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WALMART PRICE PREDICTION USING HOLT-WINTERS FORECASTING

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Abstract

Stock price prediction remains a complex challenge due to the volatile, noisy, and nonlinear nature of financial markets. This study aims to evaluate the effectiveness of the Holt-Winters Exponential Smoothing (HWES) method in forecasting the stock price of Walmart Inc. (WMT) and its application in investment decision-making. Historical monthly closing price data from January 2020 to December 2024 were collected and used to build an additive Holt-Winters model. The model was validated using out-of-sample data from January to February 2025, achieving RMSE of 4.535 USD and MAE of 4.801 USD, indicating good short-term predictive performance. The model was then used to forecast stock prices from March 2025 to December 2026, revealing a consistent upward trend with moderate seasonal fluctuations. However, deviations between predicted and actual values were observed during periods of market volatility, particularly in late 2025. To further evaluate performance, the Holt-Winters model was compared with the ARIMA model. Results show that ARIMA outperformed Holt-Winters in short-term forecasting with lower RMSE (4.71), MAE (4.26), and MAPE (4.21%), while Holt-Winters was more effective in capturing seasonal patterns. An investment simulation using a Dollar Cost Averaging (DCA) strategy combined with technical analysis indicators produced a total return of 3.45%, supported by both capital gains and dividend income. These findings suggest that while Holt-Winters provides a simple and interpretable approach for long-term forecasting, its performance can be improved by integrating adaptive models and external factors such as market sentiment and macroeconomic conditions for more robust predictions.

Keywords: Walmart; holt-winters; time series forecasting; stock price prediction; capital gain.

1. INTRODUCTION

Stock price prediction remains a critical challenge in financial time series analysis due to the inherently volatile, noisy, and nonlinear nature of market behavior. These characteristics are influenced by a combination of internal corporate performance and external macroeconomic factors, making accurate and robust forecasting models essential for supporting investment decision-making, particularly in long-term strategies. Numerous approaches have been proposed to address this problem, ranging from classical statistical models to advanced machine learning and deep learning techniques. Several statistical and machine learning models have been employed in recent years to address the complexities of stock price forecasting. One of the classic time-series techniques is the Holt-Winters Exponential Smoothing (HWES) method, which has demonstrated effectiveness in capturing seasonal trends and long-term behavior in structured datasets. In [1], HWES was applied to seasonal product demand forecasting and proved more consistent than artificial neural networks (ANN) under certain constraints. Similarly, [2] found that HWES outperformed ARIMA in managing inventory for time-series data with strong seasonality. HWES has also shown utility outside financial contexts. For instance, [3] used the model to forecast NDVI in East Africa, while [4] applied it to mortality rate predictions, both emphasizing the method's adaptability in time-series forecasting. Meanwhile, [5] explored modified HWES for sales prediction and reported high accuracy with reduced computational cost, making it attractive for automated forecasting systems.

On the other hand, more sophisticated approaches such as Long Short-Term Memory (LSTM) networks have demonstrated superior performance in capturing non-linear dependencies in stock price data. LSTM outperformed traditional models and exhibited robust results when optimized using Genetic Algorithms and Artificial Rabbits Optimization (ARO) [6]. The LSTM-ARO model achieved the highest predictive accuracy for WMT stocks, highlighting the potential of metaheuristic tuning in deep learning systems. An ensemble learning strategy [7], and feature engineering using clustering and particle swarm optimization [8] have all contributed to improved prediction performance. These studies illustrate the growing trend of combining multiple techniques to capture the complex patterns in financial time-series. At the frontier of innovation, quantum-based and generative models have also been introduced. The Quantum Leap model [9] and the Quantum Path framework [10] utilize deep quantum neural networks and temporal GANs to model stock behavior, including for WMT. These approaches excel in short-to-medium-term trend prediction, albeit at higher computational cost. Additionally, probabilistic approaches like the ARIMA-random walk hybrid in [11] provided accurate trend classification in short-term horizons using statistical filtering techniques. However, in the context of financial markets, more complex models, while these approaches achieve high accuracy, they often come at the cost of increased computational complexity and reduced interpretability. Despite these advancements, research specifically employing the Holt-Winters method to forecast Walmart's stock price over a long-term horizon remains scarce. Given its simplicity, transparency, and efficiency in capturing trend and seasonality, Holt-Winters could serve as a valuable alternative in scenarios where interpretability and computational efficiency are critical.

