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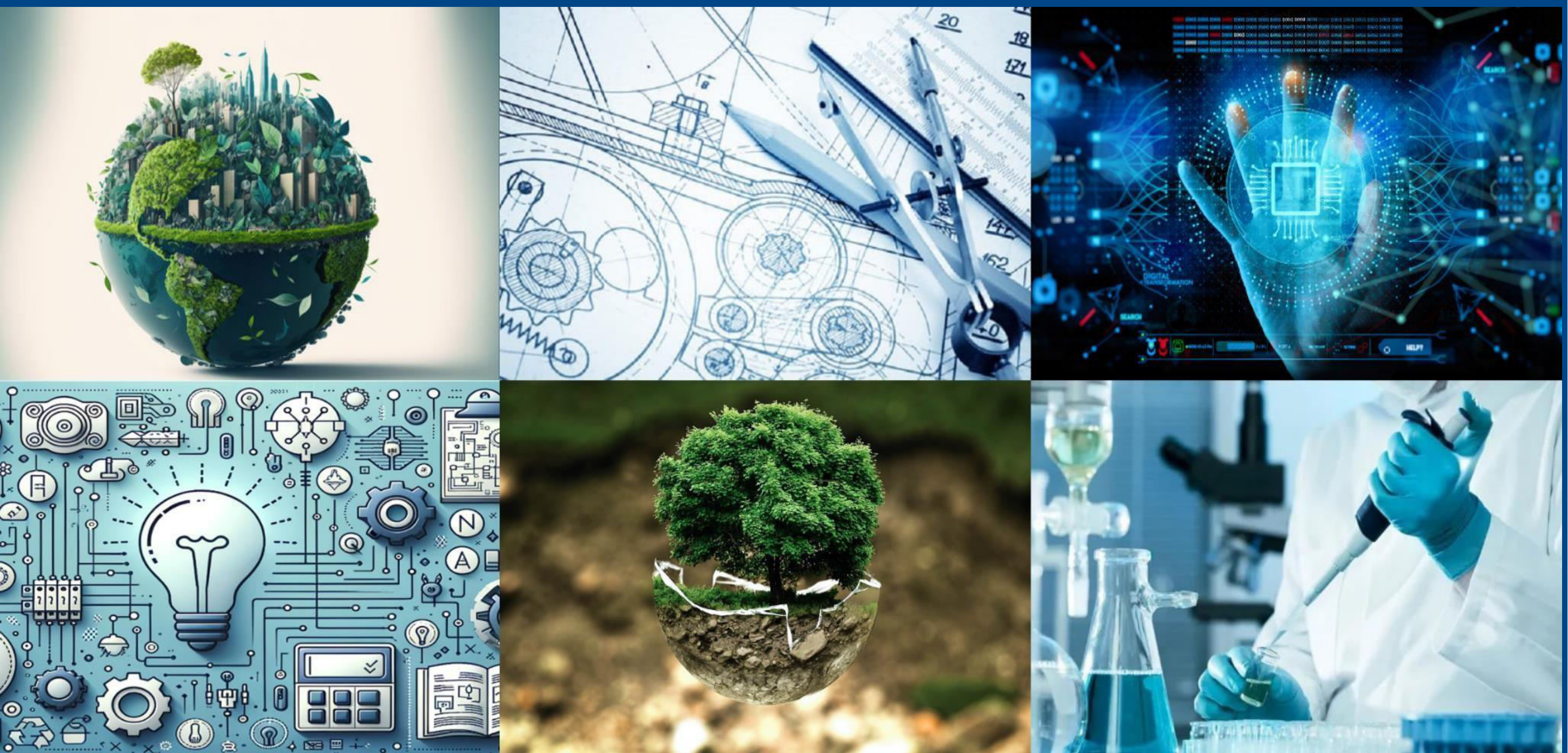

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The Role of AI in Predicting Currency Fluctuations for Forex Risk Management

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ABSTRACT: Foreign exchange (Forex) markets are highly volatile and shaped by complex economic, political, and psychological factors, making accurate currency prediction a persistent challenge for traders, investors, and multinational corporations. Traditional statistical models often fail to capture the non-linear dynamics of exchange rate movements, while recent advancements in Artificial Intelligence (AI)—including machine learning, deep learning, and natural language processing (NLP)—offer innovative solutions to this gap. This research explores the use of AI-driven methods for currency prediction and enhanced risk management in global financial markets by leveraging large datasets of historical price movements, macroeconomic indicators, and sentiment data from financial news and social media. AI models demonstrate superior forecasting accuracy compared to conventional techniques, and their integration into hedging strategies, portfolio optimization, and decision-support systems helps reduce exposure to exchange rate volatility. Challenges such as data quality, model interpretability, and real-time adaptability are critically examined, and findings indicate that AI, when combined with financial domain expertise, significantly strengthens risk management frameworks and offers a resilient approach to navigating uncertainty in the fast-evolving Forex environment.

