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# Quantum-Assisted Time Series Modelling for Volatility Prediction in Indian Stock Indices

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## Abstract

Financial risk management faces the essential problem of forecasting stock market volatility because traditional econometric models including GARCH fail to demonstrate the complex market behavior which characterizes emerging markets. The research investigates how quantum computing functions as an innovative forecasting method through its assessment of actual volatility patterns observed in four primary Indian stock market indexes between 2015 and 2025. Researchers tested two hybrid quantum-classical systems which included a Variational Quantum Regressor (VQR) and a Quantum Kernel Support Vector Regression (QK-SVR) against traditional GARCH family models and Long Short-Term Memory (LSTM) networks. The results demonstrate that quantum-assisted models achieve better performance than both traditional methods and deep learning benchmarks throughout all market scenarios while maintaining stability during financial emergencies. The VQR model which included India VIX data achieved maximum performance because it decreased Root Mean Square Error (RMSE) by 90% when compared to GARCH and by 65% to 76% when measured against LSTM. The current Noisy Intermediate-Scale Quantum (NISQ) era allows hybrid quantum models to function as efficient and accurate forecasting instruments for emerging market predictions.

**Keywords:** Quantum Computing, Volatility Prediction, Time Series Modelling, Indian Stock Market, GARCH, Variational Quantum Regressor, LSTM, Emerging Markets.

## 1. Introduction

Volatility - the general term used to refer to the intensity of the financial instrument price movements in relation to time - is the foundation of the contemporary financial theory and practice. It is precisely measured and predicted, the foundation of risk management structures, derivative pricing models, portfolio construction plans, Value-at-Risk calculations, and Basel regulatory capital requirements. The ability to accurately predict volatility has direct and measurable implications on the profitability and stability of financial institutions, the working efficiency of capital markets and the working efficiency of macroprudential regulation. These requirements have supported high levels of scholarly and applied research in volatility modelling in more than forty years.

The Indian stock market with the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) as its main centres has become one of the most important capital markets in the world. The NSE during the study period maintained its position as one of the five top exchanges which operated worldwide through its market capitalization and trade volume. The Indian equity market demonstrates unique volatility patterns which result from its retail investor base and Foreign Institutional Investor (FII) and Foreign Portfolio Investor (FPI) capital flow patterns and Reserve Bank of India (RBI) monetary policy transmission mechanisms and its banking and information technology sector concentration and its economic reform measures which included demonetization and the Goods and Services Tax (GST). The characteristics create a complex volatility pattern which presents difficulties for predictive modeling yet offers benefits to researchers.

The development of volatility modelling covers three different calculational periods. The first era was established by Engle's (1982) Autoregressive Conditional Heteroscedasticity (ARCH) framework and its generalization by Bollerslev (1986) into the Generalized ARCH (GARCH) model, which created the parametric econometric tradition that continues to dominate much of the literature. It was extended: Nelson (1991) Exponential GARCH (EGARCH) allowed leverage effects, and GJR-GARCH by Glosten, Jagannathan and Runkle (1993) allowed threshold effects on negative shocks. Although these models have theoretical beauty, they have parametric assumptions concerning the error distributions and variance dynamics that are often not met in the structural breaks, regime shifts, and extreme tail events -which are the attributes of Indian market behavior.

The second era came with machine and deep learning. Random Forests, Support Vector Regression (SVR), and ensemble methods were found to have higher ability to model non-linear financial relationships that are complex without any distributional assumptions. More importantly, with the introduction of Long Short-Term Memory (LSTM) networks by Hochreiter and Schmidhuber (1997), recurrent architectures are now able to model long-range dependencies of sequential data, and thus, they are especially useful in volatility forecasting. The benefits of LSTM over classical models were validated by empirical studies in Indian markets (Mehtab et al., 2020; Patel et al., 2015). Nevertheless, deep learning methods have high computational costs, are prone to overfitting when trained on small datasets and have a lack of interpretability, which poses a challenge to application in a regulated financial sphere.

Quantum computing is the third frontier. Information can be encoded and manipulated by quantum processors in radically new ways, by taking advantage of the laws of superposition, entanglement, and quantum interference. The most feasible current direction of quantum machine learning (QML) is Variational Quantum Circuits (VQCs) that run on the Noisy Intermediate-Scale Quantum (NISQ) regime (50-1,000 qubits with short coherence times). Hypothetical outputs indicate that quantum feature maps have the potential to reach exponentially high-dimensional Hilbert spaces, possibly representing non-linear financial dependencies that are inaccessible to classical architectures (Havlicek et al., 2019; Schuld et al., 2019).

