

Research Article

Modelling and Forecasting Somalia's Consumer Price Index Using the ARIMA Model

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Abstract

This study examines the modeling and forecasting of Somalia's Consumer Price Index (CPI) using the ARIMA model, with data from November 2022 to November 2024. Descriptive analysis reveals a mean CPI of 144.26, moderate variability, and a slight negative skew. The CPI series is unstable in its original form but achieves stability after first differencing. The ARIMA (1,1,0) model is selected as the best fit, based on its low AIC and BIC values, with diagnostic checks confirming its effectiveness in capturing the data patterns. Forecasts suggest a stable CPI of approximately 152.95 from December 2024 to November 2026, though prediction intervals widen over time, reflecting increased uncertainty. The model performs well, with a Mean Absolute Percentage Error (MAPE) of 6.18%, though slight underestimation bias is noted. These findings demonstrate that ARIMA forecasts can aid policymakers in designing effective inflation control measures in volatile economies. These insights can help the Central Bank and policymakers implement timely interventions to stabilize prices and manage inflation expectations. Future research should incorporate external economic factors for more robust long-term predictions.

Keywords

Somalia's Consumer Price Index (CPI), ARIMA Model, Time Series Forecasting, CPI Trend Analysis, Inflation Forecasting in Somalia

1. Introduction

The Consumer Price Index (CPI) is a critical economic indicator that measures the average change over time in the prices consumers pay for goods and services. It is widely used to assess inflation, a key determinant of economic stability [1]. The CPI provides insights into the purchasing power of a country's currency and plays a crucial role in formulating monetary and fiscal policies. For developing countries, like Somalia, accurate CPI data is essential for understanding inflation trends, guiding policy decisions, and ensuring economic stability.

In Somalia, where the economy is characterized by vola-

tility and vulnerability to external shocks, the CPI serves as a valuable tool for tracking inflation and cost of living adjustments [2]. Given the challenges posed by limited infrastructure, political instability, and reliance on imports, understanding CPI trends can help policymakers address inflationary pressures, stabilize the economy, and promote sustainable growth. Reliable forecasting of CPI in Somalia is especially important for planning purposes, as it enables government officials, businesses, and international organizations to make informed decisions about pricing, wages, social welfare programs, and overall economic development.

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The Somalia National Bureau of Statistics (SNBS) is responsible for collecting and disseminating CPI data and publishing monthly reports that reflect the changes in the prices of a basket of goods and services. These goods and services include essential categories such as Food and Non-Alcoholic Beverages, Alcoholic Beverages, Tobacco and Narcotics, Clothing and Footwear, Housing, Electricity, Gas, Water, and Other Fuels, Health, Transport, Communication, Education, and Restaurants and Hotels [3]. These reports are crucial for economic analysis, helping to track inflationary trends and inform national policy. However, due to factors such as inconsistent data, disruptions in supply chains, and global economic fluctuations, accurately forecasting Somalia's CPI remains a challenging task. Statistical models, such as the ARIMA model, can provide valuable insights into future CPI movements, helping policymakers and stakeholders plan for potential economic challenges and formulate strategies for economic stability.

1.1. Objectives of the Study

The specific objectives of this study are to:

To analyze the historical trends of Somalia's Consumer Price Index (CPI).

To apply the ARIMA model for forecasting Somalia's CPI.

To evaluate the accuracy of the ARIMA model in predicting future CPI values.

To provide policy recommendations based on CPI forecasting results.

1.2. Significance of the Study

Understanding the historical trends of CPI can help policymakers and economists make informed decisions about inflation control.

Accurate forecasting of Somalia's CPI will support economic planning and financial stability.

The study provides an empirical evaluation of ARIMA's performance in predicting inflation trends.

The policy recommendations based on the forecasting results can guide government and financial institutions in implementing effective inflation management strategies.

2. Literature Review

Accurate forecasting of the Consumer Price Index (CPI) is crucial for policymakers to understand inflation trends and make informed decisions. Various studies have employed ARIMA and other time series models to forecast CPI across different countries, each utilizing different methodologies and datasets.

