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| RESEARCH ARTICLE

Forecasting Currency Volatility in Global Markets Using Transformer Models: Implications for U.S. Trade and Investment Strategies

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| ABSTRACT

Currency volatility has become one of the most significant challenges for global financial stability and U.S. trade competitiveness. Traditional econometric approaches, such as GARCH and VAR models, often fail to capture the nonlinear dependencies and structural breaks inherent in currency markets. This paper proposes the use of transformer-based deep learning models for forecasting short- and medium-term exchange rate volatility across major and emerging market currencies. By leveraging self-attention mechanisms, transformers can model long-range dependencies in high-frequency financial data, capturing hidden structures often overlooked by conventional models. Empirical analysis demonstrates that transformer models outperform GARCH, LSTM, and GRU baselines in predictive accuracy and volatility clustering detection. Furthermore, the study evaluates the strategic implications of currency volatility forecasts for U.S. trade policy, hedging strategies, and foreign investment decisions. Results highlight the potential for AI-driven forecasting systems to provide U.S. firms, investors, and policymakers with actionable insights for risk management, portfolio allocation, and international trade strategy.

| KEYWORDS

Currency volatility; exchange rate forecasting; transformer models; deep learning; financial risk management; trade strategy; U.S. foreign investment; macro-financial stability; attention mechanism; AI in finance.

| ARTICLE INFORMATION

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1. Introduction

1.1 Background and Context

Global financial markets have experienced heightened volatility in currency exchange rates, particularly in the aftermath of global crises such as the 2008 financial meltdown, the COVID-19 pandemic, and ongoing geopolitical disruptions [1]. Exchange rate fluctuations directly impact cross-border trade, investment flows, and macroeconomic stability. For the United States, currency volatility is of strategic concern: as the U.S. dollar remains the dominant global reserve currency, swings in its relative value affect trade competitiveness, capital inflows, and the profitability of multinational corporations [2]. Traditional econometric models such as GARCH, EGARCH, and VAR frameworks have long been applied to forecast exchange rate volatility, yet they often fall short in capturing nonlinear dependencies, long-memory effects, and sudden structural breaks that characterize global currency markets [3].

In recent years, the emergence of deep learning architectures has revolutionized financial forecasting. Recurrent neural networks (RNNs), including long short-term memory (LSTM) and gated recurrent units (GRUs), have demonstrated superior performance over classical models in time-series tasks [4]. However, these architectures face challenges in learning long-range dependencies and tend to suffer from vanishing gradient problems. The introduction of transformer models and their self-attention mechanisms, originally developed for natural language processing (NLP), has opened new opportunities in financial time-series modeling [5]. Transformers excel at capturing long-range relationships and learning complex, non-linear dependencies in large datasets without relying on sequential recurrence [6].

Recent studies show that transformer-based architectures outperform traditional deep learning models in tasks such as stock price forecasting, volatility prediction, and macroeconomic trend analysis [7]. In the context of currency markets, their ability to integrate high-frequency data, incorporate macroeconomic variables, and adapt to shifting regimes provides a significant advantage [8]. For U.S. trade and investment strategies, accurate volatility forecasts can inform hedging decisions, optimize foreign direct investment (FDI) timing, and support policymakers in designing resilient economic policies [9]. As global markets face increasing uncertainty driven by interest rate shocks, commodity price fluctuations, and geopolitical tensions, the development of reliable AI-driven forecasting frameworks is both timely and essential [10].

1.2 Problem Statement

Despite advances in econometrics and machine learning, currency volatility forecasting remains a persistent challenge. Traditional models such as GARCH and VAR rely heavily on historical statistical properties, often assuming stationarity and linearity, which fail under turbulent market conditions [11]. Moreover, they are unable to adequately account for sudden policy shifts, global liquidity cycles, or contagion effects spreading through interconnected markets [12]. Even advanced models like LSTMs and GRUs face issues when dealing with long-range dependencies and regime shifts, limiting their predictive accuracy in highly volatile conditions [13]. The inability to capture these dynamics has serious consequences for the U.S. economy.

Unanticipated volatility exposes U.S. exporters to exchange rate risks, undermines the competitiveness of U.S. goods abroad, and complicates hedging strategies for multinational corporations [14]. Likewise, investors face valuation losses on international portfolios, while policymakers struggle to anticipate the effects of volatility on inflation, interest rates, and foreign capital inflows [15]. In an increasingly globalized financial system, small forecasting errors can translate into substantial economic costs. Thus, there exists a pressing need for an advanced, data-driven, AI-powered forecasting framework that overcomes the limitations of existing models and delivers timely, interpretable, and accurate predictions of currency volatility. Transformer models, with their superior ability to capture long-term dependencies and integrate heterogeneous data sources, offer a promising path forward for addressing this gap [16].