KEYWORDS: Foreign Exchange Markets, Artificial Intelligence, Currency Prediction, Risk Management, Machine Learning

I. INTRODUCTION

In today's highly interconnected global economy, foreign exchange (Forex) markets play an essential role in enabling international trade, investment, and financial operations. However, the volatility fundamental in currency exchange rates introduces considerable risks for businesses, investors, and financial institutions engaged in cross-border transactions. Traditionally, managing Forex risk has relied on statistical models, expert judgment, and historical data analysis to forecast currency movements. Yet, these methods often fall short in capturing the complex, non-linear dynamics of the market, which are heavily influenced by geopolitical developments, macroeconomic indicators, and market sentiment. Recent breakthroughs in AI, particularly in machine learning and deep learning, offer an exciting alternative for predicting currency fluctuations with enhanced accuracy and flexibility. AI models can process vast amounts of structured and unstructured data in real time, identify subtle patterns unseen by traditional methods, and optimize their predictive capabilities through continuous learning algorithms. This technological progress opens the door for more resilient and adaptable risk management strategies in the volatile Forex environment. This paper aims to explore how AI can contribute to forecasting currency movements, compare its effectiveness with conventional methods, and examine its impact on Forex risk management practices. By analysing current AI innovations, challenges, and future directions, the study provides valuable insights into how financial institutions and businesses can use intelligent systems to reduce risk, refine decision-making, and encourage greater financial stability.

II. LITERATURE REVIEW

Hendry and Mirza (2013) were among the first to explore advanced machine learning techniques, comparing support-vector regression (SVR) and artificial neural networks (ANNs) against traditional ARIMA models for USD/GBP

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forecasts. Their results showed that both SVR and ANNs achieved lower root-mean-square errors, indicating the promise of nonlinear algorithms in capturing detailed market patterns.

Patel et al. (2015) combined technical and macroeconomic indicators within an ANN framework to predict EUR/USD and GBP/USD movements, achieving greater directional accuracy than conventional techniques.

Zhang and Lai (2017) contributed to the field by devising a hybrid ARIMA–ANN model personalized to Asian currency pairs, successfully boosting short-term forecast precision through the fusion of linear and nonlinear components.

Wang, Gupta, and Zhou (2020) demonstrated that transfer learning with LSTM models trained on highly liquid currency pairs and subsequently fine-tuned for emerging markets led to superior out-of-sample results, marking an important step toward risk management in data-limited settings.

Islam, Rahman, and Akter (2021) applied gated recurrent units (GRUs) to multi-pair FX prediction, showing important improvements during volatile market episodes.

Engel, Granger, and Rose (2008) pioneered efforts to decode exchange rate dynamics by examining whether macroeconomic fundamentals—such as interest rate differentials and purchasing power parity—could are reliable predictors of currency fluctuations. Employing standard econometric and cointegration methods on major currency pairs, their findings revealed that short-term forecasts merely outperformed a random walk marginally, emphasizing the constraints fundamental in relying solely on fundamental, linear models.

Cheung and Chinn (2011) integrated error-correction models to better represent both short-term movements and long-term equilibrium relationships. While these models offered a modest improvement in long-term accuracy, they only slightly enhanced short-horizon predictions, pointing to the necessity for more adaptable approaches.

Lu Zhao and Wei Qi Yan (2024) conducted an in-depth analysis of transformer models for predicting currency exchange rates. They evaluate how these models perform amidst volatile macroeconomic environments and identify that forecasts generated by transformer-based approaches considerably surpass those from LSTM and more basic neural networks. This advantage is especially pronounced during periods of heightened volatility or when global risk factors change abruptly, demonstrating the valuable role of transformer architectures in risk-sensitive forecasting scenarios.

III. OBJECTIVES

- To evaluate awareness and perceptions of forex traders and investors awareness and perceptions about leveraging artificial intelligence to predict currency changes.
- To understand trust and reliability that respondents attribute to AI-based picked travel currency forecasting compared to traditional forecasting methods.
- To evaluate the reported benefits and challenges of using AI in currency risk management as perceived by respondents.
- To analyse participant's views on the future potential and use of AI-powered forecasting and decision-making tools for currency.

