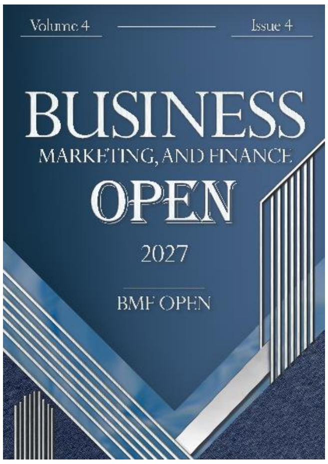
Strategic Evaluation and Implementation of Machine Learning Models for Predicting Price Volatility in the Steel Commodity Market: A Comparative Study with the Foreign Exchange Market for Commercial Decision-Making



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Abstract: This study aimed to implement and strategically compare machine-learning and deep-learning models for predicting price volatility in the Iranian steel commodity market and the EUR/USD foreign-exchange market and to evaluate their usefulness for commercial decision-making. This applied-developmental study used a descriptive-analytical design based on secondary time-series data from January 2019 to January 2024. The foreign-exchange dataset included hourly and daily EUR/USD opening, high, low, closing, and volume data extracted from MetaTrader 5. The steel dataset included daily and weekly prices of steel billets and sheets traded on the Iran Mercantile Exchange, together with the unofficial exchange rate, global 62% iron-ore prices, and seasonal demand indicators. After outlier correction, linear interpolation, logarithmic differencing, and feature engineering, Random Forest, XGBoost, Long Short-Term Memory, and Deep Q-Network models were implemented. Model validation was conducted through walk-forward validation using a three-year training window and a one-year out-of-sample testing window. Predictive and strategic performance were assessed through forecasting errors, directional accuracy, Sharpe ratio, maximum drawdown, win rate, and profit factor. LSTM significantly outperformed Random Forest and XGBoost in both markets, producing the lowest forecasting errors and the highest directional accuracy and explanatory power. In the steel market, LSTM achieved an RMSE of 0.0062, directional accuracy of 70.80%, and R^2 of 0.77. However, DQN generated the strongest strategic performance, with an annualized return of 28.90%, Sharpe ratio of 1.86, maximum drawdown of 8.70%, and profit factor of 1.84. Bootstrap comparisons confirmed that DQN significantly outperformed LSTM in risk-adjusted trading performance. The steel-market models generally exceeded the EUR/USD models because fundamental variables improved predictability. LSTM was the most accurate forecasting model, whereas DQN was the most effective model for converting market information into profitable and risk-controlled commercial decisions.

Keywords: Steel market, Price volatility, Machine learning, LSTM, Deep Q-Network, XGBoost, Foreign exchange market, Commercial decision-making

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1. Introduction

Price volatility is one of the central sources of uncertainty in financial and commodity markets because it directly affects the valuation of assets, the timing of transactions, the cost of financing, inventory policies, hedging decisions, and the stability of commercial revenues. Volatility does not merely represent random price variation; rather, it reflects the interaction of information flows, investor expectations, macroeconomic shocks, liquidity conditions, regulatory structures, production constraints, and behavioral responses. When volatility increases, firms face greater difficulty in estimating future cash flows, determining appropriate purchase and sale prices, and selecting suitable risk-management strategies. The practical significance of volatility is particularly evident in markets where price changes are transmitted across sectors and assets. For example, industry-level cash-flow volatility has been associated with a higher risk of abrupt stock-price declines, demonstrating that instability in operating conditions can be transformed into broader valuation risk [1]. Similarly, investor sentiment can affect not only market liquidity but also the volatility of liquidity, thereby strengthening the relationship between behavioral expectations and market instability [2]. Financial literacy and decision-making behavior also influence how investors interpret information and respond to price fluctuations, showing that market volatility is partly shaped by heterogeneous cognitive and behavioral characteristics [3]. More recently, financial-news sentiment and investor confidence have been identified as important determinants of stock-price volatility, indicating that the speed, tone, and interpretation of information can intensify or moderate short-term market movements [4]. These findings support the view that price volatility is a multidimensional phenomenon that cannot be explained exclusively through historical prices and requires analytical frameworks capable of processing nonlinear, dynamic, and interacting sources of information.

A substantial part of the volatility literature has focused on identifying how corporate policies, market regulations, and institutional mechanisms influence the instability of asset prices. Dividend policy has repeatedly been examined as a factor affecting share-price volatility because changes in dividend payments may alter investor expectations regarding future profitability, cash-flow stability, and firm value. Evidence from the Tehran Stock Exchange has demonstrated the importance of dividend policy in explaining differences in stock-price volatility across companies [5]. Similar relationships have been investigated among Modaraba companies listed on the Pakistan Stock Exchange, where dividend-policy decisions were analyzed in connection with share-price volatility [6]. Research on selected companies in the Nigerian Exchange has further emphasized the relevance of dividend policy to price stability and investor valuation [7], while evidence from construction firms listed on the Nairobi Securities Exchange has extended this discussion to a sector with substantial exposure to business cycles, material costs, and financing conditions [8]. In addition to corporate decisions, regulatory arrangements can affect the magnitude and persistence of market fluctuations. The relationship between short-selling regulation, return volatility, and overall market volatility in the Athens Exchange illustrates how trading restrictions and market design may modify price discovery and risk transmission [9]. Price-control mechanisms in securities exchanges have likewise been examined as institutional tools for limiting excessive fluctuations and preserving orderly trading conditions [10]. Although these studies are primarily concerned with securities markets, they establish an important analytical foundation for commodity markets: observed volatility is influenced not only by changes in supply and demand but also by market rules, participant behavior, liquidity, and the structure through which information is incorporated into prices.

Volatility is also transmitted between markets through exchange rates, energy prices, capital flows, and changes in global risk conditions. Exchange-rate movements are especially important because they affect import costs, export competitiveness, inflation expectations, foreign-currency obligations, and the domestic valuation of internationally traded commodities. Evidence from Middle Eastern countries indicates that exchange-rate volatility can influence stock prices, although the magnitude and direction of this relationship may differ according to domestic financial structures and macroeconomic conditions [11]. The dynamic relationship between exchange-rate volatility and stock prices has also been examined in the Egyptian real-estate market, with interest rates considered as a moderating macroeconomic factor [12]. In Croatia, return and volatility spillovers between stock prices and exchange rates have been analyzed through spillover methodologies, underscoring the reciprocal and time-varying nature of interactions between currency and equity markets [13]. Evidence from BRIICS economies during the COVID-19 outbreak further showed the importance of dynamic correlations and volatility transmission between stock prices and exchange rates under conditions of global disruption [14]. Volatility interdependence is not limited to traditional assets. The spillover of cryptocurrency-price volatility to the foreign-exchange market demonstrates that increasingly interconnected financial systems allow shocks from emerging digital assets to affect established currency markets [15]. These studies suggest that exchange-rate volatility should not be treated as an isolated financial indicator. In economies where imported inputs, export revenues, and domestic commodity prices are strongly linked to foreign currencies, exchange-rate changes may operate as a fundamental driver of production costs and commodity-price expectations.

