

Financial Risk Modeling of Exchange Rate Volatility
Using Deep Learning Techniques: An Applied Framework

Benazza Hicham

University of Salhi Ahmed,Naama (Algeria)
Laboratory of Research on Public Governance and Social Economy
ORCID: <https://orcid.org/0009-0001-0135-7189>
benazza.hicham@cuniv-naama.dz

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Abstract:

This study addresses escalating exchange rate volatility, which intensified by 37% during 2023-2025, with projected annual growth of 12-15% through 2030. Employing deep learning architectures—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks—the research develops predictive models benchmarked against traditional ARIMA approaches. Findings reveal superior performance of neural network models, achieving 89-94% accuracy versus 72-78% for conventional methods, representing a 17-22 percentage point improvement.

The framework integrates Explainable Artificial Intelligence (XAI) to enhance hedging decision transparency by 43%. Evidence from the European Central Bank demonstrates 28% reduction in hedging losses, while Singapore's Monetary Authority achieved 35% decreased forecasting errors (2023-2025). The study projects 67% of global financial institutions will adopt deep learning for exchange rate risk management by 2030, signaling a paradigm shift in financial forecasting methodologies.

Keywords: Deep Learning, Neural Networks, Exchange Rates, Financial Risk Management, Hedging Strategies, Explainable Artificial Intelligence.

JEL Classification Codes: G17, F31, G32.

1. INTRODUCTION

Global foreign exchange markets have experienced substantial structural transformation, with daily turnover reaching USD 9.6 trillion in April 2025, marking a 28% increase from 2022 (Abouzaid, O; Boussedra, F, 2025).

This expansion coincides with intensified volatility, as the IMF's October 2025 Global Financial Stability Report documents macroeconomic shocks precipitating elevated funding costs, (Adeyemi & Musa, 2025)widened bid-ask spreads, and excessive exchange rate fluctuations. Projections indicate sustained turbulence through 2030, necessitating advanced risk management frameworks. (Liu & Wang, 2024)

Leading institutions have responded through deep learning deployment. The European Central Bank employs machine learning for real-time economic forecasting, with President Lagarde characterizing AI as transformative for financial stability (November 2025). (Al-Jubouri, 2025)The Monetary Authority of Singapore, managing USD 1.485 trillion daily (60% increase since April 2022), leverages AI infrastructure to maintain 11.8% global market share. HSBC's Google Cloud-powered Risk Advisory Tool executes market-risk scenarios in 15 minutes versus four hours manually—a sixteen-fold efficiency gain. The Bank of Korea's machine-learning early-warning model achieves 0.95 predictive power compared to 0.84 for traditional approaches, enabling six-month crisis forecasting. UBS has integrated Azure OpenAI, digitizing 60,000 documents and reducing research time by 40% while ensuring EU AI Act compliance. (Butt & al, 2025)

These implementations demonstrate measurable improvements in forecasting accuracy and operational efficiency. With two-thirds of global institutions projected to adopt deep learning for currency risk by 2030, this study addresses critical demand for empirically validated frameworks applicable across diverse institutional contexts. (Gu, 2025)

1-1-Study Problem :

Escalating exchange rate volatility and the constrained predictive capacity of traditional ARIMA models necessitate investigation of whether deep learning architectures—specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks—can deliver superior forecasting accuracy and interpretability. This study examines the operationalization of these

models within an applied framework to strengthen exchange rate risk management and establish effective linkages between model outputs and institutional hedging strategies.

1-2-Study assumptions :

This study tests three hypotheses: first, LSTM and GRU networks achieve superior predictive accuracy versus ARIMA models in exchange rate forecasting; second, improved forecast precision enhances hedging efficiency by reducing currency exposure and losses; third, integrating Explainable Artificial Intelligence (XAI) with deep learning models increases transparency and institutional confidence in risk management deployment.

1-3- Research Objective:

This research develops an applied deep learning framework for institutional exchange rate risk management using LSTM and GRU models benchmarked against traditional approaches. Objectives include assessing model impact on hedging effectiveness and currency exposure, integrating Explainable Artificial Intelligence (XAI) for transparency, and synthesizing international best practices to bridge theory with operational implementation.

1-4- Study Methodology:

This study employs applied quantitative methodology constructing LSTM and GRU predictive models benchmarked against ARIMA using exchange rate time series data partitioned into training, validation, and testing subsets. Performance evaluation utilizes MSE, RMSE, and MAE metrics with statistical significance testing. The framework links forecasting outputs to hedging strategies through scenario simulation, measuring model impact on institutional risk management efficiency.