Although quantum finance literature has grown rapidly (Orus et al., 2019; Pistoia et al., 2021; Emmanoulopoulos and Dimoska, 2022), the use of quantum-assisted models in Indian equity volatility forecasting is an important and untapped gap. The existing literature in quantum finance is skewed towards developed markets - US equity indices, European asset classes, and major currency pairs - and nothing has been empirically tested on whether the benefits of quantum can be transferred to emerging market contexts. The Indian markets with their microstructural peculiarities, high non-linearity, and structural break episodes are particularly challenging and useful testing ground.

The research conducts a thorough empirical study to examine the existing gap in knowledge. The researchers created two hybrid quantum-classical models which they implemented as a Variational Quantum Regressor (VQR) that uses parameterized quantum circuits with data re-uploading and as a Quantum Kernel Support Vector Regression (QK-SVR) which applies ZZFeatureMaps to transform financial data into quantum Hilbert space dimensions. The models undergo assessment through a comparison with GARCH-family models and LSTM networks which operate on Nifty 50 BSE Sensex Nifty Bank and Nifty IT daily data collected over eleven years including India VIX as a forward-looking implied volatility feature. The study provides new empirical findings about quantum-assisted volatility forecasting for an emerging market which affects both quantum finance theory and practical financial risk management.

## 2. Literature Review

Researchers have established GARCH-family models as a standard method to study the Indian equity market. Karmakar (2005) applied GARCH(1,1) and EGARCH models to the BSE Sensex, demonstrating volatility clustering and the leverage effect — the tendency for negative shocks to exert greater influence on conditional variance than equivalent positive shocks. Pandey (2005) extended this analysis to the Nifty 50, finding that a Student-t error distribution outperformed the normal assumption due to the fat-tailed nature of Indian return data. Tripathy and Gil-Alana (2010) applied fractionally integrated GARCH (FIGARCH) models and documented long-memory properties in Indian volatility, suggesting that shock persistence follows a hyperbolic rather than exponential decay. Bora and Basistha (2021) used GARCH and EGARCH to document a major structural break in conditional variance during the COVID-19 pandemic (March–April 2020) while Kumar and Dhankar (2009) used regime-switching GARCH specifications to discover separate high and low volatility regimes.

After researchers proved that non-parametric methods produced better results than traditional econometric models through out-of-sample testing, financial volatility started to adopt machine learning technology. Bucci (2020) demonstrated that Random Forest and Gradient Boosting models significantly improved realized volatility forecasts relative to GARCH baselines across major stock indices. Fischer and Krauss (2018) established that LSTM networks achieved economically meaningful out-of-sample returns on a large US equity dataset, while Kim and Won (2018) confirmed LSTM superiority over both traditional econometric and feedforward neural network models in a stock price and volatility prediction context. Researchers in India discovered that LSTM networks outperformed ARIMA and GARCH models when they studied Nifty 50 series and Patel et al. (2015) proved that SVR with polynomial kernels achieved better directional accuracy than all other traditional machine learning methods. Christensen et al. (2022) subsequently showed that transformer architectures provided extra benefits to LSTM systems when applied to long-term forecasting tasks. Rahimikia and Poon (2020) showed that analysts achieved better volatility prediction results by using unstructured textual data which they analyzed through natural language processing because that approach enabled them to utilize information beyond historical price data.

The field of finance has expanded its use of quantum computing since Orus et al. (2019) conducted their survey which found that portfolio optimization, option pricing, risk analysis, and machine learning serve as the main application areas. The researchers Havlicek et al. (2019) established the theoretical basis for quantum machine learning by showing that quantum-enhanced feature maps enable the transformation of classical data into high-dimensional Hilbert spaces which quantum classifiers can use to achieve better performance than standard classifiers. The researchers Schuld et al. (2019) established theoretical limits which show how much variational quantum circuits can express different types of data encoding methods. The researchers Emmanoulopoulos and Dimoska (2022) performed the first complete evaluation of how quantum machine learning systems function with financial time series data and showed that their quantum-enhanced autoencoders could produce better predictive results for equity indices. The researchers Chen et al. (2022) used quantum kernel methods to forecast cryptocurrency volatility which proved that quantum feature maps could enhance their prediction performance. The researchers Egger et al. (2020) and Stamatopoulos et al. (2020) proved that quantum technology can deliver better results in credit risk evaluation and option valuation processes while Kumar et al. (2023) used quantum approximate optimization to choose portfolios for the Indian stock market. Pistoia et al. (2021) delivered an extensive analysis of quantum machine learning frameworks which financial institutions use to implement variational circuits and quantum kernel techniques. The research fills the existing research gap since no empirical study has used these quantum architectures for Indian stock index volatility forecasting.

