International Conference on Science, Engineering & Management Trends

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Gold Price Forecasting for Investment Decisions: A Multi-Factor Predictive Analytics Approach

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Abstract- Gold has long been considered one of the most important investment assets and safe-haven instruments in global financial markets. Rising market volatility, inflationary pressure, geopolitical uncertainty and shifting economic conditions have made accurate gold price forecasting essential for investors, financial institutions and policymakers. This study proposes a multi-factor predictive analytics approach to gold price forecasting that supports investment decision-making and risk management. The framework integrates machine learning, deep learning, econometric modelling and managerial analytics techniques to analyse the impact of macroeconomic indicators such as interest rates, exchange rates, inflation, commodity prices, climate risks and market volatility on gold price movements. Twelve studies published between 2017 and 2026 are reviewed and organised into three themes covering deep learning approaches, econometric and multi-factor models, and data mining with investment decision support. The reviewed evidence is consolidated into comparative tables that map each study to its data context, method, principal finding and contribution to the proposed design, and seven research gaps are identified and mapped to corresponding research directions. The framework is specified through five macroeconomic factor blocks and five forecasting components including Long Short-Term Memory (LSTM) networks, hybrid neural networks, ARIMA, Support Vector Machines and adaptive learning mechanisms. The findings indicate that multi-factor predictive analytics frameworks can improve forecasting accuracy, support strategic investment planning and enhance investor decision-making in uncertain financial environments.

Keywords- Gold price forecasting; predictive analytics; machine learning; deep learning; investment decision-making; multi-factor analysis; financial forecasting; LSTM; econometric models; risk management.

I. INTRODUCTION

Gold plays a critical role in the global financial system as an investment asset, an inflation hedge and a safe-haven commodity during periods of economic uncertainty. Investors, financial analysts and policymakers monitor gold price movements closely because they significantly influence portfolio management, financial risk assessment and strategic investment planning. Gold price volatility is affected by numerous economic, political and market-related factors including inflation, interest rates, exchange rates, commodity prices, global crises and investor sentiment.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

In recent years the growth of financial technologies, big data analytics and artificial intelligence has transformed traditional forecasting into advanced predictive analytics. Organisations and investors now apply machine learning, deep learning, econometric modelling and data mining techniques to improve the accuracy of gold price prediction and to support data-driven investment decisions.

Traditional forecasting approaches such as Autoregressive Integrated Moving Average (ARIMA), Vector Error Correction Models (VECM) and statistical regression have been widely used for gold price prediction. These methods face limitations in handling non-linear relationships, large-scale financial datasets and rapidly changing market dynamics. Researchers have therefore increasingly adopted machine learning and deep learning techniques such as Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, hybrid neural networks and ensemble learning frameworks to capture complex temporal dependencies and latent market patterns.

Recent studies indicate that multi-factor predictive models deliver better forecasting performance by integrating multiple economic and market indicators. Variables including interest rates, exchange rates, inflation, climate risks, commodity prices and market volatility significantly influence gold price behaviour, and their integration into predictive frameworks enables more informed investment decisions.

Beyond forecasting accuracy, modern investment analytics systems increasingly emphasise decision-support capabilities such as portfolio optimisation, risk management, scenario analysis and adaptive learning. Predictive investment systems help investors identify market trends, minimise risk and optimise asset allocation under uncertain conditions.

Despite these advances, many existing studies focus primarily on prediction accuracy while giving limited attention to managerial decision support, risk optimisation and multi-factor integration. There is therefore a growing need for comprehensive predictive analytics frameworks that combine economic intelligence, machine learning techniques and investment strategy optimisation into a unified forecasting environment. This study proposes such a framework, integrating deep learning, econometric analysis, feature engineering and intelligent decision-support systems to improve forecasting reliability and support strategic investment management.

1. Contributions of this Study

The study makes four contributions. First, it consolidates twelve studies on gold price forecasting into a structured thematic review supported by comparative tables rather than narrative description alone. Second, it specifies the macroeconomic factor blocks that supply inputs to the proposed framework and links each block explicitly to the literature that motivates it. Third, it sets out the forecasting components of the framework together with the analytical function each performs, so that method selection is justified rather than assumed. Fourth, it identifies seven research gaps and maps each to a corresponding research direction.