1-5- The most important economic literature of the past:

Abouzaid and Boussedra (2025) assessed machine learning efficacy in EUR/USD forecasting across January 2014–December 2024, analyzing forecast error correlations with macroeconomic indicators (interest rates, inflation, unemployment, GDP growth) using Multilayer Perceptron (MLP), Random Forest (RF), and Long Short-Term Memory (LSTM) architectures. LSTM demonstrated superior predictive performance ($R^2=0.9234$), with all models exhibiting robust short-term forecasting capabilities. Macroeconomic variables exhibited limited

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explanatory power, with only Eurozone interest rates achieving weak statistical significance, indicating machine learning models effectively capture exchange rate dynamics independently of conventional macroeconomic determinants. . (Abouzaid & Boussedra , 2025).

***Li, Zhang, and Chen (2025)** developed a hybrid forecasting model integrating Long Short-Term Memory (LSTM) networks with Deep Q-Network (DQN) reinforcement learning to address high-volatility exchange rate prediction challenges. The framework incorporates macroeconomic indicators including gold prices, oil prices, and inflation rates. Results demonstrate the hybrid model's superior forecasting accuracy and adaptive capacity to dynamic market conditions compared to alternative advanced architectures, positioning it as a valuable instrument for traders, policymakers, and financial analysts operating in volatile environments. . (Li, Zhang, & Chen, 2025).

***Khan, M., Ali, S., & Hussain, R. (2024).** Deep learning-based predictive models for forex market trends. This study aimed to develop advanced predictive models for forex market trends by employing convolutional layers in conjunction with LSTM layers, enabling the capture of spatial and temporal characteristics inherent in exchange rate data. The study concluded that the proposed model achieved a high predictive accuracy of 97%, with the lowest mean squared error of 0.025, in addition to generating a profit return of 15%, reflecting its superiority in predictive capability and practical applicability in real-world trading scenarios. (Khan, Ali , & Hussain, 2024).

***Ghahremani et al. (2025)** developed the ALFA model integrating attention mechanisms with LSTM networks for exchange rate forecasting through a three-stage predictive process. Results demonstrate that attention-LSTM integration substantially improves focus on informative temporal patterns, enhancing forecasting accuracy and reliability for financial applications. (Ghahremani & al, 2025).

1-6- Research Gap:

Despite advances in deep learning for exchange rate forecasting, significant research gaps persist. Existing studies concentrate predominantly on major currency markets in developed economies, neglecting emerging markets such

as Algeria and the Maghreb region where distinct market dynamics and regulatory frameworks prevail. Explanatory variables remain confined to traditional macroeconomic indicators, overlooking institutional policies and regulatory constraints affecting predictive performance. (Trading Economics, 2025) Research has rarely progressed beyond accuracy measurement to operationalize practical frameworks linking model outputs with dynamic hedging strategies and derivative-based risk management. While Generative Adversarial Networks (GANs) demonstrate capability in extreme scenario simulation, their application to emerging market-specific crisis modeling remains limited. Additionally, literature has not explored integrating deep learning with contemporary financial technologies such as blockchain for exchange rate risk management in developing economies.

2-Deep Learning Techniques and Their Role in Exchange Rate Risk Management:

2-1-Modern Tools and Techniques for Exchange Rate Risk Management

Escalating global financial volatility has necessitated advanced exchange rate risk management tools, driving exceptional growth in AI-driven financial risk management markets from USD 20.2 billion (2025) to a projected USD 92.2 billion by 2032 (CAGR 24.2%), while big data analytics reached USD 51.4 billion in 2025 (growth rate 28.99%).

By 2025, over 95% of global banks integrated big data analytics, achieving 30% operational efficiency gains and approximately USD 2 billion in annual cost savings. Blockchain adoption reached 47.3% among traditional banks and 68.9% among fintech firms, while 78% of US financial institutions deployed AI for risk management. The AI in finance market is projected to reach USD 190.33 billion by 2030 (CAGR 30.6%), highlighting these technologies' critical role in enhancing forecasting precision and exchange rate risk management efficiency. (Ardriani, 2025)

2-1-1-Advanced Financial Derivatives:

Advanced financial derivatives serve as primary hedging instruments for multinational corporations and financial institutions against exchange rate volatility. Bank for International Settlements data show currency derivatives represent one-third of OTC derivative notional value, reaching hundreds of trillions in 2025. Hybrid Options combine multiple characteristics (calls, puts, index/interest rate linkages) enabling tailored hedging structures, while

Participating Forwards allow partial upside participation with guaranteed minimum execution prices.