Ali and Mohamed (2022) compared multiple time series models, including ARIMAX, STL decomposition, robust exponential smoothing (ROBETS), single exponential smoothing (SES), and artificial neural networks (ANN), to

forecast Puntland's CPI from July 2017 to February 2021. Their study found that ANN and STL decomposition models outperformed others based on accuracy metrics like AIC, AICc, and BIC. They recommended the use of these models for forecasting and suggested that inflation management policies should focus on maintaining CPI stability [4].

Poudel et al. (2024) modeled and forecasted Nepal's National Consumer Price Index (NCPI) using annual data from 1972/73 to 2022/23. Employing the Box-Jenkins methodology and ARIMA models, they identified ARIMA (1, 2, 8) as the most suitable model. The study concluded that the NCPI would experience rapid growth in the coming years, emphasizing the relevance of the model for both academic and policy applications. The study's results are crucial for understanding future inflationary pressures in Nepal and guiding economic policy [5].

Mohamed (2020) used ARIMA and regression with ARIMA errors models to forecast Somaliland's CPI using monthly data from 2013 to 2020. The study identified ARIMA (0, 1, 3) as the most suitable model based on accuracy measures like AIC and BIC. The study forecasted an upward trend in Somaliland's CPI, suggesting the need for stringent monetary and fiscal policies to manage inflation. This study highlighted the importance of using ARIMA for forecasting in countries with volatile economic conditions [6].

Mwanga (2020) developed an ARIMA model to forecast Uganda's CPI using monthly data from January 2010 to July 2020. The study identified ARIMA (1, 1, 1) (0, 1, 1) 12 as the best model, based on its low AIC and BIC values and the statistical significance of its coefficients. The forecasts predicted fluctuations in inflation between 4.7% and 6% from August 2020 to July 2021. The study suggested that this model could be adopted by the Uganda Bureau of Statistics and the Central Bank for more accurate inflation forecasting [7].

Nyoni (2019) used the Box-Jenkins ARIMA technique to forecast Germany's CPI using annual data from 1960 to 2017. The study identified ARIMA (1, 1, 1) as the most suitable model for forecasting, with diagnostic tests confirming the model's stability. The study suggested that Germany's CPI would continue to rise in the next decade, and recommended the use of tight monetary and fiscal policies to manage inflation. This study provides valuable insights for developed economies, showing the applicability of ARIMA for long-term forecasting [8].

Hu (2024) conducted a forecasting analysis of Hungary's Consumer Price Index (CPI) using the ARIMA model, based on data from 1990 to 2021. The study employed the ADF test, autocorrelation, and partial autocorrelation plots to determine the series parameters, resulting in the ARIMA (1, 1, 0) model. The forecasts indicated that while Hungary's CPI is expected to continue growing in the next decade, the growth rate will slow down compared to the exponential increase observed after 2017. This suggests economic stability and a reduction in price fluctuations in the future [9].

IMF and World Bank (2024) analyzed the macroeconomic developments and prospects of low-income countries (LICs), highlighting ongoing economic challenges despite some improvements in 2023. The study projected that median GDP growth would gradually return to pre-pandemic levels; however, it remains insufficient for the poorest and most fragile LICs. The report identified persistent inflation, high debt levels, and rising debt service obligations as major constraints on development spending [16].

Carrière-Swallow et al. (2023) analyzed Guinea's inflation dynamics from the early 2000s, a period marked by significant shocks including pandemics, commodity price fluctuations, and military coups. Their findings indicate that external factors, notably global commodity and transport prices, were primary drivers of inflation, which averaged 12% during this time. Monetary policy's influence was generally moderate, reflecting a neutral stance; however, during certain periods, such as 2021–2022, contractionary monetary measures effectively mitigated inflationary pressures from high commodity prices. The study underscores a robust link between monetary aggregates and the exchange rate, highlighting the exchange rate channel as a key conduit for monetary policy transmission in Guinea [17].

3. Materials and Methodologies

3.1. Research Design

This study follows an explanatory research design to forecast Somalia's Consumer Price Index (CPI) using time series data. The ARIMA model is chosen for its ability to model and predict univariate time series.

3.2. Source and Nature of Data

CPI data was obtained from the Somalia National Bureau of Statistics (SNBS) (<https://nbs.gov.so/>) and covered monthly data from November 2022 to November 2024. Data pre-processing involved addressing missing values, removing outliers, and ensuring stationarity before analysis. Data analysis was conducted using E-Views statistical software, which facilitated the application of the Box–Jenkins approach for modelling.