Among many publicly traded companies, Walmart Inc. (WMT) stands out as a global retail giant with a significant impact on the consumer sector, making its stock an important subject of long-term prediction studies. In 2024, Walmart's stock achieved an impressive 72% gain, outperforming the S&P 500 index and highlighting the company's resilience amid economic uncertainty [12]. However, forecasts for 2025 and 2026 indicate potential headwinds due to rising inflation, consumer spending slowdowns, and tariff risks [13], [14]. Despite these challenges, Walmart continues to attract higher-income shoppers, signaling evolving market dynamics that may influence future price trajectories [15]. Thus, this study aims to explore the effectiveness of Holt-Winters forecasting in predicting WMT stock prices up to the year 2026, providing a statistical perspective that complements existing deep learning and hybrid approaches in the literature. The main contributions of this study are as follows: (1) an empirical evaluation of Holt-Winters in long-term financial forecasting, (2) an analysis of its limitations in handling market volatility when compared to alternative approaches, and (3) the integration of forecasting outputs into an investment simulation framework to bridge the gap between predictive modeling and financial decision-making.

2. RESEARCH METHODS

2.1. Holt-Winters

This study employs the Holt-Winters Exponential Smoothing (additive) method to forecast the monthly closing prices of Walmart Inc. (WMT) stock up to the end of 2026. The model is developed to support a simulated Dollar Cost Averaging (DCA) investment strategy, with the aim of evaluating long-term investment potential based on trend and seasonal behavior. The additive Holt-Winters model consists of three main components: level, trend, and seasonality. The forecast equation is as follow:

$$y_{t+h} = (l_t + h \,.\, w_t) + s_{t+h-p(k+1)} \tag{1}$$

where:
y_{t+h} : forecasted value at time t + h
l_t : estimated level at time t
w_t : estimated trend at time t
s_t : estimated seasonal component at time t
p : length of seasonal period (e.g., 12 for monthly data)
k : integer part of $\frac{h-1}{p}$, used to align seasonal index

The three main components updates equation are as follows:

$$l_t = \alpha\left(\frac{y_t}{s_{t-m}}\right) + (1 - \alpha)(l_{t-1} - m_{t-1}) \tag{2}$$

$$w_t = \beta(l_t - l_{t-1}) + (1 - \beta)w_{t-1} \tag{3}$$

$$s_t = \gamma\left(\frac{y_t}{l_t}\right) + (1 - \gamma)s_{t-p} \tag{4}$$

where:
y_t : actual observed value at time t
α, β, γ : smoothing parameters for level, trend, and seasonality respectively, with values in [0, 1]

This model assumes that seasonal effects are additive, meaning the magnitude of seasonality does not change proportionally with the level of the series. The initial values for l_0, w_0 , and seasonal components s_t are typically initialized using heuristic approaches.

2.2. Data Collection

Historical stock data for WMT was collected from Yahoo Finance, covering the period January 2020 to December 2024. The dataset consists of monthly closing prices, which provides a smoothed view of long-term price trends and minimizes high-frequency noise. The dataset used in this study consists of monthly closing prices of Walmart Inc. (WMT), organized as a univariate time series. Throughout the data preprocessing stage, no missing values were detected, ensuring the continuity and reliability of the series. To facilitate effective forecasting, the time series was decomposed into its fundamental components—trend, seasonality, and residual—based on a seasonal period of 12 months, which assumes one complete annual cycle. This decomposition enables the model to isolate underlying patterns and better capture the temporal dynamics of the stock's behavior.

2.3. Forecasting Method

The Holt-Winters additive model is applied, which is suitable for data exhibiting both trend and additive seasonal patterns. The model is implemented using AI Studio (formerly Rapid Miner), a visual data science platform that provides built-in forecasting operators. Model parameters are Trend smoothing coefficient (α), Seasonal smoothing coefficient (β), and Level smoothing coefficient (γ), with Seasonal period is equal to 12 (monthly). The Holt-Winters additive model was trained using monthly closing price data from January 2020 to December 2024. To evaluate the model's ability to generalize beyond the training period, validation was conducted on an out-of-sample basis using data from January and February 2025. Following this validation phase, the model was applied to forecast WMT stock prices from March 2025 through December 2026, resulting in a total of 22 months of forward-looking predictions. The performance of the model was evaluated using two standard error metrics: Root Mean Square Error (RMSE), which measures the average magnitude of prediction error, and Mean Absolute Error (MAE), which quantifies the average absolute differences between predicted and actual values. Both metrics were computed for the validation phase as well as for the overall forecasting performance to ensure robustness and accuracy of the model.

$$RMSE = \sqrt{\frac{1}{n}} \left(\sum(\varphi - y)^2\right) \tag{5}$$

$$MAE = \sqrt{\frac{1}{n} \left(\sum|\varphi - y|\right)} \tag{6}$$

where:
n : number of data
φ : actual price
y : predicted price

2.4. Investment Simulation Strategy

A Dollar Cost Averaging (DCA) investment strategy was simulated based on the forecasted stock prices, with monthly investments commencing in March 2025 following the validation period. A fixed amount of $10 USD was allocated each month to purchase shares at the predicted closing prices. The stock purchasing window was set between the 2nd and 15th of each month, during which buy decisions were made by considering both market sentiment and basic technical analysis indicators. Although sentiment and technical indicators were not directly integrated into the forecasting model, they were used qualitatively to guide decision-making and assess the associated investment risks in each period.