2. Organisation of the Paper

Section 2 reviews the literature across three themes and consolidates it in comparative tables. Section 3 presents the structure of the proposed forecasting framework. Section 4 sets out the research gaps. Section 5 concludes, and Section 6 details future work.

II. LITERATURE REVIEW

Gold price forecasting has become an important research area in financial analytics and investment decision-making because of increasing volatility in global markets and the strategic role of gold as a safe-haven asset. Researchers have adopted econometric models, machine learning algorithms, deep

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

learning architectures and predictive analytics frameworks to improve forecasting accuracy and support investment planning. This section reviews the literature across three themes: deep learning approaches, econometric and multi-factor models, and data mining with investment decision support.

1. Machine Learning and Deep Learning Approaches for Gold Price Forecasting

Machine learning and deep learning techniques have improved the ability to forecast gold prices by capturing non-linear relationships and latent market patterns. Soni and Tandan (2026) proposed a computational framework for forecasting global gold market trends using predictive analytics and computational intelligence, and demonstrated that advanced analytical frameworks improve forecasting precision and support investment decision-making in dynamic markets.

Zainuddin and Rachmat (2026) developed a multi-time-frame gold price forecasting model using LSTM networks, and found that LSTM effectively captures temporal dependencies in price movements and provides reliable short-term and medium-term forecasts. Lambang, Prastya and Barata (2026) compared simple and stacked LSTM architectures for Indonesian gold price forecasting with an expanding window, and concluded that stacked LSTM outperforms simpler neural architectures on sequential financial data. Read together, these two studies indicate that both temporal depth and architectural depth contribute to forecasting performance.

Harif, AbdulHassan and Al-Nuaimy (2025) introduced a feedback-matching algorithm for future gold price prediction, and demonstrated that adaptive learning mechanisms enhance forecasting stability and improve responsiveness to changing market conditions. ul Sami and Junejo (2017) explored machine learning approaches for predicting future gold rates and highlighted the effectiveness of data-driven algorithms in capturing complex market behaviour; as the earliest study in the corpus, it establishes the baseline against which subsequent deep learning gains are measured.

Collectively these studies indicate that deep learning and machine learning approaches provide robust solutions for gold price forecasting by analysing historical price trends, temporal dependencies and market volatility. They also share a common limitation relevant to this study: each evaluates model accuracy in isolation rather than in terms of the investment decisions the forecast is intended to support.

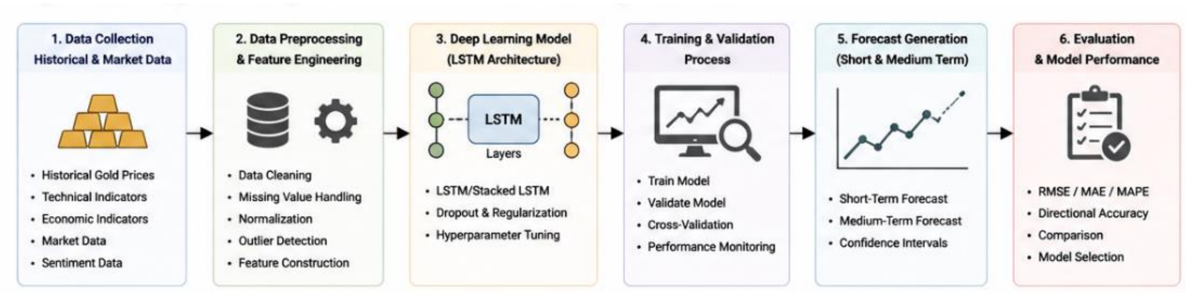

Figure 1: Deep learning-based gold price forecasting framework

Figure 1 illustrates a deep learning-based framework for gold price forecasting using historical prices, time-series data and financial indicators. The framework covers data collection, preprocessing, feature extraction, LSTM and neural network model training, prediction generation and forecast evaluation, and shows how these techniques improve short-term and medium-term forecasting accuracy for investment decision-making.

2. Econometric Models and Multi-Factor Predictive Analytics

Econometric and multi-factor models continue to play a significant role in gold price forecasting because of their capacity to incorporate macroeconomic indicators and long-run market relationships.

Makala and Li (2021) compared ARIMA and SVM models for gold price prediction and found that combining statistical and machine learning techniques improves forecasting performance and predictive reliability.