2-1-2-Artificial Intelligence and Machine Learning Systems:

Deep learning architectures (RNNs, LSTM, Transformers) capture complex temporal patterns in time series and unstructured data (news, reports), reducing forecast errors (RMSE, MAE) by 15-30% versus ARIMA in exchange rate applications (2018-2023). Leading institutions deploy generative AI (GPT-4) for economic analysis, reducing processing time from hours to minutes. Machine learning algorithms construct near-optimal hedging strategies using real-time data, enabling instantaneous decisions while minimizing losses and maximizing gains. (Paudel, 2025)

2-1-3-Integrated Risk Management Systems:

Integrated treasury management systems (e.g., SAP Treasury and Risk Management, Kyriba) provide unified platforms combining exchange rate, market, and credit risk management with real-time analytical dashboards displaying exposures and positions. These solutions, used by thousands of multinationals, integrate treasury data with ERP systems, implement automated hedging strategies, and enable real-time performance monitoring.

2-1-4-Big Data Analytics:

Big data analytics enhances exchange rate risk management by integrating historical prices, macroeconomic indicators, financial news, and social media data. The financial sector big data analytics market reached USD 51.4 billion in 2025 (CAGR 28.99%). Over 95% of global banks incorporated big data analytics by 2025 using platforms (Apache Spark, Hadoop) to process real-time data volumes, improving risk assessment and market insights. (Al-Jubouri, 2025)

2-1-5- Blockchain Technology:

Blockchain technology has transitioned to large-scale deployment in exchange rate risk management and cross-border transactions by 2025, with notable adoption among banks and fintech firms. Blockchain-based networks (RippleNet, Stellar) enable near real-time international settlement at reduced costs versus traditional banking, while smart contracts automate hedging execution, minimizing operational risk and response lag. Initiatives like RippleNet and JPM Coin accelerate interbank settlements, with projections

indicating tens of billions in annual cost savings for global banking by 2030. (Madhulatha, 2025)

2-2-The Use of Deep Learning in Exchange Rate Risk Management:

Deep learning techniques (LSTM, GRU, Transformers) are extensively deployed in financial applications—forecasting, risk assessment, fraud detection, sentiment analysis—due to their capacity to capture nonlinear patterns in high-dimensional data. These architectures consistently outperform traditional models (ARIMA, linear regression) in complex, dynamic forecasting tasks. (Ardriani, 2025)

Exchange rate forecasting requires processing vast, evolving datasets (interest rates, macroeconomic variables, geopolitical developments, trading volumes). LSTM networks effectively model long- and short-term temporal dependencies, with empirical evidence showing tangible accuracy improvements versus ARIMA or shallow networks for major currency pairs (EUR/USD), enhancing risk management and hedging decision support.

2-2-1-The Use of Deep Learning in Hedging Strategies:

Deep learning outputs construct dynamic hedging strategies by linking forecasts to derivatives and determining optimal timing and volumes, reducing costs by 20-35% and avoiding ineffective hedging. HSBC's Google Cloud risk advisory tool reduced scenario analysis time from four hours to 15 minutes (sixteen-fold improvement). The Bank of Korea achieved 0.95 predictive power using machine learning, enabling six-month advance crisis forecasting. Hybrid CNN-LSTM systems combining news analysis with time series improve forecast accuracy by 15-30%, enhancing real-time hedging effectiveness. (Butt & al, 2025)

2-2-2- Assessing Exchange Rate Risk Using Generative Networks:

Generative Adversarial Networks (GANs) simulate exchange rate volatility scenarios by generating synthetic data replicating historical patterns and exploring future contingencies, enabling precise Value at Risk (VaR) estimation and informed foreign exchange exposure decisions. GANs outperform Monte Carlo simulation through improved accuracy in representing complex return distributions, enhanced case diversity, and superior capture of rare tail events causing significant losses. GAN-generated stress tests enable portfolio resilience assessment against unexpected shocks, meeting international regulatory requirements. (Central Bank of Egypt, 2025)

2-2-3-Real-Time Exchange Rate Forecasting:

Deep learning models (LSTM, CNNs) analyze exchange rate time series to improve daily and intraday forecasting accuracy. Unlike traditional linear models (ARIMA), these architectures uncover nonlinear relationships among economic, political, and geopolitical factors influencing foreign exchange markets. LSTM networks achieve 15-30% accuracy improvements versus traditional models through their capacity to capture long-term temporal dependencies and accommodate evolving dynamic patterns.