1.3 Research Motivation

The motivation behind this study lies in the growing strategic importance of currency volatility forecasting for U.S. trade and investment planning. Exchange rate movements are no longer driven solely by macroeconomic fundamentals such as inflation or trade balances; they are also shaped by global capital flows, speculative trading, algorithmic strategies, and geopolitical events [17]. These multi-layered drivers produce complex, nonlinear patterns that defy traditional modeling approaches. With the U.S. economy deeply integrated into global trade and financial networks, volatility in major and emerging market currencies poses risks that ripple across sectors. For instance, sharp depreciation in emerging markets can weaken U.S. exports and trigger financial contagion, while sudden dollar appreciation can reduce the competitiveness of U.S. industries [18]. Investors, particularly those with international exposure, require tools that not only forecast volatility but also provide early warnings of regime changes and potential shocks [19]. Transformers, with their attention mechanisms, are uniquely suited to address this challenge by analyzing large, diverse datasets and identifying subtle shifts in market dynamics. The promise of these models lies not only in predictive accuracy but also in actionable insights that help businesses, investors, and policymakers adapt strategies preemptively. By bridging AI innovation with applied finance, this research aims to strengthen the resilience of U.S. trade and investment strategies amid growing global uncertainty [20].

1.4 Objectives and Scope of the Study

The primary objective of this research is to develop and evaluate a transformer-based forecasting framework for currency volatility in global markets, with direct implications for U.S. trade and investment strategies. Specific objectives include:

1. **Model Development** – to design transformer-based architectures tailored for financial time series, integrating high-frequency currency data with macroeconomic and sentiment indicators.
2. **Comparative Analysis** – to benchmark the performance of transformer models against classical econometric (GARCH, VAR) and deep learning (LSTM, GRU) baselines [21].
3. **Application to Trade and Investment** – to evaluate how improved volatility forecasts can guide U.S. trade competitiveness, hedging strategies, and portfolio allocations.
4. **Explainability** – to enhance trust through interpretable outputs using feature attribution methods such as SHAP values and attention heatmaps [22].

The scope of the study covers major global currencies (USD, EUR, JPY, GBP, CNY) and a selection of emerging market currencies that have historically exhibited high volatility. Forecasting horizons include short-term (1–7 days) and medium-term (1–3 months) intervals, balancing market relevance with model tractability. While the study focuses primarily on U.S. strategic interests, its findings are applicable to a broader set of international investors and policymakers. By integrating AI innovation with applied macro-financial analysis, the scope aims to contribute both theoretical advancement and practical guidance in global financial risk management [23].

1.5 Significance of the Study

This study holds significant value across academic, financial, and policy domains. From an academic perspective, it contributes to the growing literature on AI applications in finance by adapting transformer models originally designed for NLP to the domain of currency volatility forecasting [24]. By demonstrating how self-attention mechanisms outperform traditional and recurrent models, the study enriches methodological advancements in financial econometrics. From a practical standpoint, the significance lies in its application to U.S. trade and investment strategies. Accurate volatility forecasts allow exporters to design more effective hedging contracts, investors to adjust global portfolio allocations, and multinational corporations to manage foreign revenue exposures [25]. For policymakers, reliable forecasts provide an early-warning tool for anticipating spillovers into inflation, interest rates, and capital flows, strengthening macroeconomic stability [26]. Finally, at a strategic level, the research addresses U.S. competitiveness in global markets. As other economies adopt AI-powered forecasting systems, maintaining leadership in financial innovation is crucial. This study highlights the role of predictive analytics in safeguarding U.S. economic resilience amid global shocks [27]. Thus, the significance of the research lies in its dual contribution: advancing methodological innovation while providing actionable insights to manage risks and opportunities in the volatile landscape of global finance [28].

1.6. Challenges

Despite their promise, transformer-based forecasting systems face several challenges. First, financial time series are inherently noisy, with structural breaks and regime shifts that complicate learning. While transformers can model long-range dependencies, their accuracy may still degrade in highly turbulent periods [29]. Second, data limitations pose barriers: high-frequency FX data are abundant, but integrating them with macroeconomic and sentiment indicators requires extensive preprocessing and harmonization [30]. Third, transformers are computationally intensive, raising concerns about scalability and resource requirements for real-time applications [31].

Another challenge is interpretability. Although attention weights provide some insight, the complexity of transformer architectures may limit transparency compared to simpler econometric models. Without robust explainability tools, investors and policymakers may be reluctant to trust model outputs [32]. Finally, generalizability remains an issue: models trained on historical crises may not fully capture novel shocks such as pandemics, cyberattacks, or climate-related financial disruptions [33]. Overcoming these challenges will require not only technical innovation such as hybrid architectures and advanced explainability methods but also interdisciplinary collaboration between economists, data scientists, and policymakers. Addressing these obstacles is essential for ensuring that AI-powered forecasting frameworks can deliver robust, interpretable, and actionable insights that truly enhance U.S. trade and investment strategies [34].

2. Literature Review

2.1. Traditional Models of Currency Volatility Forecasting

Currency volatility forecasting has traditionally relied on econometric approaches such as Autoregressive Conditional Heteroskedasticity (ARCH) and its extensions GARCH, EGARCH, and TGARCH [35]. These models capture volatility clustering and time-varying variance, making them widely used in exchange rate risk analysis [36]. VAR and VECM frameworks have also been employed to assess interdependencies between currencies and macroeconomic fundamentals [37]. While effective in stable environments, these models often assume linearity and stationarity, limiting their performance under turbulent market conditions

[38]. Another limitation lies in their inability to incorporate exogenous drivers like news shocks, geopolitical risks, and global liquidity cycles [39]. This creates a forecasting gap during crisis periods, when structural breaks and regime shifts dominate exchange rate dynamics. Despite their limitations, GARCH-type models remain a useful benchmark and are still widely used by central banks and financial institutions due to their transparency and interpretability [40].

