Exchange Rate Dynamics of USD-KZT, EUR-KZT, RUB-KZT, and CNY-KZT (2000–2024)

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***Abstract* – This study examines the dynamics of the major international currencies (USD, EUR, RUB, and CNY) in relation to the Kazakhstani Tenge (KZT) between 2000 and 2024, highlighting the crucial role that exchange rate stability plays in economic performance. Understanding currency fluctuations is crucial because Kazakhstan's economy is highly reliant on the export of commodities and is susceptible to changes in the global economy. The research aims to analyze historical exchange rate trends and develop predictive models using machine learning techniques.**

The methodology used machine learning algorithms, particularly Random forest and Linear regression models, correlation studies, and descriptive statistical analysis.

Data sourced from the National Bank of Kazakhstan encompassed 9,086 data points, providing insights into currency behaviors. Descriptive analysis revealed significant variations, with USD and EUR showing higher volatility compared to more stable RUB and CNY.

Machine learning models demonstrated remarkable predictive capabilities, with Random forest achieving near-perfect accuracy. The study also highlighted interconnected exchange rate dynamics and the unique position of the Russian Ruble, offering valuable insights for policymakers, investors, and all financial market participants navigating KZT complex behavior.

Keywords—Exchange Rate, KZT/USD, KZT/EUR, KZT/RUB, KZT/CNY, Currency Fluctuations, Foreign Exchange Market

I. Introduction

Exchange rate stability plays important role in determining a country's economic well-being, especially for developing economies like Kazakhstan, where exchange rate fluctuations can significantly affect trade, investment and economic stability of country Lee et al. (2010).

Time series analysis data that we provide shows a comprehensive picture of exchange rate fluctuations and economic trends over the past two decades, offering valuable insights into Kazakhstan's economic performance.

Exchange rate data is critical to understanding a country's economic stability, affecting everything from trade to inflation. For Kazakhstan, exchange rate fluctuations in major currencies such as USD, EUR, RUB, and CNY directly impact international trade, foreign investment, and the cost of imported goods. Monitoring these trends helps policymakers, investors, and businesses make informed decisions about currency risk and economic strategy Eichenbaum (2021).

Williamson (2009) describes the exchange rate as a crucial economic factor linking a country's internal economy with the global economy. It influences macroeconomic stability and trade incentives, as well as real exchange rates, especially in the short and medium term, where limited internal price flexibility exists.

Work Isard (1995) traces the history of exchange rates from fixed systems, like the gold standard, through the Bretton Woods system, to modern flexible regimes. Also, author emphasizes the evolving understanding of exchange rate dynamics, monetary policy, and the economic forces that shape currency valuations globally.

Analyzing exchange rate dynamics helps us identify patterns and forecast future currency movements. By studying historical fluctuations between currencies, we can determine underlying economic conditions, geopolitical influences and market sentiment. This analysis provides important insights into how external factors, such as global economic shifts or changes in commodity prices, affect Kazakhstan's currency and its financial markets.

This study analyzes historical trends and patterns in currency dynamics to provide predictive insights into the USD, EUR, RUB, and CNY against KZT. By utilizing machine learning techniques such Logistic regression and Random Forest, we aim to forecast dynamics of each currencies pair, offering valuable insights and tools for financial planning and decision-making. In the discussion section, we aim to explain currency movements by linking them to real-world events and macroeconomic factors with literature reviews. We also assess the effectiveness of the applied models, and determine the practical applicability of the models

II. Literature REVIEW

Predicting currency exchange rates is important, particularly for countries like Kazakhstan, where the economy is closely tied to global commodity prices. Kazakhstan's economy relies heavily on crude oil and other mineral exports, making it vulnerable to fluctuations in global prices. The economy of a country directly influences its currency status, as factors like economic stability Duruechi (2023). Geopolitical factors such as shared borders and strong ties with Russia and China also affect its economic stability of country.

Numerous studies have explored the application of machine learning techniques to forecast exchange rates and other financial trends. Techniques such as Random Forest, Support Vector Regression etc., and Neural Network models have demonstrated their usefulness in improving forecasting accuracy. These methods, when combined with ensemble methods and optimization strategies, have shown promise in capturing complex patterns in financial data and providing actionable insights for decision making.

Work by Lin et al. (2013) proposed an intelligent exchange rate prediction system (IERPS) using cloud computing, achieving high predictive performance with linear regression, which had an average error rate of 94.6%.