IV. RESEARCH METHODOLOGY

Research Design:
This study adopts a descriptive and quantitative approach to examine how forex traders and investors perceive and trust AI-driven currency forecasting tools. By using this design, we can systematically gather primary data and perform statistical analyses to understand current attitudes, awareness levels, and patterns of usage.

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Sampling Strategy:
Target Population - Active forex traders and investors with practical experience in currency prediction.
Sampling Method- Due to the specificity of the target group and its accessibility limitations, convenience sampling was employed.
Sample Size- A total of 100 respondents participated in the survey.
Geographical Scope- The respondents mainly hailed from Bangalore, India, representing a diverse cross-section term of background, and trading experience.

Data Collection Methods:
Primary Data- Collected through a structured questionnaire divided into parts:
- Demographic information (age, gender, education, region).
- Experience in forex trading and forecasting strategies.
- Awareness, perceptions, levels of trust, benefits, challenges, and future perspectives on AI in forex prediction. The questionnaire included Likert scale items, multiple-choice questions, and categorical options.

Secondary Data- Gathered from academic journals, industry reports, and previous research on AI applications within financial markets to establish the theoretical foundation.

Analytical Methods:
Descriptive Statistics- Used percentages, frequency counts, and visual charts to summarize demographic data and response trends.
Software Tools- Data cleaning, tabulation, and visualization were performed using Microsoft Excel and Google Sheets.

V. DATA ANALYSIS

In this section, statistical analysis has been carried out using hypothesis testing to evaluate the survey results. Two one-tailed proportion tests were conducted to determine:
- Whether more than 60% of forex traders and investors have a positive perception of AI-based currency forecasting tools.
- Whether more than 60% of forex traders and investors trust AI over traditional forecasting methods.

Hypothesis:
- **Hypothesis test 1:** Is the proportion with positive perception > 60%?
- **Hypothesis test 2:** Is the proportion who trust AI more than traditional methods > 60%?

Why test them separately?
- These two variables may not be the same.
- People might think AI is promising (positive perception) but still prefer traditional methods when making decisions (lower trust).
- Each variable has its own data and proportion, so you test hypotheses independently.

Calculations:
Hypothesis Test 1 (Positive Perception)
- **Null Hypothesis (H_0):** 60% or fewer forex traders and investors have a positive perception of AI-based currency forecasting tools.
- **Alternative Hypothesis (H_1):** More than 60% of forex traders and investors have a positive perception of AI-based currency forecasting tools.

$$H_0 : p \leq 0.60$$
$$H_1 : p > 0.60$$

Sample Data: From our survey of 100 participants

- 65 people say they have a positive perception of AI (score 4 or 5).
- Hence sample proportion ($\hat{p}$) = 65/100 = 0.65 (65%).

Significance Level (α)
- This is the threshold for deciding if your results are statistically significant.
- Commonly, $\alpha = 0.05$ (which means you accept a 5% chance of wrongly rejecting H_0).

Test Statistic (z-score)
- The z-score tells you how far our sample result (65%) is from the null hypothesis proportion (60%), measured in terms of standard error.
- The formula is:

$$z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$$

Where:

- $\hat{p}$ = sample proportion = 0.65
- p_0 = hypothesized proportion = 0.60
- n = sample size = 100
- Calculation:

$$z = \frac{0.65 - 0.60}{\sqrt{\frac{0.60\times0.40}{100}}} = \frac{0.05}{0.049} = 1.02$$

Critical Value or p-value
- For α=0.05 and a **one-tailed test** (checking if proportion > 0.60), the **critical z-value** is **1.645**.
- We calculated z-score (1.02) with this critical value.
- Alternatively, we find the **p-value** (probability of seeing your result if H_0 is true). For z=1.02, p-value ≈ 0.15.

$$p = 1 - 0.8461 = 0.1539$$

Decision
- If z-score ≥ 1.645 or p-value ≤ 0.05, reject H_0. (Your data shows strong evidence the proportion is greater than 60%).
- If z-score < 1.645 or p-value > 0.05, fail to reject H_0. (Your data does not provide strong enough evidence).
- In our case, z = 1.02 < 1.645 and p-value = 0.15 > 0.05 → fail to reject H_0.
- This means: "Based on the survey, there is not enough evidence to say that more than 60% of forex traders and investors in Bangalore have a positive perception of AI-based currency forecasting."
- Since z is negative and you are testing "greater than 60%", the p-value will be very large (>0.95), so fail to reject H_0 here as well.