The transmission of energy-price shocks provides another important perspective on the structure of market volatility. Oil-price fluctuations can affect transportation costs, industrial production, inflation, exchange rates, investment expectations, and the profitability of energy-intensive industries. Research on the Pakistan Stock Exchange has examined how oil-price volatility affects different sectors, indicating that exposure to energy shocks is heterogeneous across industries [16]. The relationship between oil-price volatility and the economic performance reflected in the Nairobi Securities Exchange Index has similarly demonstrated the relevance of commodity shocks to capital-market outcomes in developing economies [17]. Within Iran, the spillover of oil-price volatility to the returns of selected industries in the Tehran Stock Exchange has been studied through regime-switching and variance-decomposition approaches, highlighting the possibility that volatility transmission differs across market regimes [18]. Multivariate GARCH modeling has also been used to measure volatility spillovers among Iran, the United Arab Emirates, and the global oil-price index, illustrating the usefulness of conditional-variance models for examining cross-market risk transmission [19]. The effect of exchange-rate volatility on the price index of petroleum products listed on the Tehran Stock Exchange has further demonstrated that domestic asset prices may respond jointly to currency instability and commodity-market conditions [20]. At a broader level, oil-price volatility shocks may contribute to systemic financial risk rather than remaining confined to individual firms or sectors [21]. Consequently, the strategic management of commodity-price risk requires approaches that consider both direct price movements and the networks through which shocks are transmitted across currencies, inputs, industries, and financial institutions.

The steel market is particularly exposed to this multidimensional form of volatility. Steel is simultaneously an industrial input, a tradable commodity, an infrastructure requirement, and a strategic product whose price is affected by energy costs, raw-material prices, exchange rates, construction demand, industrial policy, supply-chain disruptions, environmental regulations, and technological change. In the Iranian market, fluctuations in the unofficial exchange rate can alter the domestic value of exportable steel, the cost of imported machinery and inputs, and the opportunity cost of selling products domestically rather than internationally. Global iron-ore prices influence upstream cost expectations, while domestic seasonal demand from construction and manufacturing can create recurring but unstable price patterns. Furthermore, the steel supply chain includes numerous interdependent actors, from mines and producers to commodity exchanges, distributors, manufacturers, exporters, and large industrial consumers. Research on digital supply-chain risk factors in the steel industry has emphasized the need for integrated decision-support systems capable of identifying, prioritizing, and managing interconnected operational and informational risks [22]. This requirement is becoming more important as digitalization expands the volume and speed of market information available to commercial decision-makers.

The strategic environment of the steel industry is also being transformed by technological innovation and environmental pressures. The development of green innovations such as FINEX technology illustrates how steel producers are attempting to improve production efficiency, reduce environmental impacts, and create new technological trajectories within an industry traditionally characterized by capital intensity and path dependence [23]. Life-cycle assessment and optimization of carbon-emission-reduction pathways have also become important for calculating the costs associated with the transition toward lower-carbon steel production [24]. These changes can affect expected production costs, capital expenditure, market competitiveness, and the pricing of steel products. Consequently, future steel-price behavior may increasingly reflect not only conventional demand and input-cost variables but also technological transitions, environmental compliance costs, and changes in global trade policies. Financial-risk management in energy-related industrial projects has similarly emphasized the value of hedging models for controlling the combined consequences of currency and oil-price volatility [25]. For steel producers, traders, and industrial purchasers, a forecasting framework must therefore support more than a statistical estimate of future prices; it should facilitate decisions regarding procurement timing, inventory accumulation, sales contracts, export allocation, hedging, and exposure limits.

Traditional volatility research has made extensive use of econometric models, including autoregressive specifications, GARCH-family models, vector autoregression, Markov regime-switching models, and spillover indices. These methods remain valuable because they provide interpretable parameters and well-established procedures for estimating conditional variance, persistence, and cross-market transmission. Nevertheless, commodity and financial time series commonly exhibit nonlinear relationships, abrupt regime changes, asymmetric reactions to information, long-range temporal dependencies, and complex interactions among technical and fundamental variables. Under such conditions, the assumptions of linearity, fixed functional form, and stable parameter relationships may restrict predictive performance. A comparison of statistical volatility-analysis models with a numerical water-drop-motion algorithm for the Tehran Stock Exchange price index demonstrates the growing interest in combining conventional statistical analysis with computational optimization methods [26]. Artificial multi-asset market models have likewise been used to examine the interaction of static and dynamic information factors, showing that computational environments can reproduce and analyze complex patterns generated by heterogeneous agents and multiple information sources [27]. These developments indicate a transition from purely explanatory volatility modeling toward data-driven predictive systems capable of learning relationships directly from large and multidimensional datasets.

Machine-learning methods are well suited to this transition because they can identify nonlinear associations, interaction effects, thresholds, and high-dimensional patterns without imposing a single predefined functional relationship between predictors and outcomes. Tree-based methods such as Random Forest can capture nonlinear structures and provide relatively robust baseline predictions through ensemble learning. Gradient-boosting models such as XGBoost sequentially correct prediction errors and can effectively model complex relationships among technical indicators, macroeconomic variables, and lagged market observations. Deep recurrent networks such as Long Short-Term Memory models are designed to retain information from previous observations and may therefore be particularly appropriate for financial and commodity series with temporal dependence. Deep reinforcement-learning models approach the problem from a different perspective. Rather than predicting price or volatility as an isolated statistical target, they learn a sequence of actions intended to maximize cumulative reward under changing market conditions. This distinction is strategically significant because the model with the lowest forecasting error is not necessarily the model that produces the highest risk-adjusted commercial return. A forecasting system may correctly estimate average market movement but still generate excessive turnover, large drawdowns, or unprofitable decisions after transaction costs are included.