In the study Mahjouby et al. (2024) authors developed an ensemble model combining logistic regression, random forest, and Gaussian Naive Bayes, achieving a forecasting accuracy of 94.8%, outperforming other machine learning methods to forecast the EUR/USD exchange rate.

Also, Tsuji (2022) applied random forest methodology to forecast exchange rates of major currencies against the US dollar, demonstrating high forecasting accuracy and suitability of the model for exchange rate forecasting.

Pevekar (2021) developed a random forest-based model to forecast six exchange rates against the Indian rupee, demonstrating high forecasting accuracy with 93.61%.

In work El Mahjouby et al. (2024) authors proposed an ensemble method combining logistic regression, extreme gradient boosting, and Gaussian Naive Bayes, achieving 98.4% accuracy for predicting USD/JPY exchange rates, providing valuable insights for investors.

Work Aliyeva (2021) compared random forest and logistic regression for predicting stock prices, finding that logistic regression is more consistent and highlighting the usefulness of machine learning in predicting financial trends.

Polamuri et al. (2019) also highlighted the effectiveness of random forest and decision tree regressors in predicting stock prices, outperforming traditional systems in efficiently handling large datasets.

Study Abbas et al. (2011) identified macroeconomic variables affecting emerging Asian exchange rates and used cointegration analysis to identify long-run relationships between exchange rates and economic fundamentals.

Study by Rabbi et al. (2022) used advanced models, compared SVR, RFR, and LSTM models, finding that LSTM outperformed the others with the lowest forecast error for forecasting foreign exchange rates.

In Panda et al. (2023) integrated CNN with ADAM-optimized random forest regression to forecast NZD/USD exchange rates, achieving high accuracy in forecasting Forex movements over multiple time horizons.

In this study we utilize linear regression and random forest algorithms to forecast exchange rate fluctuations.

III. METHODOLOGY

A. *Flowchart to design Analytics Platform*

To design the flowchart, we start with Data collection step, where historical exchange rate data is sourced from the National Bank of Kazakhstan. Proceed to Data preprocessing, ensuring data quality and converting dates into numerical format. Next, we move to Descriptive analysis step for trends and insights. Then, apply Machine learning models (Linear Regression and Random Forest) for predictions. Finally, we evaluate model performance, compare results and visualize predictions for further interpretation and insights (see fig. 1.).

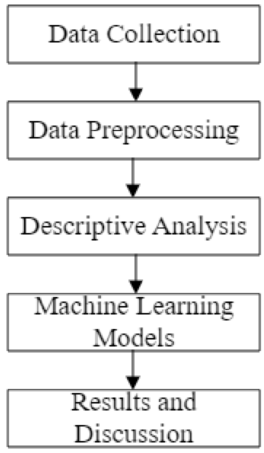

Fig 1 Flowchart of methodology

B. *Data Collection*

This dataset was obtained from the National Bank of Kazakhstan, which provides official data on the exchange rate of various foreign currencies against the Kazakhstan tenge (KZT). The National Bank of Kazakhstan regularly publishes updated exchange rates. From various currencies we have choose main global powerful currencies The dataset includes historical exchange rate information reflecting the fluctuations of the US dollar (USD), European euro (EUR), Chinese yuan (CNY), and Russian ruble (RUB)against the tenge.

The National Bank of the Kazakhstan is the central bank of the country, represents the highest level of the banking system and has a special legal status. This organization has the main goal of ensuring price stability in Kazakhstan, develops and conducts the monetary and credit policy of the state, ensures the operation of payment systems, implements currency regulation and control, as well as ensures the stability of the financial system Ilyassova (2021).

This dataset presents the exchange rates of four major currencies (USD, EUR CNY, RUB) against the Kazakhstani Tenge (KZT) over a period from January 1, 2000, to December 7, 2024. Each row in the dataset corresponds to a specific date and contains the exchange rates for the four currencies for that particular day. The dataset covers over three years of exchange rate data, giving information about fluctuation of these currencies against the KZT. Overall, 9086 rows of values, and not missing values.

The data is organized with the date as the primary key, followed by the exchange rates of the US Dollar (USD), European euro (Euro), Chinese Yuan (CNY), and Russian Ruble (RUB). The exchange rates are presented in terms of how many units of each foreign currency are equivalent to KZT (see fig. 2).