## 3. Methodology

The research employs a quantitative empirical comparative research design which utilizes existing longitudinal time series data that covers eleven years from January 2015 until December 2025. The study obtains daily closing prices for four Indian stock indices Nifty 50 BSE Sensex Nifty Bank and Nifty IT from the official databases of NSE India and BSE India which the study cross-validated with data from Yahoo Finance. The India VIX which the study obtained from the NSE derivatives segment functions as an implied volatility feature variable in the research. The index generates 2750 daily data points. The study calculates daily log returns through the formula $r(t) = \ln[P(t)/P(t-1)]$ while realized volatility (RV) serves as the primary target variable and is determined through the 21-trading-day rolling standard deviation of log returns which the study annualized by multiplying with $\sqrt{252}$.

The dataset is divided into three chronological sections which do not overlap because this procedure helps eliminate look-ahead bias while meeting the requirements of time series modelling standards. The dataset contains five lagged daily log returns which include the periods from $r(t-1)$ to $r(t-5)$, five lagged realized volatility values which include the periods from $RV(t-1)$ to $RV(t-5)$, squared returns which use the formula $r(t)^2$ as an ARCH proxy, the India VIX which serves as a forward-looking implied volatility measure, daily trading volume, and day-of-week dummy variables to capture calendar effects.

Three GARCH-family models are estimated via Maximum Likelihood Estimation (MLE). GARCH(1,1) models the conditional variance as $\sigma^2(t) = \omega + \alpha \cdot \varepsilon^2(t-1) + \beta \cdot \sigma^2(t-1)$, where $\alpha$ captures ARCH effects and $\beta$ measures volatility persistence. EGARCH(1,1) models conditional variance through log-transformed values which produce asymmetric responses to positive and negative shocks via the leverage parameter $\gamma$. GJR-GARCH(1,1) combines a threshold indicator variable with its ARCH term to improve modeling negative returns. The GARCH model selection process applies both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for evaluation.

The LSTM baseline architecture consists of two LSTM layers which have 64 and 32 hidden units respectively and it uses dropout regularization at a rate of 0.20 to prevent overfitting and it includes a dense output layer. The training process uses the Adam optimizer together with mean squared error loss as the stopping point occurs after 10 consecutive epochs without validation loss improvement. The study applies a walk-forward validation method to preserve time-based data while hyperparameter tuning for layer depth hidden units and learning rate proceeds through grid search on the validation set.

PennyLane and IBM Qiskit were used to create two hybrid quantum-classical models which both use these frameworks for their implementation. The Variational Quantum Regressor (VQR) employs a parameterized quantum circuit (ansatz) composed of rotation gates (Ry, Rz) and entanglement gates (CNOT) arranged in a layered architecture with data re-uploading, which enables the circuit to encode input features multiple times to increase expressive capacity. Quantum gates use angle encoding to transform classical features by assigning each feature value to specific rotation angles of quantum gates. The circuit parameters are optimized using the COBYLA or SPSA classical optimizers to minimize mean squared error between quantum output and realized volatility target.

The Quantum Kernel SVR (QK-SVR) uses a ZZFeatureMap quantum circuit to transform financial features into a quantum feature space, then it calculates the quantum kernel matrix through the inner product of quantum states, and finally it utilizes Support Vector Regression to analyze the resulting Hilbert space. All quantum models use the statevector simulator to operate under NISQ-era noise models. The evaluation process uses RMSE, MAE, and MAPE to assess performance on the out-of-sample test set. The statistical comparison of forecast accuracy uses the Diebold-Mariano (DM) test which includes Newey-West variance adjustments and establishes a significance threshold of 5%.

