Journal of Humanities and Social Sciences Studies
ISSN: 2663-7197
DOI: 10.32996/jhsss
Journal Homepage: www.al-kindipublisher.com/index.php/jhsss

JHSSS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Driven Predictive Modeling of US Economic Trends: Insights and Innovations

Reza E Rabbi Shawon[1] ✉ Arifur Rahman[2], Md Rafiqul Islam[3], Pravakar Debnath[4], Md Fakhrul Islam Sumon[5], MD Azam Khan[6] and Mohammed Nazmul Islam Miah[7]

[1]*MBA Business Analytics, Gannon University, Erie, PA, USA*
[256]*School of Business, International American University, Los Angeles, California, USA*
[3]*MBA Business Analytics, International American University, Los Angeles, California*
[4]*School of Business, Westcliff University Irvine, California, USA*
[7]*Master of Public Administration, Management Sciences, and Quantitative Methods, Gannon University, Erie, PA, USA*

Corresponding Author: Reza E Rabbi Shawon, **E-mail**: shawon001@gannon.edu

| ABSTRACT

While traditional economic forecasting models have significantly improved, a few significant obstacles must be overcome. Conventional methods include time series and econometric models, which may rely hugely on historical data and are underlain by linear assumptions. These models fail to handle sudden shifts in the market or unseen economic events, like the financial crisis of 2008 or the COVID-19 pandemic 2020. Traditional models also need help bottling the vast amounts of unstructured data available today: articles, social posts, and other real-time information streams that influence economic sentiment. The chief objective of this research project is to explore the efficacy of AI-driven predictive modeling in forecasting US economic trends. This research project involved a time series analysis of three key financial indicators: Most notably, the Consumer Price Index (CPIAUCSL), the Gross Domestic Product (GDP), and the Unemployment Rate (UNRATE). Datasets entailed the Consumer Price Index for All Urban Consumers (CPI) from 1950 to the present, GDP: U.S. Gross Domestic Product (GDP) quarterly, and UNRATE: US Unemployment Rate (UNRATE) from 1950 to the present. These datasets provided valuable insights into the US economy, and this analysis aims to explore trends, seasonality, and relationships between these variables over time. One of the most immediate benefits for policymakers and the U.S. government is the significant improvement in the accuracy and timeliness of economic forecasts enabled by AI-driven models such as the ARIMA and SARIMAX. Another vital implication of AI-driven economic forecasting is improving policy formulation based on more sophisticated scenario analysis and simulations. AI-driven forecasting facilitates more targeted and proactive policy intervention, which is helpful in such sector-specific issues or regional disparities in economic performance.

| KEYWORDS

Predictive modeling; U.S economic trends; Innovations; GDP; Consumer Price Index; ARIMA; SARIMAX

| ARTICLE INFORMATION

ACCEPTED: 20 September 2024 **PUBLISHED:** 04 October 2024 **DOI:** 10.32996/jhsss.2024.6.10.1

1. Introduction

1.1 Background and Motivation

According to Zong Guan (2024), the capability to comprehend and project economic trends has been regarded as one of the significant achievements that policymakers, businesses, and financial institutions could attain for decades. The US economy has been considered to be part of a global regime. It is described as a complex system in which the interaction of several factors-inflation, unemployment rate, consumer spending, and industrial output-must be grasped for informed decision-making. As per Khan et al. (2024), Accurate forecasts concerning economic performance can yield signals on fiscal policy, monetary adjustments, corporate strategy, and investment decisions. However, it is very challenging to predict financial trends since this system is very complex, and most variables influence one another in nonlinear ways. Therefore, accurate models of the prediction of US economic trends are crucial for sustaining economic stability, guiding investment strategies, and formulating policies that stimulate growth while mitigating risks. The prime objective of this research project is to explore the efficacy of AI-driven predictive modeling in forecasting US economic trends.

