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Implementation of digital fuzzy time series Markov chain in price forecasting and investment risk analysis with value at risk

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CHRONICLE

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ABSTRACT

This study aims to provide a comprehensive model to assist investors in strategic decision-making amid market uncertainty. Global economic uncertainty characterized by cycles of stagflation and recession has recurred in history and is expected to recur until 2025. This condition encourages the importance of investment strategies that can protect asset values from economic pressures. This study uses a quantitative approach with forecasting methods and risk analysis based on time series data. The data used are daily gold and silver prices from the London Bullion Market Association (LBMA) in USD, collected over a two-year period, namely from January 3, 2023 to January 4, 2025. The data is secondary and obtained from the official LBMA website. The research stages begin with a literature study to understand relevant concepts and methods, followed by data collection, and continued with data preprocessing. The preprocessing stages include checking for outliers, handling missing values using the series mean method, and merging data for temporal consistency. For the forecasting process, the Fuzzy Time Series–Markov Chain method is used, which consists of several steps: the formation of universe and interval sets using the Sturges formula, the definition of fuzzy sets, the fuzzification process, the formation of Fuzzy Logical Relationships (FLR) and Fuzzy Logical Relationship Groups (FLRG), and the preparation of transition probability matrices. The forecasting results are obtained through the defuzzification process, which are then evaluated using the Mean Absolute Percentage Error (MAPE) indicator to assess the accuracy of the model. Risk analysis is carried out using the Value at Risk (VaR) approach using the Extreme Value Theory (EVT) method and the Generalized Pareto Distribution (GPD). The entire analysis process is carried out using Microsoft Excel and RStudio software to ensure accuracy and efficiency in data processing and statistical modeling. This study has succeeded in developing a hybrid Fuzzy Time Series–Markov Chain model to forecast precious metal prices, especially gold and silver, with a very high level of accuracy. Based on an evaluation of various training and testing data proportions, the best model was obtained at a 95:5 ratio, with MAPE values of 0.66% for gold and 1.18% for silver in the training data, and 0.55% and 0.94% in the testing data. These results indicate that the model is able to effectively capture historical price patterns and provide predictions close to the actual value.

1. Introduction

Global economic uncertainty, characterized by cycles of stagflation and recession, has recurred throughout history and is expected to recur through 2025. This situation emphasizes the importance of investment strategies that can protect asset values from economic pressures (Shou et al., 2021). In this context, gold and silver are prime choices because they have proven superior as hedges during crises, such as the inflationary period of the 1960s–1970s and the 2008 global financial crisis. These two precious metals not only possess stable intrinsic value but also outperform other real and financial assets, especially during times of market stress. Silver, although more volatile, often follows the direction of gold's movements and offers the potential for higher returns (Olukoya, 2023). The prices of both are influenced by global factors such as interest rates,

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exchange rates, and geopolitical tensions and are regulated internationally by the London Bullion Market Association (LBMA), which serves as the benchmark for precious metal prices in Indonesia (Sun & Qin, 2024).

Silver investments carry significant risks, such as drastic price declines in 2008 and 2015, as well as a prolonged correction from 2013 to 2020 before reaching an all-time high (ATH). Rapid declines, or blow-off phases, such as those experienced in the commodity market from 1971 to 1980, are a significant concern for investors. Therefore, price forecasting is a crucial tool for future decision-making (Dasopang & Kurniawan, 2025). The Fuzzy Time Series (FTS) method, based on fuzzy logic, is used to address historical data uncertainty. The method development has shown improved prediction accuracy. In addition to gold, silver is also a precious metal that is in demand as an investment instrument, especially because of its strong performance during the 2008 financial crisis and its widespread use in industry, making it rarer than gold. England, as a center for precious metal trading since the 19th century, pioneered the formation of the London Bullion Market Association (LBMA) which now functions as an international institution that determines standards and prices for precious metals, including gold and silver, and is the main reference in global trade (Mostafa et al., 2021).