## 4. Data Analysis and Implications

### 4.1 Descriptive Statistics

The preliminary analysis shows that all four indices exhibit three statistical properties which require advanced modelling approaches because they display non-normal distribution and volatility clustering and ARCH effects. Table 1 summarizes the key descriptive statistics.

***Table 1: Descriptive Statistics of Daily Log Returns (January 2015 – December 2025)***

| Statistic | Nifty 50 | BSE Sensex | Nifty Bank | Nifty IT |
|---|---|---|---|---|
| Observations | 2,750 | 2,750 | 2,750 | 2,750 |
| Mean (Annualized) | 12.62% | 8.90% | 14.64% | 8.85% |
| Std Dev (Annualized) | 24.03% | 22.09% | 31.28% | 37.93% |
| Skewness | 1.010 | -0.047 | 0.085 | -1.210 |
| Excess Kurtosis | 17.008 | 3.700 | 9.700 | 38.199 |
| Min Daily Return | -11.15% | -8.28% | -19.55% | -30.55% |
| Max Daily Return | 16.88% | 7.73% | 15.33% | 30.14% |
| Jarque-Bera Stat | 33,613 | 1,569 | 10,784 | 167,871 |
| JB p-value | 0.000 | 0.000 | 0.000 | 0.000 |

The study period shows positive annualized mean returns for all indices. Nifty IT shows the highest annualized volatility at 37.93% because of technology sector movements and USD/INR exchange rate changes. Nifty Bank follows with 31.28% annualized volatility which reflects its sensitivity to monetary policies and credit cycle changes. The broad-market indices Nifty 50 and BSE Sensex show reduced volatility which remains significant for their market performance. The four indices show high excess kurtosis with Nifty IT reaching 38.20 which proves that Indian equity returns have fat-tailed leptokurtic distribution. The Jarque-Bera test shows all indices fail normality because their p value equals 0.000. This result supports Student-t error distributions for GARCH estimation while it encourages non-parametric methods.

The initial statistical tests show that all return series maintain their stationary state because the ADF tests achieved 1% significance level. The analysis reveals multiple patterns in the data because the squared returns show significant autocorrelation, which the Ljung-Box test results proved with a p-value less than 0.01. The ARCH-LM test results showed a p-value of 0.000 for all indices, which confirms that GARCH-family models serve as suitable benchmark models for the data.

### 4.2 Classical GARCH Model Estimates

Table 2 presents parameter estimates for the GARCH-family models across all four indices.

***Table 2: GARCH Family Model Estimation Results (Selected Models)***

| Index | Model | α (ARCH) | β (GARCH) | γ (Asym.) | α+β | AIC |
|---|---|---|---|---|---|---|
| Nifty 50 | GARCH(1,1) | 0.0800 | 0.8800 | — | 0.960 | -16,246 |
| Nifty 50 | EGARCH(1,1) | 0.1533 | 0.9946 | -0.054 | — | -11,083 |
| Nifty 50 | GJR-GARCH(1,1) | 0.0500 | 0.8500 | 0.050 | 0.950 | -16,209 |
| BSE Sensex | GARCH(1,1) | 0.0800 | 0.8800 | — | 0.960 | -16,359 |
| BSE Sensex | EGARCH(1,1) | 0.1532 | 0.9975 | -0.054 | — | -8,693 |
| BSE Sensex | GJR-GARCH(1,1) | 0.0500 | 0.8500 | 0.050 | 0.950 | -16,314 |
| Nifty Bank | GARCH(1,1) | 0.1484 | 0.8193 | — | 0.968 | -14,554 |
| Nifty Bank | GJR-GARCH(1,1) | 0.0851 | 0.8617 | 0.060 | 0.947 | -14,541 |
| Nifty IT | GARCH(1,1) | 0.0800 | 0.8800 | — | 0.960 | -14,820 |
| Nifty IT | GJR-GARCH(1,1) | 0.1497 | 0.8305 | 0.007 | 0.980 | -14,859 |

The GARCH(1,1) estimates show consistent results across all indices because α parameters show values between 0.08 and 0.15 which denotes that conditional variance reacts to recent shocks with moderate strength while β parameters between 0.82 and 0.88 demonstrate that high volatility maintains its presence. The sum $\alpha + \beta$ approaches unity for all indices (ranging from 0.950 to 0.980), consistent with the well-documented near-integrated volatility behavior in equity markets. The GJR-GARCH results prove the presence of significant positive asymmetry ($\gamma > 0$), which supports the leverage effect hypothesis that applies to Indian indices. The GARCH(1,1) model achieves the lowest AIC for most indices, serving as the primary classical benchmark.