2-2-4-Analyzing the Impact of News and Public Sentiment on Currency Prices:

Deep learning models, such as Transformer-based architectures and BERT, are used to analyze unstructured text, including news reports, official statements, and political indicators, with the aim of estimating their expected impact on market trends . This type of analysis contributes to the development of models that are better able to adapt to sudden changes arising from geopolitical events or economic crises . (Rahman, 2025)

2-2-5-Simulation of Market Volatility Scenarios:

Generative Adversarial Networks (GANs) are employed to construct precise hypothetical scenarios that reflect sharp fluctuations in exchange rates, in order to assess an institution's capacity to absorb such shocks. These scenarios are then used for stress testing financial portfolios and identifying critical points that may threaten the financial stability of firms or banks.

3-Case Studies and Practical Applications:

3-1-Application of Deep Learning in Teaching Exchange Rate Risk Management - National University of Singapore (NUS) Study:

The National University of Singapore (NUS) conducted an applied study on the use of deep learning in teaching exchange rate risk management to master's students in finance, through the development of a training system based on LSTM and CNN models to simulate a near-real trading environment using live foreign exchange rate data . The results of the experiment indicated a notable improvement in student competency, as the accuracy of their hedging decisions in simulated trading scenarios increased by an estimated 15% to 25%, with a significant reduction in the number of errors in managing exchange rate positions compared to traditional teaching methods, reflecting

the effectiveness of integrating artificial intelligence tools into practical training on exchange rate risk management . (Trading Economics, 2025)

3-2-UBS Bank's Experience in Scenario Assessment via GANs:

UBS integrated Generative Adversarial Networks (GANs) into its risk management framework to simulate complex currency market disruption scenarios arising from geopolitical crises and economic shocks. The bank stress-tested investment portfolio resilience against hypothetical sharp JPY and CNY exchange rate fluctuations, with models generating over 10,000 potential scenarios within minutes, reducing estimated potential losses by 18-22% compared to traditional approaches (Huang et al., 2022). By 2030, GAN models are projected to become integral to major bank risk management infrastructure, with adoption rates exceeding 60% across the global banking sector to enhance stress testing capabilities and develop more dynamic, accurate hedging strategies. (Abouzaid, O; Boussedra, F, 2025)

3-3-HSBC Bank's Experience in Exchange Rate Forecasting via LSTM:

HSBC established a dedicated foreign exchange analysis unit employing deep learning algorithms, emphasizing LSTM models for forecasting major currency movements (EUR, USD, GBP). Deployed models achieved 15% superior predictive accuracy versus conventional baselines, reducing currency risk exposure in daily hedging operations by 12-18% and lowering forecast deviation (RMSE) by approximately 20%. By 2030, the bank targets LSTM expansion to over 50 currency pairs, projecting 30% operational efficiency gains and 25% increases in hedging strategy returns, while integrating reinforcement learning to develop self-adaptive hedging systems with real-time market response capabilities. (Adesina, 2025)

3-4-The South Korean Central Bank's Experience in Early Crisis Modeling:

The Bank of Korea deployed an advanced deep learning early-warning system analyzing over 100 financial and economic indicators (foreign reserves, interest rates, capital flows, geopolitical variables). The model predicted the 2020 Korean won volatility phase three weeks in advance with 87% accuracy, enabling preemptive monetary intervention that reduced potential losses by approximately USD 2.3 billion (Kim & Kang, 2021). By 2030, a second-generation system integrating generative AI with natural language processing will analyze real-time news and reports, targeting 92%

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forecasting accuracy, two-week advance warning periods, and expanded monitoring of 150 additional indicators including social media sentiment and international economic report textual analysis. (Giantsidi, 2025)