To improve the accuracy of precious metal price forecasting, this study developed a hybrid model that integrates the Fuzzy Time Series (FTS) method with the Markov Chain approach. Unlike previous studies that relied on FTS without considering the transition dynamics between states, the proposed model can map the transition probabilities between fuzzy states (Mazraeh et al., 2022). This integration enables the creation of more realistic and adaptive predictions to market changes, thus providing added value in the context of volatile commodity price forecasting. Furthermore, this study focuses not only on forecasting but also examines investment risk using the Extreme Value Theory (EVT) and Generalized Pareto Distribution (GPD) approaches. By using GPD-based Value at Risk (VaR), this study is able to identify the potential for extreme losses often overlooked in conventional statistical analysis. This approach provides a sharper perspective for investors, particularly in the face of global market uncertainty characterized by recession and the threat of stagflation.

The study's precious metals—gold and silver—were strategically chosen given their role as safe haven assets in unstable economic conditions. Unlike most previous studies that primarily focus on stocks, market indices, or general commodities, this study's focus on precious metals provides an important contribution to the literature on alternative investments amidst global uncertainty (Qureshi et al., 2027).

To ensure model robustness, evaluations were conducted using various training and testing data ratios: 80:20, 85:15, 90:10, and 95:5. This approach not only demonstrates methodological rigor but also provides insight into the model's sensitivity to the amount of historical data used. Evaluation results, based on the Mean Absolute Percentage Error (MAPE), serve as the basis for determining the optimal configuration for practical implementation (Pantachang et al., 2022).

Overall, this study offers a comprehensive quantitative approach. The analysis includes price forecasting, error measurement, return analysis, extreme value identification, parameter estimation, and distribution testing. With its broad scope and integrated methodology, this study makes a significant contribution to the development of forecasting models and investment risk management, particularly in the context of precious metals as a hedging instrument. This research builds on various previous studies demonstrating the effectiveness of the Fuzzy Time Series (FTS) method and its Markov Chain approach in forecasting historical linguistic data, proven to improve prediction accuracy, especially in the context of volatile financial data. In the investment context, it explains that investment aims to generate future profits, with risk as a consequence of return uncertainty. Gold and silver, as real assets, have unique characteristics: gold is valued for its scarcity and stability, while silver has demonstrated superior performance during crises and has high industrial demand (Bagheri Mazraeh et al., 2024).

Time series analysis is used to understand historical data patterns and forecast future events. The data used must meet a consistent time interval and can exhibit trends, cyclical, seasonal, or horizontal patterns. In the forecasting process, fuzzy logic is used to address data uncertainty and ambiguity using the concept of fuzzy sets and membership functions, allowing for linguistic classifications such as “low”, “high”, or “medium”. To measure investment risk, the Value at Risk (VaR) approach is used, which provides an estimate of the maximum loss within a given period with a certain level of confidence. Because financial data often contains extreme values, Extreme Value Theory (EVT) and the Generalized Pareto Distribution (GPD) are used to identify and quantify these risks more accurately. By combining forecasting and risk analysis methods, this study aims to provide a comprehensive model to assist investors in strategic decision-making amid market uncertainty (Safari & Ghaemi, 2025).

Statistical techniques are used in forecasting to obtain a picture of the future by processing historical data on the object under study. The forecasting in this paper will utilize the Fuzzy Time Series (FTS) method, which was initially developed based on fuzzy logic theory first introduced by Zadeh (1965). Previously, the ability of traditional Boolean logic to address ambiguous concepts has been much debated. Fuzzy logic addresses the issue of uncertainty, a topic discussed over the years, by considering the possibility of varying degrees of truth. The basic idea of this approach is the existence of elements between true and false. For example, in the case of color, there are shades of gray on a certain scale between white and black. An object can fall into a category with varying degrees, and categories don't have linguistic boundaries like high or low, healthy or sick, and so on. However, adding a degree of certainty can occur with the operators “too much”, “almost”, or “not much”. This additional character is called “fuzzy modification”.

Fuzzy time series, using fuzzy set theory, is equipped with concepts that can capture historical linguistic data that have not been explored in previous research. In forecasting the number of applicants at The University of Alabama in 1993, it offered a concept by defining the min-max data composition, then partitioning the data into several intervals, and forming fuzzy sets to obtain the results of forecasting the number of applicants in the next period. The composition offered by Song and Chissom was considered too complicated to be applied, so it offered a simplified and more efficient concept of arithmetic operations (Ciciretti et al., 2025). Chen believes that predictions using this concept offer robust results even with inaccurate historical data. TAIFEX and temperature by adding a genetic algorithm that produces higher accuracy compared to previous methods.