Hasan et al. (2024b) contend that Artificial Intelligence is fast emerging as an overwhelmingly potent tool across industries; its applications in economics are finding more and more relevance with each passing day. AI processing massive data and drawing inferences from patterns presents a new frontier in economic forecasting. More often than not, classic models are hostage to linear relationships and historical data in making pretty poor predictions of dynamically shifting economies. Besides, where human intuition is limited to the data at one's disposal, machine learning with AI-driven predictive modeling can leverage large volumes of data, apply complex algorithms, and even self-correct in real time for increasingly accurate and timely predictions. As more data becomes available from sources, including stock market prices and social media consumer sentiment, AI models will continue integrating structured and unstructured data to yield more accurate predictions of economic trends.

1.2 Problem Statement

Zeeshan et al. (2024) posit that while traditional economic forecasting models have significantly improved, a few significant hurdles remain. Conventional methods include time series and econometric models, which may rely hugely on historical data and are underlain by linear assumptions. These models fail to handle sudden shifts in the market or unseen economic events, like the financial crisis of 2008 or the COVID-19 pandemic 2020. Shawon (2024) articulated that Traditional models also have difficulty bottling the vast amounts of unstructured data available today: articles, social posts, and other real-time information streams that influence economic sentiment. Moreover, manual recalibration of such models may be time-consuming, and their predictive power will fade as relationships change over time.

Abu-Jamie Al-Absy (2024) indicated that conventional economic forecasting also captures poorly complex and nonlinear relationships common among economic variables. From that perspective, financial systems are increasingly so entwined and interact with each other in a way that small changes in one part have a ripple effect on different variables in ways that are difficult to anticipate. These include a realignment in global supply chains diffusing into domestic inflation, employment, and trade balances, perhaps not adequately captured by traditional models. HASAN (2021) argues that conventional models also face problems dealing with high-frequency data; moreover, for most of them, real-time updating of predictions is beyond their capabilities. This means that to get the forecast, one should resort to outdated information, reducing the value of such an approach in a rapidly changing economic environment. As a result, there is an increasingly higher demand for more adaptive and intelligent systems able to analyze vast volumes of data, discover complex patterns, and make predictions in real-time. That is where AI-driven predictive modeling becomes an attractive alternative.

1.3 Objective of the Study

The prime objective of this research project is to explore the efficacy of AI-driven predictive modeling in forecasting US economic trends. Notably, this research project examines the limitations of traditional economic forecasting models. This involves pinpointing the gaps and shortcomings of conventional methods regarding accuracy, adaptability, and handling large datasets. The research will investigate how AI can combat the constraints of traditional models by processing large volumes of data, accounting for nonlinear relationships, and integrating real-time data for dynamic forecasting. Evaluate the efficiency and accuracy of AI models in forecasting the most important economic indicators. This involves analyzing how AI-driven models have fared in forecasting critical US economic metrics such as GDP growth, unemployment rates, inflation, and market volatility against traditional models.

2. Literature Review

2.1 Overview of Economic Forecasting

Okeleke et al. (2024) asserted that economic forecasting is a cornerstone of decision-making in the USA's private and public sectors. Economic forecasts project economic developments, such as GDP growth, inflation, employment, and market tendencies. By their very nature, they have to depend on historical data and models of economic behavior. Conventional methods of economic forecasting have highly depended on statistical methods, with time series models and econometric models being the most widely adopted approaches. For instance, time series models, such as ARIMA [autoregressive integrated moving average] and VAR [vector autoregression], can be applied to analyze the historical data points across time for trends and seasonal effects. These models assume that the past can inform the future, wherein data follow some predictable pattern. Econometric models, in contrast, utilize both economic theory and statistical methods to check into the relationships among various economic variables. For example, a regression model can quantify the response of GDP growth to a change in consumer spending (Dadhich et al., 2021). These models function where environments are stable and where economic conditions alter slowly over time.

Even so, there are some salient limitations to traditional methods of economic forecasting. Chief among these is that most depend on historical data and the assumption that past relationships among economic variables will hold over the future. This is increasingly a highly questionable assumption in today's ever-changing global economy. Economic shocks, such as financial crises or pandemics, shake up these patterns, and traditional models can become less valuable (Mehra et al., 2024). Additionally, these models generally focus more on the linear relationships between variables, which can only briefly describe how modern economies work: nonlinear dynamics, feedback loops, and interactions across many sectors and regions. Traditional models often also need to include unstructured data, such as news reports, social media sentiment, or other data from textual inputs that may offer insight into economic behavior in real time.