The distinction between statistical accuracy and commercial usefulness is fundamental to the evaluation of predictive models. Standard measures such as root mean square error, mean absolute error, mean absolute percentage error, directional accuracy, and the coefficient of determination assess how closely predictions correspond to observed values. However, commercial decision-makers are also concerned with the profitability, stability, and downside risk of decisions generated from those predictions. The Sharpe ratio evaluates return relative to risk, maximum drawdown measures the largest decline in accumulated capital, win rate indicates the proportion of successful transactions, and profit factor compares gross profits with gross losses. A model that performs well according to statistical criteria may fail strategically if its signals are unstable or if small expected gains are eliminated by transaction costs. Conversely, a model with moderate forecasting accuracy may perform well if it selectively enters positions with favorable reward-to-risk characteristics. This issue is particularly relevant in the steel market, where transactions may involve larger costs, lower frequency, contractual restrictions, delivery considerations, and less continuous liquidity than the foreign-exchange market.

The foreign-exchange market provides a useful comparative benchmark for evaluating whether machine-learning models can generalize across markets with different structural characteristics. The EUR/USD pair is highly liquid, continuously traded during global market hours, and rapidly responsive to macroeconomic information. Its depth and informational efficiency may reduce persistent forecasting opportunities, but its high-frequency data and relatively standardized market structure make it suitable for model development and backtesting. The steel market, by contrast, is less continuous and more strongly affected by local institutional conditions, production costs, exchange-rate changes, global raw-material prices, and seasonal demand. Comparing the two markets can therefore reveal whether a model’s performance is driven by general learning capacity or by market-specific predictability. It also allows the strategic value of technical variables to be compared with that of combined technical and fundamental features.

Despite the extensive literature on stock-price volatility, exchange-rate interactions, oil-price spillovers, dividend policies, investor behavior, and regulatory mechanisms, comparatively limited attention has been devoted to the integrated prediction of steel-market volatility through machine-learning and deep-learning models combined with realistic strategic backtesting. Existing studies provide important evidence regarding the transmission of currency and commodity shocks, but many concentrate on explanatory relationships rather than the direct conversion of forecasts into commercial actions. Moreover, studies conducted in stock and foreign-exchange markets cannot automatically be generalized to the steel commodity market because steel prices reflect distinct production, supply-chain, institutional, and seasonal conditions. A comprehensive framework should therefore integrate historical transaction data with technical indicators, exchange-rate changes, global iron-ore prices, and seasonal demand measures; compare conventional machine-learning algorithms with deep sequential models; preserve chronological order through walk-forward validation; and evaluate performance after incorporating actual trading costs and downside-risk criteria.

Accordingly, the aim of this study was to implement and strategically evaluate Random Forest, XGBoost, Long Short-Term Memory, and Deep Q-Network models for predicting steel commodity-market price volatility and supporting commercial decisions, while comparatively assessing their predictive and risk-adjusted trading performance against the EUR/USD foreign-exchange market.

2. Methodology

This applied-developmental study adopted a descriptive-analytical design based on the secondary analysis of financial and commodity-market time-series data. The primary objective was to develop, implement, and strategically evaluate machine learning models for predicting price volatility in the steel commodity market and to compare their predictive and trading performance with those obtained in the foreign exchange market. The research process consisted of four interconnected phases: data collection, data preprocessing and feature engineering, algorithmic model development, and strategic evaluation within a historical backtesting environment. Because the study relied exclusively on archival market data, it did not involve human participants. The units of analysis were sequential observations of prices, transaction volumes, technical indicators, and selected fundamental variables recorded between January 2019 and January 2024. Two independent datasets were examined. The foreign exchange dataset consisted of hourly and daily observations for the EUR/USD currency pair, whereas the steel-market dataset included daily and weekly observations relating to steel billet and steel sheet transactions conducted through the Iran Mercantile Exchange. The selection of EUR/USD as the comparative financial market was based on its high liquidity, continuous price formation, substantial transaction volume, and suitability as a benchmark for evaluating the performance of predictive algorithms under relatively mature market conditions. The steel commodity market was selected because its price dynamics are influenced by both market-based signals and fundamental economic variables, including exchange-rate movements, global raw-material prices, and seasonal changes in industrial demand.

Foreign exchange data were extracted from the MetaTrader 5 trading platform. The dataset included opening, highest, lowest, and closing prices, commonly represented as OHLC variables, together with tick or transaction volume for each hourly and daily interval. Steel-market data were obtained from the historical transaction records of the Iran Mercantile Exchange and included the daily and weekly transaction prices of steel billets and steel sheets. To improve the explanatory capacity of the steel-price forecasting models, the dataset was supplemented with fundamental variables consisting of the unofficial Iranian rial–US dollar exchange rate and the global price of iron ore with a 62% iron content. These variables were selected because exchange-rate fluctuations directly affect the domestic replacement cost, export attractiveness, and import-related components of steel pricing, while global iron-ore prices represent a major upstream cost factor in the international steel value chain. The collected datasets were integrated according to their observation dates and adjusted to account for differences in trading calendars and data frequencies. All data extraction, integration, cleaning, and transformation procedures were conducted using Python-based computational tools. The Pandas and NumPy libraries were used for data manipulation and numerical calculations, while Scikit-learn, XGBoost, TensorFlow, and Keras were employed to construct and train the predictive models. Technical indicators were generated programmatically from historical price and volume variables to ensure consistency across the steel and foreign exchange datasets.

Data analysis began with preprocessing procedures intended to improve data quality and reduce distortions in model estimation. Extreme observations were identified through a standard-deviation-based approach and were corrected when they represented abnormal deviations unrelated to plausible market movements. Missing observations were reconstructed using linear interpolation, provided that the missing intervals were sufficiently limited to preserve the temporal structure of the series. Because raw price series are commonly nonstationary, logarithmic returns were calculated by taking the first logarithmic difference of consecutive prices. This transformation reduced trend-related instability and enabled the models to learn relative price movements rather than absolute price levels. Feature engineering included the construction of exponential moving averages, the Relative Strength Index, Moving Average Convergence Divergence, Bollinger Bands, and the Average True Range. These technical variables represented trend direction, price momentum, market dispersion, and volatility. For the steel market, additional fundamental features included the rate of change in the unofficial exchange rate, the growth rate of the global iron-ore price, and an index reflecting seasonal fluctuations in steel demand.

Four algorithmic models were implemented. Random Forest was used as the baseline tree-based model and consisted of 500 decision trees with a maximum depth of 15. The XGBoost model was developed with a learning rate of 0.01, a maximum tree depth of 6, and a subsampling ratio of 0.80. The Long Short-Term Memory network consisted of two sequential LSTM layers with 64 and 32 processing units. Dropout layers were incorporated to mitigate overfitting, and the rectified linear unit activation function was used in the relevant dense layers. The Deep Q-Network model was designed as a reinforcement-learning trading agent with three possible actions: buying, selling, and holding. Its architecture incorporated a Q-value evaluation network, an experience replay buffer, and an epsilon-greedy policy that balanced exploration with exploitation during training.