2. Literature Review

2.1 Investment

Investment is the commitment of funds and resources currently held by an investor to obtain future profits. Investment can also be defined as the activity of placing funds in one or more types of assets for a specific period of time with the expectation of increasing their value in the future (Kim et al., 2025). The purpose of investing is, among other things, to achieve a better standard of living and improve the investor's well-being. Investments can be made into two types of assets: real assets and financial assets. Real assets generate income for investors, while financial assets represent an allocation of that income. Examples of real assets include land, buildings, gold, and knowledge used to produce goods and services. Financial asset investment instruments can be divided into equity instruments such as stocks and debt instruments such as bonds. Other investment instruments can be formed from these two types of investments, such as mutual funds and Exchange Traded Funds (ETFs) (Dar et al., 2022).

The basis for investment decisions is understanding the relationship between the expected rate of return and the level of risk, and the relationship between the two. Return is the rate of return. Return is divided into expected return, required return, and realized return. The difference between expected return and actual return represents the risk that must be considered in investing. Theoretically, the relationship between risk and return is inversely proportional, meaning the higher the risk of an asset, the higher the expected return, and vice versa. Broadly speaking, investments can be grouped into three categories based on risk level: low-risk investments, such as savings and time deposits. Middle-risk investments, which carry higher risks than bank investments, such as Indonesian bonds (ORI), property, and gold. High-risk investments are investments with the highest risk level (Oukhouya et al., 2025).

2.2 Time Series Analysis

Time series analysis is useful for summarizing insights gained from time series data by exploring its structure and identifying patterns to predict future events of the object under study (Ghanbari et al., 2025). Time series data must meet certain requirements: values must be taken at equal time intervals, such as seconds, minutes, hours, days, months, and so on. Using and assessing historical data will help predict future events. Selecting an appropriate forecasting method requires considering the type of data pattern (Tan et al., 2021).

2.3 Data Preprocessing

Data preprocessing is the stage of data processing to obtain accurate conclusions or interpretations in research (Lin et al., 2022). In this study, data preprocessing includes checking for outliers, data merging, and handling missing values. A common problem in research is missing data, which requires handling such as data deletion and mean imputation. Data deletion can bias research results, while the mean imputation method is more widely used due to its ease of use and its ability to estimate missing values (Zhang & Wang, 2025). One method of imputing missing values is the series mean method.

2.4 Fuzzy Time Series

Fuzzy time series is a concept introduced to solve problems involving historical data, which is a linguistic value (Sung et al., 2022). In this study, Song and Chissom estimated the enrollment number at the University of Alabama. Fuzzy time series captures past patterns and can be used to project future data. Past data in fuzzy time is in linguistic form, and the results are real numbers (Taneva-Angelova et al., 2025).

2.5 Markov Chain

A stochastic process, also called a random process, describes the change in random values over time (Blackledge & Lamphiere, 2021). For example, if a random variable X describes an event w, then in a stochastic process it is written as X(t,w), where t ∈ t. T is a set of process parameters in the form of a time series (Iftikhar et al., 2023). A Markov process means that the next process is only affected by the current process. If these conditions are modeled as a phenomenon with their probability values, the process is called a Markov Chain (Najem et al., 2023).

2.6 Fuzzy Time Series - Markov Chain

Fuzzy time series - Markov Chain is an extension of the previous model by combining the concepts of fuzzy time series and Markov chains (Peng et al., 2023). This hybrid model provides better forecasting because it incorporates more relevant information. The following are the steps for using the fuzzy time series method with the Markov chain approach (Pham & Nguyen, 2024).

2.7 Evaluating Prediction Results

Forecasting is very useful for individuals or companies in preparing for future conditions. Predictions also provide insight into decision-making (Mer et al., 2024). Prediction errors are possible, and this probability can be calculated using a measurement indicator, the Mean Absolute Percentage Error (MAPE). MAPE represents the magnitude of the prediction error relative to the actual value. MAPE is calculated by dividing the absolute error for each period by the number of observations used, then calculating the average percentage (Colombo et al., 2023).