3. RESULTS AND DISCUSSION

To evaluate the predictive power of the Holt-Winters additive model, the validation phase was conducted using data from January and February 2025, which were not part of the training set. The forecasted values were compared against the actual closing prices obtained from Yahoo Finance. The model yielded the following error metrics on the validation set RMSE: 4.535 USD and MAE: 4.801 USD. These results indicate that the model effectively captures the underlying trend and seasonal structure of WMT stock prices, demonstrating reliable performance in short-term forecasting.

3.1. Long-Term Forecast

The model was used to forecast monthly closing prices from March 2025 through December 2026. The forecast results show a continuation of the long-term trend with minor seasonal fluctuations. The predicted values were plotted to visualize the expected evolution of WMT stock prices over this 22-month period.

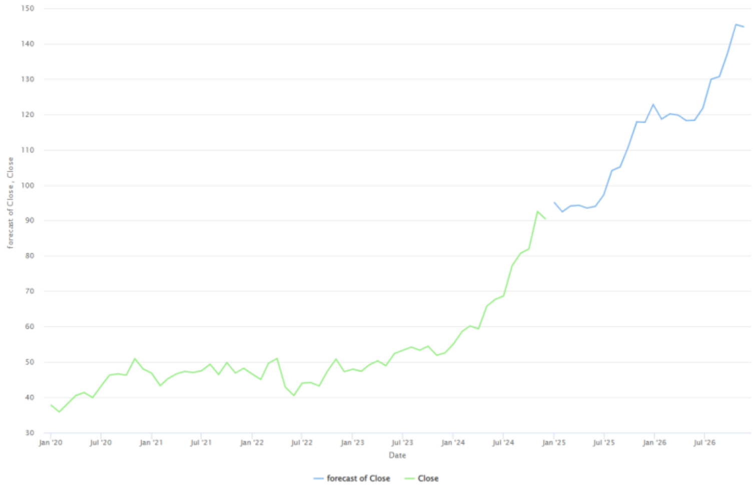

Figure 1. Long-Term Forecasting up to 2026

The data presented in Figure 1 illustrate the Holt–Winters time series forecast of WMT’s closing price from 2025 to 2026. During the first half of 2025 (January to June), the forecast indicates a relatively stable and subdued price movement, fluctuating within a narrow range of USD 92.5 to USD 95.2. However, beginning in July 2025, when the price is projected to reach USD 97.2, a strong upward momentum emerges. The forecast shows the price breaking the USD 100 threshold in August and continuing to rise, peaking at approximately USD 117.8 in November, before closing the year at USD 117.7.

In 2026, the forecast reveals a clear and sustained upward trend throughout the year. During the first half of 2026 (January to June), prices are expected to remain relatively stable, fluctuating between USD 118.2 and USD 122.8. A pronounced rally is then projected to occur in the second half of the year, with prices surpassing USD 130 by September and continuing to increase sharply, reaching an estimated peak of USD 145.3 in November, before ending the year at USD 144.7.

3.2. Technical Analysis

To assess both the short-term and long-term price momentum of Walmart's stock (WMT), this study incorporates Technical Analysis using a set of specific indicators applied to the stock chart (Figure 2, sourced from the TradingView platform). The methodology is primarily based on moving average crossover strategies and automated trend identification. The core strategy employed to identify long-term buy and sell signals utilizes the crossover of two Exponential Moving Averages (EMAs): Golden Cross (Buy Signal): A buy signal is confirmed when the 50-day EMA crosses above the 200-day EMA. This crossover is interpreted as a shift in medium-term momentum toward a strong upward trend. Dead Cross (Sell Signal): A sell signal is confirmed when the 50-day EMA crosses below the 200-day EMA. This event signals the potential commencement of a long-term bearish trend. Short-term price action and confirmation of entry/exit points are analyzed using two additional, more sensitive EMAs: the EMA 13 and the EMA 21. These indicators provide quicker responsiveness to daily price volatility and aid in fine-tuning trading decisions within the context of the larger, established trend. To maintain objectivity in identifying significant price patterns and support/resistance levels, the analysis leverages the Autotrendline feature available on the TradingView platform. This tool automatically detects and draws critical trend lines (connecting higher highs and lower lows), offering a visual and structured basis for analyzing WMT's price movement.