To prevent future observations from influencing the estimation of past outcomes, model validation was performed through walk-forward validation rather than random data splitting. A rolling three-year window was used for model training, followed by a one-year out-of-sample testing window, thereby preserving the chronological order of the observations and reducing the risk of data leakage . Predictive performance was assessed using forecast-error and directional-accuracy criteria, while strategic performance was examined through historical trading simulations. The backtesting framework incorporated realistic transaction costs and evaluated each model according to the Sharpe ratio, maximum drawdown, win rate, and profit factor. These measures made it possible to distinguish statistical forecasting accuracy from practical commercial usefulness and to determine whether a model capable of predicting price movements could also generate a stable, profitable, and risk-adjusted decision strategy in the steel and foreign exchange markets.

3. Findings and Results

The raw foreign exchange dataset contained 31,320 hourly and 1,305 daily EUR/USD observations covering the period from January 2019 to January 2024. Following the removal of duplicated timestamps, synchronization of trading calendars, treatment of missing values, and exclusion of the initial observations required for calculating lagged technical indicators, 30,984 hourly observations and 1,298 daily observations remained available for analysis. The raw steel-market dataset consisted of 1,118 daily steel-billet observations, 1,106 daily steel-sheet observations, and 261 weekly observations for each steel product. After matching steel transaction dates with the unofficial exchange rate and the global 62% iron-ore price, the final integrated daily steel dataset contained 1,041 complete observations. The proportion of missing observations before interpolation was 0.63% in the EUR/USD dataset and 2.14% in the steel-market dataset. Fewer than 1% of the observations in either market were identified as extreme values through the standard-deviation criterion. Examination of the chronological distribution of the observations showed that the dataset covered periods of relatively stable market activity, the market disruptions associated with the COVID-19 pandemic, post-pandemic commodity-price adjustments, exchange-rate shocks, and episodes of elevated geopolitical and inflationary uncertainty. Therefore, the final data structure provided adequate variation for evaluating model behavior under different volatility regimes.

Table 1. Descriptive Statistics for the Main Market Variables

Market variable	Number of observations	Mean	Standard deviation	Minimum	Maximum

EUR/USD logarithmic return	1,298	0.00004	0.00470	-0.03210	0.02780
EUR/USD realized volatility	1,298	0.00680	0.00320	0.00120	0.02460
Steel-billet logarithmic return	1,041	0.00170	0.02940	-0.11850	0.13920
Steel-sheet logarithmic return	1,041	0.00140	0.02680	-0.10270	0.12640
Unofficial exchange-rate change	1,041	0.00200	0.02310	-0.08940	0.11260
Global iron-ore price growth	1,041	0.00030	0.02080	-0.08130	0.09470
Seasonal steel-demand index	1,041	100.00	12.60	74.20	128.70

As presented in Table 1, the average daily logarithmic return of EUR/USD was close to zero, which was consistent with the relatively balanced positive and negative movements of the currency pair across the study period. However, its realized volatility varied considerably, ranging from 0.0012 to 0.0246, indicating the presence of both low-volatility and high-volatility periods. The standard deviation of EUR/USD returns was 0.0047, which was substantially lower than the corresponding values for steel billets and steel sheets. The mean logarithmic returns of steel billets and steel sheets were 0.0017 and 0.0014, respectively, suggesting a generally positive long-term price tendency during the study period. Nevertheless, their standard deviations were 0.0294 and 0.0268, showing that daily steel-price movements were considerably more dispersed than EUR/USD movements. Steel billets demonstrated slightly greater volatility than steel sheets, as reflected in both their standard deviation and their wider minimum-to-maximum return range. The lowest observed billet return was −0.1185, whereas the highest was 0.1392, indicating that the billet market experienced occasional abrupt price corrections and upward jumps.

The unofficial exchange-rate variable also displayed substantial variability, with a mean daily change of 0.0020 and a standard deviation of 0.0231. Its relatively wide range supported the inclusion of the exchange rate as an important fundamental predictor of domestic steel prices. The global iron-ore growth variable had a lower mean but remained volatile, with observed changes ranging from −0.0813 to 0.0947. The seasonal steel-demand index had a mean standardized value of 100 and a standard deviation of 12.60, with values varying between 74.20 and 128.70. This dispersion confirmed that domestic steel-market demand was subject to meaningful seasonal fluctuations. The descriptive findings therefore indicated that the steel market was characterized by a more heterogeneous and shock-sensitive data-generating process than the foreign exchange market. This difference was expected to influence the relative performance of the machine-learning models, particularly because the steel models incorporated both technical and fundamental predictors, whereas the EUR/USD models relied primarily on price-, volume-, momentum-, and volatility-based indicators.

Before model estimation, stationarity was examined for the logarithmic returns and transformed fundamental variables. The augmented Dickey–Fuller tests rejected the null hypothesis of a unit root for all transformed series at the 0.01 significance level. In contrast, the original price-level series were nonstationary. These results supported the use of logarithmic differences and growth rates in model development. Correlation analysis also showed that no pair of predictors exceeded an absolute correlation coefficient of 0.85 after feature screening. Variance inflation factors were below 5 for the retained variables, indicating that severe multicollinearity was not present. The rolling three-year training and one-year out-of-sample testing procedure was then implemented without random shuffling to preserve the temporal order of the observations.

Table 2. Out-of-Sample Predictive Performance of the Machine-Learning and Deep-Learning Models

Market	Model	RMSE	MAE	MAPE (%)	Directional accuracy (%)	R^2
Steel commodity market	Random Forest	0.0087	0.0064	14.80	61.80	0.57
Steel commodity market	XGBoost	0.0071	0.0052	11.90	66.90	0.69

Steel commodity market	LSTM	0.0062	0.0045	10.10	70.80	0.77
EUR/USD foreign exchange market	Random Forest	0.0024	0.0018	13.70	60.50	0.51
EUR/USD foreign exchange market	XGBoost	0.0020	0.0015	11.20	65.70	0.64
EUR/USD foreign exchange market	LSTM	0.0017	0.0013	9.50	69.60	0.72

Table 2 presents the out-of-sample forecasting results for the Random Forest, XGBoost, and LSTM models. The Deep Q-Network was excluded from the point-forecast error comparison because its principal output was a trading action policy rather than a continuous volatility forecast. It was therefore evaluated separately within the strategic backtesting framework. Across both markets, the LSTM model generated the lowest forecasting errors and the highest explanatory and directional performance. In the steel commodity market, LSTM achieved an RMSE of 0.0062, an MAE of 0.0045, and a MAPE of 10.10%. These values represented reductions of approximately 28.74%, 29.69%, and 31.76%, respectively, compared with the Random Forest model. The LSTM model also correctly predicted the direction of the next-period change in steel-market volatility in 70.80% of the out-of-sample observations. Its R^2 value of 0.77 indicated that approximately 77% of the out-of-sample variation in steel-market volatility was explained by the model.