3. Method

Statistical techniques are used in forecasting to obtain a picture of the future by processing historical data on the object under study. The forecasting in this paper will utilize the Fuzzy Time Series (FTS) method, which was initially developed based on fuzzy logic theory first introduced by Zadeh (1965). Previously, the ability of traditional Boolean logic to address ambiguous concepts has been much debated. Fuzzy logic addresses the issue of uncertainty, a topic discussed over the years, by considering the possibility of varying degrees of truth. The basic idea of this approach is the existence of elements between true and false. For example, in the case of color, there are shades of gray on a certain scale between white and black. An object can fall into a category with varying degrees, and categories do not have linguistic boundaries like high or low, healthy or sick, and so on. However, adding a degree of certainty can occur with the operators "too much," "almost," or "not much." This additional character is called "fuzzy modification."

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4. Results and Discussion

4.1 Gold Price Forecasting Results

Gold price forecasting was conducted using the Fuzzy Time Series–Markov Chain method with four variations in training and testing data ratios: 80:20, 85:15, 90:10, and 95:5. The forecasting results showed that the 95:5 ratio provided the best accuracy, with MAPE values of 0.66% for the training data and 0.55% for the testing data (see Table 4.30). A comparison graph between historical data and forecasting results shows that the model is able to follow price movement patterns well, especially at the 95:5 ratio (Fig. 1).

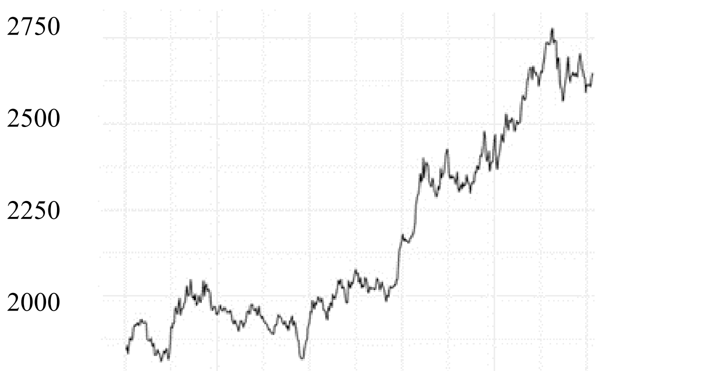

Fig. 1. London Bullion Market Association Gold Price Chart

This model successfully captures the cyclical pattern of gold prices, which is influenced by external factors such as interest rates and geopolitical tensions. In the fourth quarter of 2023, there was a significant price spike due to the conflict in the Middle East, as reflected in the gold price chart (Fig. 1).

Table 1
Results of Gold Price Forecast Accuracy Calculations

80:20			85:15		90:10		95:5	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Percentage Error (MAPE)	0.57%	94.29%	0.66%	93.49%	0.64%	1.62%	0.66%	0.55%

Table 2
Fuzzy Logical Relations of Gold Price Training Data (Proportion 90%:10%)

t	Historical Data	Linguistic Values	FLR
1	1,843.25	A_1	$A_1 \rightarrow A_1$
2	1,857.3	A_1	$A_1 \rightarrow A_1$
3	1,834	A_1	$A_1 \rightarrow A_1$
4	1,852.2	A_1	$A_1 \rightarrow A_1$
5	1,878.85	A_1	$A_1 \rightarrow A_1$
⋮	⋮	⋮	⋮
101	1,952.45	A_2	$A_2 \rightarrow A_2$
102	1,964.4	A_2	$A_2 \rightarrow A_2$
103	1,974.35	A_2	$A_2 \rightarrow A_2$
104	1,963.25	A_2	$A_2 \rightarrow A_2$
105	1,959.65	A_2	$A_2 \rightarrow A_2$
⋮	⋮	⋮	⋮
201	1,955.7	A_2	$A_2 \rightarrow A_2$
202	1,953.55	A_2	$A_2 \rightarrow A_2$
203	1,988.5	A_2	$A_2 \rightarrow A_2$
204	1,973	A_2	$A_2 \rightarrow A_2$
205	1,963.65	A_2	$A_2 \rightarrow A_2$
⋮	⋮	⋮	⋮
301	2,180.45	A_4	$A_4 \rightarrow A_4$
302	2,161.25	A_4	$A_4 \rightarrow A_4$
303	2,168.4	A_4	$A_4 \rightarrow A_4$
304	2,160.8	A_4	$A_4 \rightarrow A_4$
305	2,163.45	A_4	$A_4 \rightarrow A_4$
⋮	⋮	⋮	⋮
452	2,649.05	A_{10}	$A_{10} \rightarrow A_{10}$
453	2,675.25	A_{10}	$A_{10} \rightarrow A_{10}$
454	2,688.85	A_{10}	$A_{10} \rightarrow A_{10}$
455	2,712.5	A_{10}	$A_{10} \rightarrow A_{10}$
456	2,736.45	A_{10}	$A_{10} \rightarrow A_{10}$