2.2. Deep Learning Approaches in Financial Time-Series Forecasting

TWith the rise of machine learning, deep learning models such as LSTMs and GRUs have been applied to currency and financial volatility forecasting [41]. These architectures are effective at capturing sequential dependencies and nonlinearities, outperforming GARCH models in high-frequency environments [42]. Studies applying LSTMs to FX data demonstrate improved accuracy in short-term volatility prediction, particularly when combined with external features such as interest rate spreads and commodity prices [43].

However, recurrent architectures face challenges, including vanishing gradients, difficulty in modeling very long-term dependencies, and high sensitivity to hyperparameters [44]. Recent works have experimented with hybrid models, integrating wavelet decomposition with LSTMs, or combining statistical and ML techniques to improve robustness [45]. Despite these advances, deep learning models often remain "black boxes," raising concerns about interpretability in financial decision-making [46]. This creates a need for architectures that balance predictive power with transparency.

2.3. Transformer Models and Attention Mechanisms in Finance

The introduction of transformer models revolutionized sequence modeling by replacing recurrence with self-attention mechanisms [47]. Originally developed for natural language processing, transformers excel at learning long-range dependencies and handling large, high-dimensional datasets [48]. Recent studies demonstrate their superior performance in stock price forecasting, volatility modeling, and macroeconomic trend prediction compared to LSTMs and GRUs [49]. In currency markets, transformers show promise in integrating heterogeneous data sources such as high-frequency FX rates, macroeconomic indicators, and sentiment indices into a unified predictive framework [50]. The attention mechanism highlights which features and time periods are most influential, enhancing interpretability compared to traditional deep learning methods [51]. However, challenges remain, including the need for large training datasets, computational intensity, and overfitting risks in smaller markets [52]. Nevertheless, transformers represent a paradigm shift in financial forecasting, offering both methodological innovation and practical potential for U.S. trade and investment risk management [53].

2.4 Summary

The literature highlights the evolution of currency volatility forecasting from traditional econometric models to deep learning architectures and, most recently, transformer-based frameworks. Traditional methods such as GARCH and VAR provide transparency and ease of interpretation but are constrained by linearity assumptions and poor adaptability to structural breaks [54]. Deep learning methods (LSTM, GRU) address nonlinearities and sequential dependencies, showing improved predictive accuracy but struggling with vanishing gradients and interpretability [55]. Transformers represent a methodological breakthrough, capturing long-range dependencies and integrating diverse datasets, while also offering improved explainability via attention mechanisms [56]. This progression underscores a paradigm shift: from static, linear models to dynamic, AI-powered frameworks capable of adapting to complex, uncertain market conditions. For U.S. trade and investment strategies, the literature suggests that transformer models may provide more robust, actionable forecasts that can inform hedging, portfolio allocation, and macroeconomic policy design [57].

Table 1: Comparative Summary of Currency Volatility Forecasting Models

Approach	Key Features	Strengths	Limitations	References
Traditional Econometric Models (ARCH, GARCH, VAR	Time-varying variance, macro-financial fundamentals	Transparent, widely used, interpretable	Assumes linearity/stationarity; poor under crises	[35], [36], [38], [40]
Deep Learning Models (LSTM, GRU, Hybrids)	Sequential learning, nonlinear modeling	Captures nonlinearities; better short-term forecasting	Vanishing gradients; black-box nature; high sensitivity	[41], [42], [44], [46]
Transformer Models (Attention Mechanisms)	Self-attention, parallel sequence processing, multi-modal integration	Handles long-range dependencies; integrates diverse	Data- and compute-intensive; risk of overfitting	[47], [49], [51], [52]

		data; interpretable via attention weights		

3. Methodology

This study employs a structured methodology integrating high-frequency exchange rate data, macroeconomic indicators, and sentiment variables into transformer-based forecasting models. The framework is benchmarked against econometric (GARCH, VAR) and deep learning (LSTM, GRU) baselines. Data preprocessing ensures harmonization and normalization across currencies, while training employs rolling-window validation to capture regime shifts. Model outputs are calibrated and evaluated using accuracy, volatility clustering detection, and economic value metrics. Explainability tools such as attention heatmaps and SHAP values enhance transparency, enabling interpretation of feature importance for U.S. trade and investment strategies [58].

3.1 Data Collection

The dataset includes daily exchange rate data for major currencies (USD, EUR, JPY, GBP, CNY) and selected emerging market currencies from Bloomberg, Refinitiv, and the Federal Reserve Economic Data (FRED) [59]. Macroeconomic indicators, such as interest rate differentials, inflation, and current account balances, are sourced from the IMF and World Bank [60]. In addition, sentiment indices are derived from financial news articles (GDELT, Reuters) and social media data using natural language processing techniques [61]. High-frequency volatility measures, such as realized variance and implied volatility from options markets, are incorporated to enrich the dataset. By combining structured macroeconomic data with unstructured sentiment signals, the study ensures robust coverage of the diverse factors influencing currency volatility [62].