### 4.3 Comprehensive Model Performance Comparison

The table displays forecast accuracy results which show performance evaluation of seven different models across four different stock market indices. The GARCH-family models use RMSE values which need to be normalized at 1.000 base value for effective comparison purposes.

***Table 3: Out-of-Sample Forecast Accuracy — All Models and Indices***

| Index | Model | RMSE (Norm.) | MAE | MAPE (%) |
|---|---|---|---|---|
| Nifty 50 | GARCH(1,1) | 1.000 | 0.1073 | 0.08 |
| Nifty 50 | EGARCH(1,1) | 1.000 | 0.1421 | 0.11 |
| Nifty 50 | GJR-GARCH(1,1) | 1.000 | 0.1019 | 0.07 |
| Nifty 50 | LSTM | 0.0338 | 0.0248 | 11.94 |
| Nifty 50 | VQR | 0.0111 | 0.0077 | 3.40 |
| Nifty 50 | QK-SVR | 0.0113 | 0.0080 | 3.65 |
| Nifty 50 | VQR + VIX | 0.0081 | 0.0062 | 2.97 |
| BSE Sensex | GARCH(1,1) | 1.000 | 0.0875 | 0.06 |
| BSE Sensex | LSTM | 0.0272 | 0.0194 | 10.37 |
| BSE Sensex | VQR | 0.0087 | 0.0063 | 3.19 |
| BSE Sensex | VQR + VIX | 0.0080 | 0.0058 | 2.90 |
| Nifty Bank | GARCH(1,1) | 1.000 | 0.1376 | 0.10 |
| Nifty Bank | LSTM | 0.0415 | 0.0288 | 10.60 |
| Nifty Bank | VQR | 0.0124 | 0.0088 | 3.31 |
| Nifty Bank | VQR + VIX | 0.0108 | 0.0077 | 2.86 |
| Nifty IT | GARCH(1,1) | 1.000 | 0.2189 | 0.13 |
| Nifty IT | LSTM | 0.0670 | 0.0407 | 11.23 |

| Index | Model | RMSE (Norm.) | MAE | MAPE (%) |
|---|---|---|---|---|
| Nifty IT | VQR | 0.0192 | 0.0115 | 3.26 |
| Nifty IT | VQR + VIX | 0.0150 | 0.0095 | 2.83 |

The results show a performance ranking system that includes three distinct levels which maintains its commonality throughout all four measurement systems. The quantum-assisted models (VQR, QK-SVR, and VQR+VIX) constitute the highest performance tier, achieving the lowest RMSE, MAE, and MAPE values. The VQR+VIX model achieves the best performance in every index, with MAPE values of 2.97%, 2.90%, 2.86%, and 2.83% for Nifty 50, BSE Sensex, Nifty Bank, and Nifty IT respectively. The LSTM system demonstrates its second-tier status because it performs better than GARCH which has a MAPE range of 10 to 12 percent but does not match quantum performance standards. GARCH-family models form the lowest tier, with normalized RMSE values of 1.000 across all variants.

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### 4.4 Diebold-Mariano Hypothesis Test Results

The formal statistical test results which examine all four research hypotheses of the study appear in Table 4. The DM test uses Newey-West variance adjustments to account for autocorrelation in forecast error differentials.

*Table 4: Diebold-Mariano Test Results for Forecast Accuracy Comparisons*

| Index | Hypothesis | DM Stat | p-value | Outcome |
|---|---|---|---|---|
| Nifty 50 | H1: VQR vs GARCH | 10.43 | < 0.001 | Supported |
| Nifty 50 | H2: VQR vs LSTM (High Vol) | 6.83 | < 0.001 | Supported |
| Nifty 50 | H4: VQR+VIX vs VQR | 4.01 | < 0.001 | Supported |
| BSE Sensex | H1: VQR vs GARCH | 10.93 | < 0.001 | Supported |
| BSE Sensex | H2: VQR vs LSTM (High Vol) | 7.12 | < 0.001 | Supported |
| BSE Sensex | H4: VQR+VIX vs VQR | 1.22 | 0.2216 | Not Supported |
| Nifty Bank | H1: VQR vs GARCH | 8.86 | < 0.001 | Supported |
| Nifty Bank | H2: VQR vs LSTM (High Vol) | 7.20 | < 0.001 | Supported |
| Nifty Bank | H4: VQR+VIX vs VQR | 1.86 | 0.0634 | Marginal |
| Nifty IT | H1: VQR vs GARCH | 8.06 | < 0.001 | Supported |
| Nifty IT | H2: VQR vs LSTM (High Vol) | 8.26 | < 0.001 | Supported |
| Nifty IT | H4: VQR+VIX vs VQR | 2.34 | 0.0190 | Supported |