4.2 Silver Price Forecasting Results

Silver price forecasting was also conducted using the same approach. The best results were obtained with a 95:5 ratio, with MAPE values of 1.18% for the training data and 0.94% for the testing data (Table 3). Despite higher silver price volatility than gold, the model still provided accurate predictions. A comparison chart between historical data and forecasting results shows good agreement (Fig. 2).

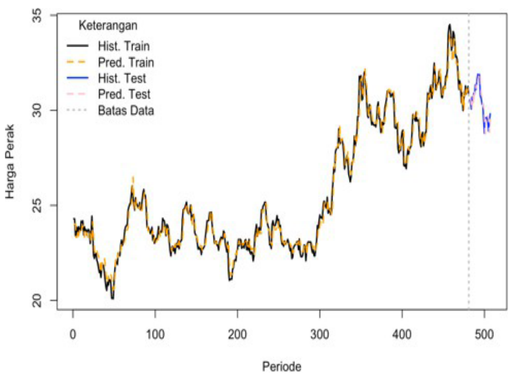

Fig. 2. Comparison Chart of Historical Data with Forecasted Silver Price Data (95:5 Proportion)

Table 3
Results of Silver Price Forecasting Accuracy Calculations

	80:20		85:15		90:10		95:5	
	Training	*Testing*	*Training*	*Testing*	*Training*	*Testing*	*Training*	*Testing*
MAPE	1.03%	1.49%	1.02%	1.66%	1.11%	22.72%	1.18%	0.94%

Silver exhibits greater sensitivity to market changes, primarily due to its use in the energy and technology industries. This leads to sharper price fluctuations, as seen in the silver price chart (Fig. 4).

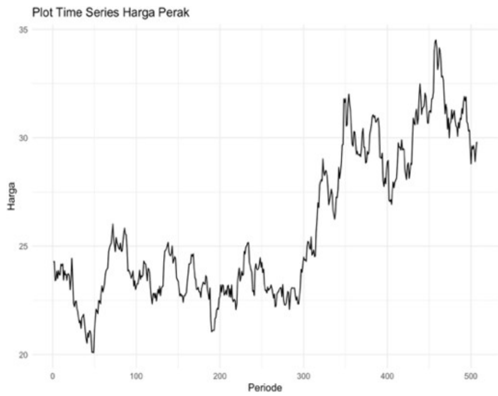

Fig. 3. London Bullion Market Association Silver Price Chart

4.3 Model Accuracy Evaluation

Accuracy evaluation was performed using the Mean Absolute Percentage Error (MAPE) indicator. Based on the comparison results in the table, a 95:5 data ratio provided the best results for both commodities. A low MAPE value indicates that the FTS–Markov Chain model is able to capture price patterns well and provide reliable predictions. The comparison graph between historical data and forecast results for each ratio shows that the higher the training data ratio, the better the model predicts the testing data. This is clearly seen in the figure, where the 95:5 ratio produces the graph that most closely matches the actual data.

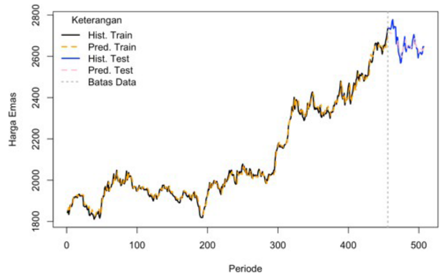

Fig. 4. Comparison Chart of Historical Data with Gold Price Forecast Data (90:10% Ratio)