Jahnavi et al. (2025) conducted a comparative analysis of econometric and machine learning models for gold price forecasting, and demonstrated that hybrid approaches integrating econometric indicators with machine learning provide better accuracy than standalone models, emphasising the value of combining economic intelligence with advanced analytics.

Nupap et al. (2026) proposed a forecasting framework using correlation-based feature selection and the Vector Error Correction Model for Thai gold prices, highlighting the importance of selecting relevant economic indicators and of representing long-run equilibrium relationships between gold prices and macroeconomic variables. Their emphasis on feature selection is directly relevant to the multi-factor design proposed in Section 3.

Gupta and Banerjee (2025) examined a machine learning gold timing system by decomposing trend following, forecast quality and the cost of look-ahead bias, and emphasised that forecasting performance depends not only on model selection but on signal quality and bias control. This is an important methodological caution for any framework claiming predictive gains. Bureau for Economic Research (2025) discussed economic prospects for 2025 and 2026 and emphasised the influence of economic activity, inflation and financial uncertainty on commodity and gold market performance.

Gupta et al. (2024) explored the relationship between climate risks and real gold returns over a 750-year historical period, and found that macroeconomic instability and environmental risk significantly influence gold price behaviour. The exceptional length of that sample provides unusually strong evidence for including climate-related variables among the forecasting inputs. Overall, this theme demonstrates that integrating economic indicators, financial variables and market intelligence into predictive frameworks enhances forecasting accuracy and investment strategy development.

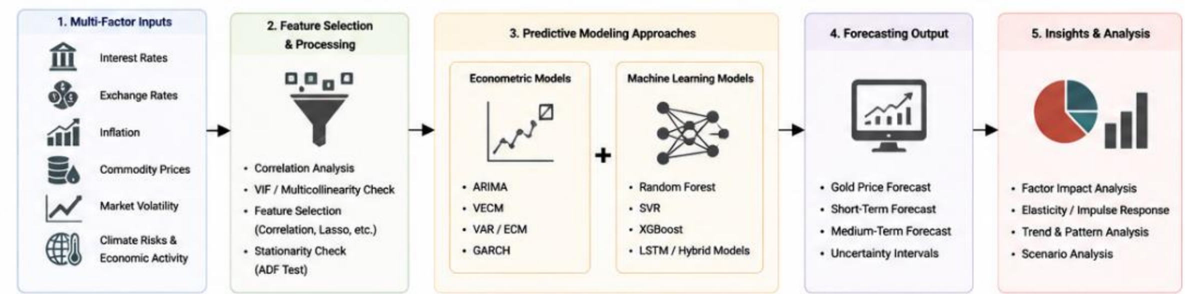

Figure 2: Multi-factor predictive analytics model for gold price forecasting

Figure 2 presents a multi-factor predictive analytics framework integrating macroeconomic indicators such as interest rates, inflation, exchange rates, commodity prices, climate risks and market volatility into gold price forecasting. The framework shows how econometric models, feature selection techniques and hybrid machine learning approaches analyse relationships among financial variables to improve forecasting reliability and support strategic investment planning.

3. Data Mining, Predictive Analytics and Investment Decision Support

The growing availability of financial big data has encouraged the development of data mining and predictive analytics frameworks for investment decision-making. Gozali and Kusuma (2025) investigated gold price forecasting using large-scale Indonesian price datasets and data mining techniques implemented in the KNIME platform, and demonstrated that data mining approaches can process large financial datasets effectively and support predictive investment analysis.

Recent work in this area emphasises integrating multiple market indicators into forecasting systems that aim not only to predict prices but also to help investors manage risk and optimise portfolio strategy. Modern systems increasingly rely on adaptive learning, multi-factor modelling and real-time market monitoring, combining machine learning, deep learning, econometric analysis and feature optimisation to improve reliability and reduce uncertainty in volatile markets.

This theme is the thinnest in the corpus, containing a single primary study. That imbalance is itself a finding: forecasting methodology is well served in the literature while the translation of forecasts into managerial decisions is not. Existing work still lacks a comprehensive managerial analytics framework integrating multi-factor predictive modelling, deep learning architectures, macroeconomic indicators and investment decision-support systems into a unified forecasting environment, and few studies evaluate how forecasting models directly support investor decision-making and risk management.