3.3. Model Identification

This study employed the Box–Jenkins methodology (Box and Jenkins, 1976), a widely recognized technique for short-term forecasting. The Autoregressive Integrated Moving Average (ARIMA) model is a widely utilized statistical approach for time series analysis and forecasting. It is defined by three key parameters: p (autoregressive order), d (degree of differencing), and q (moving average order). These parameters collectively determine the model's structure and are essential for effectively capturing the inherent patterns and

dynamics within time series data [10].

The autoregressive model of order p , AR (p) is as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \dots + \alpha_2 y_{t-2} + \dots + \alpha_p y_{t-p} + \varepsilon_t \quad (1)$$

Where:

y_t = the actual series at time t

α_0 = autocorrelation parameter at y_{t-1}

ε_t = the white noise

And the moving average model of order q , MA (q);

$$y_t = \beta_0 + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \dots + \beta_q \varepsilon_{t-q} \quad (2)$$

Where:

y_t = the actual series at time t

β_0 = autocorrelation parameter at y_{t-1}

ε_t = the white noise

The ARIMA (Autoregressive Integrated Moving Average) model incorporates the AR and MA components along with the Integration (I) component to make the time series stationary. The general equation for an ARIMA (p, d, q) model is:

$$z_t = \alpha_0 + \sum_{i=1}^p \alpha_i z_{t-i} + \varepsilon_t + \sum_{j=1}^q \beta_j \varepsilon_{t-j} \quad (3)$$

Where:

$z_t = (1 - B)^d y_t$: the differenced series after applying the integration component, where d represents the number of differences applied to the original series y_t

p : The order of the AR component (number of lagged terms).

q : The order of the MA component (number of lagged error terms).

α_i : Coefficients for the AR terms.

β_j : Coefficients for the MA terms.

ε_t : The white noise error term.

3.4. Testing for the Stationary of the Data

3.4.1. Augmented Dickey-Fuller Test

The study used the Augmented Dickey-Fuller (ADF) test to check the stationarity of the time series data. Stationarity is a critical assumption for ARIMA models, as it ensures that the statistical properties of the series, such as mean and variance, remain constant over time [11]. The ADF test examines the null hypothesis (H_0) that a unit root is present in the time series, indicating non-stationarity, against the alternative hypothesis (H_1) that the series is stationary. The ADF test is based on the regression equation:

$$\Delta Y_t = \alpha_0 + \beta X_{t-1} + \alpha_t + \sum_{i=1}^k \beta_i \Delta X_{t-i} + \mu_t \quad (4)$$

Where:

ΔY_t : The first difference of the time series.

α : Constant term (drift)

βX_{t-1} : Lagged level of the series, testing for the presence of a unit root.

α_t : Linear time trend (optional, included depending on the series behaviour.

μ_t : White noise error term.

K: number of lagged differences included in the model, chosen based on criteria like AIC or BIC.

3.4.2. Inspect ACF and PACF Plots

The study employed the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to analyse the time series data. These plots were used to identify the nature of autocorrelations in the data and guide the selection of appropriate p and q parameters for the ARIMA model.

3.5. Model Selection

3.5.1. Parameter Estimation

The study employed Least Squares Estimation (LSE) to estimate the parameters of the ARIMA model. This method minimizes the sum of squared differences between the observed and predicted values of the Consumer Price Index (CPI), ensuring the best fit for the data. LSE is a straightforward and computationally efficient method, making it well-suited for time series analysis.

The ARIMA model used for forecasting the CPI is given by:

$$CPI_t = \phi_1 CPI_{t-1} + \phi_2 CPI_{t-2} + \dots + \phi_p CPI_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots + \theta_q e_{t-q} + e_t \quad (5)$$

Where:

CPI_t = the observed Consumer Price Index at time t.

$\phi_1, \phi_2, \dots, \phi_p$ Are the autoregressive (AR) coefficients.

$\theta_1, \theta_2, \dots, \theta_q$ Are the moving average (MA) coefficients.

e_t : The error term at time t is assumed to be white noise.