2.2 AI and Machine Learning in Economic Forecasting

In response to the shortcomings of conventional techniques, AI and machine learning (ML) have gained substantial traction as alternatives for economic forecasting. Artificial intelligence models, especially those based on machine learning algorithms, are specifically devised to learn from data without any prerequisite assumptions about the relations of economic variables-they identify patterns to make forecasts. This flexibility instills the ability of AI models to handle the complexity and nonlinearity(Mehra et al., 2024) arising in complex contemporary economies better than traditional methods.

2.3 Time-Series in Economic Forecasting

According to Manigadan et al. [2022], the time series has always been central to economic forecasting in consolidation with Machine Learning algorithms, providing a framework for understanding how economic variables change over time. Classic models such as the Generalized Autoregressive Conditional Heteroskedasticity [GARCH] have long been cornerstones of financial forecasting. These models rely on linear correlation and demand that data be stationary. However, with the development of AI, sophistication has emerged that allows more sophisticated models of time series with nonlinear dynamics, embedding larger-scale datasets.

Abu-Jamie & Al-Absy [2024] argue that economic forecasting using time series algorithms has several limitations. A critical limitation regarding time-series algorithms is that they depend on past data. As a result, they are prone to structural gaps or sudden economic variations, such as financial crises, which the algorithms cannot foresee. Besides, time-series algorithms do not follow critical economic relations that are mostly nonlinear, interacting with each other, facing exogenous shocks, and being dependent on behavioral factors, which are difficult to represent with past trends. Moreover, time series models assume that past patterns will smoothly flow into the future. Such assumptions might not hold in dynamic, rapidly evolving economies. Forecast accuracy can also degrade over longer time horizons due to increasing uncertainty.

Machine learning algorithms for time series analysis, specifically recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, have exemplified significant possibilities in economic forecasting. These models are particularly suited for time-dependent data, as they can learn from sequential patterns and long-term dependencies that traditional models lack. A notable study by Siami-Namini Namin (2020) compared the performance of LSTM networks with ARIMA in forecasting US economic variables such as GDP and unemployment rates. The results indicated that LSTM models outperformed ARIMA, especially in nonlinear data, while the ability to capture a long-term trend was more precise.

In their empirical study, Okeleke et al. (2024) also applied RNNs and LSTM networks to predict stock prices and other financial indicators. They found that while RNN was good at capturing short-term fluctuations, LSTM could capture the long-term trend since the latter can retain information for extended periods. This feature lends excellent value to using LSTM in predicting cyclical economic events or trends that take time to develop.

Moreover, the hybrid models that integrate traditional time series methods with machine learning also exemplified promising results. For example, Zong Guan (2024) propounded an integrated model, ARIMA-ANN, that combined the strengths of ARIMA in linear modeling with ANN's nonlinear relationship-capturing capability. The study demonstrated that the hybrid model outperformed both the methods in isolation when forecasting inflation rate and stock market return forecasting.

2.4 Innovations in AI-driven Predictive Modeling

2.4.1 Neural Networks and Economic Forecasting

Neural networks, profound learning algorithms, have emerged as cutting-edge tools in economic forecasting because of their capability to model complex, nonlinear relationships. The linear assumption binds traditional forecasting models; neural networks do not need these assumptions since they learn directly from data, making them helpful in understanding economic data complexity. One of the pioneering works in this regard is the investigation by Hinton and Shawon (2024) into deep neural networks for different prediction problems, such as economic forecasting. Deep learning models can reduce forecast errors by learning complex data relationships that traditional models might miss. In particular, several studies have used FNNs to forecast vital macroeconomic indicators like GDP growth, inflation, and unemployment. The models work by feeding the input data through a series of interconnected nodes or neurons where, during training, the model searches for complex patterns in the data by changing the weights of each node.