XGBoost produced the second-best predictive results in the steel market. Its RMSE of 0.0071 was approximately 18.39% lower than that of Random Forest, while its directional accuracy was 66.90%. The Random Forest model provided acceptable baseline performance, with a directional accuracy exceeding 60%, but it was less capable of representing temporal dependencies and nonlinear interactions extending across multiple previous periods. Block-bootstrap comparisons of the absolute forecast errors indicated that the improvement of XGBoost over Random Forest was statistically significant, with a mean absolute-error difference of −0.0012 and a 95% confidence interval ranging from −0.0018 to −0.0006. The improvement of LSTM over XGBoost was also statistically significant, with a mean difference of −0.0007 and a 95% confidence interval ranging from −0.0012 to −0.0002. These results suggested that the superior performance of the recurrent neural network was not attributable solely to random variation in a particular test window.

A comparable ranking was observed in the EUR/USD market. LSTM produced an RMSE of 0.0017, an MAE of 0.0013, and a MAPE of 9.50%. Its directional accuracy was 69.60%, and its R^2 was 0.72. XGBoost achieved an RMSE of 0.0020 and directional accuracy of 65.70%, whereas Random Forest recorded an RMSE of 0.0024 and directional accuracy of 60.50%. Although the absolute errors were smaller in the foreign exchange market because the scale of EUR/USD volatility was lower, the relative ordering of the models remained unchanged. The slightly lower R^2 and directional accuracy values obtained in the foreign exchange market indicated that EUR/USD price information was more rapidly incorporated into market prices, thereby limiting the amount of exploitable predictability available to the models. In contrast, the steel models benefited from the inclusion of the unofficial exchange rate, global iron-ore prices, and seasonal demand indicators, which increased the amount of economically meaningful information available for volatility prediction.

Analysis of feature importance further clarified the predictive mechanisms. In the XGBoost steel model, the change in the unofficial exchange rate was the most influential variable, accounting for 24.60% of total gain-based importance. The Average True Range accounted for 18.90%, global iron-ore price growth for 15.40%, Bollinger Band width for 12.70%, the Relative Strength Index for 9.80%, and seasonal demand variation for 8.60%. The remaining importance was distributed across the EMA spread, MACD, transaction volume, and lagged return variables. In the EUR/USD model, the Average True Range had the greatest importance at 25.10%, followed by Bollinger Band width at 20.70%, MACD at 16.40%, the difference between short-term and long-term exponential moving averages at 14.90%, and RSI at 10.60%. These findings indicated that steel-market volatility was driven by a combination of market microstructure, exchange-rate exposure, international input costs, and demand conditions, whereas foreign exchange volatility was explained predominantly by technical and price-derived information.

The LSTM training process also demonstrated stable convergence. The difference between the final training and validation losses was less than 8% in both markets, suggesting that the Dropout layers and walk-forward validation procedure adequately controlled overfitting. Early stopping was activated after 67 epochs in the steel model and after 59 epochs in the EUR/USD model. No substantial deterioration was observed when the models were evaluated in the final out-of-sample periods. Prediction errors increased during extreme volatility episodes, but the LSTM model retained the best relative ranking under both ordinary and high-volatility conditions.

Table 3. Net Strategic Backtesting Performance after Transaction Costs

Market	Strategy	Annualized net return (%)	Sharpe ratio	Maximum drawdown (%)	Win rate (%)	Profit factor	Number of completed trades
Steel commodity market	Passive market benchmark	12.10	0.58	26.40	—	—	—
Steel commodity market	Random Forest strategy	15.30	1.03	14.10	55.10	1.30	118
Steel commodity market	XGBoost strategy	20.40	1.38	11.30	58.90	1.51	134
Steel commodity market	LSTM strategy	25.20	1.63	9.50	61.40	1.69	127
Steel commodity market	DQN strategy	28.90	1.86	8.70	63.80	1.84	141
EUR/USD foreign exchange market	Passive market benchmark	3.40	0.29	17.80	—	—	—
EUR/USD foreign exchange market	Random Forest strategy	10.60	0.86	12.90	53.60	1.22	186
EUR/USD foreign exchange market	XGBoost strategy	15.70	1.23	10.40	57.10	1.41	204
EUR/USD foreign exchange market	LSTM strategy	20.30	1.48	8.60	59.90	1.58	193
EUR/USD foreign exchange market	DQN strategy	23.80	1.71	7.70	62.40	1.75	219

The strategic backtesting results shown in Table 3 demonstrated that forecasting accuracy did not translate mechanically into identical trading performance, although models with better predictive capability generally generated stronger financial outcomes. All algorithmic strategies outperformed their corresponding passive market benchmarks after the inclusion of transaction costs. The backtesting calculations incorporated an assumed total transaction cost of 0.35% for each completed steel-market position and an average spread-equivalent cost of 1.2 pips for each completed EUR/USD trade. The Deep Q-Network generated the strongest overall strategic performance in both markets. In the steel market, the DQN strategy produced an annualized net return of 28.90%, a Sharpe ratio of 1.86, a maximum drawdown of 8.70%, a win rate of 63.80%, and a profit factor of 1.84. This performance was achieved through 141 completed trades. The DQN strategy therefore generated approximately 16.80 percentage points more annualized return than the passive steel benchmark while reducing maximum drawdown by 17.70 percentage points.

The LSTM strategy was the second-best approach in the steel market. It generated an annualized return of 25.20%, a Sharpe ratio of 1.63, a maximum drawdown of 9.50%, a win rate of 61.40%, and a profit factor of 1.69. Although LSTM provided the highest point-forecast accuracy, DQN produced superior trading results because it optimized the sequential relationship between actions and cumulative rewards rather than minimizing forecast error alone. DQN was able to remain outside the market during periods in which the expected reward did not compensate for risk and transaction costs. Its learned policy selected the hold action in 41.80% of decision periods, the buy action in 30.60%, and the sell action in 27.60%. This relatively selective behavior reduced unnecessary turnover and limited exposure during unstable market conditions.