Figure 2. Technical Analysis of Walmart's stock

3.3. Consideration of Market Sentiment

Although market sentiment was not used as a formal feature in the forecasting model, it remains an important external factor. News in early 2025 highlights concern over inflation, tariffs, and shifts in consumer behavior. These sentiments may lead to deviations between predicted and actual prices, especially in case of unexpected macroeconomic shocks. As indicated in the chart (Figure 3), the Trump Tariff announcement around March–April 2025 corresponded with a sharp reversal and a significant decline in WMT's stock price. As a massive global retailer, Walmart is particularly exposed to trade policy changes, which can increase the cost of goods sold and pressure profit margins. This sentiment immediately translated into a bearish reaction, highlighting the market's sensitivity to perceived threats to Walmart's core retail economics. The US Government Shutdown, which began in October 2025, introduced another layer of political risk and market uncertainty. The chart shows that the stock experienced volatility and faced downward pressure leading into and during the shutdown period. Shutdowns typically dampen consumer confidence and spending, particularly among federal workers who face delayed paychecks. Although WMT often performs relatively well during economic downturns due to its low-price model, the political uncertainty still affected investor sentiment, contributing to the observed price fluctuation and validating the need for the short-term technical indicators (EMA 13 and 21) used in this study.

Figure 3. WMT Weekly Timeframe Analysis Highlighting Macroeconomic Event Impact.

Table 1 compares the Observed Closing Stock Prices of WMT against the Holt-Winters Model's Forecasted Prices for 2025, detailing the prediction errors in the "Difference (Close – Pred)" column. The data shows a significant and increasing degree of inaccuracy in the forecast, particularly during the second half of the year. While the differences in the first half (January to July) were relatively small, ranging from -0.78 to -6.1, the magnitude of the error sharply escalated towards the end of the year. The model's inability to accurately predict the observed closing price is highlighted by the substantial difference in November, which reached a high of 12.48. This indicates that the forecasting model failed to capture the true price movement of WMT, especially during the volatility observed in the final quarter of 2025. In future work, integration of sentiment indicators or news analytics could improve forecasting robustness and provide deeper insight into short-term volatility.

Table 1. Observed vs Forecasted Stock Prices and Differences (2025)

Date	Open	High	Low	Close	Volume	Prediction	Difference (Close − Pred)
01/01/2025	89,98	99	89,52	98,16	301,854,300	95,2	-3
01/02/2025	96,77	105,3	92,12	98,61	393,516,500	92,5	-6,1
01/03/2025	97,98	99,49	90,76	91,72	117,097,200	94,1	2,4
01/04/2025	87,54	97,78	79,81	97,25	509,840,000	94,3	-2,95
01/05/2025	97,02	99,74	91,89	98,72	393,140,100	93,5	-5,22
01/06/2025	98,84	100,89	98,05	99,98	32,588,400	94	-5,98
01/07/2025	97.60	99.35	94.23	97.98	289,967,200	97,2	-0,78
01/08/2025	98.00	104.72	95.42	96.98	397,878,500	104,1	7,12
01/09/2025	97.23	106.11	96.51	103.06	326,990,400	105,1	2,04
01/10/2025	102.56	109.58	99.87	101.18	348,809,500	111	**9,82**
01/11/2025	100.82	108.15	98.88	105.32	301,024,900	117,8	**12,48**

3.4. Investment Simulation

The investment simulation was conducted using the Pluang platform, and the strategy was guided by technical signals (as detailed in the preceding section). The simulation resulted in the following financial position as of the end of the observed period. It must be noted that the initial plan to maintain a consistent investment of $10 USD per month could not be strictly adhered to. This deviation was necessary due to changes in internal financial policy, leading to adjustments in the frequency and volume of transactions. As documented in Table 1, the total gross investment in WMT shares (net purchase) amounted to $275 USD. The majority of this position has been subsequently realized through sale transactions totaling $274.8 USD, which represents the net value after accounting for all relevant fees and taxes. While the buying and selling activities show a near-balance of funds, the overall total return on the capital invested stands at 3.45%. This figure is derived from the net combined realized and unrealized gains, including the current unrealized running profit of $9.95 USD held within the remaining WMT stock portfolio.

The resulting 3.45% return over approximately one year is considered a moderate annual gain in the context of stock market investments. Historically, major broad market indices (such as the S&P 500) typically yield an average annual return ranging from 7% to 10% over long periods. However, for a short-term, technically-driven simulation focusing on a single stock, a positive return of 3.45% is still successful as it demonstrates an ability to generate alpha while mitigating risk compared to simply holding cash or fixed-income instruments. Furthermore, achieving a positive return through a simulated technical strategy, despite deviations from the planned investment schedule, validates the underlying EMA crossover methodology as a viable tool for active trading strategies.