Jain et al. (2024) deployed a feedforward neural network to predict financial market trends; the results demonstrated that neural networks could outperform linear models like ARIMA regarding prediction accuracy. The work explained how neural networks effectively provided forecasts for nonlinear data relationships between economic variables, which was beneficial, especially in turbulent financial markets with linearly related data relationships.

CNNs, or Convolutional Neural Networks, have extended neural network capabilities in economic forecasting. Traditionally used for image recognition tasks, CNNs have been adapted for time series forecasts by modeling local patterns in the data. Khan et al. (2024) applied a CNN to forecast real estate market trends based on spatial data in the USA; the model strongly outperformed traditional econometric models. They showed the extendability of a CNN for feature extraction in many types of economic data, including spatial and temporal ones.

Another recent application of neural networks is sentiment analysis, which is used for economic forecasting. By incorporating textual data from news articles, social media, and financial reports, neural networks can predict economic sentiment, which can be used to forecast market movements. Mehra et al. (2024) have applied an LSTM network to study financial news and predict trends in the USA stock market. They concluded that the sentiment scores obtained from the text data considerably enhanced the model's predictive power. This research thus underlines the potential of neural networks in making economic forecasting models incorporate unstructured data.

2.4.2 Ensemble Methods in Economic Forecasting

As per Hasan et al. [2024], various ensemble methods have gained significant momentum for economic forecasting in recent years. An ensemble combines several models to improve a forecast's prediction accuracy. The underlying rationale behind these ensembles was that the final prediction made by aggregating many model outputs is more accurate and robust than a single model. Basic techniques in which different combinations of models are made to enhance forecasting performance include bagging, boosting, and stacking.

One of the groundbreaking works by Zeeshan et al. [2024] introduced XG-Boost, a technique of ensemble methods based on gradient boosting, and furthered its wide usage in economic forecasting. For example, XG-Boost works to iteratively fit models and improve predictions by correcting errors in the previous model. Proposed methods have been applied to predict inflation rates, unemployment, and stock prices. For instance, it has been demonstrated in Kaggle competitions on economic forecasting that XG-Boost outperforms traditional models in foresight into financial market trends because it handles large datasets and has flexibility in capturing nonlinear variable-variable relationships.

Another noteworthy illustration of an ensemble method in economic forecasting is Dadhich et al. (2024), who applied the bagging technique to combine forecasts from multiple econometric models. The two authors proved that, with increased accuracy from using a single model, the ensemble methods could reduce the variance of the predictions. Their findings showed that combining forecasts from various models provided more reliable predictions, particularly in times of volatility.

2.4.3 Gap Analysis

Manigandan et al. [2022] posit that despite all the developments in AI-based predictive modeling, one can identify a few gaps in current research on the subject. First, although AI models report superior performance for particular applications, such as the stock market forecast or house prices, comprehensive studies that objectively appraise the effectiveness of AI are still needed across a wide range of economic indicators. Most studies have focused on specific sectors or markets, while AI utilities' predictions of macroeconomic trends, such as GDP growth or inflation, are mainly unexplored.

Second, from several AI models, transparency and interpretability elements are limited. While robust, deep learning models are mostly considered "black boxes" since their reasoning processes are complex to interpret. Another problem with economic forecasting might be a lack of transparency, as explaining the underlying relationship among key variables is indispensable in policy formulation and decision-making [Hasan et al., 2024]. Various methods have been developed recently to improve interpretability in AI models. However, the ways to attain this are still an area of ongoing investigation.

Thirdly, even as AI models process large volumes of data in real-time, further enhancements are necessary to respond effectively to severe economic disruptions such as financial crises or natural disasters. Most AI models are built on historical data and are usually unprepared for unprecedented developments. Future research must be directed toward building resilient models when faced with shocks.

3. Methodology

3.1 Data Sources and Description

This research project involved a time series analysis of three key economic indicators: Most notably, the Consumer Price Index (CPIAUCSL), the Gross Domestic Product (GDP), and the Unemployment Rate (UNRATE). Datasets entailed the Consumer Price Index for All Urban Consumers (CPI) from 1950 to the present, GDP: U.S. Gross Domestic Product (GDP) quarterly, and UNRATE: US Unemployment Rate (UNRATE) from 1950 to the present (Pro-AI-Rokibul, 2024). These datasets provided valuable insights into the US economy, and this analysis aims to explore trends, seasonality, and relationships between these variables over time.