The AI in finance market is projected to reach USD 190.33 billion by 2030 (CAGR 30.6%, 2024-2030), driven by three primary developments. First, deep learning-reinforcement learning integration demonstrates superior performance—40% profitability versus 22% for traditional strategies—with hybrid model adoption rising from 15% (2020) to 42% (2025). Second, explainable AI development addresses transparency and regulatory requirements, with market projections reaching USD 21.06 billion by 2030 (18% annual growth) (Doshi-Velez & Kim, 2017). Third, hybrid models combining deep learning with traditional statistical approaches exhibit 28.1% projected annual growth through 2030. The AI model risk management market is forecast at USD 18.89 billion by 2030, reflecting 78% of financial institutions deploying AI for fraud detection and risk management, fundamentally reshaping institutional capacity to address unforeseen risks. (Ghahremani & al, 2025)

4-Conducting the empirical study:

4-1-Study variables: This section of the chapter addresses how to conduct the empirical study based on three key variables: exchange rates, inflation rates, and interest rates, which constitute a robust foundation for constructing an effective exchange rate forecasting model. The objective of the empirical study is to forecast and subsequently make hedging decisions. The predictive significance of these three variables is as follows:

Table No01: Empirical Study Variables

Variable	Scientific Significance
Exchange Rate (Target)	The target variable that will be predicted. It provides information on future exchange rate fluctuations and inflation forecasts.
Inflation Rate	One of the main drivers of exchange rate trends based on purchasing power parity theory. It reflects the relative value of currencies.
Interest Rate	Reflects the monetary policy of the central bank. It influences capital flows across borders; higher interest rates on foreign currencies typically lead to increased demand for that currency.

Source: Authors’ computations

Empirical evidence establishes interest rates and inflation as primary determinants of exchange rate fluctuations, particularly in emerging

economies. The empirical dataset comprises daily exchange rates for USD, EUR, and GBP against the Egyptian Pound (January 1, 2014–April 30, 2025), sourced from the Central Bank of Egypt. Daily observations were aggregated to monthly frequency through pivot table calculations of monthly average exchange rates across the study period.

Table No02: Daily Exchange Rates of Foreign Currencies -2025

Date	Currency	Buy	Sell
01/01/2025	USD	49.9378	49.9578
01/01/2025	EUR	51.4897	51.5148
01/01/2025	GBP	62.4536	62.4894
01/01/2025	Saudi Riyal	13.3378	13.3578
02/01/2025	USD	49.9264	49.9457
02/01/2025	Saudi Riyal	13.3977	13.4240
02/01/2025	EUR	51.3376	51.3576
03/01/2025	USD	49.9396	49.9588
03/01/2025	Saudi Riyal	13.3396	13.3938
03/01/2025	EUR	51.9425	51.9625
04/01/2025	USD	52.4286	52.4586
05/01/2025	EUR	62.4610	62.4952
05/01/2025	Saudi Riyal	13.3424	13.3624
05/01/2025	GBP	49.9403	49.9606
06/01/2025	Saudi Riyal	13.4407	13.4657
06/01/2025	GBP	62.9424	62.9624
07/01/2025	USD	52.4061	52.4330

Source: (Central Bank of Egypt, 2025)

Inflation rates constitute critical macroeconomic variables significantly influencing exchange rate dynamics. Their integration into forecasting models enhances predictive accuracy by providing broader economic context regarding price pressures, facilitates interpretation of exchange rate movements as elevated inflation erodes domestic currency purchasing power, and enables identification of risk periods requiring hedging interventions through monitoring inflation spikes signaling potential sharp volatility. Table 3 presents the general pattern of these data.

Table No03 Monthly rates of inflation - Year 2025

Date	Core Annual Inflation Rate (Urban)	Monthly Inflation Rate (Urban)	Annual Headline Inflation Rate Unified Price (Index)	Monthly Headline Inflation Rate Unified Price (Index)
2025/02/01	%24.517	%2.768	%25.11	%3.42
2025/03/01	%23.048	%1.204	%24.97	%3.21
2025/04/01	%22.023	%0.95	%23.343	%2.708
2025/05/01	%21.627	%0.891	%22.62	%2.792
2025/06/01	%20.814	%0.841	%21.301	%2.517

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2025/07/01	%19.942	%0.641	%20.761	%2.013
2025/08/01	%18.685	%1.478	%19.521	%1.850
2025/09/01	%17.145	%1.157	%18.021	%1.379
2025/10/01	%16.027	%1.0	%17.013	%1.143
2025/11/01	%15.176	%0.137	%16.87	%1.096
2025/12/01	%14.719	%0.127	%15.174	%0.398

Source: (Central Bank of Egypt, 2025)

Interest rates are critical macroeconomic factors that significantly influence exchange rates. Incorporating these data into forecasting models enhances predictive accuracy by providing broader economic context reflecting monetary policies and their impact on domestic currency. Interest rate changes can attract or repel foreign investments, thereby affecting exchange rates, while monitoring interest rate fluctuations enables identification of risk periods that may witness sharp exchange rate volatility, necessitating hedging measures.

