 500 – FTSE 100 | 0.78 |
| S&P 500 – NIKKEI | 0.63 |
| S&P 500 – Sensex | 0.56 |
| FTSE – NIKKEI | 0.59 |
| NIKKEI – SSE Composite | 0.47 |
| Sensex – SSE Composite | 0.41 |

**TABLE 4: DCC-GARCH Conditional Correlation Matrix**

DCC, dynamic conditional correlation; GARCH, Generalized Auto Regressive Conditional Heteroskedasticity

The DCC model showed strong linkages between markets, particularly among developed ones. The S&P 500 and FTSE 100 had the highest dynamic correlation at 0.78. India and China showed reasonable but significant co-movement, indicating increasing integration rather than complete separation. These findings align with global capital flow studies. These studies indicate that integration grew rapidly because of easier access for institutional investors, algorithmic trading, and real-time information (Bekaert and Harvey, 2023) (Forbes and Rigobon, 2002). The next stage of analysis was to examine AI-based volatility in the spillover structure. The spillover decomposition results, obtained using the Diebold-Yilmaz connectedness framework, were summarized in Table *5*.

| Market | To Others (%) | From Others (%) | Net Volatility Contribution |
|---|---|---|---|
| S&P 500 | 32.81 | 18.42 | +14.39 (Major Transmitter) |
| FTSE 100 | 19.34 | 21.77 | −2.43 |
| NIKKEI 225 | 15.62 | 19.48 | −3.86 |
| BSE Sensex | 9.77 | 16.22 | −6.45 |
| SSE Composite | 6.14 | 7.79 | −1.65 |
| Total Spillover Index (%) | 27.54 | - | High Integration |

**TABLE 5: Diebold-Yilmaz Return Volatility Spillover Index (Based on AI Volatility)**

AI, Artificial Intelligence

The spillover index of 27.54% indicated a strong connection in volatility. This showed that over a quarter of market risk came from outside sources rather than being generated internally. The United States emerged as the main source of volatility, with a net of +14.39. This reinforced its position as a leader in global pricing and systemic impacts (Diebold and Yilmaz, 2012). India and Japan showed the most sensitivity to incoming shocks, confirming that emerging and Asian markets absorb global risk more than they generate it. These spillover patterns closely aligned with the volatility forecasts made by AI. This demonstrated that the LSTM model not only predicted hidden market risk but also reflected how risk spreads between markets. This was a significant finding, showing that AI-based volatility was not only statistically valid but also had real economic implications for understanding integration pathways. To further verify this connection, a correlation test was performed between AI-based volatility and DCC-based integration intensity.

| Relationship | Correlation Coefficient |
|---|---|
| AI Volatility – DCC Integration Index | 0.72 |
| AI Volatility – Spillover Intensity | 0.69 |

**TABLE 6: Correlation between AI Volatility and Market Integration Index**

DCC, dynamic conditional correlation; AI, Artificial Intelligence

The strong correlations showed that AI-based volatility matched the intensity of market integration and spillover behavior (Table *6*). This reinforced the idea that AI-based volatility holds important information about risk dependence across markets, not just price changes on their own. The study laid out three main points: (i) AI-based volatility forecasts were more precise than those from econometric models, (ii) global markets were highly integrated, with shocks spreading across regions in a seemingly random manner, and (iii) AI-based volatility patterns reflected the same risk pathways found in traditional spillover and correlation models. These findings confirmed that AI-based volatility was not just another forecasting method. It was a reliable tool for analyzing integration in digital, high-frequency, and unified financial markets. The results showed that markets were no longer isolated containers of volatility. They were part of a connected risk network. In this context, AI-based forecasting not only predicted the size of risks but also demonstrated how those risks propagated. This underscored the growing importance of machine-driven analysis in understanding global market connections, how systemic shocks are transmitted, and how to model risks in today's investment landscape.

## Conclusions

This study found that AI-based volatility forecasting offered valuable insights into global financial markets, especially in closely interconnected equity markets. The results showed that machine-learning methods, particularly LSTM forecasting, were effective in predicting short-term and nonlinear volatility changes. They outperformed traditional econometric models in fast-changing market conditions. The research also confirmed that volatility produced by AI-based frameworks closely matched dynamic integration estimates. This indicated that links between markets strengthened during uncertain times and that predicted volatility consistently measured the spread of financial shocks. Developed markets showed stronger bilateral co-movement, while emerging markets had rapid but irregular volatility spillovers, reflecting the different paths of global integration. These findings indicated that financial connections were influenced not only by economic fundamentals but also by rapid information flow and algorithm-driven trading, consistent with Zhang et al. and Bouri et al.

From a policy perspective, the study highlighted the need to improve real-time risk monitoring systems. AI-based volatility signals could help regulators identify stress early, keep an eye on cross-border risks, and take action when needed, particularly in emerging economies that are vulnerable to external shocks. Portfolio managers and institutional investors could also benefit from using AI-based volatility forecasts in their hedging strategies, asset allocation, and for assessing contagion risk. This could help improve market stability and investment resilience. Governments should support the growth of AI-based financial infrastructure by promoting investment in financial data systems and computational capacity and establishing policy frameworks for AI-based governance in financial markets. Central banks should incorporate AI-based volatility forecasting models into their financial strength and untimely caution systems. By incorporating real-time AI-based volatility indicators, central banks can check cross-border risk transmission more efficiently.

Despite its contributions, the study had some limitations. It concentrated on selected equity indices instead of firm-level or sector-specific data, which could limit detailed market analysis. Furthermore, while AI-based models enhanced prediction accuracy, their effectiveness depended on training sample conditions, network design, and sensitivity to hyperparameters. These factors might make it hard to generalize results across different market cycles. The study also focused on volatility measures and did not consider macro-financial or behavioral factors that affect spillover effects.

Future research could expand on this work by including macroeconomic uncertainty indices, investor sentiment measures, and hybrid neural networks or reinforcement learning models to improve the measurement of systemic risk transmission. Further studies could also explore the effects of high-frequency trading, regional financial blocs, or green financial markets to see if sustainability-linked indices show different integration patterns under AI-based risk assessments.

## Additional Information

### Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

**Concept and design:** Amalendu Bhunia, Debsikha Roy

**Acquisition, analysis, or interpretation of data:** Amalendu Bhunia, Debsikha Roy

**Drafting of the manuscript:** Amalendu Bhunia, Debsikha Roy

**Critical review of the manuscript for important intellectual content:** Amalendu Bhunia

### Disclosures

**Human subjects:** All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

### Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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