3.5.2. Information Criteria

To evaluate and compare the fit of different ARIMA models, the study used two widely accepted information criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria balance model fit and complexity, helping to prevent over-fitting by penalizing models with more parameters. According to Gujarati [13], the AIC is given by:

$$AIC = -2 \ln(L) + 2k \quad (6)$$

Where: $\ln(L)$; is the log-likelihood of the Model and k is the number of estimated parameters.

The BIC is given by:

$$BIC = -2 \ln(L) + k \ln(n) \quad (7)$$

Where: $\ln(L)$ is the log-likelihood of the model, K is the number of estimated parameters and n is the number of observations.

3.6. Model Diagnostics

To assess the adequacy of the ARIMA model, the study used the Ljung-Box Test to check for autocorrelation in the residuals. Autocorrelation indicates that the model has not fully captured the data patterns, suggesting the need for further refinement [12]. The Ljung-Box Test statistic is given by the following equation:

$$Q(m) = n(n+2) \sum_{k=1}^m \frac{r_k^2}{n-k} \quad (8)$$

Where:

Q (m) is the Ljung-Box statistic for lag m, n is the sample size (number of observations). r_k^2 : is the sample autocorrelation at lag and m is the number of lags being tested.

3.7. Forecasting

Following the identification and validation of the optimal ARIMA model, forecasting of the Consumer Price Index (CPI) for subsequent periods was carried out. The best model, determined based on diagnostic checks, information criteria (AIC and BIC), and model adequacy, was employed for generating future forecasts.

4. Results

4.1. Exploratory Data Analysis

Table 1. Descriptive Statistics of the Actual data.

Parameters	CPI
Mean	144.264
SE Mean	1.192
Std. Dev.	5.962
Variance	35.547
Minimum	134.0
Q1	142.1
Median	143.7
Q3	150.6
Maximum	152.9
Skewness	-0.204
Kurtosis	-0.868

The CPI data exhibits a mean of 144.264 and a standard deviation of 5.962, indicating moderate variability around the mean. The values range from a minimum of 134.0 to a maximum of 152.9, with the middle 50% of observations lying between the first quartile (142.1) and third quartile (150.6). The median of 143.7 suggests a balanced central tendency, while slight negative skewness (-0.204) implies a distribution with a marginal tail to the left. Additionally, the kurtosis value of -0.868 indicates a flatter distribution than the normal curve, reflecting a more uniform data spread.

4.2. Stationarity Test

The stationarity of the CPI data was tested using the Augmented Dickey-Fuller (ADF) test. Stationarity is a critical assumption for ARIMA models, ensuring that the statistical properties of the series remain constant over time. The ADF test results confirmed that the CPI series is non-stationary at levels ($p > 0.05$) but becomes stationary after first differencing ($p < 0.05$).

Table 2. Augmented Dickey-Fuller test for unit root of CPI.

Values				First Difference		
	t-statistic	Test critical value 5% level	Prob*	t-statistic	Test critical value 1% level	Prob*
CPI	1.492	-3.00	0.076	-3.097	-3.00	0.015

The Augmented Dickey-Fuller (ADF) test results for the Consumer Price Index (CPI) indicate that the series is non-stationary in levels but becomes stationary after first differencing. In levels, the t-statistic (1.492) is greater than the critical value at the 5% significance level (-3.00) with a p-value of 0.076, suggesting the null hypothesis of a unit root cannot be rejected. However, after first differencing, the t-statistic (-3.097) is less than the critical value at the 1% significance level (-3.00) with a p-value of 0.015, indicating the null hypothesis is rejected. This confirms that the CPI series is stationary after first differencing.

4.3. Arima Model

The ARIMA (Autoregressive Integrated Moving Average) model is a widely used tool for time series forecasting. It combines three components: autoregression (AR), differencing (I), and moving averages (MA), making it effective for analyzing and predicting univariate time series data. In this study, the model was employed to identify trends and forecast Somalia's CPI with high accuracy.

Table 3. ARIMA Model Comparison.