Table 2 details the historical trading activity for WMT shares, executed between March and November 2025, which involved numerous Market Buy and Market Sell orders across a fluctuating price range. The summary reveals that the investor actively traded, accumulating a total purchase value of $275 while realizing total sales of $274.8. This activity leaves the investor with a small net balance, shown in the Portfolio Summary as a remaining position currently valued at $9.95. The active trading strategy is evidenced by the range of prices, with purchases as low as $86.68 and sales reaching up to $106.30, indicating a dynamic approach to managing the WMT holdings throughout the year.

The Dividend Payment Summary, logs two dividend payments received from WMT stock via the Pluang platform in 2025, both maintaining a consistent rate of $0.235 per share as in Table 3. The first payment on April 8 was based on a small fractional holding, yielding a Gross Dividend of $0.0264 and a Net Dividend of only $0.02, with no tax deducted. By the second payment on September 3, the investor had increased their holding to 0.48797066 shares, resulting in a Gross Dividend of $0.11, though this payment incurred a $0.02 tax deduction, leaving a Net Dividend of $0.09. In total, these two transactions contributed a small combined Net Dividend of $0.11 to the investor's total income, reflecting the nature of fractional share ownership.

Table 2. Historical Trading Data for WMT

Order Number	Order Type	Status	Date	Quantity Purchased	Price (USD)	Net Purchase Value (USD)
4639127	Buy - Market	Executed	Mar 10, 2025 22:39	0,112467	88,65	9,97

4858833	Buy - Market	Executed	Apr 04, 2025 21:01	0,115023	86,68	9,97
4939686	Sell - Market	Executed	Apr 10, 2025 21:57	0,227491	90,6	20,6
5285156	Buy - Market	Executed	May 12, 2025 23:39	0,623151	96	59,82
5514909	Sell - Market	Executed	Jun 02, 2025 17:04	0,623151	98,31	61,25
5911619	Buy - Market	Executed	Jul 07, 2025 21:47	0,508279058	97,96	49,79
6152741	Buy - Market	Executed	Jul 23, 2025 22:19	0,260520203	$95,58	$24,90
6355787	Sell - Market	Executed	Aug 06, 2025 23:17	0,76879926	$102,92	$79,12
6370524	Buy - Market	Executed	Aug 07, 2025 22:05	0,194096199	$102,58	$19,91
6447849	Buy - Market	Executed	Aug 13, 2025 22:09	0,195318631	$101,94	$19,91
6466008	Buy - Market	Executed	Aug 14, 2025 22:56	0,098555835	$100,96	$9,95
6480051	Buy - Market	Executed	Aug 15, 2025 21:40	0,099551318	$99,85	$9,94
6602101	Buy - Market	Executed	Aug 26, 2025 21:23	0,103702005	$95,95	$9,95
7441473	Sell - Market	Executed	Oct 22, 2025 16:38	0,691223988	$106,30	$73,47
7562469	Buy - Market	Executed	Oct 29, 2025 19:06	0,48438564	$102,79	$49,79
7807531	Sell - Market	Executed	Nov 13, 2025 03:09	0,39	$103,49	$40,36
Buy Summary Sell Summary **Portfolio Summary**						$275 $274,8 **$9,95**

Table 3. Dividend Payment Summary

Payment Date	Platform	Stock Symbol	Shares Held	Dividend per Share (USD)	Gross Dividend (USD)	Tax (15%)	Net Dividend (USD)
Tue, Apr 8, 2025	Pluang	WMT	0,112467	0,235	$0,0264	$0	$0,02
Wed, Sep 3, 2025	Pluang	WMT	0,48797066	0,235	$0,11	$0,02	$0,09

The simulation helps to illustrate the potential growth of a small but consistent investment over time using predictive support. The final portfolio value can be compared to the cumulative investment to assess return.

3.5. Update Return Value

The overall outcome of the simulated investment in Walmart Inc. (WMT) confirmed a Total Return Value of $9.86 USD, which translates to a cumulative return rate of 3.45% over the observation period. This total return metric provides the foundational data for evaluating the effectiveness of the applied EMA crossover technical strategy. The achievement of the 3.45% return was driven by two distinct financial components. The primary driver was the Capital Gains component, totaling $9.75 USD, which was realized through the active trading strategy. These gains were computed from the difference between the selling price and the average purchase price of the shares, with all proceeds recorded net of transaction fees. The secondary source of financial return was Net Dividend Income, which contributed $0.11 USD. This income was precisely calculated based on the actual number of WMT fractional shares held during the respective ex-dividend dates. The dividend data was accurately tracked and automatically credited by the Pluang application, highlighting the seamless management of dividends even with fractional share ownership (e.g., the receipt of a net dividend of \$0.02 for \$0.112467286\$ WMT shares in April 2024). By combining these two streams of income, the study concludes that the simulated short-term strategy successfully generated a positive return, validating the viability of the technical indicators used. Furthermore, the fundamental status of WMT as the global revenue leader (Fortune Global 500, 2025) suggests high future profit potential and stability, particularly for large-scale capital deployment. The dividend return, while small (\$0.11 USD) on the initial capital, scales significantly with investment size. The analysis of WMT's price movement highlights significant profit potential achievable through strategic lump-sum investing. Based on the transaction history, the initial purchase price of WMT shares was \$88.65. Assuming the closing price as of November 24, 2025, is approximately \$105.45, this reflects a price appreciation of 18.95% over the holding period. If an investor had made a lump-sum purchase with a substantial nominal capital at the price of \$88.65, the resulting profit from this 18.95% appreciation would have been massive. This underscores the argument that WMT's profit potential is highly dependent on the scale of the capital deployed.