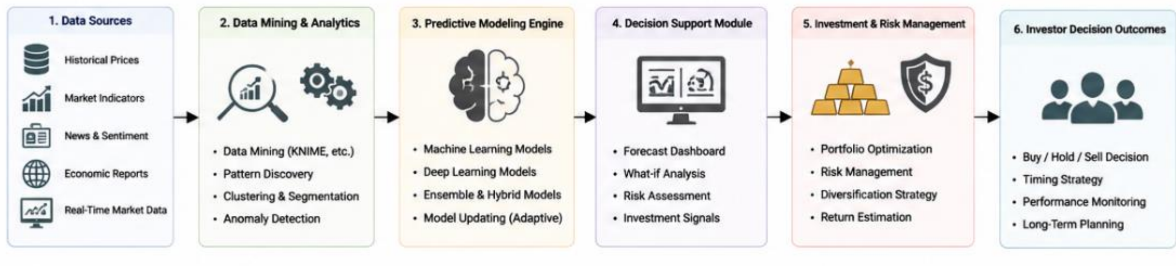

Figure 3: Predictive investment decision support system for gold market analysis

Figure 3 depicts an intelligent investment decision-support system integrating data mining, predictive analytics, real-time market monitoring and portfolio risk assessment for gold investment management. It illustrates how forecasting models, adaptive learning systems and market intelligence tools support investors in optimising strategy, managing financial risk and improving decision-making efficiency in volatile markets.

4. Consolidated Summary of the Reviewed Literature

Table 1 organises the reviewed studies by theme, and Table 2 compares each study on data context, method, principal finding and the specific contribution it makes to the design of the proposed framework.

Table 1: Thematic organisation of the reviewed literature

Theme	Analytical focus	Studies	Count
T1. Machine learning and deep learning approaches	Sequential modelling of price series using LSTM, adaptive and data-driven algorithms	Soni & Tandan (2026); Zainuddin & Rachmat (2026); Lambang et al. (2026); Harif et al. (2025); ul Sami & Junejo (2017)	5
T2. Econometric models and multi-factor analytics	ARIMA, VECM, hybrid econometric-ML comparison, feature selection and macroeconomic drivers	Makala & Li (2021); Jahnavi et al. (2025); Nupap et al. (2026); Gupta & Banerjee (2025); Bureau for Economic Research (2025); Gupta et al. (2024)	6
T3. Data mining and investment decision support	Large-scale data processing and translation of forecasts into investment decisions	Gozali & Kusuma (2025)	1

Table 2: Comparative summary of the reviewed studies

Study	Data context	Method	Principal reported finding	Contribution to the proposed framework
Soni & Tandan (2026)	Global gold market	Computational intelligence framework	Advanced analytical frameworks improve forecasting precision	Supports the overall computational framework design
Zainuddin & Rachmat (2026)	Gold price series, multiple time frames	LSTM	LSTM captures temporal dependencies for short and medium-term forecasts	Direct precedent for the LSTM component and horizon design
Lambang et al. (2026)	Indonesian gold prices	Simple vs stacked LSTM, expanding window	Stacked LSTM outperforms simpler architectures on sequential data	Justifies depth in the sequential model component
Harif et al. (2025)	Gold price prediction	Feedback-matching algorithm	Adaptive mechanisms improve stability and market responsiveness	Motivates the adaptive learning component
ul Sami & Junejo (2017)	Gold rates	Machine learning approaches	Data-driven algorithms capture complex market behaviour	Establishes the machine learning baseline
Makala & Li (2021)	Gold price series	ARIMA and SVM comparison	Combining statistical and ML techniques improves reliability	Supports retaining ARIMA and SVM as benchmarks
Jahnavi et al. (2025)	Gold price forecasting	Econometric vs machine learning comparison	Hybrid approaches outperform standalone models	Directly motivates the hybrid design
Nupap et al. (2026)	Thai gold prices	Correlation-based feature selection and VECM	Feature selection and long-run equilibrium relationships matter	Justifies the feature selection stage and factor blocks
Gupta & Banerjee (2025)	Gold timing system	Alpha decomposition and bias analysis	Signal quality and look-ahead bias control drive real performance	Imposes bias control as an evaluation requirement
Bureau for Economic Research (2025)	Macroeconomic outlook 2025-2026	Economic survey and prospects analysis	Economic activity, inflation and uncertainty affect commodity markets	Supports the macroeconomic factor block
Gupta et al. (2024)	Real gold returns, 750-year sample	Long-horizon climate risk analysis	Macroeconomic instability and climate risk influence gold returns	Justifies inclusion of climate risk variables
Gozali & Kusuma (2025)	Large-scale Indonesian gold data	Data mining via KNIME	Data mining processes large financial datasets effectively	Supports the data processing and decision-support layer