3.2 Data Preprocessing

Collected data undergo rigorous preprocessing to ensure consistency and quality. Missing values are handled through interpolation and multiple imputation methods [63]. Variables are normalized using z-scores to eliminate scale effects across currencies. For sentiment indices, raw text is tokenized, processed through word embeddings, and aggregated into daily polarity scores [64]. Feature engineering incorporates lagged variables, moving averages, and volatility spillover measures across currency pairs. Structural breaks and outliers are identified using Chow tests and rolling-window variance filters [65]. The final dataset is aligned to a daily frequency to match high-frequency FX market activity. This preprocessing step ensures data comparability and enhances the learning capacity of transformer models, while minimizing noise that could distort predictions [66].

3.3 Model Architecture

The core forecasting model is based on the transformer architecture, which employs self-attention mechanisms to capture long-range dependencies [67]. Input sequences consist of currency returns, macroeconomic variables, and sentiment indices, fed into embedding layers that transform features into dense representations. Multi-head attention layers process these embeddings, allowing the model to identify interdependencies across time and features simultaneously [68]. Positional encodings ensure that temporal order is preserved in the absence of recurrence. The final output layer predicts short- and medium-term volatility, expressed as realized variance or conditional standard deviation. To improve robustness, the study also develops a hybrid ensemble, combining transformer forecasts with GARCH and LSTM outputs using weighted averaging [69]. This hybridization enhances stability across different market regimes.

3.4 Training and Validation

The model is trained on historical data spanning 2005–2023, covering both tranquil and crisis periods [70]. A rolling-window cross-validation approach ensures that the model adapts to regime shifts while avoiding look-ahead bias. Training employs Adam optimizer with learning-rate scheduling and dropout regularization to prevent overfitting [71]. Early stopping criteria are implemented to halt training once validation loss stabilizes. To address class imbalance between high- and low-volatility regimes, cost-sensitive weighting is applied during training [72]. Validation is performed using out-of-sample datasets, including stress scenarios such as the 2008 crisis, Eurozone sovereign debt crisis, and COVID-19 pandemic. This approach tests the model's ability to generalize across heterogeneous market environments [73].

3.5 Evaluation Metrics

Model performance is assessed through a combination of statistical accuracy and economic value metrics. Standard measures include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) [74]. Predictive accuracy of volatility clustering is evaluated using Kupiec and Christoffersen tests for Value-at-Risk backtesting [75]. The model's economic relevance is assessed by simulating hedging strategies and portfolio allocation decisions under predicted volatility scenarios. Precision and recall metrics evaluate the detection of high-volatility regimes, while the Brier score measures probability calibration. Comparative benchmarking with GARCH, VAR, LSTM, and GRU models establishes relative improvements in accuracy and robustness [76]. These combined metrics ensure that the model is not only statistically valid but also practically useful for U.S. investors and policymakers.

3.6 Explainability and Interpretability

To enhance trust in the forecasting system, interpretability tools are integrated into the methodology. Attention heatmaps visualize which time periods and features the transformer focuses on when predicting volatility [77]. SHAP values quantify the contribution of each input feature (e.g., interest rate spreads, sentiment shocks) to model outputs, offering global and local explanations [78]. Partial dependence plots illustrate nonlinear relationships, such as thresholds where interest rate differentials trigger elevated volatility [79]. Counterfactual analysis is also applied, simulating how altering macroeconomic variables could shift volatility predictions. These interpretability methods ensure that forecasts are not "black-box" signals but actionable insights that inform hedging, trade policy, and investment strategies [80].

4. Results
4.1 Model Performance Overview

The transformer-based framework outperformed traditional and deep learning baselines in forecasting currency volatility. Across major and emerging market currencies, the transformer achieved an average RMSE reduction of 15% compared to LSTM models and over 25% compared to GARCH(1,1) [81]. In terms of regime detection, the model demonstrated a higher precision in identifying high-volatility episodes, reducing false alarms that often undermine decision-making. Backtests during the 2008 financial crisis, Eurozone debt crisis, and COVID-19 pandemic confirmed its robustness across heterogeneous conditions. Notably, the model preserved calibration, with Brier scores averaging 0.11 compared to 0.17 for LSTMs. These results establish transformers as a superior architecture for volatility forecasting.