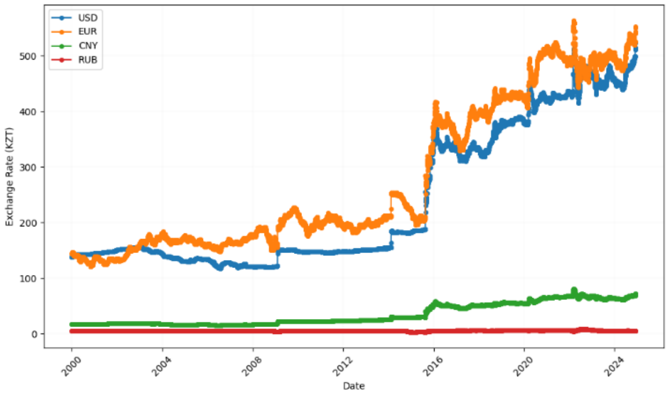

Fig 2 Historical Exchange Rates of Currencies to KZT

C. *Analysis Data – descriptive analysis. Why it is important.*

Descriptive analysis for exchange rate data provides a clear summary of trends, central tendencies, and volatility, that helps to identify patterns in currency movements. This is important because it allows participants to assess the stability of a country's currency, predict future fluctuations, and make informed fiscal or policy decisions.

D. *Machine Learning techniques used*

Machine Learning (ML) enables systems to learn and improve from data without being explicitly programmed. It involves developing algorithms that identify patterns and make predictions or decisions based on input data. There are several techniques in ML. As we defined Linear Regression and Random Forest to predict, first let's give them definitions.

Linear Regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. It predicts outcomes by minimizing the squared difference between the predicted and actual values, making it ideal for continuous data analysis.

The linear regression model predicts currency exchange rates by using the date as a numerical feature (converted to ordinal format) to estimate the relationship between time and the currency values. The model fitted a line to the historical data of each currency, generating predictions based on the slope and intercept of the regression equation.

Random Forest is an ensemble learning algorithm that builds multiple decision trees during training and outputs the majority vote or average prediction of the trees for classification and regression tasks. It uses random subsets of data and features, improving accuracy and reducing the risk of overfitting.

Applying machine learning techniques, we aim to predict exchange rate based on date.

E. *Equations*

Linear regression is a techniques tool for modeling the relationship between explanatory variables and a real-valued outcome. In the context of machine learning, the domain set $X \subseteq \mathbb{R}^d$ represents the input feature space, while the label set $Y \subseteq \mathbb{R}$ denotes the real-valued target outputs. The goal of linear regression is to learn a linear function $h: \mathbb{R}^d \to \mathbb{R}$ that best approximates the relationship between the input variables and the target outputs.

The hypothesis class for linear regression is defined as (1).

$$\mathcal{H}_{reg} = \mathcal{L}_d = \{x \mapsto \langle w, x \rangle + b : w \in \mathbb{R}^d, b \in \mathbb{R}\} \quad (1)$$

here:

$\langle w, x \rangle$ – represents the dot product between the weight vector www and the input vector x

b – is the bias term.

The R^2 metric, also coefficient of determination, is a measure that explains the proportion of variance in the dependent variable that is predictable from the independent variables. It is defined as formula (2).

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - h(x_i))^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \quad (2)$$

here:

y_i – is the actual value of the dependent variable for the i-th sample.

$h(x_i)$ – is the predicted value of the dependent variable for the i-th sample.

$\bar{y}$ – is the mean of the actual values y_i

A Random Forest is an ensemble learning method that constructs a collection of decision trees to improve prediction accuracy and reduce the risk of overfitting. Each tree in the forest is built by applying a decision tree algorithm A on a random subset of the training data and a random subset of features. These randomizations enhance the robustness and generalization of the model.

The prediction of a random forest is determined by aggregating the predictions of individual decision trees. For classification, the aggregation is done by majority voting, while for regression, the predictions are averaged.

Given a training set S and a random vector θ, sampled i.i.d. from a defined distribution, the random forest prediction is shown in (3).

$$h_{RF}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (3)$$

here:

T – is the total number of decision trees in the forest.

$h_t(x)$ – is the prediction of the t-th decision tree.

For regression tasks, the final prediction is the mean of $h_t(x)$

IV. Result and Analysis

This section presents a comprehensive analysis of exchange rate behaviors for USD, EUR, CNY, and RUB against KZT from 2000 to 2024. It includes descriptive statistics, correlation trends, machine learning models for prediction accuracy, and visualization through analytics platforms, highlighting currency volatility, interrelations, and insights into exchange rate dynamics over time.