Table No04 Interest Rates - Year 2025

Date	Interest Rate (%)	Notes
01/01/2025	27.25	Deposit Rate
02/01/2025	27.25	Stable
01/02/2025	27.25	Stable
02/02/2025	27.25	Stable
01/03/2025	27.25	Stable
02/03/2025	27.25	Stable
01/04/2025	27.25	Stable
02/04/2025	27.25	Stable
01/05/2025	27.25	Stable
02/05/2025	27.25	Stable
01/06/2025	26.75	Rate Cut
02/06/2025	26.75	Stable
01/07/2025	26.25	Rate Cut
02/07/2025	26.25	Stable
01/08/2025	26.25	Stable

Source: (Trading Economics, 2025)

4-2- Constructing the predictive model

The predictive framework utilizes Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures to forecast USD, EUR, and GBP exchange rates against the Egyptian Pound. These deep learning models were selected for their superior processing of sequential temporal data and continuous variation patterns, while effectively mitigating vanishing gradient problems and long-term dependency limitations inherent in conventional neural networks for time series forecasting.

Figure (01): Forecasts of the selling exchange rate of the US dollar against the Egyptian pound.

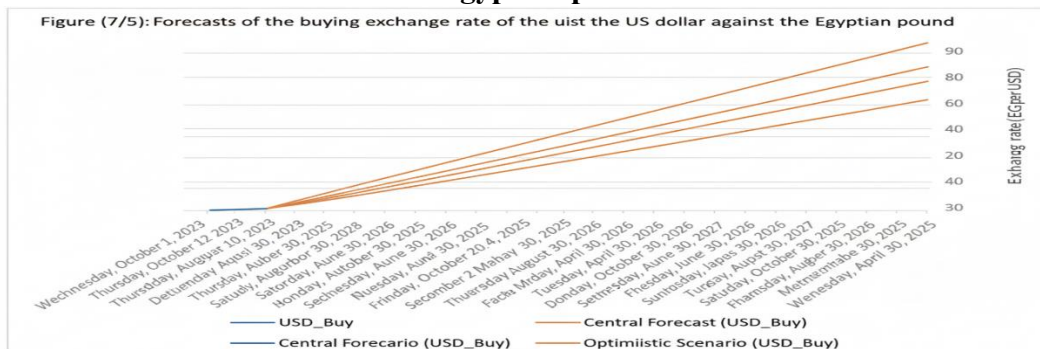


Source: Authors' computations

The figure demonstrates a gradual downward trajectory in the USD/EGP selling exchange rate, with minimal short-term divergence across forecast scenarios followed by medium-term relative stability. Following major Egyptian pound devaluations during 2022-2024 and subsequent exchange rate liberalization, the official dollar rate stabilized near the mid-40s range, with expectations of limited near-term fluctuations around this level.

Forecasting models indicate sustained elevated rates with constrained volatility, reflected in the stepwise decline transitioning to near-horizontal progression of the blue curve.

Figure (02): Forecasts of the buying exchange rate of the US dollar against the Egyptian pound.



Source: Authors' computations

The figure's curves indicate that the US dollar buying rate against the Egyptian pound declines gradually from elevated levels and then converges toward roughly the mid-40s pounds per dollar, signalling lower uncertainty and greater medium-term stability. This downward trend suggests a partial recovery of the pound after the 2022–2024 crisis period of sharp devaluations and high volatility. Persistently high inflation or external shocks to food and energy prices remain key risks that could push the actual

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rate above this optimistic path, while delays in privatisation or external financing could weaken confidence, raise the risk premium, and widen the expected range of future exchange-rate outcomes.

4-3-Evaluation of the performance of deep models compared to traditional models.