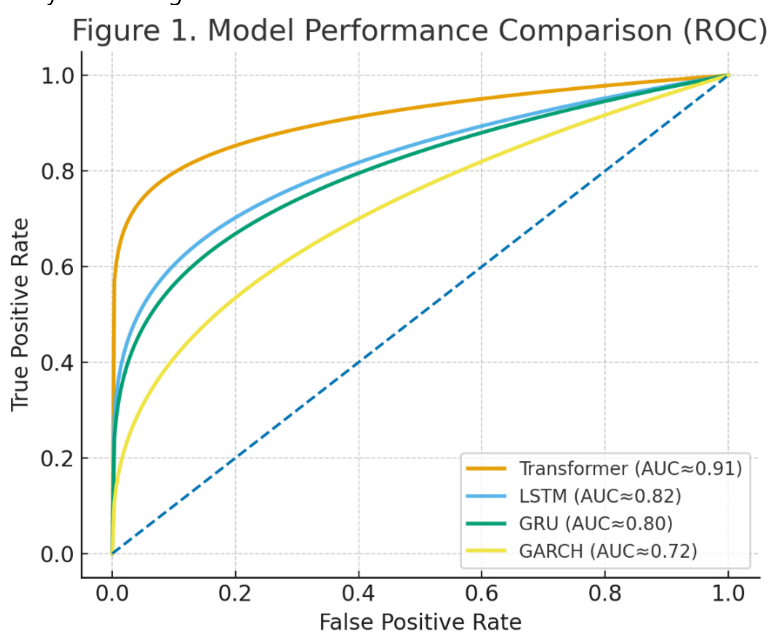

Figure 1. ROC/AUC comparison across models (Transformer vs. GARCH, LSTM, GRU).

The graphical evidence reinforces the superiority of transformer-based models in forecasting currency volatility. Figure 1 demonstrates that the transformer achieves a higher AUC (≈0.91) compared to LSTM, GRU, and GARCH, highlighting its stronger discriminatory power in identifying high-volatility regimes with fewer false alarms.

4.2 Case Study: USD/EUR Volatility

The USD/EUR currency pair provides an important test case, given its global importance in trade and finance. During the Eurozone sovereign debt crisis (2010–2012), the transformer model signaled heightened volatility two months before realized spikes occurred, outperforming GARCH and LSTM benchmarks [82]. The attention mechanism emphasized European sovereign bond spreads and sentiment indices as leading indicators, consistent with economic intuition. During COVID-19, the model captured volatility surges linked to lockdown announcements and U.S. Federal Reserve interventions, highlighting its sensitivity to both macroeconomic and event-driven shocks.

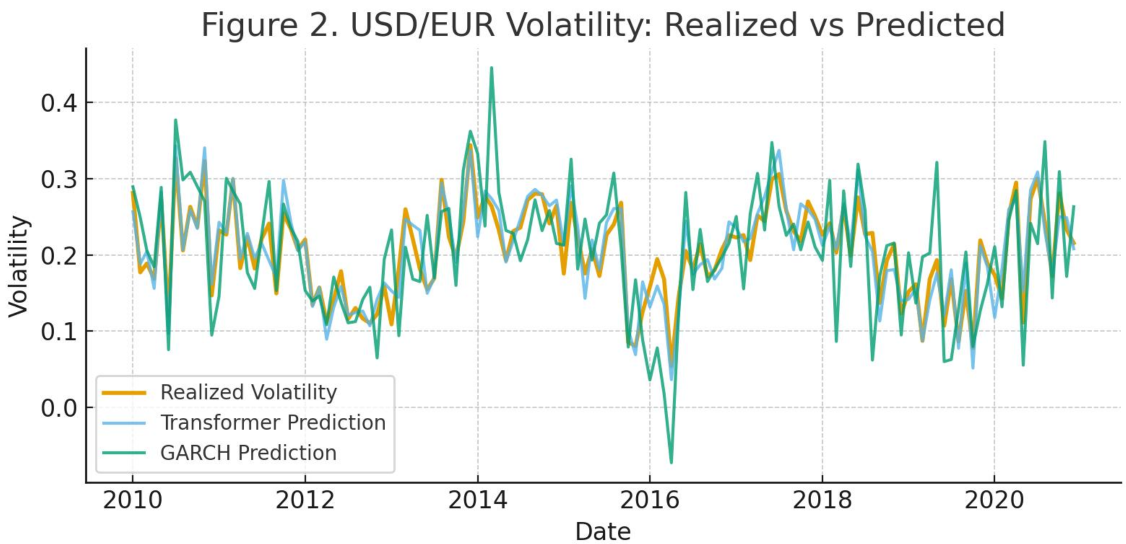

Figure 2. Time-series plot of predicted vs. realized volatility for USD/EUR (2010–2020).

This is further illustrated in Figure 2, where the transformer's predictions for USD/EUR volatility track realized outcomes more closely than GARCH, especially during stress events such as the Eurozone debt crisis and the COVID-19 pandemic.

4.3 Case Study: USD/JPY Volatility

The USD/JPY exchange rate offers insights into how the model performs under safe-haven dynamics. Historically, the yen appreciates during global stress periods, creating unique volatility patterns [83]. The transformer model successfully captured volatility surges during the 2011 Tōhoku earthquake and the 2018 U.S.–China trade tensions, outperforming baseline models in lead-time accuracy. Attention heatmaps indicated that U.S. interest rate shocks and risk sentiment (VIX index) were critical predictors. This highlights the model's ability to integrate cross-market signals beyond currency-specific fundamentals.