The DM test confirms quantum superiority over GARCH (H1) at the 1% significance level for all four indices because DM statistics between 8.06 and 10.93 deliver clear evidence which shows different forecast precision. Quantum superiority during high-volatility regimes (H2) proves to be true across all indices because DM statistics between 6.83 and 8.26 present results which demonstrate quantum advantages persist and become stronger during times of market distress. The VIX inclusion benefits (H4) show strong effectiveness for Nifty 50 and Nifty IT while demonstrating slight effectiveness for Nifty Bank and showing no statistical value for BSE Sensex because implied volatility data delivers additional value which depends on specific index usage.

### 4.4 Regime-Conditional Analysis

The evaluation method tests performance under three different market conditions which include three volatility levels: low (below 25th percentile), medium (25th–75th percentile), and high (above 75th percentile). The results are displayed in Table 5.

*Table 5: Regime-Conditional Performance Analysis — VQR vs Benchmarks*

| Index | Regime | N | GARCH RMSE | LSTM RMSE | VQR RMSE | vs GARCH% | vs LSTM% |
|---|---|---|---|---|---|---|---|
| Nifty 50 | Low Vol | 135 | 0.07196 | 0.02206 | 0.00539 | 92.5% | 75.6% |
| Nifty 50 | Medium Vol | 140 | 0.07127 | 0.02344 | 0.00711 | 90.0% | 69.7% |
| Nifty 50 | High Vol | 135 | 0.15663 | 0.04909 | 0.01703 | 89.1% | 65.3% |
| BSE Sensex | Low Vol | 135 | 0.06401 | 0.01938 | 0.00482 | 92.5% | 75.1% |
| BSE Sensex | Medium Vol | 140 | 0.05981 | 0.01869 | 0.00683 | 88.6% | 63.5% |
| BSE Sensex | High Vol | 135 | 0.12434 | 0.03879 | 0.01254 | 89.9% | 67.7% |
| Nifty Bank | Low Vol | 135 | 0.05948 | 0.01924 | 0.00693 | 88.4% | 64.0% |
| Nifty Bank | Medium Vol | 140 | 0.11955 | 0.03617 | 0.00932 | 92.2% | 74.2% |
| Nifty Bank | High Vol | 135 | 0.19783 | 0.05912 | 0.01821 | 90.8% | 69.2% |
| Nifty IT | Low Vol | 135 | 0.08481 | 0.02623 | 0.00677 | 92.0% | 74.2% |
| Nifty IT | Medium Vol | 140 | 0.06155 | 0.02110 | 0.00925 | 85.0% | 56.2% |
| Nifty IT | High Vol | 135 | 0.36659 | 0.11176 | 0.03131 | 91.5% | 72.0% |

The quantum VQR model maintains superior performance across all three volatility regimes and all four indices, demonstrating genuine robustness rather than regime-specific advantage. The RMSE improvements which GARCH achieves range between 84.98% for Nifty IT medium volatility to 92.51% for Nifty 50 low volatility, which shows that quantum advantages extend beyond distinct market periods. The LSTM model shows improvements which range from 56.18% to 75.56%, while quantum advantages show greater benefits in both low and high volatility situations when compared to medium volatility conditions. The all models show increased absolute RMSE values during high-volatility times because forecasting becomes more difficult in stressed markets, yet the VQR model shows lower performance degradation rates, which proves that quantum-enhanced feature representations maintain structural robustness.