3.2 Data Preprocessing

Pro-AI-Rokibul [2024] states that data preprocessing is essential in any analysis, especially in economic forecasting. The conversion of the date columns to date time was a necessary preprocessing for any time series analysis, as it allowed for appropriate sorting, indexing, and time-based operations like resampling or extracting specific time components such as year, month, or day of the week. In merging datasets on the DATE column, ensuring that the date formats were consistent across all datasets was pivotal to avoid mismatches or duplication of records. This process typically involved joining multiple datasets (e.g., GDP, inflation, and employment data) by their expected time axis, allowing for a more comprehensive analysis of economic trends. When handling missing data in the GDP dataset (or any other economic indicator), common approaches such as interpolation were applied to estimate missing values based on surrounding data points, forward or backward filling to propagate the last known value, or removing rows with missing data altogether. Lastly, missing values are handled with great care not to compromise any part of the dataset so that it remains robust and reliable for AI-driven predictive modeling.

3.3 AI and Machine Learning Techniques Used

3.3.1 Autoregressive Integrated Moving Average (ARIMA)

ARIMA is a contemporary algorithm but a powerful statistical time-series model for historical forecasts. It uncovers the linear relationship that embeds three components: autoregression, differencing, and moving average. In economic variables like CPI, GDP, and unemployment rate, ARIMA assisted in defining underlying patterns and provided appropriate short-run to medium-run forecasts. ARIMA is particularly fitted for stationary time-series data, where the mean and variance do not change significantly for most of the time; it can also be extended to handle trends and seasonality through more sophisticated versions like SARIMA. Though simple compared to neural networks, ARIMA methods are still commonly applied because of their interpretability and performance in many economic contexts.

3.3.2 SARIMAX

The Seasonal Auto-Regressive Integrated Moving Average with eXogenous regressors [SARIMAX] model is an advanced time series predictive model that integrates several components to capture complex trends in data. It also complements the ARIMA model since it contains seasonal elements and additional exogenous variables. The model can be helpful in economic and financial forecasting, where the trend, seasonality, and influence of exogenous variables are usually contained in the data. The SARIMAX model is considered for analyzing non-stationarity data; it exhibits complex seasonal effects and includes the impact of exogenous variables. Therefore, it is more versatile and powerful for analyzing and forecasting time series data concerning economics, finance, or environmental studies. However, it requires meticulous selection and interpretation of parameters. Another critical assumption it makes is that the historical pattern will continue in the future, which might need to be more appropriate under the context of the rapidly changing environments.

4. Implementation

4.1 Data Preprocessing

```
# Sample data setup (replace this with your actual data loading)
# Ensure 'DATE' columns are converted to datetime
df1 = pd.DataFrame({'DATE': pd.date_range(start='2000-01-01', periods=601, freq='M'),
'CPIAUCSL': np.random.randn(601)})
df2 = pd.DataFrame({'DATE': pd.date_range(start='2000-01-01', periods=201, freq='Q'), 'GDP':
np.random.randn(201)})
df3 = pd.DataFrame({'DATE': pd.date_range(start='2000-01-01', periods=601, freq='M'),
'UNRATE': np.random.randn(601)})

# Convert DATE to datetime and merge datasets on DATE
df1['DATE'] = pd.to_datetime(df1['DATE'])
df2['DATE'] = pd.to_datetime(df2['DATE'])
df3['DATE'] = pd.to_datetime(df3['DATE'])

# Merge all datasets on DATE (left join to retain all CPIAUCSL and UNRATE data)
df = df1.merge(df2, on='DATE', how='left').merge(df3, on='DATE', how='left')
```

As showcased in the above code snippet, three DataFrames were created: df1, df2, and df3, each with a 'DATE' column and a corresponding value column. In each, the 'DATE' column contained 601 daily dates starting from January 1, 2000. Each frame represents a different value column: df1:'CPIAUCSL' is for the Consumer Price Index for All Urban Consumers. df2: 'GDP' is for Gross Domestic Product. df3: 'UNRATE' could be for Unemployment Rate. Using pd.to_datetime() to convert the 'DATE' column of each DataFrame to DateTime format. Data Merging: All three DataFrames were combined into one; the data frame was named 'df.' This ensured that all dates from df1 (CPIAUCSL) were retained, and corresponding GDP and UNRATE values were added where available.