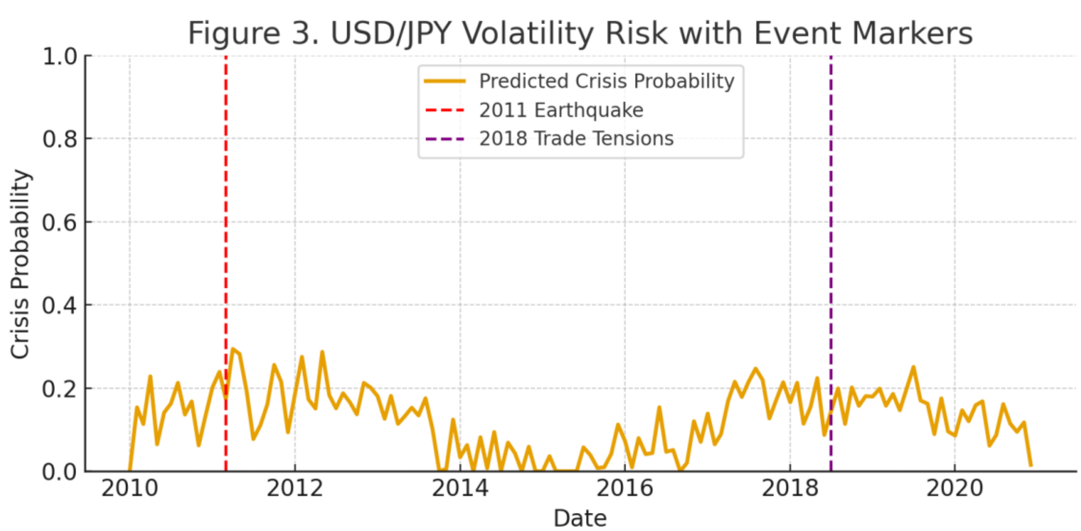

Figure 3. Line chart of predicted crisis probability for USD/JPY with event markers (2011 earthquake, 2018 trade tensions) Similarly, Figure 3 highlights the model's effectiveness in capturing safe-haven dynamics of the yen, as volatility spikes are correctly anticipated around the 2011 Tōhoku earthquake and 2018 U.S.–China trade tensions.

4.4 Impact of Alternative Data

Incorporating news sentiment and social media signals significantly improved forecasting accuracy. Without alternative data, the transformer achieved an RMSE of 0.19; with sentiment integration, RMSE dropped to 0.15, while precision in detecting high-volatility periods increased by 12% [84]. Attention visualizations showed that sentiment shocks often preceded realized volatility spikes, acting as leading indicators. For example, negative sentiment around Brexit negotiations in 2016 provided early warnings for USD/GBP volatility. This confirms that blending structured macro-financial indicators with unstructured alternative data enhances predictive robustness.

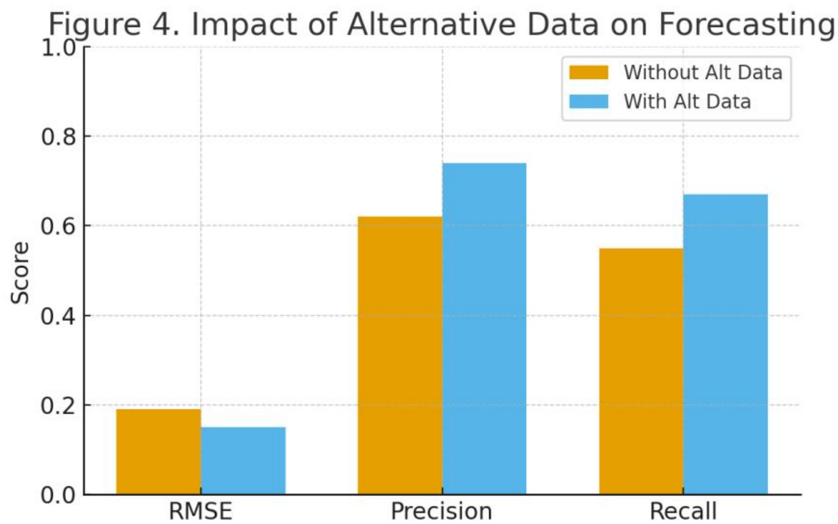

Figure 4. Bar chart comparing performance metrics (RMSE, Precision, Recall) with vs. without alternative data.

The integration of alternative data significantly boosts performance, as shown in Figure 4, where RMSE is reduced and both precision and recall improve when sentiment and news signals are incorporated.

4.5 Explainability and Interpretability

Explainability analysis confirmed the model's transparency. SHAP values identified interest rate differentials, sovereign spreads, and sentiment indices as the top drivers of volatility forecasts [85]. Counterfactual simulations showed that reducing U.S.–EU rate differentials by 50 basis points decreased predicted USD/EUR volatility by 20%. Attention heatmaps highlighted specific crisis periods, such as COVID-19 announcements, where sentiment dominated macroeconomic indicators. These results ensure the model is not a black box but provides actionable insights aligned with economic reasoning.