The XGBoost steel strategy generated an annualized return of 20.40%, a Sharpe ratio of 1.38, and a maximum drawdown of 11.30%. Its win rate of 58.90% and profit factor of 1.51 indicated that the strategy remained commercially viable after transaction costs. Random Forest provided the weakest algorithmic results but still exceeded the passive benchmark in risk-adjusted terms. Its annualized return was 15.30%, and its Sharpe ratio was 1.03, compared with a Sharpe ratio of 0.58 for the passive steel-market benchmark. Random Forest also reduced maximum drawdown from 26.40% to 14.10%. Therefore, even the baseline model generated a meaningful improvement in risk control, although its return and profit factor remained below those of the more advanced models.

The same strategic ordering was observed in the EUR/USD market. The DQN strategy achieved an annualized net return of 23.80%, a Sharpe ratio of 1.71, a maximum drawdown of 7.70%, a win rate of 62.40%, and a profit factor of 1.75. The LSTM strategy generated an annualized return of 20.30% and a Sharpe ratio of 1.48, while XGBoost generated an annualized return of 15.70% and a Sharpe ratio of 1.23. The Random Forest strategy produced an annualized return of 10.60%, which remained substantially higher than the 3.40% return of the passive EUR/USD benchmark. The passive benchmark also had the lowest Sharpe ratio and one of the largest drawdowns, confirming that continuous exposure to the currency pair was less efficient than model-based position management during the study period.

Comparison of the two markets indicated that the algorithmic strategies generally achieved higher returns and profit factors in the steel market. This result suggested that the steel market contained stronger exploitable relationships between price movements and the selected fundamental variables. Nevertheless, the foreign exchange strategies completed more trades because EUR/USD provided more frequent and continuous trading opportunities. The greater number of trades did not lead to superior risk-adjusted returns, partly because repeated exposure increased cumulative transaction costs. In contrast, steel-market signals occurred less frequently but were more strongly associated with exchange-rate movements, iron-ore prices, and seasonal demand conditions.

Robustness analysis confirmed that the strategic superiority of DQN was maintained when transaction costs were increased by 25%. Under the higher-cost scenario, the annualized return of the steel DQN strategy declined from 28.90% to 26.70%, while its Sharpe ratio declined from 1.86 to 1.73. The EUR/USD DQN return decreased from 23.80% to 21.90%, and its Sharpe ratio decreased from 1.71 to 1.59. Despite these reductions, DQN continued to outperform the LSTM, XGBoost, and Random Forest strategies. When transaction costs were increased by 50%, all algorithmic strategies remained profitable, although the advantage of Random Forest became comparatively small. These findings indicated that the superior performance of the deep-learning strategies was not dependent on unrealistically low transaction costs.

Performance was also examined separately during low-, medium-, and high-volatility regimes. In the steel market, the DQN Sharpe ratio was 1.49 during low-volatility periods, 1.92 during medium-volatility periods, and 1.78 during high-volatility periods. LSTM achieved corresponding Sharpe ratios of 1.34, 1.70, and 1.51. Random Forest performance deteriorated more substantially during high-volatility periods because individual decision trees were less effective in adapting to abrupt changes in the interaction between technical and fundamental variables. In the EUR/USD market, all strategies experienced lower win rates during the highest-volatility regime, but DQN maintained a win rate above 58%. The ability of DQN and LSTM to preserve positive performance during market stress supported their relative robustness.

Block-bootstrap testing of Sharpe-ratio differences showed that the DQN strategy significantly outperformed the LSTM strategy in the steel market, with an estimated Sharpe-ratio difference of 0.23 and a bootstrap probability value of 0.026. The corresponding difference in the EUR/USD market was 0.23 and was also statistically significant at a probability value of 0.039. The DQN advantage over XGBoost was larger and statistically significant in both markets. The LSTM strategy also significantly outperformed Random Forest in terms of annualized return, maximum drawdown, and profit factor. Taken together, the predictive and strategic findings showed that LSTM was the most accurate model for forecasting future volatility, whereas DQN was the most effective model for translating market information into risk-adjusted commercial decisions. The comparative analysis further demonstrated that machine-learning performance was stronger in the steel market when fundamental variables were combined with technical indicators, while the highly liquid EUR/USD market remained more difficult to predict because of its greater informational efficiency.

4. Discussion and Conclusion

The present study compared the predictive and strategic performance of Random Forest, XGBoost, Long Short-Term Memory, and Deep Q-Network models in forecasting volatility and supporting trading decisions in the Iranian steel commodity market and the EUR/USD foreign-exchange market. The findings showed that the LSTM model achieved the highest forecasting accuracy in both markets, as indicated by the lowest RMSE, MAE, and MAPE values and the highest directional accuracy and coefficient of determination. In the steel market, LSTM explained approximately 77% of the out-of-sample variation in volatility and correctly predicted the direction of subsequent movements in more than 70% of observations. XGBoost ranked second, while Random Forest provided the weakest, although still acceptable, predictive performance. In contrast, the DQN model generated the strongest strategic backtesting outcomes. It produced the highest annualized return, Sharpe ratio, win rate, and profit factor and the lowest maximum drawdown in both markets. These results demonstrate that forecasting accuracy and trading effectiveness are related but conceptually distinct outcomes. LSTM was more effective in estimating future volatility, whereas DQN was more successful in converting information into sequential buy, sell, and hold decisions that maximized cumulative risk-adjusted reward. This distinction is important because a model with low statistical error does not necessarily provide the most profitable strategy after transaction costs, position timing, and downside risk are considered.

The superior predictive performance of LSTM can be explained by the sequential and path-dependent nature of financial and commodity-market data. Steel and foreign-exchange volatility are influenced by previous returns, changing momentum, lagged reactions to information, volatility clustering, and interactions that develop over multiple periods. A recurrent neural network can retain and update information from earlier observations, enabling it to represent temporal dependencies that are more difficult for conventional tree-based models to capture. The finding that LSTM outperformed Random Forest and XGBoost is therefore consistent with the broader transition from static volatility analysis toward computational methods designed to identify dynamic and nonlinear patterns. The comparison of conventional statistical volatility models with the water-drop-motion algorithm in the Tehran Stock Exchange similarly indicates that numerical and intelligent algorithms may improve the representation of complex price behavior when traditional assumptions are restrictive [26]. Likewise, information-based artificial multi-asset market research has demonstrated that market dynamics emerge from the combined influence of static information, evolving signals, and interactions among heterogeneous agents [27]. The current findings extend this computational perspective to the steel commodity market by showing that models capable of processing nonlinear and temporally ordered information can outperform a baseline ensemble-tree approach.