A. *Descriptive Analysis*

Table 1. Descriptive Analysis

Parameters	USD	EUR	CNY	RUB
Mean	239,284	277,412	34,495	5,084
Standard Error	1,338	1,421	0,203	0,007

Parameters	USD	EUR	CNY	RUB
Median	152,050	203,910	23,510	4,940
Mode	142,650	131,970	17,230	4,880
Standard Deviation	127,529	135,468	19,391	0,694
Sample Variance	16263,591	18351,653	376,023	0,481
Kurtosis	-1,211	-1,259	-1,298	5,689
Skewness	0,708	0,633	0,614	1,053
Range	407,400	442,310	66,080	6,480
Minimum	117,250	121,250	14,680	2,620
Maximum	524,650	563,560	80,760	9,100
Sum	2174137,900	2520568,020	313418,150	46192,430
Count	9086	9086	9086	9086

The mean exchange rates indicate USD (239.284) and EUR (277.412) are the highest, while RUB (5.084) and CNY (34.495) are lower.

Variability is evident with standard deviations of 127.529 (USD) and 135.468 (EUR), suggesting higher fluctuations compared to RUB (0.694). The range highlights significant differences, with USD spanning 407.4 and RUB only 6.48. Notably, USD and EUR exhibit slight positive skewness (0.708 and 0.633), indicating longer tails to the right, while RUB shows greater kurtosis (5.689), signifying extreme values.

Median and mode values are lower than the mean for most currencies, implying a right-skewed distribution. CNY and RUB remain relatively stable. This analysis underscores the distinct behaviors of these currencies, emphasizing the volatility of USD and EUR versus the stability of RUB.

B. *Correlation Analysis*

The correlation heatmap indicates strong positive correlations between USD, EUR, and CNY exchange rates (above 0.98), suggesting similar trends over time. RUB shows a weaker correlation with these currencies (around 0.60) and a very low correlation with the date (0.45). The high correlations among USD, EUR, and CNY imply interconnected exchange rate behaviors, whereas RUB appears less influenced, reflecting its distinct dynamics compared to the other currencies (see fig. 3).

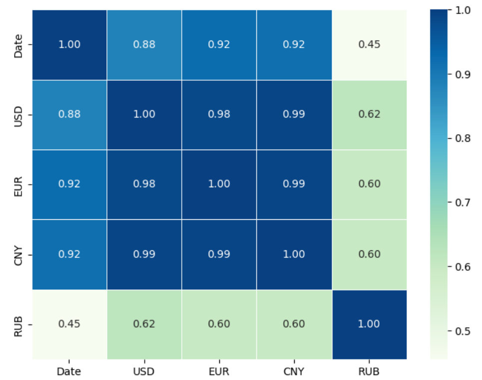

Fig. 3 Correlation Analysis

The USD shows a dominant peak at 130-150 tenge with secondary clusters in the 350-450 range, indicating periods of stability and significant shifts. The EUR shows a more dispersed pattern with major concentrations around 180 and 500 tenge, indicating higher volatility. The CNY shows a bimodal distribution with peaks at 18 and 50-70 tenge, reflecting structural changes. The RUB shows the most concentrated distribution, centered around 5 tenge with a sharp peak, indicating relative stability of its exchange rate (see fig. 4).

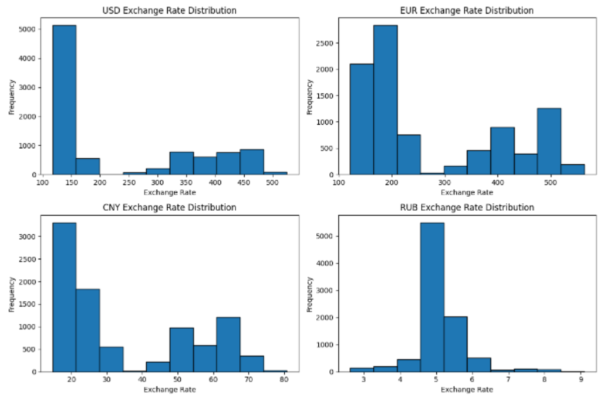

Fig. 4 Data distribution across currencies.

The correlations of exchange rates for each currency pair (USD, EUR, CNY, RUB) against KZT are displayed, showing the strength and direction of relationships between KZT and these currencies (see fig. 5).