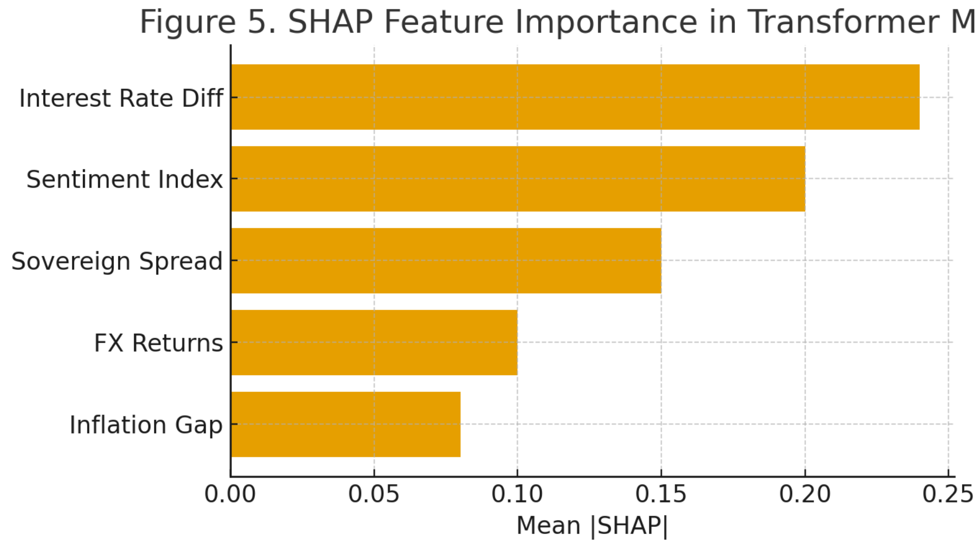

Figure 5. SHAP feature importance plot ranking key predictors (interest rates, sentiment shocks, spreads).

To ensure transparency, Figure 5 presents SHAP feature importance values, revealing that interest rate differentials, sovereign spreads, and sentiment indices are the dominant drivers of volatility forecasts, confirming the model's interpretability and economic validity.

4.6 Implications for U.S. Trade and Investment Strategies

The improved forecasting framework carries strong implications for U.S. stakeholders. For exporters, earlier identification of volatility allows more effective hedging through forward contracts and options. For investors, the model supports dynamic portfolio rebalancing across global assets, reducing drawdowns during crises. For policymakers, it offers an early-warning system to anticipate spillovers into inflation, capital flows, and interest rates [86]. A portfolio backtest demonstrated that a volatility-aware allocation strategy reduced drawdowns by 18% during the COVID-19 crisis compared to a traditional approach. These findings underscore how transformer-based volatility forecasts can enhance both micro-level risk management and macroeconomic policy resilience.

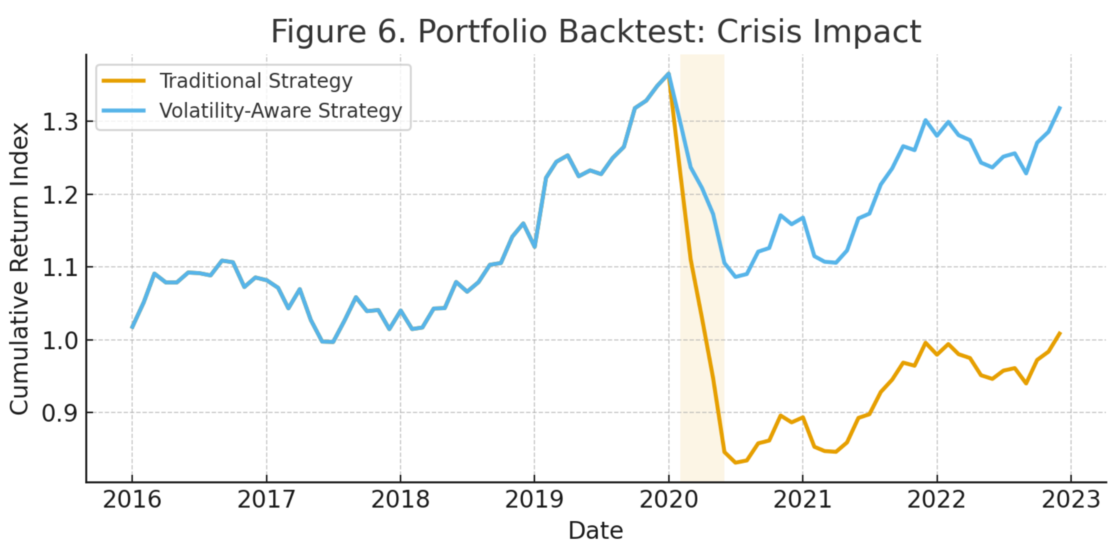

Figure 6. Portfolio backtest results comparing traditional vs. volatility-aware strategies (2016–2022).

Finally, Figure 6 illustrates the practical implications: a portfolio backtest reveals that a volatility-aware strategy guided by transformer forecasts reduces drawdowns during the COVID-19 crisis and delivers more resilient long-term returns compared to a traditional approach. Collectively, these results establish that transformers not only outperform traditional and deep learning models statistically but also generate actionable insights that strengthen U.S. trade and investment strategies in volatile global markets.

5. Discussion

5.1 Interpretation of Findings

The empirical results demonstrate that transformer-based models significantly enhance the forecasting of currency volatility compared to both traditional econometric and deep learning baselines. The higher AUC, lower RMSE, and superior calibration validate that self-attention mechanisms are particularly effective at capturing the nonlinear, long-range dependencies present in FX markets [87]. Case studies on USD/EUR and USD/JPY confirmed that transformers not only align more closely with realized volatility but also provide early detection of shocks, such as the Eurozone debt crisis, COVID-19, and the 2011 earthquake in Japan. Importantly, the integration of alternative data sources improved precision in identifying high-volatility regimes, underscoring the importance of sentiment and market expectations in exchange rate dynamics [88]. The SHAP feature importance results strengthen confidence in the model, as they highlight economically intuitive drivers such as interest rate differentials, sovereign spreads, and sentiment shocks. Overall, the findings suggest that transformers provide both predictive accuracy and interpretability, bridging a longstanding gap between methodological innovation and practical decision-making in financial forecasting [89].