The strong performance of XGBoost relative to Random Forest also reflects differences in the learning structure of the two models. Random Forest constructs a large collection of relatively independent trees and averages their predictions, making it robust to noise but less capable of sequentially correcting systematic errors. XGBoost, by contrast, builds trees iteratively so that each stage focuses on residual errors from the previous stage. This mechanism appears to have been advantageous in modeling the complex interaction among technical indicators, exchange-rate changes, iron-ore prices, and seasonal steel demand. The Random Forest model nevertheless exceeded the passive benchmark in the strategic simulation, suggesting that even a comparatively simple nonlinear ensemble can identify commercially meaningful regularities. This finding is relevant to research on market volatility-control mechanisms because it indicates that risk control can be strengthened not only through formal exchange regulations but also through data-based decision-support tools that reduce poorly timed transactions and uncontrolled market exposure [10]. The results also correspond with evidence showing that market regulations and trading structures can influence return and market volatility, as demonstrated in research on short-selling regulation in the Athens Exchange [9]. Algorithmic position management can be viewed as an internal commercial-control mechanism that complements external market regulation by determining when market exposure is justified.

The higher explanatory power of the steel-market models can be attributed to the incorporation of fundamental variables alongside technical indicators. The feature-importance analysis identified changes in the unofficial exchange rate as the most influential predictor of steel-market volatility, followed by the Average True Range, global iron-ore price growth, Bollinger Band width, RSI, and seasonal demand. This result supports the argument that domestic steel prices cannot be understood solely through their own historical movements. Exchange-rate changes affect the rial value of internationally traded steel, export incentives, imported equipment and input costs, replacement costs, and the relative profitability of domestic and foreign sales. Previous evidence from Middle Eastern economies has shown that exchange-rate volatility can transmit instability to asset prices [11]. Research on the Egyptian real-estate market has likewise demonstrated a dynamic relationship between exchange-rate volatility and sectoral stock prices, with interest rates influencing the strength of that relationship [12]. The current findings transfer this logic from securities to physical commodities and indicate that currency instability is a central component of steel-price risk in an import- and export-sensitive economy.

The identified importance of exchange-rate movements also aligns with evidence of return and volatility transmission between currency and equity markets. Research in Croatia has demonstrated that shocks can spill between exchange rates and stock prices in a time-varying manner [13]. Similar evidence from BRIICS economies during the COVID-19 period showed that correlations and volatility spillovers intensified under crisis conditions [14]. The current results suggest that this spillover mechanism extends to the steel commodity market, particularly because exchange-rate movements alter both expected costs and market participants' anticipatory behavior. Even volatility generated in emerging asset classes can affect currency-market conditions, as indicated by evidence of spillovers between cryptocurrency prices and foreign exchange in Nigeria [15]. Consequently, the predictive contribution of the exchange rate in the steel model should not be interpreted as a simple bilateral correlation. It is more appropriately viewed as part of a wider network through which macroeconomic uncertainty, capital-market expectations, and commodity values are transmitted.

The importance of global iron-ore prices and volatility indicators further confirms that steel-market behavior is linked to upstream commodity shocks. Although the present study focused on iron ore rather than oil, earlier studies of energy-price volatility provide a relevant explanation of how international commodity shocks are transmitted into sectoral values and financial performance. Oil-price volatility has been shown to affect sectors of the Pakistan Stock Exchange differently, indicating that exposure depends on cost structures and sectoral sensitivity [16]. Evidence from Kenya also links oil-price volatility to changes in economic performance reflected in the Nairobi Securities Exchange Index [17]. In Iran, volatility in global oil prices has been found to spill over to the returns of selected industries, with the strength of the effect varying across market regimes [18]. Multivariate GARCH evidence concerning Iran, the United Arab Emirates, and the global oil-price index further demonstrates that commodity shocks can propagate across national and financial boundaries [19]. These findings support the present conclusion that a steel-price forecasting system should incorporate global raw-material variables because upstream shocks are gradually transmitted through production costs, inventories, expectations, and commercial quotations.

The results are also consistent with research indicating that exchange-rate volatility can influence the market valuation of petroleum-product firms in Iran [20]. Although petroleum products and steel differ in production technology, both sectors are capital-intensive, energy-dependent, and exposed to international pricing. The combined influence of currency and commodity-price movements can therefore create nonlinear volatility that is difficult to capture through univariate models. Recent research has also linked oil-price volatility shocks to systemic financial risk, implying that commodity instability may affect the broader financial system rather than remaining limited to a single market [21]. This systemic interpretation helps explain why the steel models benefited from multiple categories of predictors. Steel prices reflect not only internal transaction dynamics but also macroeconomic instability, global input markets, financial expectations, and changes in industrial demand.

The DQN strategy's superior financial performance can be explained by the difference between supervised prediction and reinforcement learning. LSTM was trained to minimize prediction error, whereas DQN was trained to select actions that maximized cumulative rewards after considering market states, transaction costs, and future consequences. The DQN agent frequently selected the hold action, thereby avoiding trades when the expected reward was insufficient to compensate for cost and risk. This selective behavior reduced unnecessary turnover and produced lower drawdowns. The result is strategically important because frequent accurate predictions may still be commercially ineffective when changes are too small to cover trading costs. The DQN model effectively learned that not trading is itself a meaningful decision. This outcome is consistent with the general risk-management principle that the objective of commercial decision-making is not to maximize the number of successful forecasts but to improve the balance among return, exposure, and loss severity.

The DQN model also remained superior when transaction costs were increased and when performance was assessed across different volatility regimes. This robustness suggests that its performance was not merely the result of unrealistically low market frictions. The finding has practical relevance for industrial financial-risk management, where hedging models must remain useful despite currency and commodity-price variability. Research on petrochemical development projects has similarly emphasized the need for integrated hedging approaches that consider currency and oil-price volatility simultaneously [25]. In the steel market, an intelligent sequential strategy can perform an analogous role by modifying exposure according to expected changes in volatility and reward. The lower drawdown obtained by DQN is particularly valuable for steel traders and firms because large losses may have consequences beyond portfolio value, including working-capital shortages, disrupted procurement plans, and inability to meet contractual obligations.