Model	Log-Likelihood	AIC	BIC	RMSE	MAPE	MAE	ME
ARIMA (1,1,0)	-44.53	93.07	95.43	1.51	0.85	1.22	0.38
ARIMA (0,1,1)	-45.22	94.43	96.79	1.56	0.87	1.23	0.51
ARIMA (2,1,1)	-44.17	96.34	101.05	1.48	0.84	1.48	0.47
ARIMA (1,1,2)	-43.34	94.68	99.39	1.42	0.81	1.17	0.39
ARIMA (3,1,0)	-43.46	94.92	99.63	1.44	0.83	1.19	0.49
ARIMA (2,1,2)	-43.34	96.68	102.57	1.41	0.75	1.08	0.50

The ARIMA (1, 1, 0) model is chosen as the best model based on its lowest AIC (93.07) and BIC (95.43), indicating a good balance between model fit and complexity. Despite slightly better RMSE values for ARIMA (2, 1, 2) and ARIMA (1, 1, 2), these models have higher AIC and BIC, which suggests they are more complex without providing significant improvements in fit.

Therefore, ARIMA (1, 1, 0) is preferred for its simplicity and optimal performance according to these criteria.

4.4. Ljung-Box Test

The Ljung-Box test was used to assess the presence of au-

to correlation in the residuals of the time series model. This test helps determine whether any significant autocorrelation exists at multiple lags, ensuring that the residuals resemble white noise and that the model has adequately captured the underlying structure of the data. A significant p-value suggests that the model may not have fully captured the autocorrelations in the data.

The results of the Ljung-Box test applied to the residuals of the

ARIMA (1, 1, 0) model with drift indicate no significant autocorrelation in the residuals at the 5% significance level. The test statistic (X^2) is 25.866 with 20 degrees of freedom, yielding a p-value of 0.1703. Since the p-value is greater than 0.05, we fail to reject the null hypothesis, suggesting that the residuals are uncorrelated and the ARIMA model is appropriate for the data. This implies that the model captures the temporal dependencies effectively, and the residuals behave like white noise.

Table 4. Ljung-Box test.

Statistic	Value	degree of freedom (df)	p-value
X^2	25.866	20	0.1703

4.5. Data Visualization

4.5.1. The Actual CPI Plot

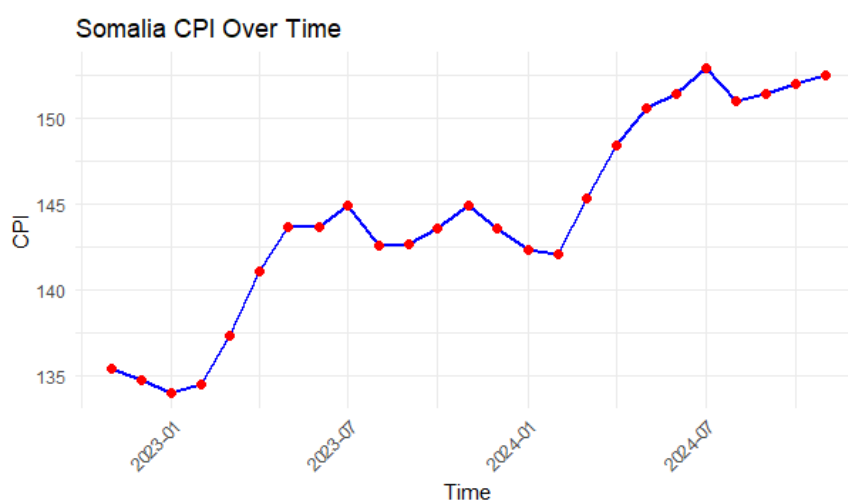


Figure 1. Line plot of the actual CPI.

The graph illustrates the trend of Somalia's Consumer Price Index (CPI) from November 2022 to November 2024, highlighting an overall upward trajectory in price levels. After a slight decline in late 2022 and early 2023, the CPI begins a steady rise, reflecting increasing inflationary pressures. While minor fluctuations are observed in late 2023 and early 2024, the general trend remains upward, with the CPI stabilizing at a higher level by late 2024. This indicates a sustained rise in the cost of goods and services over the two years.

4.5.2. ACF and PCF Plots

The AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) plots were used to examine the correlation of the CPI time series with its past values, helping to identify the appropriate model for forecasting.