3.6. Update and Comparison Model

In this study, the previously developed Holt-Winters model was updated by incorporating the most recent data up to September 2025. This update aimed to capture the latest patterns in historical data, including seasonal and trend changes throughout 2025. The extended dataset was used to retrain the Holt-Winters model, adjusting the trend and seasonal parameters to minimize prediction errors measured by RMSE, MAE, and MAPE. To evaluate model performance, forecasts were generated for the validation period from October and November 2025 and compared with actual data. In addition to Holt-Winters, an ARIMA model was applied to the same dataset as a benchmark. ARIMA parameters (p,d,q) were selected automatically using the auto_arima method, taking into account monthly seasonality to fit the data patterns effectively. Several previous studies have demonstrated that classical time series methods, particularly Holt-Winters and ARIMA, remain widely applied in various forecasting domains. [22] Compared the Holt-Winters method with a Multi-Layer Perceptron model in predicting shallot production and found that exponential smoothing techniques remain competitive for seasonal agricultural data. Similarly, [23] conducted a comparative analysis between ARIMA and Holt-Winters in forecasting automobile sales in Indonesia, highlighting the robustness of statistical approaches in capturing trend and demand fluctuations. [24] applied the Holt-Winters method to forecast retail furniture sales, demonstrating its practical effectiveness in business decision-making contexts. Furthermore, [25] compared additive and multiplicative Holt-Winters models with grid search optimization for predicting red chili prices, emphasizing the importance of parameter tuning to improve forecasting accuracy.

These studies collectively confirm that Holt-Winters and ARIMA continue to serve as reliable baseline models in time series forecasting research across agricultural, commercial, and economic sectors. The comparison between the two models revealed their respective strengths and performance based on the latest data up to November 2025. Holt-Winters demonstrated superior capability in capturing seasonal patterns, but tended to overestimate prices in the short term, as reflected by an RMSE of 11.08, MAE of 10.28, and MAPE of 10.14% for October and November. In contrast, ARIMA provided greater flexibility in adjusting to short-term trend fluctuations, showing lower error metrics with an RMSE of 4.71, MAE of 4.26, and MAPE of 4.21% for the same period. These error metrics indicate that, although Holt-Winters is effective for modeling seasonality, ARIMA performed better for short-term forecasting in this instance.

Table 4 presents a comparison of WMT's monthly closing price forecasts for 2026 generated by the updated Holt–Winters and ARIMA models. Overall, both models indicate an upward price trajectory throughout the year, although with notable differences in magnitude and timing. In the early months of 2026 (January to March), the Holt–Winters model predicts relatively higher prices than the ARIMA model, with forecasts of USD 120.5 in January gradually declining to USD 112.6 in March. In contrast, the ARIMA model projects a steady increase over the same period, rising from USD 112.1 in January to USD 117.2 in March. From April to June, the Holt–Winters forecasts remain relatively flat and slightly volatile, fluctuating between USD 114.1 and USD 116.8. Meanwhile, the ARIMA model continues to show a consistent upward trend, with predicted prices increasing from USD 120.0 in April to USD 125.6 in June.

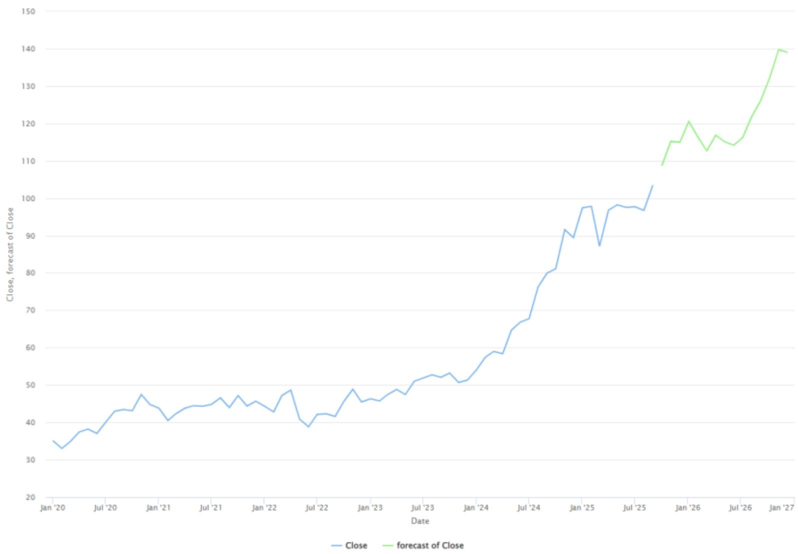

Figure 4. Updated Holt-Winters Forecasting Model

Table 4. Holt-Winters and ARIMA Time Series Forecasting of WMT Closing Price (2026)