The finding that the steel strategies generally produced higher returns and profit factors than the EUR/USD strategies can be interpreted in terms of differences in market efficiency and information structure. EUR/USD is one of the world's most liquid and closely monitored currency pairs. Information is incorporated rapidly into its price, and exploitable patterns may disappear quickly. The steel commodity market is less continuous and is affected by domestic exchange-rate conditions, production constraints, global iron-ore prices, seasonal demand, regulatory decisions, and supply-chain conditions. These influences may create slower and more structured adjustment processes that machine-learning models can exploit. The higher predictive performance in the steel market therefore does not imply that it is more stable; rather, it suggests that a larger part of its volatility is associated with observable fundamental conditions.

The importance of combining technical and fundamental features is also consistent with research on risk factors in the digital supply chain of the steel industry. A decision-support system developed for the country's steel industries has highlighted the interconnected nature of supply-chain risks and the need to analyze them systematically [22]. The current study complements this perspective by showing that digital decision support can extend to market-price risk. Exchange-rate changes, raw-material prices, technical volatility, and seasonal demand can be integrated into a unified predictive architecture that supports purchasing, selling, and hedging decisions. This integrated approach is increasingly necessary because the steel industry is undergoing technological and environmental transformation. Green innovation and the development of FINEX technology have altered the strategic landscape of steel production by linking technological capability, environmental performance, and competitive development [23]. Life-cycle assessment and optimization of carbon-reduction pathways also demonstrate that environmental transition creates measurable costs that may ultimately influence production economics and market prices [24]. As such structural variables become more influential, machine-learning models may offer greater flexibility than fixed-form econometric specifications.

The present findings additionally show that market volatility is not generated only by macroeconomic and production variables. Investor and trader behavior can affect liquidity, expectations, and the speed of price adjustment. Evidence from the Tehran Stock Exchange indicates that investor sentiment influences both liquidity and its volatility [2]. Financial-news sentiment and investor confidence have also been identified as determinants of price volatility [4], while behavioral experiments indicate that financial literacy and decision-making patterns affect responses to market information [3]. Although the steel-market dataset did not directly include sentiment variables, part of the predictive power of technical indicators may reflect the aggregated consequences of market participants' expectations. RSI, MACD, Bollinger Bands, and moving averages summarize buying and selling pressure and may therefore indirectly capture behavioral reactions to news, exchange-rate changes, and expected shortages.

The strategic superiority of the algorithmic models over passive benchmarks is also compatible with studies showing that price volatility is influenced by policy and firm-level decision structures. Dividend-policy research in Iran, Pakistan, Nigeria, and Kenya demonstrates that corporate financial decisions can alter the stability of asset prices [5-8]. While the present study did not examine dividends, these findings reinforce the broader conclusion that volatility reflects decision processes rather than random market noise alone. Industry cash-flow volatility has similarly been associated with stock-price crash risk, showing that operating uncertainty can accumulate and generate abrupt market losses [1]. In the steel industry, failures to manage inventory, currency exposure, and procurement timing may produce comparable financial stress. A machine-learning-based decision system can reduce such exposure by providing earlier warnings and more disciplined transaction rules.

Overall, the findings confirm that deep-learning and reinforcement-learning approaches provide distinct but complementary advantages. LSTM is most appropriate when the principal objective is accurate forecasting of future volatility, whereas DQN is more appropriate when the objective is to select risk-adjusted commercial actions over time. XGBoost offers a strong intermediate option, especially when interpretability, computational efficiency, and feature importance are required. Random Forest remains useful as a robust baseline and may be appropriate for organizations with limited computational infrastructure. The comparative results also demonstrate that models should not be selected solely according to prediction-error measures. Commercial implementation requires simultaneous evaluation of profitability, transaction costs, drawdown, stability across regimes, and sensitivity to market frictions.

The study had several limitations. First, the numerical results were derived from a defined historical period and may therefore reflect market conditions specific to January 2019 through January 2024, including the COVID-19 crisis, exchange-rate shocks, inflationary pressures, and unusual commodity-market disruptions. Second, differences in data frequency between the steel and foreign-exchange markets limited the direct comparability of the available information. The steel market also had fewer observations and lower transaction continuity than EUR/USD. Third, the fundamental steel variables were limited to the unofficial exchange rate, global iron-ore prices, and seasonal demand, while other potentially relevant determinants such as energy prices, production volume, export restrictions, inventory levels, construction permits, interest rates, sanctions, freight costs, and policy announcements were not incorporated. Fourth, the backtesting environment approximated transaction costs but could not fully represent all real-world constraints, including order slippage, delayed execution, limited market depth, delivery obligations, price limits, and temporary trading interruptions. Finally, the model architecture and hyperparameters were selected according to a predefined framework, and alternative configurations might produce different results.

Future studies should evaluate the models over longer periods and include multiple structural regimes to determine whether performance remains stable across economic expansions, recessions, exchange-rate crises, and major policy changes. Researchers should incorporate additional explanatory variables such as energy costs, domestic production, inventories, export and import volumes, construction activity, freight rates, interest rates, inflation, sanctions, and textual sentiment extracted from financial news and policy announcements. Comparative studies could extend the analysis to other steel products, international steel exchanges, other commodity markets, and additional currency pairs. Hybrid models combining LSTM, attention mechanisms, transformers, gradient boosting, and reinforcement learning should also be examined. Future research should apply explainable artificial-intelligence techniques to clarify how specific variables influence predictions and trading actions. More detailed simulations could model slippage, liquidity constraints, position-size limits, delayed settlement, and different risk-aversion parameters. Finally, prospective or real-time paper-trading studies are needed to examine whether the models retain their effectiveness when decisions are generated from newly arriving data rather than historical records.

Steel producers, commodity traders, industrial purchasers, and financial managers should use machine-learning systems as decision-support instruments rather than as automatic substitutes for managerial judgment. LSTM can be employed to generate short-term volatility forecasts and identify periods requiring more cautious pricing, procurement, or inventory policies. DQN-based systems may support the timing of market exposure, but their actions should be subject to position limits, loss thresholds, and human oversight. Organizations with limited technical resources may initially implement XGBoost because it provides strong predictive performance while allowing clearer assessment of variable importance. Forecasting platforms should integrate steel prices with exchange rates, raw-material prices, demand indicators, and operational data and should be updated as new information becomes available. Before live implementation, every strategy should be evaluated through walk-forward testing, stress testing, and transaction-cost sensitivity analysis. Firms should also establish governance procedures for model validation, monitoring, cybersecurity, data quality, and periodic retraining so that algorithmic recommendations remain aligned with commercial objectives and changing market conditions.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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