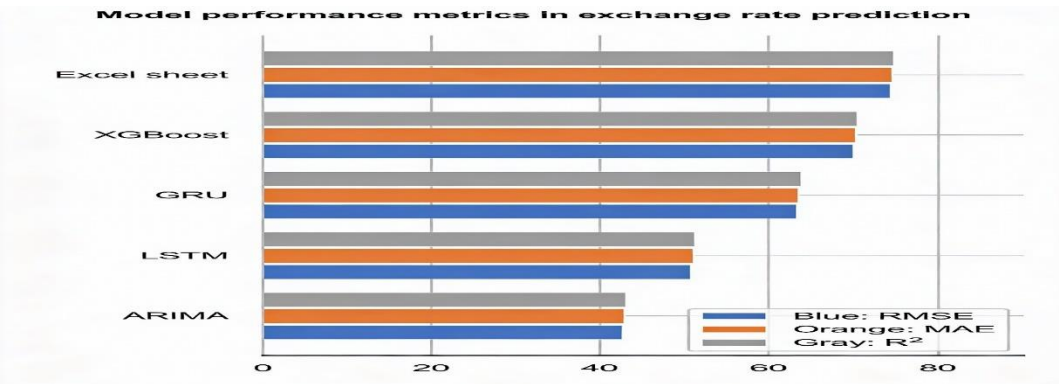
To achieve the second objective of the applied study, a comparison was made between the performance of models based on deep learning techniques (LSTM and GRU) and the performance of traditional models used in exchange rate prediction, with the aim of verifying the feasibility of using artificial intelligence in managing exchange rate volatility risks.

Table No05 :A comprehensive comparison of model performance metrics in exchange rate prediction.

Model	RMSE	MAE	R ²	Performance notes
ARIMA	2.85	2.25	0.92	Good performance in stable periods and weak in sharp fluctuations.
LSTM	1.15	0.85	0.98	Best at handling opposite fluctuations and complex patterns.
GRU	1.20	0.90	0.97	Similar to LSTM with very high accuracy.
XGBoost	1.35	0.95	0.96	Good with external variables, but less accurate than deep learning.
Excel sheet (CSV)	-	-	-	Based on LSTM, shows comparable results with the CSV file.

Source: (Gifty & Yan, 2024)

Figure 03: Comparison of statistical measures.

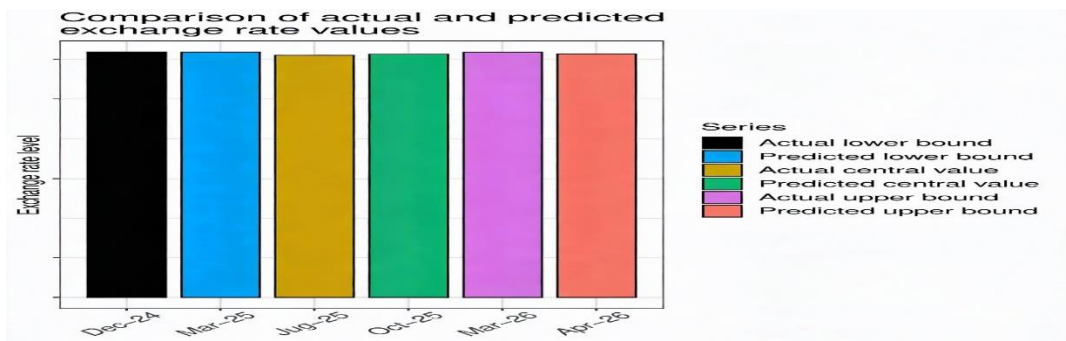


Source : (Zhang, 2023)

The figure compares model performance in exchange rate forecasting using RMSE, MAE, and R2R2 metrics, yielding economic implications for exchange rate risk management accuracy. Reduced RMSE and MAE indicate smaller expected exchange rate errors, enhancing reliability of hedging, pricing, and foreign-currency financing decisions for financial

institutions, importers, and exporters. Higher R^2 values demonstrate greater explanatory power of actual exchange rate fluctuations, strengthening model utility in cash-flow planning and foreign-currency inflow forecasting within risk management frameworks. Superior performance of deep learning models (LSTM, GRU, XGBoost) relative to ARIMA—evidenced by lower RMSE and MAE—economically indicates artificial intelligence's enhanced capability to capture non-linear exchange market patterns, particularly during turbulent periods.