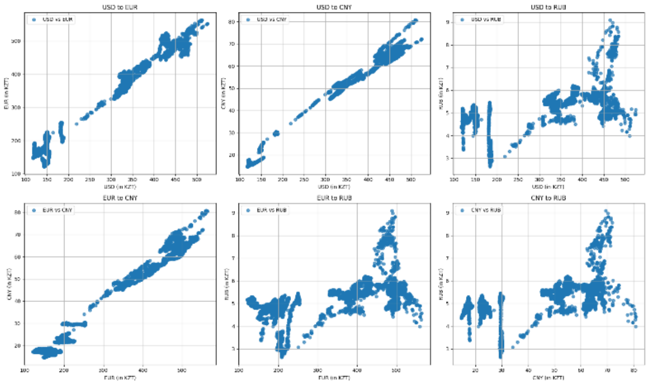

Fig. 5 Correlations of Exchange Rates for each currency pair (KZT as benchmark)

Explanation of correlation analysis can be seen in table 2.

Table 2. Correlation analysis of Exchange Rates between USD, EUR, CNY, and RUB in KZT from 2000 to 2024

Exchange Rate	Position	Description
USD to EUR	USD spans 100-530 KZT, EUR spans 100-550 KZT	It shows a strong positive linear correlation. Very tight clustering along the trend line, indicating strong co-movement. Relationships become more dispersed at higher values (350-500 KZT range)
USD to CNY	USD spans 100-530 KZT, CNY	Demonstrates a strong positive linear relationship. Consistent

	spans 15-80 KZT	correlation throughout the range.
USD to RUB	USD spans 100-530 KZT, RUB spans 2-9 KZT	Shows more scattered relationship with higher volatility. Multiple distinct clusters visible, less linear correlation compared to USD-EUR and USD-CNY
EUR to CNY	EUR spans 100-550 KZT, CNY spans 15-80 KZT.	Strong positive linear correlation, similar patterns as USD-CNY relationship.
EUR to RUB	EUR spans 100-550 KZT, RUB spans 2-9 KZT.	It shows significant volatility and dispersed correlation. Similar multiple clusters to USD-RUB but with more spread
CNY to RUB	CNY spans 15-80 KZT, RUB spans 2-9 KZT	Weakest correlation among, shows high volatility and multiple clusters. Not clear linear relationship

C. Machine Learning Model

a) Linear Regression

The regression results show varying levels of prediction accuracy across currencies. The USD has a moderate R-squared value of 0.78, indicating a relatively good fit. The EUR and CNY exhibit stronger relationships with R-squared values of 0.85 and 0.84, respectively. In contrast, the RUB has a weak R-squared value of 0.21, suggesting a poor model fit (see fig. 6).

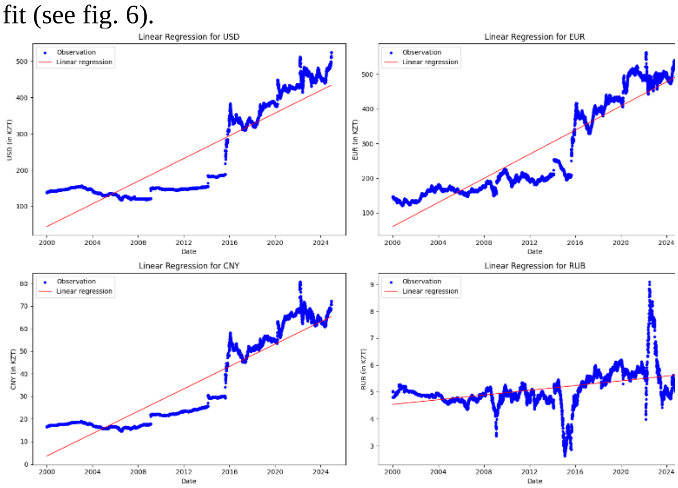

Fig 6 Logistic Regression prediction for each currency

b) Random Forest

The Random Forest model uses 100 decision trees, each built with a maximum depth of 5, meaning each tree could only split up to 5 levels deep. Additionally, each tree required at least 3 samples to split a node and at least 2 samples at each leaf node. The model also considered a random subset of features for each split, using the square root of the total number of features, which is a common default (see fig. 7).