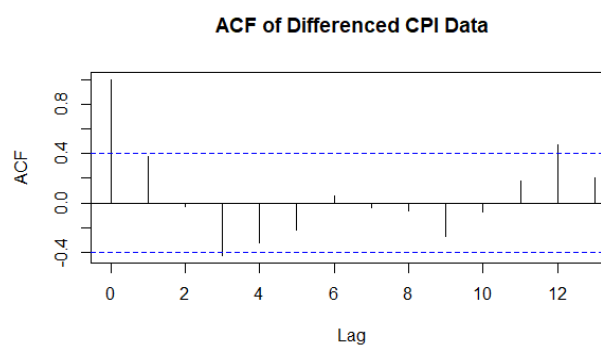


Figure 2. ACF PLOT of Differenced CPI.

The ACF plot of the differenced CPI data shows significant autocorrelation at lag 1, indicating a relationship with recent past values. Beyond lag 1, autocorrelation quickly diminishes, suggesting the data is now mostly stationary and suitable for ARIMA modeling.

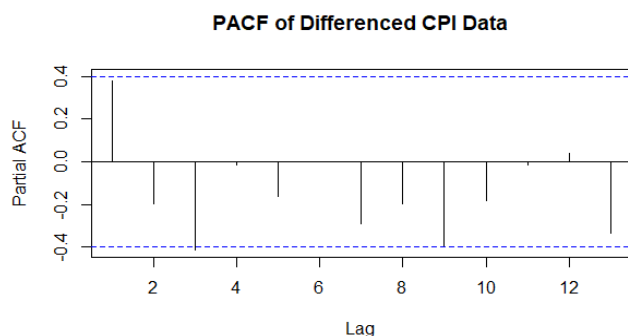


Figure 3. PCF PLOT of Differenced CPI.

The PACF plot of the differenced CPI data shows a significant partial autocorrelation at lag 1, with subsequent lags mostly within the confidence bounds. This indicates that only the immediate past value (lag 1) strongly influences the current differenced CPI, supporting the use of an ARIMA model with a low AR order.

The residual plot of the ARIMA model indicates that the residuals, which represent the differences between observed and predicted values, are randomly distributed around the zero line, as shown by the horizontal red line. This random-

ness, coupled with the lack of discernible patterns or trends, suggests that the ARIMA model has effectively captured the underlying structure of the data. The residuals fluctuate within a range of approximately -3 to +3, reflecting the variability in prediction errors. Overall, the plot confirms that the ARIMA model provides an adequate fit for the data, as the residuals do not exhibit systematic bias or autocorrelation.

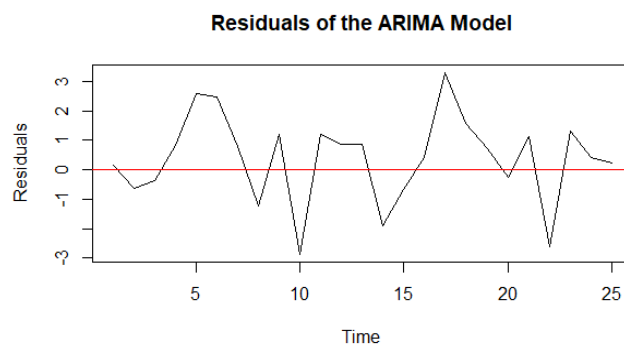


Figure 4. Residual Plot of the ARIMA Model.

4.6. Forecast

An ARIMA (1, 1, 0) model was used for forecasting the Composite Price Index (CPI). This model incorporates one autoregressive term, one differencing step to achieve stationarity, and no moving average component. The ARIMA (1, 1, 0) model is appropriate for capturing the trend and autocorrelation present in the CPI data, providing reliable short-term forecasts.

Table 5. Future forecasts from ARIMA (1, 1, 0).

Date	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Dec 2024	152.74	150.72	154.42	149.74	155.4
Jan 2025	152.85	149.11	155.35	147.45	157.01
Feb 2025	152.9	147.53	156.21	145.23	158.5
Mar 2025	152.93	146.57	157.04	143.8	159.81
Apr 2025	152.94	146.25	157.83	143.19	160.89
May 2025	152.95	146.13	158.46	142.87	161.72
Jun 2025	152.95	145.82	158.88	142.36	162.33
Jul 2025	152.95	145.21	159.17	141.51	162.87
Aug 2025	152.95	144.51	159.5	140.54	163.47
Sep 2025	152.95	143.99	159.94	139.77	164.16
Oct 2025	152.95	143.72	160.43	139.3	164.85
Nov 2025	152.95	143.54	160.87	138.95	165.45
Dec 2025	152.95	143.26	161.2	138.52	165.95
Jan 2026	152.95	142.86	161.46	137.93	166.39