Date	Close Prediction (Updated Model) Holt Winter	Close Prediction (Updated Model) ARIMA
01/01/2026	120.5	112.1
01/02/2026	116.4	114.6
01/03/2026	112.6	117.2
01/04/2026	116.8	120
01/05/2026	115.1	122.7
01/06/2026	114.1	125.6
01/07/2026	116.2	128.5
01/08/2026	121.8	131.5
01/09/2026	126.1	134.6
01/10/2026	132.2	137.8
01/11/2026	139.7	141.1
01/12/2026	139	144.4

In the second half of 2026 (July to December), both models forecast a strong bullish movement. However, the ARIMA model consistently predicts higher closing prices than the Holt–Winters model. By July, ARIMA forecasts reach USD 128.5 compared to USD 116.2 under Holt–Winters, and this divergence persists toward the end of the year. The Holt–Winters model projects a peak of USD 139.7 in November before slightly declining to USD 139.0 in December, while the ARIMA model forecasts continued growth, culminating at USD 144.4 in December. These results suggest that while both models capture the overall upward trend in WMT's closing prices for 2026, the ARIMA model anticipates a stronger and more persistent growth pattern, whereas the Holt–Winters model reflects more conservative dynamics with short-term fluctuations.

3.7. Discussion

The findings of this study demonstrate that the Holt-Winters additive model is capable of capturing long-term trends and seasonal patterns in WMT stock prices, as evidenced by relatively low validation errors (RMSE: 4.535 USD; MAE: 4.801 USD). The long-term forecast indicates a consistent upward trajectory through 2026, suggesting that the model effectively represents underlying growth patterns. However, further analysis reveals that the model tends to overestimate prices, particularly during periods of high volatility, as seen in late 2025 where prediction errors increased significantly.

The comparison with the ARIMA model highlights important differences in forecasting behavior. While Holt-Winters performs well in modeling seasonality, ARIMA demonstrates superior performance in short-term forecasting, with lower RMSE, MAE, and MAPE values. This suggests that ARIMA is more responsive to recent trend changes, whereas Holt-Winters is more stable but less adaptive to sudden market shifts.

Additionally, the integration of technical analysis and investment simulation shows that predictive modeling alone is insufficient to fully capture market dynamics. External factors such as macroeconomic events (e.g., tariffs and government shutdowns) significantly influenced stock price movements, causing deviations from forecasts. The investment simulation yielded a moderate return of 3.45%, indicating that combining forecasting with technical indicators can produce positive outcomes, although returns remain sensitive to strategy execution and market conditions.

Overall, this study highlights the strengths of Holt-Winters in long-term forecasting while emphasizing the importance of hybrid approaches that incorporate statistical models, technical analysis, and external factors for improved robustness.

4. CONCLUSION

This study evaluated the application of the Holt-Winters exponential smoothing model in forecasting long-term stock price behavior for Walmart Inc. (WMT). The model was able to capture general trend and seasonality patterns in historical data, projecting a bullish outlook with the closing price expected to increase from \$117.7 in December 2025 to a peak of \$145.3 in November 2026. However, empirical evaluation revealed that the model's predictive accuracy declined over time, particularly in the second half of 2025, where the error gap widened significantly, reaching a maximum difference of 12.48 in November. When compared with alternative models, the results indicate that ARIMA provided superior forecasting performance, particularly in handling short-term fluctuations and market volatility. This suggests that while Holt-Winters is effective for capturing long-term structural patterns, it is less robust in dynamic market conditions where rapid price changes occur. The integration of the Holt-Winters forecast into a Dollar Cost Averaging (DCA) simulation, along with \$0.11 in net dividend income, demonstrated the practical feasibility of the strategy, resulting in a modest return of 3.45%. This outcome reflects the characteristics of a passive investment approach, with a total purchase value of \$275 compared to sales of \$274.8, and a remaining portfolio value of \$9.95.