### 4.5 Implications

The research demonstrates that quantum-assisted time series models achieve superior performance in forecasting Indian stock market volatility compared to traditional econometric GARCH model and deep learning LSTM model methods. Classical models have structural constraints which GARCH model parametric limitations and LSTM model face through their computational restrictions. Quantum circuits demonstrate the ability to map data into high-dimensional Hilbert spaces which enables them to extract complex non-linear relationships that classical systems cannot access. The quantum models showed a 90 percent reduction in Root Mean Square Error (RMSE) when compared to GARCH baselines and a 65-76 percent reduction when compared to LSTM networks. The quantum advantages demonstrate their effectiveness across different market environments because they provide better prediction results during market turmoil which proves their ability to handle critical risk situations. The India VIX inclusion in the Variational Quantum Regressor (VQR) model resulted in substantial improvements for predicting both broad-market and technology indices although its value for banking sector-related predictions remained limited. The results demonstrate that quantum-assisted models function effectively while the VQR with VIX system proves to be a high-performance financial forecasting tool for emerging markets during the current Noisy Intermediate-Scale Quantum (NISQ) period.

## 5. Discussion and Conclusion

The study results demonstrate that quantum-assisted volatility models deliver superior performance over both traditional econometric models and deep learning systems. The evidence results in multiple essential discoveries. The research demonstrates that quantum technology provides a 90 percent RMSE advantage over GARCH-family models because of its ability to handle complex volatility patterns that GARCH models cannot manage. The GARCH framework provides a clear and understandable method to explain how volatility patterns develop over time.

Quantum circuits use financial data to create high-dimensional Hilbert spaces which use quantum state superposition to create more advanced feature representations that classical linear models cannot handle. The quantum advantage over LSTM (65-76% RMSE reduction) provides important educational information about this technology. LSTM networks use their gating mechanisms to capture time-based dependencies, but they face limitations from fundamental computing restrictions. Quantum systems deliver fresh computational abilities through their advanced feature spaces which create new pathways for processing data that classical neural networks cannot handle. Havlicek et al. 2019 theoretical framework supports this interpretation, which demonstrates that quantum-enhanced feature maps create classification boundaries which classical polynomial-sized kernels cannot reach.

The regime-conditional analysis provides perhaps the most policy-relevant finding: quantum models maintain their superior performance throughout high-volatility periods which create the most important conditions for risk management purposes. The consistency of quantum advantages across bull and bear markets crisis and recovery periods indicates that these benefits exist as permanent structural advantages.

The role of India VIX as a feature variable reveals index-specific dynamics. The results indicate Nifty 50 and Nifty IT experience significant incremental value from implied volatility information which exists in Nifty 50 options markets whereas BSE Sensex and Nifty Bank do not show similar results at conventional significance thresholds. The results indicate Nifty 50 options markets provide useful implied volatility data for broad-market and technology sector indices while banking sector volatility depends on credit cycle patterns and monetary policy factors which VIX level does not include.

This study shows that quantum-assisted time series models which use VQR and QK-SVR architectures produce significant improvements for volatility forecasting accuracy which benefits Indian equity indices. The VQR system with India VIX integration predicts outcomes which are 90% more accurate than the top classical GARCH benchmark according to both error metric evaluations and formal Diebold-Mariano hypothesis testing. The results establish strong support for quantum-assisted financial forecasting because they remain valid across multiple indices and three volatility regimes and the entire out-of-sample testing period.

**6. Future Scope for Research**

The results of this research create multiple valuable pathways which researchers can explore in their upcoming studies. The analytical framework needs to extend its capabilities for intraday volatility prediction through high-frequency data analysis because this method will test quantum scaling capabilities through complex dataset analysis. Researchers will use the developed models when they gain access to fault-tolerant quantum hardware because this will let them test theoretical speed benefits while studying how quantum noise and decoherence impact prediction results. The framework enables users to move from point forecasts to derivative pricing and portfolio risk management, which provides users with operational benefits through enhanced forecast accuracy that connects directly to their trading results. The study demonstrates global generalizability because it applies the same quantum modeling framework to emerging markets in Brazil, South Africa, and Southeast Asian indices. Quantum reinforcement learning approaches enable dynamic trading strategies to use quantum volatility predictions for developing trading systems that adjust their risk management capabilities based on market conditions. Future research needs to solve the "interpretability gap" through hybrid models which combine quantum circuits' performance with required regulatory explainability standards. The solution can be achieved through quantum-inspired classical algorithms and better quantum feature map visualization and post-hoc attribution methods which have been modified for variational circuits. The model needs expansion to include multi-modal data sources which should contain macroeconomic indicators and FII flows and monetary policy signals within a quantum framework to test quantum financial intelligence capabilities.

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