Date	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Feb 2026	152.95	142.41	161.73	137.3	166.84
Mar 2026	152.95	142.04	162.05	136.75	167.34
Apr 2026	152.95	141.79	162.4	136.33	167.86
May 2026	152.95	141.58	162.74	135.97	168.34
Jun 2026	152.95	141.33	163.03	135.58	168.77
Jul 2026	152.95	141.02	163.27	135.13	169.16
Aug 2026	152.95	140.69	163.51	134.64	169.55
Sep 2026	152.95	140.39	163.78	134.2	169.97
Oct 2026	152.95	140.15	164.06	133.83	170.39
Nov 2026	152.95	139.94	164.34	133.48	170.8

The ARIMA (1,1,0) model offers an intriguing forecast for Somalia's Consumer Price Index (CPI) from December 2024 to November 2026, predicting a stable CPI averaging around 152.95. This suggests a period of price stability, which is positive for economic planning. However, the increasing width of the prediction intervals—starting with narrower ranges and expanding towards the end of 2026—introduces an element of uncertainty, highlighting the challenges of long-term forecasting. While the stable CPI points to a generally balanced economic trend, the rising variability suggests potential underlying factors that could influence Somalia's economic future in unpredictable ways.

Table 6. Forecast accuracy metrics for the CPI prediction model.

Metric	Value
Mean Error (ME)	-8.67
Mean Absolute Error (MAE)	8.67
Root Mean Squared Error (RMSE)	10.44
Mean Absolute Percentage Error (MAPE)	6.18%

The forecast accuracy metrics indicate that the model performs reasonably well in predicting the Composite Price Index (CPI), with some areas for improvement. The Mean Error (ME) of -8.67 suggests that, on average, the forecasts slightly underestimate the actual values, indicating a small bias in the model. The Mean Absolute Error (MAE) of 8.67 shows that, on average, the predictions deviate from the actual values by 8.67 units, while the Root Mean Squared Error (RMSE) of 10.44 highlights the presence of a few larger forecast errors, as RMSE is more sensitive to outliers than MAE. Importantly, the Mean Absolute Percentage Error (MAPE) is 6.19%, which is considered excellent for eco-

nomical and financial forecasting, signifying that the model achieves a high level of relative accuracy. Overall, the model demonstrates strong forecasting ability, but further refinements could address the slight underestimation bias and reduce the impact of outliers to enhance performance.

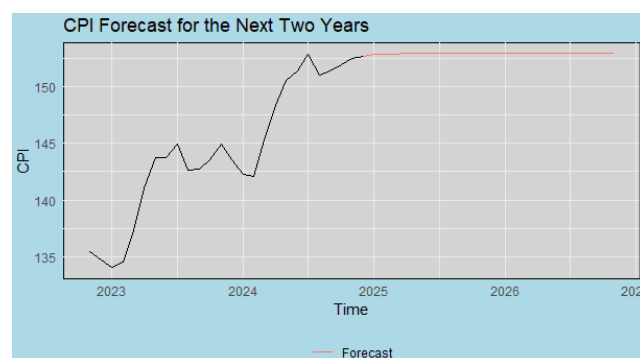


Figure 5. CPI Forecast from January 2025 to December 2026.

The graph shows the Consumer Price Index (CPI) over time, with historical data extending to 2023 and a forecast for the next two years until 2025. Initially, the CPI experienced gradual increases, followed by a significant rise in 2024. From 2025 onward, the forecast indicates that the CPI will stabilize at a higher level, showing minimal changes. This suggests that after a period of growth, price levels are expected to maintain consistency soon.

5. Discussion of Findings

The results of this study indicate that the Consumer Price Index (CPI) in Somalia has shown a consistent upward trend from November 2022 to November 2024. The descriptive statistics reveal moderate variability in CPI, with a mean of

144.264 and a standard deviation of 5.962, suggesting a relatively stable inflation rate over the study period. The distribution of CPI is slightly negatively skewed, indicating that lower CPI values are slightly more frequent, while the kurtosis value of -0.868 suggests that the distribution is flatter than the normal curve, signifying a uniform spread of CPI values.