This research remains ongoing until the end of 2026. Future work will incorporate real-time market data to continuously update and validate the forecasting models. Additionally, further studies will explore hybrid approaches that combine statistical methods such as Holt-Winters and ARIMA with machine learning or deep learning models to improve predictive accuracy under volatile conditions. The inclusion of external variables, such as market sentiment, macroeconomic indicators, and news-based features, is also recommended to enhance model robustness.

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REFERENCES

[1] G. Rumbe, M. Hamasha, and S. Al Mashaqbeh, "A comparison of Holts-Winter and Artificial Neural Network approach in forecasting: A case study for tent manufacturing industry," *Results in Engineering*, vol. 21, Mar. 2024, doi: 10.1016/j.rineng.2024.101899.

[2] L. Kumar, S. Khedlekar, and U. K. Khedlekar, "A comparative assessment of holt winter exponential smoothing and autoregressive integrated moving average for inventory optimization in supply chains," *Supply Chain Analytics*, vol. 8, Dec. 2024, doi: 10.1016/j.sca.2024.100084.

[3] M. S. Omar and H. Kawamukai, "Prediction of NDVI using the Holt-Winters model in high and low vegetation regions: A case study of East Africa," *Sci. Afr.*, vol. 14, Nov. 2021, doi: 10.1016/j.sciaf.2021.e01020.

[4] Q. Shao, A. Aldhafeeri, S. Qiu, and S. Khuder, "A multiplicative Holt–Winters model and autoregressive moving-average for hyponatremia mortality rates," *Healthcare Analytics*, vol. 4, Dec. 2023, doi: 10.1016/j.health.2023.100262.

[5] A. Kotsialos, M. Papageorgiou, and A. Poulimenos, "HOLT-WINTERS AND NEURAL-NETWORK METHODS FOR MEDIUM-TERM SALES FORECASTING," 2005.

[6] B. Gülmez, "Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm," *Expert Syst. Appl.*, vol. 227, Oct. 2023, doi: 10.1016/j.eswa.2023.120346.

[7] S. Elsayed, A. Salah, I. Elhenawy, and M. Abdellah, "Predicting stock prices using ensemble learning techniques," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 15, no. 2, p. 1783, Apr. 2025, doi: 10.11591/ijece.v15i2.pp1783-1792.

[8] M. Ashrafzadeh, H. M. Taheri, M. Gharehgozlou, and S. Hashemkhani Zolfani, "Clustering-based return prediction model for stock pre-selection in portfolio optimization using PSO-CNN+MVF," *Journal of King*

Saud University - Computer and Information Sciences, vol. 35, no. 9, Oct. 2023, doi: 10.1016/j.jksuci.2023.101737.
[9] E. Paquet and F. Soleymani, "QuantumLeap: Hybrid quantum neural network for financial predictions," *Expert Syst. Appl.*, vol. 195, Jun. 2022, doi: 10.1016/j.eswa.2022.116583.
[10] F. Soleymani and E. Paquet, "Long-term financial predictions based on Feynman–Dirac path integrals, deep Bayesian networks and temporal generative adversarial networks," *Machine Learning with Applications*, vol. 7, p. 100255, Mar. 2022, doi: 10.1016/j.mlwa.2022.100255.
[11] F. Achury-Calderón, J. A. Arredondo, and L. C. Sánchez Ascanio, "A novel predictive analytics model for forecasting short-term trends in equity assets prices," *Decision Analytics Journal*, vol. 14, Mar. 2025, doi: 10.1016/j.dajour.2024.100534.
[12] Nasdaq, "Walmart's Stock Beat the Market in 2024. Can It Do It Again in 2025?," https://www.nasdaq.com/. Accessed: Apr. 29, 2026. [Online]. Available: https://www.nasdaq.com/articles/walmart-stock-beat-market-2024-can-it-repeat-2025
[13] The Feed, "Walmart's Fiscal 2026 profit forecast falls short of estimates – Stock drops 7% as inflation, consumer spending, and tariff concerns loom," https://economictimes.indiatimes.com/. Accessed: Apr. 29, 2026. [Online]. Available: https://economictimes.indiatimes.com/news/international/us/walmarts-fiscal-2026-profit-forecast-falls-short-of-estimates-stock-drops-7-as-inflation-consumer-spending-and-tariff-concerns-loom/articleshow/118422060.cms?from=mdr
[14] J. Bradley, "Oppenheimer Cuts Its Price Target on Walmart Stock," https://www.investopedia.com/. Accessed: Apr. 29, 2026. [Online]. Available: https://www.investopedia.com/oppenheimer-cuts-its-price-target-on-walmart-stock-11710213
[15] S. Gelsi, "Walmart's secret weapon may be its appeal with wealthier shoppers," https://www.marketwatch.com/. Accessed: Apr. 29, 2026. [Online]. Available: https://www.marketwatch.com/story/walmarts-secret-weapon-may-be-its-appeal-with-wealthier-shoppers-97772f8d