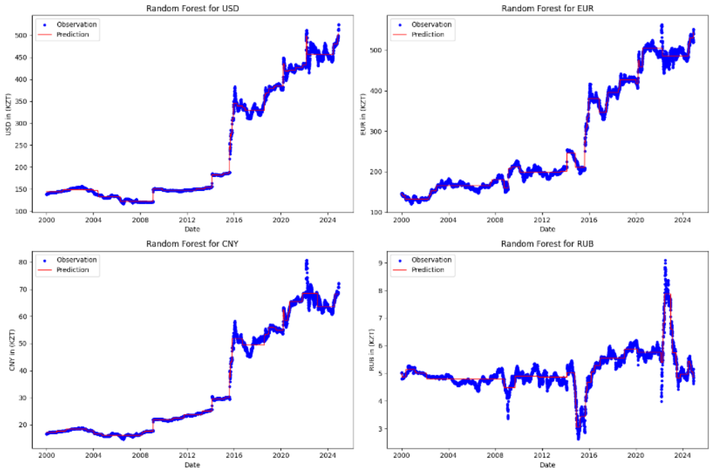

Fig 7 Random Forest prediction for each currency

The Random Forest results with regularization demonstrate excellent prediction accuracy across all currencies. The USD, EUR, and CNY show very high R-squared values, above 0.99, indicating near-perfect fits. The RUB, while still strong, has a slightly lower R-squared value of 0.94, suggesting that the model fits the RUB data well but with slightly less precision than the others.

D. Analytics Platform using Things Board

Exchanges rates line chart shows the minimum, maximum, and average exchange rates for four currencies (CNY, EUR, RUB, and USD) against the KZT over a period of time from 2000 to 2003. The y-axis represents the exchange rate, and the x-axis shows the time progression from July 2000 to July 2003. The chart allows us to visualize the fluctuations in the exchange rates for each currency over the given timeframe (see fig. 8).

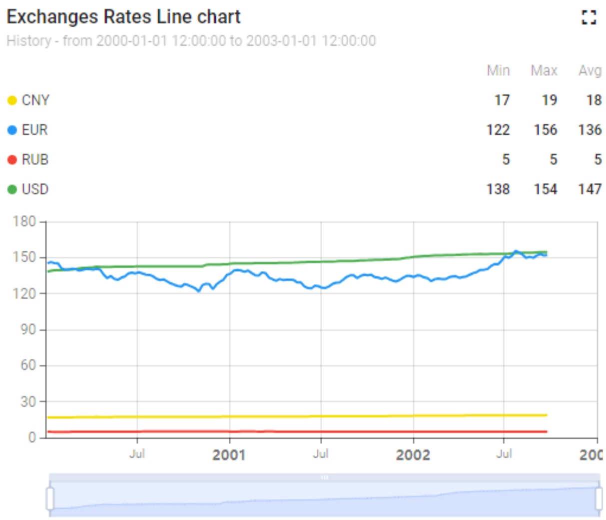

Fig 8 Exchanges Rates Line Chart

Point chart for USD-KZT specifically focuses on the USD-KZT exchange rate. It plots the exchange rate values over time, showing the trend from July 2000 to July 2003. The chart provides a clear visual representation of how the USD-KZT exchange rate has changed during this period (see fig. 9).

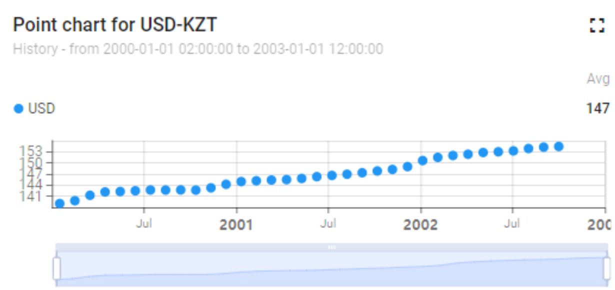

Fig 9 Exchanges rates line chart USD-KZT

Point chart for EUR-KZT similar to the USD-KZT chart, this one shows the exchange rate trend for the EUR-KZT pair over the same time period (see fig. 10).

Fig 10 Exchanges rates line chart EUR-KZT

Point chart for CNY-KZT focuses on the CNY-KZT exchange rate, plotting the values over the July 2000 to July 2003 timeframe (see fig. 11).

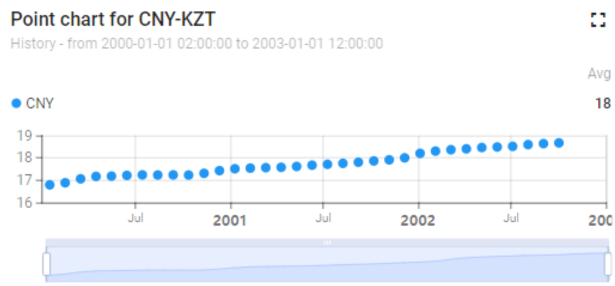

Fig 11 Exchanges rates line chart CNY-KZT

Point chart for RUB-KZT displays the exchange rate trend for the RUB-KZT currency pair (see fig. 12).