The stationarity test, specifically the Augmented Dickey-Fuller (ADF) test, confirmed that the CPI series is non-stationary at the levels but becomes stationary after first differencing. This is crucial for ensuring that any model applied, including the ARIMA model, is appropriate for forecasting.

The ARIMA model selection process demonstrated that the ARIMA (1,1,0) model was the most suitable for forecasting Somalia's CPI. This model was chosen based on its lowest AIC and BIC values, indicating an optimal balance between fit and complexity. Despite the presence of other ARIMA configurations with better RMSE values, ARIMA (1, 1, 0) outperformed others in terms of simplicity and robustness. The residuals of the chosen ARIMA model were further validated by the Ljung-Box test, which confirmed no significant autocorrelation, supporting the model's adequacy.

In terms of forecasting, the ARIMA (1, 1, 0) model predicts a stable CPI of approximately 152.95 from December 2024 to November 2026. Although the forecast indicates a stable trend, the increasing width of the prediction intervals over time suggests growing uncertainty in the long-term outlook, possibly due to external economic shocks or volatility. The forecast accuracy metrics such as the Mean Absolute Percentage Error (MAPE) of 6.18% further highlight the model's good predictive performance, making it useful for economic planning, despite some slight underestimation bias and the presence of outliers.

The stable CPI forecast of 152.95 has significant implications for monetary policy and social welfare planning in Somalia. A stable CPI provides the Central Bank with a clearer understanding of inflation trends, enabling more informed decisions on interest rates and inflation-targeting strategies [14]. If the forecast holds, the Central Bank could adopt a more cautious stance on monetary tightening, maintaining stability while avoiding overreaction to short-term fluctuations. This stability allows for a more predictable economic environment, which can help investors and businesses make long-term plans.

For social welfare planning, a stable CPI allows the government to better estimate the future cost of living and adjust social programs accordingly [15]. For example, the government could use this forecast to adjust poverty alleviation programs, social transfers, or subsidies to ensure that vulnerable populations are protected from inflationary pressures. With a clearer outlook on inflation, policymakers can design targeted interventions to minimize the social impact of price fluctuations, thereby supporting economic stability and promoting social welfare in the face of external shocks.

In summary, the stable CPI forecast not only informs monetary policy decisions but also plays a critical role in shaping social welfare strategies, helping to ensure that economic growth benefits the wider population while maintaining macroeconomic stability.

6. Conclusion

This study presents a comprehensive approach to modeling and forecasting Somalia's Consumer Price Index (CPI) using the ARIMA model. The findings demonstrate that while Somalia's CPI has shown a steady upward trend, the forecast indicates a period of price stability over the next few years. The ARIMA (1, 1, 0) model has proven to be the most appropriate for forecasting, offering reasonable accuracy and a balanced trade-off between model fit and complexity.

However, while the model is effective in the short to medium term, the increasing uncertainty in longer-term forecasts suggests that external variables, such as global commodity prices, political stability, and foreign exchange rates, should be incorporated into future models to improve the reliability of long-term predictions.

7. Recommendations

Monitoring Inflation: Given the steady upward trend in the CPI, policymakers should continue to monitor inflationary pressures and consider implementing measures such as tightening monetary policy or controlling commodity price fluctuations.

Data-Driven Decision Making: The ARIMA (1, 1, 0) model can aid in economic forecasting, enabling policymakers to plan more effectively for future price stability. Future forecasts should include external variables for more accurate predictions.

Further Research: Additional research can incorporate external shocks (e.g., political instability, global supply chain disruptions) and the use of other models like ARIMAX or VAR for better accuracy and robustness in forecasts.

Abbreviations

ARIMA	AutoRegressive Integrated Moving Average
CPI	Consumer Price Index
SES	Single Exponential Smoothing
VARX	Vector Autoregressive with Exogenous Variables

Author Contributions

Abdirashid Mohamed Hussein: Conceptualization, Data curation, Formal Analysis, Methodology, Visualization, Writing –original draft, Writing –review & editing

Ahmed Hassan Abdillahi: Funding acquisition, Resources, Supervision, Validation

Conflicts of Interest

The authors declare no conflicts of interest.

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