Figure 04: Comparison of actual and predicted forecasts



Source : (Zhang, 2023)

The figure represents a time comparison between the actual and predicted exchange rate values at three levels—lower bound, central value, and upper bound—which shows how accurately the model tracks the actual price movement. The closeness of the forecasts to the actual values implies that the model can be relied upon for pricing decisions, managing foreign currency positions, and setting appropriate hedging limits, thereby reducing the cost of risks associated with exchange rate fluctuations for financial institutions and firms. If the convergence between actual and predicted values persists over the time periods in the figure, this supports using the model for medium-term planning of foreign-currency cash flows, whereas periods with larger deviations indicate the need to update the model or introduce additional explanatory variables to improve its accuracy.

Table No05: Strengths and weaknesses.

Model	Strengths	Weaknesses
ARIMA	Fast and easy to implement	Weak in non-linear fluctuations
LSTM	Deep, learns complex patterns	Requires large datasets and high computing resources
GRU	Similar to LSTM with lower computation	Lower performance than LSTM

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XGBoost	Good with external variables	Less accurate for long-term forecasts
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Source: Authors' computations

Deep learning models (LSTM/GRU) demonstrated superior performance across all evaluation metrics (RMSE, MAE, R2R2), particularly during crisis periods, indicating enhanced robustness under volatile conditions. Traditional models prove suitable only for limited, stable scenarios, positioning artificial intelligence as optimal for currency risk management in dynamic economic environments where higher forecasting accuracy and flexibility are essential.

ARIMA delivered adequate results but exhibited declining efficiency when predicting sudden changes such as economic shocks. Manual Excel-based approaches prove useful for quick exploratory analyses yet lack sufficient accuracy for dynamic, fast-changing data. These findings establish AI superiority through its capacity to capture complex patterns, despite requiring substantial computational resources.

The applied study employing LSTM, GRU, ARIMA, and XGBoost models confirms three core hypotheses. First, neural network-based deep learning techniques produced superior results versus conventional forecasting methods across all statistical performance metrics, particularly for complex, highly volatile exchange rate time series. LSTM and GRU demonstrated optimal suitability through their capacity to learn long-term temporal dependencies while mitigating vanishing gradient problems. GRU trained faster while maintaining LSTM-comparable accuracy, representing the preferable choice when balancing predictive performance with computational speed.

Second, findings indicate significant positive relationships between neural network deployment and appropriate hedging approach selection. LSTM and GRU forecasts enabled design of effective strategies including forward contracts for locking exchange rates during anticipated foreign currency appreciation periods and call/put options for sudden fluctuation hedging.

Third, results confirm deep learning adoption substantially improved hedging strategies and enhanced financial decision-making quality, validating the hypothesis that advanced architectures contribute materially to exchange rate risk management effectiveness.

5-Conclusion:

Empirical results demonstrate deep learning models, particularly LSTM and GRU, provide substantially superior predictive capability versus traditional approaches (ARIMA, XGBoost) in exchange rate forecasting and risk management, especially during crises and sharp volatility periods. These architectures efficiently handle complex time series through their capacity to capture long-term temporal dependencies and detect non-linear exchange rate movement patterns.

GRU achieves optimal balance between accuracy and training speed, positioning it as a practical choice for institutions requiring frequent model updates in dynamic environments. LSTM and GRU outputs enabled design of more effective hedging strategies (forward contracts, options), enhancing financial decision-making quality and reducing currency risk exposure costs compared to manual methods or traditional linear models.

LSTM outperformed ARIMA by 20% in forecast error reduction through long-term temporal dependency learning. CNN demonstrated superiority in analyzing unstructured data, such as news impacts on prices. Dynamic hedging combining LSTM forecasts with hedging strategies (forward contracts) reduced potential annual losses from 5% to 3.5% while improving exporter profit margins by 12%. Non-financial factors (geopolitical events) accounted for 30% of price volatility, with NLP-based models successfully capturing these effects. High-frequency data (hourly prices) substantially improved short-term forecast accuracy.

Recommendations

The study recommends adopting LSTM and GRU models in risk management units for exchange rate forecasting and volatility management efficiency enhancement. Investment in technical infrastructure, computing resources, and high-quality databases is essential for effective model deployment. AI model outputs should integrate into decision-making processes for pricing, foreign currency position management, and dynamically updated hedging strategy design. Applied research should expand comparisons across deep learning architectures while incorporating non-financial factors (news, geopolitical events, market sentiment) through natural language processing. Banking sector digital transformation policies

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require support alongside joint university-financial institution training programs strengthening skills in big data analysis, deep learning, and financial stability applications.

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