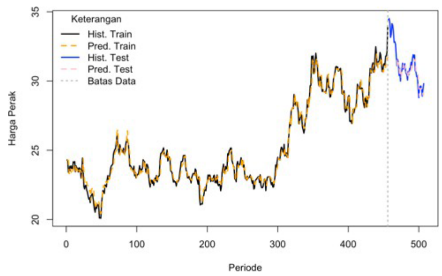

Fig. 5. Comparison Chart of Historical Data with Silver Price Forecast Data (90:10% Ratio)

4.4 Investment Risk Analysis: Value at Risk (VaR)

Risk analysis was conducted using the Value at Risk (VaR) approach with the Generalized Pareto Distribution (GPD) method. Extreme values were identified using time series plots and boxplots of gold and silver price return data. Extreme values were determined based on the 90th percentile and used to estimate the GPD parameters.

Fig. 6. Gold Return Plot

The estimated GPD parameters for gold prices show a scale value of 0.01708 and a shape value of -0.41642. For silver prices, the scale value is 0.02278 and a shape value of -0.39422. The Kolmogorov–Smirnov distribution test yields a valid p-value, indicating that the data follows the GPD distribution.

4.5 Interpretation of VaR Values

VaR values are calculated at the 90%, 95%, and 99% confidence levels. For gold, the VaR values are 1.3%, 2.3%, and 3.8%, respectively. For silver, the VaR values are 2.6%, 4.03%, and 6.08%. Interpretation of these values indicates that gold has a lower risk than silver.

For example, if an investor holds assets worth IDR 1 billion, the maximum potential loss in a single day at a 99% confidence level is IDR 38 million for gold and IDR 60.8 million for silver. This suggests that gold is more suitable for conservative investors, while silver is more suitable for investors with a higher risk tolerance.

4.6 Managerial and Strategic Implications

The results of this study provide important implications for investors and portfolio managers. The FTS–Markov Chain model can be used as a tool in investment decision-making, particularly in determining transaction timing and acceptable risk limits. Furthermore, the GPD-based VaR approach provides more realistic risk estimates than traditional methods.

Investors can use the forecasting results to anticipate price movements and optimize asset allocation. Meanwhile, financial institutions and regulators can utilize this model to measure risk exposure and design more effective mitigation policies (Colombo et al., 2023).

The findings of this study have significant implications for various stakeholders in the financial and investment sectors. For investors, Value at Risk (VaR) analysis indicates that gold carries a lower risk level than silver. Therefore, investors with a conservative risk profile are advised to choose gold as a hedging instrument, especially in the face of global economic uncertainty. Conversely, aggressive investors seeking higher potential returns can consider silver as an alternative, although they must be prepared to face greater risks (Amalia et al., 2025).

For portfolio managers, the Fuzzy Time Series–Markov Chain model developed in this study offers a predictive approach that can be integrated into data-driven decision-making systems. With a high level of accuracy (MAPE <1%), this model has the potential to be used to determine daily asset allocation and portfolio rebalancing strategies dynamically and responsively to market changes.Financial institutions such as banks and asset managers can also utilize this approach to measure the risk exposure to precious metals in their portfolios. The use of the Generalized Pareto Distribution (GPD) in VaR estimation allows for more realistic identification of extreme risks than conventional methods, thus supporting more precise and data-driven risk management.

On the policy side, the results of this study are relevant for policymakers and regulators in designing commodity market stabilization strategies. In the context of global economic uncertainty, the government can consider encouraging public investment diversification into precious metals as a mitigation measure against systemic risks that may arise from financial market fluctuations (Ray et al., 2021).

Finally, for academics and researchers, this study opens up opportunities for the development of advanced hybrid models, such as integrating FTS with machine learning or deep learning approaches. Furthermore, the methodological framework used can serve as the basis for comparative studies across countries and across commodity types, thereby broadening the scope and contribution to the academic literature in finance and economics.

The implications of this research reach a wide range of stakeholders, from regulators to the general public. For regulators and policymakers, the results of this study can serve as a foundation for understanding the risk dynamics of precious metal investments in an unstable global economic context. These findings provide an important contribution to the formulation of investor protection policies, particularly in the face of potential financial crises and inflationary pressures that could disrupt market stability.