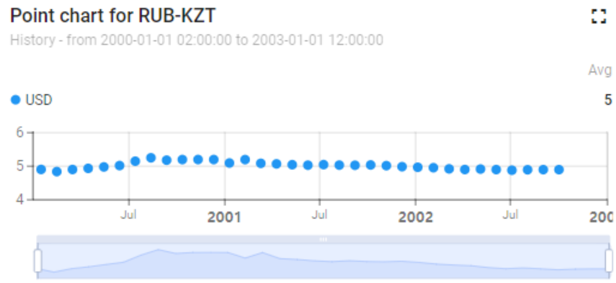

Fig 12 Exchanges rates line chart RUB-KZT

Bars for Currencies against KZT provides a comparison of the total values for different currencies (USD, EUR, CNY, and RUB) against the KZT. The bars represent the total values, allowing you to quickly compare the relative magnitudes of the different currencies (see fig. 13).

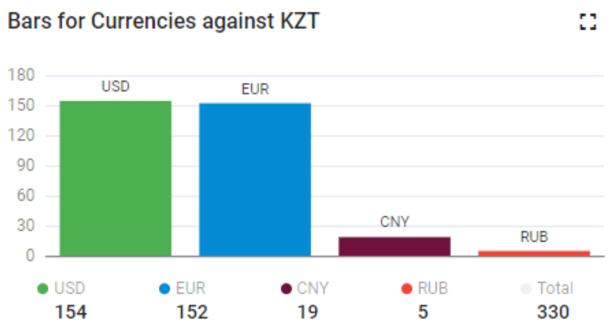

Fig 13 Bars for currencies rate

USD statistics provides a specific statistic related to the USD-KZT exchange rate, showing the current value of 154 KZT per USD, along with the last update timestamp see fig. 14).

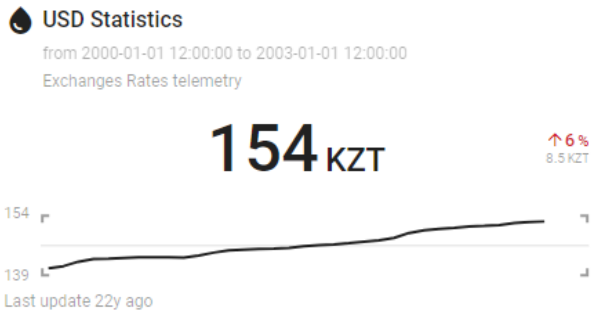

Fig 14 USD statistics

Overall, these charts and statistics provide a comprehensive overview of the exchange rates and trends for various currencies against the Kazakh tenge (KZT) over the specified time period. The line charts and point charts allow for visual analysis of the exchange rate fluctuations, while the bar chart offers a comparative view of the total values. The USD statistic further enhances the understanding of the current exchange rate situation.

V. DISCUSSION

This section summarizes key findings from various studies on global and regional financial markets. It highlights impacts of crises, oil price fluctuations, exchange rate dynamics, and geopolitical tensions on economies, with a focus on Kazakhstan's financial market resilience, diversification needs, and responses to global disruptions

Table 3. Key observations in financial market.

Study	Findings
Mitra, P. (2010)	Analyzes the impact of the 2008–09 global economic crisis on Central Asia, with Kazakhstan experiencing capital flow stop and highlighting the need for fiscal reforms.
Grauwe, P. (2016)	Discusses the Eurozone crisis (2010–2016), emphasizing the unsustainable government debt levels and lack of reforms in the monetary union.
Kalyuzhnova, Y., and Patterson, K. (2016)	Investigates Kazakhstan's oil sector impact on GDP growth, concluding oil has been a blessing due to its positive influence on