Three observations follow from Table 2. First, the corpus is methodologically strong but evaluation-narrow: nearly every study reports accuracy metrics and only Gupta and Banerjee (2025) examines whether apparent accuracy survives bias control. Second, coverage of the macroeconomic factor set is fragmented, with individual studies addressing climate risk, inflation or feature selection separately rather than jointly. Third, only one study addresses the translation of forecasts into investment decisions, which is the specific gap this framework targets.

III. STRUCTURE OF THE PROPOSED FRAMEWORK

The proposed framework organises the factors and techniques described above into a single multi-factor forecasting structure. This section states its factor blocks and its forecasting components; empirical estimation and validation lie outside the scope of the present study and are set out as future work in Section 6.

1. Macroeconomic Factor Blocks

Table 3 specifies the five factor blocks that supply inputs to the framework, together with the variables in each block and the reviewed studies that motivate their inclusion. Organising inputs into blocks rather than a flat variable list allows the contribution of each category to be assessed separately, and supports the correlation-based feature selection stage recommended by Nupap et al. (2026).

Table 3: Macroeconomic factor blocks of the proposed framework

Factor block	Variables	Supporting studies
F1. Historical price and market series	Historical gold prices, trading volume, time-series lags	Zainuddin & Rachmat (2026); Lambang et al. (2026); Gozali & Kusuma (2025)
F2. Monetary and rate variables	Interest rates, exchange rates	Nupap et al. (2026); Bureau for Economic Research (2025)
F3. Inflation and economic activity	Inflation, economic growth and financial uncertainty indicators	Bureau for Economic Research (2025); Jahnavi et al. (2025)
F4. Commodity and market volatility	Commodity prices, market volatility measures	Makala & Li (2021); Gupta & Banerjee (2025)
F5. Climate and external risk	Climate risk indicators and related environmental risk measures	Gupta et al. (2024)

2. Forecasting Components

Table 4 lists the forecasting components incorporated in the framework and the analytical function each performs. The set is deliberately mixed: econometric models are retained as interpretable benchmarks and for long-run relationships, sequential deep learning models represent temporal structure, and adaptive mechanisms allow the system to respond to changing market conditions.

Table 4: Forecasting components and their analytical function

Component	Function within the framework	Rationale for inclusion
ARIMA and econometric models	Baseline modelling of price series and long-run equilibrium relationships	Interpretable benchmark comparable with the existing literature
Support Vector Machines	Non-linear regression on engineered macroeconomic features	Effective on moderate-sized structured financial datasets
LSTM networks	Modelling sequential dependence across multiple forecast horizons	Demonstrated effectiveness on gold price series
Hybrid neural networks	Combining econometric signals with deep learning representations	Hybrid designs reported to outperform standalone models
Adaptive learning mechanisms	Updating model behaviour as market conditions change	Improves forecast stability and responsiveness in volatile markets

Consistent with Gupta and Banerjee (2025), evaluation is treated as a design requirement rather than a reporting step: forecasting components must be assessed with strict separation of training and evaluation data so that reported gains are not an artefact of look-ahead bias. Interpretability is a parallel requirement, since investors and analysts need to understand which factors drive a forecast before acting on it.

IV. RESEARCH GAP

Although substantial research has been conducted on gold price forecasting using econometric models, machine learning algorithms and deep learning architectures, seven gaps remain in the existing literature. They are stated below and mapped to corresponding research directions in Table 5.

First, many traditional forecasting studies rely heavily on statistical and econometric models such as ARIMA and regression techniques, which often struggle to capture non-linear relationships and dynamic interactions among the financial variables influencing gold prices.

Second, although machine learning and deep learning techniques such as LSTM, SVM and hybrid neural networks have improved accuracy, most studies focus on model performance rather than integrating forecasting outputs with practical investment decision-making and portfolio optimisation.

Third, many current frameworks use limited input variables and fail to incorporate a comprehensive set of macroeconomic and market indicators such as interest rates, exchange rates, inflation, climate risks, commodity prices and market volatility into unified predictive systems.