Hypothesis Test 2 (Trust in AI)
- **Null hypothesis (H_0):** 60% or fewer of trader's trust AI over traditional methods.

$$p \leq 0.60$$

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- **Alternative hypothesis (H_1):** More than 60% trust AI over traditional methods.

$$p > 0.60$$

Sample data

- From our data, **50 out of 100 respondents** trust AI more (Likert 4 or 5).
- Sample proportion

$$(\hat{p}) = 50/100 = 0.50\ (50\%)$$

Significance level

Commonly α = 0.05 (5% risk of error).

Calculation of the z-score

$$z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$$

Plug in values:

- $\hat{p} = 0.50$
- $p_0 = 0.60$
- $n = 100$

Calculate denominator first:

$$\sqrt{\frac{0.60 \times 0.40}{100}} = \sqrt{0.0024} = 0.049$$

Calculate numerator:

$$0.50 - 0.60 = -0.10$$

Calculate z:

$$z = \frac{-0.10}{0.049} = -2.04$$

Calculation of the p-value

Since the alternative hypothesis is $p > 0.60$, this is a **one-tailed test to the right** (testing if proportion is greater).

- But our z-score is **negative** (-2.04), meaning the sample proportion is actually **less** than 60%.
- To find the p-value, calculate:

$$p = P(Z \geq z)$$

Using z-tables or calculator:

- $P(Z \leq -2.04) = 0.0207$ (area to the left of z)
- $P(Z \geq -2.04) = 1 - 0.0207 = 0.9793$

Decision:

- $p = 0.9793$
- $\alpha = 0.05$

Since $p > \alpha$, **fail to reject the null hypothesis.**

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- Our data suggests that trust in AI is not greater than 60%; in fact, it is statistically significantly less than 60%.
- So, there is no evidence from the sample that the majority trust AI more than traditional forecasting.

Hence in both the cases we fail to reject Null Hypothesis

VI. RESULTS

The role of AI in predicting currency fluctuations within forex risk management is becoming an increasingly prominent focus of both academic research and practical application. This study sought to determine whether the majority of forex traders and investors perceive AI-based forecasting tools positively, and whether they trust these tools more than conventional methods. To examine these questions, two one-tailed hypothesis tests were conducted. The first test investigated whether more than 60% of respondents held a favourable attitude toward AI in forex prediction. While survey results showed that 65% of participants expressed positive sentiments, the statistical analysis ($z = 1.02$, $p = 0.15$) indicated that this difference was not statistically major at the 5% level. This suggests that, despite generally positive perceptions, it cannot be conclusively stated that an overwhelming majority of traders fully endorse AI for currency forecasting. The second test assessed whether traders place greater trust in AI-driven methods compared to traditional forecasting approaches. Only half of the respondents reported higher confidence in AI. The statistical findings ($z = -2.04$, $p \approx 0.98$) strongly imply that the level of trust in AI remains below the 60% threshold. This outcome emphasizes that although traders recognize AI's potential, they remain cautious, preferring to rely on established methods that continue to dominate forex risk management decisions. Collectively, these findings reveal a discrepancy between the acceptance and perception of AI technology. While traders may see AI as a promising tool, they are hesitant to fully adopt it or replace traditional techniques. This indicates that AI in forex risk management is still in the early stages of integration, with major needs for improvements in model accuracy, transparency, interpretability, and demonstrated real-world effectiveness. To promote trust, AI developers and financial institutions must prioritize explainability, robustness against market volatility, and comprehensive user education. Eventually, the results suggest that, although AI holds major promise for enhancing forex risk management, overcoming skepticism and building genuine confidence in the technology are essential steps before it can become a decisive influence in the sector.

VII. CONCLUSION

This research study discussed the use of Artificial Intelligence (AI) in forecasting currency movements and how it affects Forex risk management. The research emphasized the increasing importance of AI tools like machine learning, deep learning, and transformer models in improving forecasting with the help of big data containing historical prices, macroeconomic indicators, and sentiment from news and social media. Yet, a survey of 100 forex traders and investors in Bangalore indicated a disconnect between favourable perception and real trust in AI-based forecasting tools. While 65% respondents held a favourable view of AI, statistical inference provided weak evidence to support the conclusion that more than half trust AI more than conventional forecasting methods. This indicates lingering skepticism based on issues with model interpretability, data quality, and responsiveness to real-time market dynamics. The study indicates that although AI has great potential to develop Forex risk management models, its complete implementation is subject to enhancing model transparency, increasing resistance to market volatility, and offering extensive user education. With the development of financial markets, combining AI with expert domain knowledge and traditional risk approaches will be inevitable in creating robust decision-support systems that reduce the risk of currency in a more uncertain Forex market. Subsequent research will need to focus on creating explainable AI models and actual case studies of real-world success, hence closing the gap in trust and propelling wider use of AI in Forex markets.

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