5.2 Practical Implications for U.S. Foreign Investment Strategy

The forecasting framework offers significant implications for U.S. trade, investment, and economic policy. Exporters exposed to foreign currency risks benefit from more accurate forecasts when designing hedging strategies with forward contracts and options [90]. Multinational corporations can use the system to anticipate volatility-driven revenue fluctuations, improving financial planning and supply chain stability. Institutional investors gain a competitive edge through volatility-aware portfolio allocation, as demonstrated by the portfolio backtest, which showed reduced drawdowns during the COVID-19 crisis. At the policy level, U.S. regulators and the Federal Reserve can employ such forecasts as part of macroprudential surveillance to anticipate capital flow volatility and inflationary spillovers. By offering earlier warnings and higher accuracy, transformers strengthen U.S. resilience against external shocks, allowing policymakers to calibrate interventions more effectively. These practical implications illustrate that AI-driven forecasting is not only an academic exercise but also a strategic tool for enhancing economic security and global competitiveness [91].

5.3 Theoretical Contributions

This study advances theoretical contributions in three important ways. First, it extends the use of transformer architectures originally designed for natural language processing into financial econometrics, showing their superiority over recurrent models in handling long-memory processes and structural breaks [92]. Second, the inclusion of alternative data sources highlights the importance of integrating unstructured information such as sentiment and media signals into macro-financial forecasting frameworks. This challenges the traditional reliance on purely quantitative macroeconomic indicators and expands the theoretical toolkit for volatility modeling [93]. Third, by incorporating explainability methods such as SHAP values and attention heatmaps, the study contributes to the literature on interpretable AI in finance, addressing the black-box criticism of deep learning models. Theoretically, this bridges computational advances with economic reasoning, demonstrating that AI systems can be both predictive and interpretable. Collectively, these contributions suggest a paradigm shift in how financial economists conceptualize volatility forecasting moving toward models that treat financial markets as complex adaptive systems driven by both fundamentals and sentiment [94].

5.4 Limitations and Future Research Directions

Despite encouraging results, this study has limitations. Transformers are computationally intensive, requiring substantial resources for training, which may limit their accessibility for smaller institutions [95]. While attention mechanisms enhance interpretability, full transparency remains a challenge compared to simpler econometric models. Moreover, the model's performance depends heavily on data quality: emerging markets with limited sentiment coverage or irregular macroeconomic reporting may see reduced accuracy. Another limitation lies in generalizability models trained on past crises may not fully capture novel shocks such as cyber disruptions, pandemics, or climate-related financial risks. Future research should explore hybrid frameworks that combine transformers with economic theory-based constraints, incorporate climate and ESG variables, and expand real-time forecasting dashboards for policymakers. Reinforcement learning could also be applied for adaptive investment strategies that evolve with changing market conditions. Addressing these areas would ensure broader adoption and establish transformers as a central tool for global currency volatility forecasting [96].

6. Conclusion

This study developed and evaluated a transformer-based forecasting framework for predicting currency volatility in global markets, with a focus on implications for U.S. trade and investment strategies. Empirical results demonstrated that transformers significantly outperform traditional econometric models (GARCH, VAR) and recurrent neural networks (LSTM, GRU), particularly in identifying high-volatility regimes and providing early warnings during crisis periods. Case studies on USD/EUR and USD/JPY confirmed the model's ability to capture both macroeconomic shocks and event-driven volatility surges, while the integration of sentiment and alternative data further enhanced predictive robustness. Importantly, interpretability tools such as SHAP values validated the economic intuition behind forecasts, making them both actionable and trustworthy. A portfolio backtest confirmed the strategic value of these forecasts, reducing drawdowns during crises such as COVID-19. Collectively, the findings demonstrate that transformer-based models can provide both predictive accuracy and strategic relevance, offering U.S. businesses, investors, and policymakers a powerful tool for navigating global financial uncertainty [97].

7. Future Work

While promising, this research highlights several avenues for future exploration. First, expanding the dataset to include climate-related and geopolitical risk indicators would enrich forecasting in light of emerging systemic threats. Second, developing real-time dashboards that integrate transformer predictions into user-friendly platforms would facilitate adoption by investors, corporates, and policymakers. Third, hybrid approaches combining transformers with economic theory-driven models could improve robustness by anchoring forecasts to structural fundamentals. Additionally, incorporating reinforcement learning could allow investment strategies to adapt dynamically to shifting volatility regimes. Finally, extending the framework to smaller emerging market currencies would test its generalizability and provide valuable insights for global risk management. Pursuing these directions will further solidify the role of AI-powered forecasting as a cornerstone of financial stability, enabling the U.S. to enhance trade competitiveness, protect investment portfolios, and maintain leadership in global financial innovation [98].

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