Fourth, limited research explores the integration of adaptive learning mechanisms, feature optimisation techniques and real-time financial analytics into gold forecasting systems; most models rely on historical datasets and lack the dynamic updating capability required in rapidly changing markets.

Fifth, many predictive models operate as opaque systems without sufficient interpretability. Investors and analysts require understandable predictive insight and factor-impact analysis to support confident investment decisions and risk assessment.

Sixth, there is limited research on combining predictive forecasting, investment risk management, scenario analysis and intelligent decision-support systems into a comprehensive managerial analytics framework capable of supporting both short-term and medium-term investment planning.

Finally, existing studies rarely evaluate how predictive forecasting systems contribute to investor behaviour, portfolio diversification and strategic financial decision-making under uncertain economic conditions.

Table 5: Research gaps mapped to corresponding research directions

No.	Identified research gap	Corresponding research direction
G1	Reliance on linear econometric specifications	Benchmark non-linear and sequential models against ARIMA and regression on identical gold price data
G2	Accuracy prioritised over investment application	Evaluate forecasts by portfolio and risk outcomes, not error metrics alone
G3	Limited macroeconomic input coverage	Estimate a unified multi-factor model spanning all five factor blocks in Table 3

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

No.	Identified research gap	Corresponding research direction
G4	Adaptive learning and real-time analytics absent	Incorporate online updating, feature optimisation and real-time market data feeds
G5	Models operate as opaque systems	Apply explainable AI and report factor-impact analysis alongside forecast accuracy
G6	Forecasting not combined with managerial decision support	Integrate scenario analysis, risk management and decision support into one framework
G7	Investor-level outcomes not evaluated	Assess effects on investor behaviour, diversification and strategic planning under uncertainty

V. CONCLUSION

Gold price forecasting has become increasingly important for investors, financial institutions and policymakers because of rising market uncertainty, economic volatility and changing global financial conditions. Advances in machine learning, deep learning, econometric modelling and predictive analytics have improved the capacity to analyse complex market behaviour and forecast future price movements.

This study proposed a multi-factor predictive analytics approach to gold price forecasting that integrates deep learning models, econometric techniques, feature engineering and intelligent investment decision-support systems into a unified framework. The framework was specified through five macroeconomic factor blocks and five forecasting components, each linked explicitly to the reviewed literature that motivates its inclusion.

The review of twelve studies demonstrates that techniques such as LSTM networks, hybrid neural networks, ARIMA, SVM and ensemble learning effectively capture temporal dependencies and non-linear relationships in financial data, and that incorporating inflation, interest rates, exchange rates, climate risks and commodity prices enhances predictive performance. It also shows that the literature evaluates forecasts almost entirely on accuracy metrics, that only one reviewed study addresses look-ahead bias, and that only one addresses the translation of forecasts into investment decisions.

The framework contributes to academic research and financial management practice by connecting forecasting accuracy with investment decision-making, and by specifying what an integrated multi-factor gold forecasting system would need to contain. Its principal limitation is that it is presented as a design rather than an estimated model; empirical validation is required before claims about forecasting accuracy can be made.

Future Work

Future research can extend this study in several directions, presented here in order of priority. First, the framework should be empirically validated using large-scale real-time gold market datasets from international exchanges, with forecasting accuracy assessed out of sample and under strict controls against look-ahead bias.

Second, advanced techniques including reinforcement learning, federated learning, graph neural networks, generative AI and transformer-based architectures should be benchmarked against the components in Table 4 so that any accuracy gain can be weighed against the loss of interpretability.

Third, real-time financial news analytics, social media sentiment analysis, geopolitical event monitoring and investor behaviour analysis should be tested as supplementary inputs, with attention to whether they add incremental predictive value beyond the macroeconomic factor blocks.

Fourth, broader macroeconomic and environmental variables including climate risk, energy prices, cryptocurrency market interactions, central bank policy and global uncertainty indicators should be incorporated to extend the multi-factor design.

Fifth, explainability and transparency should be advanced through explainable AI techniques and interactive visualisation dashboards that help investors understand forecast outputs and factor impacts. Finally, longer-term work may develop intelligent financial decision-support ecosystems integrating predictive analytics, portfolio optimisation, risk management, automated trading and personalised investment recommendation into a comprehensive investment platform.

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