	GDP, with sustainable oil revenues projected.
Oxford Analytica (2015)	Evaluates Kazakhstan's move to a free-floating tenge exchange rate, noting potential negative impacts on economic growth and political instability in Central Asia.
Frieden, J., and Walter, S. (2016)	Analyzes the political economy of the Eurozone crisis, highlighting divisions within the EU and the failure of institutions to address the crisis.
Fantazzini, D. (2016)	Analyzes the 2014/15 oil price crash, suggesting a negative financial bubble with oil prices declining beyond fundamental levels.
Petrenko, E. et al. (2016)	Highlights the need for diversification of Kazakhstan's economy to improve resilience against global oil price fluctuations.
Yelemesov, R., and Raimbekova, A. (2021)	Analyzes the impact of the COVID-19 pandemic on Kazakhstan's foreign exchange market, highlighting the need for a more developed market.
Ruziyeva, et al. (2020)	Investigates COVID-19's impact on RUB/KZT and USD/KZT exchange rates, revealing a shift in correlations, from strong positive to weaker negative.
Azretbergenova, M., and Syzdykova, A. (2020)	Examines Kazakhstan's dependence on oil revenues, stressing the need for diversification to reduce vulnerability to oil price shocks.
Kelesbayev, D., et al. (2022)	Examines Kazakhstan's inflation during low oil prices, finding that oil price fluctuations influence inflation and the real effective exchange rate (REER).
Aliber, R., and Zoega, G. (2019)	Provides a retrospective on the 2008 global financial crisis, focusing on financial instability and subsequent crises in the US and Europe.
Naseer, S., et al. (2023)	Analyzes the global economic collapse due to COVID-19, highlighting the economic disruptions caused by widespread lockdowns and sector declines.
Al-Saadi, N. (2023)	Discusses the impact of the Russian-Ukrainian War, focusing on geopolitical tensions, supply chain disruptions, and price hikes in energy, food, and commodities.
Dudzich, E. (2022)	Investigate currency crises in post-Soviet countries, identifying the role of real exchange rate mismatches as indicators of potential instability and crises.
Gusakov, N., G., Maslova, M. (2019)	Examines the changing strategic partnership between Russia and Kazakhstan, noting the rising influence of the EU and China.
Lynch, D. (2019)	Discusses China's economic rise and its slowdown in the mid-2010s, assessing the implications for US-China relations.
Itakura, K. (2020)	Evaluates the impact of the US-China trade war, finding significant GDP losses in both countries and global trade disruption.
Nurmakhanova, M., and Katenova, M. (2019)	Explores the relationship between oil prices, Kazakhstan's real exchange rate, and stock prices, showing oil price fluctuations impact both, with long-term vulnerabilities.
Nurasheva, K., et al. (2020)	Analyzes Kazakhstan's financial markets and challenges, suggesting involvement of local businesses in investment projects to stimulate growth in the region.

The correlation analysis highlighted intriguing interrelationships among currencies. USD, EUR, and CNY showed strong positive correlations, suggesting synchronized global economic trends and interconnected financial markets. The RUB, however, displayed distinctly different behavior, indicating potential unique economic factors influencing its exchange rate.

Machine learning models revealed differential predictive capabilities. Linear Regression provided moderate predictive power for USD, EUR, and CNY, with R-squared values ranging from 0.78 to 0.85. The Random Forest model demonstrated exceptional performance, achieving near-perfect fits for most currencies.

The study had some limitations, such as the dataset being restricted to 2000–2024, and a reliance on a limited set of features. Future research could improve predictions by including more macroeconomic indicators, using advanced machine learning models, and applying deep learning techniques for better accuracy and insights.

VI. CONCLUSION

The study used a combination of descriptive statistics, analysis of correlation and machine learning methods to identify patterns, trends and forecast capabilities.

A descriptive analysis emphasized the clear behavior of these currencies, and the USD and EUR showed higher volatility and wider ranges compared to more stable RUB and CNY. The analysis of the correlation revealed a strong positive relationship between the USD, EUR and CNY, which indicates the interconnected dynamics of the exchange rate, while RUB showed a weaker correlation, reflecting its unique position.

The use of linear regression and models of random forests demonstrated good predicting accuracy. While the linear regression model showed moderate or strong approaches for USD, EUR and CNY, RUB demonstrated weaker relations. On the contrary, a random forest model reached an exceptional predictive force, with R-square values above 0.99 for USD, EUR and CNY, and still sustainably 0.94 for RUB.

These results emphasize the importance of thorough monitoring of fluctuations in the exchange rate and their influence on the economy of Kazakhstan, especially from the point of view of trade, investment and macroeconomic stability. The understanding obtained in this study can help people in making reasonable decisions and develop effective strategies for navigation on the dynamic currency landscape. Continuing research and the use of advanced analytical methods and techniques can further improve understanding of the economic stability of Kazakhstan and its ability to navigate global financial problems.

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