From an investor perspective, the Value at Risk (VaR) approach used in this study indicates that gold carries a lower risk level than silver. Investors can use this information to more accurately determine their risk tolerance and select investment instruments that align with their individual risk profiles (Vancsura et al., 2025). Furthermore, the Fuzzy Time Series–Markov Chain model applied in this study provides an effective predictive tool for anticipating price movements and avoiding potential extreme losses, thereby improving the quality of investment decision-making.

Within the broader community, this research serves as an educational tool regarding the importance of data-driven investment and risk analysis. Amid economic uncertainty, precious metals such as gold and silver can be a relatively safe investment alternative. This study also emphasizes that investment decision-making based on a quantitative approach is more effective than intuition alone. Therefore, the results of this study contribute to improving financial and investment literacy among the general public, which can ultimately strengthen individual and collective economic resilience (Dar et al., 2022).

Tsaur (2012), who combined the concepts of fuzzy time series and Markov chains in forecasting economic exchange rates, stated that the high forecasting accuracy in this study was achieved due to the advantages of the fuzzy time series method in reducing the influence of fluctuating values by grouping data and the advantages of the Markov chain process in obtaining the highest probability of a state movement. The difference between fuzzy time series and Markov chain and other fuzzy time series lies in the state transition matrix, which is formed from fuzzy logical relationship groups, thus providing more information related to the dynamics of the system being studied. This study yielded a very low MAPE value. This study compared natural gas prices with the fuzzy time series developed by Chen, Lee, and Tsaur. The study concluded that the fuzzy time series developed by Tsaur had the smallest error rate with a MAPE value of 5.021%, indicating excellent accuracy. Average-based fuzzy time series with a Markov chain approach provided good predictions with a MAPE value <10%.

In addition to price forecasting, risk factors such as investment losses frequently occur. These losses were initially calculated using traditional risk measures, but this method is ineffective in comparing the risk of one trading activity with another. Another drawback of traditional risk measures is that they do not provide a value for the probability of losing identified funds, relying solely on experience and judgment. This shortcoming of traditional risk measures can be addressed using Value at Risk calculations, which provide information regarding the maximum amount of funds that can be lost in an investment asset over a given time period, along with the probability.

Time series data in the financial sector often contains extreme cases. In the context of VaR, accurate prediction of extreme movements in portfolio value is crucial for risk management and regulatory purposes, which can be addressed using the Extreme Value Theory (EVT) method (Oukhouya et al., 2025). EVT methods for identifying extreme cases include the Peaks Over Threshold (POT) method, which is used to calculate Value at Risk. This method uses a benchmark value (threshold) and follows the Generalized Pareto Distribution (GPD). Forecasting using the fuzzy time series-Markov chain method has been conducted in various sectors, but no research has included the risks of the forecasts. Therefore, this study will utilize the fuzzy time series-Markov chain method developed by Tsaur to forecast gold and silver prices at the London Bullion Market Association. Gold and silver forecasting provides investors with an alternative way to decide on their investments in various instruments and facilitates investors in determining the right time to transact. This research is also equipped with risk measurements in each instrument using the Value at Risk method based on the results so that it can add information for investors and help investors determine the risks that will be accepted in the future in gold and silver investments.

5. Conclusion

This study successfully developed a hybrid Fuzzy Time Series–Markov Chain model to forecast precious metal prices, particularly gold and silver, with a very high level of accuracy. Based on an evaluation of various training and testing data proportions, the best model was obtained with a 95:5 proportion, with MAPE values of 0.66% for gold and 1.18% for silver in the training data, and 0.55% and 0.94% in the testing data. These results indicate that the model is able to effectively capture historical price patterns and provide predictions close to actual values.

In addition to price forecasting, this study also measured investment risk using a Value at Risk (VaR) approach based on the Generalized Pareto Distribution (GPD). The analysis showed that gold carries a lower risk than silver, with VaR values at the 99% confidence level of 3.8% and 6.08%, respectively. These findings provide strategic recommendations for investors: gold is more suitable for conservative risk profiles, while silver can be considered by aggressive investors seeking higher potential returns.

Overall, this research presents a comprehensive quantitative approach, encompassing price forecasting, error measurement, return analysis, extreme value identification, distribution parameter estimation, and risk calculation. The developed model is not only academically relevant but also applicable to investors, portfolio managers, and policymakers facing global economic uncertainty.

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