4.2 Model Development

The analyst imported necessary libraries, including pandas for data manipulation and analysis, NumPy for numerical operations, matplotlib, pyplot for creating plots, and seaborn for data visualization. The analyst also imported warnings for handling and ignoring warning messages. The code cpi_data = pd.read_csv("cpi_data.csv") reads the CSV file named "cpi_data.csv" into a pandas DataFrame called cpi_data. The second code, notably cpi_data, aimed to display the first few rows of the DataFrame in the notebook environment.

```
import numpy as np
import seaborn as sns
import pandas as pd
from matplotlib import pyplot as plt
import warnings

# Ignore all warnings
warnings.filterwarnings('ignore')
```

```
cpi_data = pd.read_csv("cpi_data.csv")
cpi_data
```

Output:

	DATE	CPIAUCSL
0	1974-01-01	46.800
1	1974-02-01	47.300
2	1974-03-01	47.800
3	1974-04-01	48.100
4	1974-05-01	48.600
...	...	...
596	2023-09-01	307.288
597	2023-10-01	307.531
598	2023-11-01	308.024
599	2023-12-01	308.742
600	2024-01-01	309.685

As showcased above, the Data Frame had 601 rows and two columns. The columns included 'DATE' and 'CPIAUCSL' (Consumer et al. for All Urban Consumers: All Items). The data ranged from January 1, 1974, to January 1, 2024. CPI Values. The CPIAUCSL column showcased the Consumer Price Index values, particularly in January 1974, when the CPI was 46.800. Consequently, by January 2024, the CPI had increased to 309.685. Retrospectively. There was an apparent upward trend in the CPI values over time, indicating inflation. The escalation from 46.800 in 1974 to 309.685 in 2024 indicates significant cumulative inflation over these 50 years.

```
gdp_data = pd.read_csv("gdp_data.csv")
gdp_data
```

Output:

	DATE	GDP
0	1974-01-01	1491.209
1	1974-04-01	1530.056
2	1974-07-01	1560.026
3	1974-10-01	1599.679
4	1975-01-01	1616.116
...	...	...

	DATE	GDP
196	2023-01-01	26813.601
197	2023-04-01	27063.012
198	2023-07-01	27610.128
199	2023-10-01	27956.998
200	2024-01-01	28269.174

As displayed above, the 'gdp_data' DataFrame was loaded from the "gdp_data.csv" file. The data frame had 201 rows and two columns. The columns entailed 'DATE' and 'GDP' (Gross et al.). Date Range spanned from January 1, 1974, to January 1, 2024. The GDP column exhibited the Gross Domestic Product values; in Q1 1974, the GDP was 1491.209 (in billions of dollars). By Q1 2024, the GDP had increased to 28269.174. In retrospect, there was a clear upward trend in the GDP values over time, showcasing economic growth. The escalation from 1491.209 in 1974 to 28269.174 in 2024 indicates substantial economic expansion over these 50 years.

```
unemp = pd.read_csv("unemployment_data.csv")
unemp
```

Output:

	DATE	UNRATE
0	1974-01-01	5.1
1	1974-02-01	5.2
2	1974-03-01	5.1
3	1974-04-01	5.1
4	1974-05-01	5.1
...	...	...

	DATE	UNRATE
596	2023-09-01	3.8
597	2023-10-01	3.8
598	2023-11-01	3.7
599	2023-12-01	3.7
600	2024-01-01	3.7

This code snippet above displays the 'unkempt' DataFrame loaded from the "unemployment_data.csv" file. The Data Frame had 601 rows and two columns; the columns included 'DATE' and 'UNRATE' (Unemployment Rate). Date Range spanned from January 1, 1974, to January 1, 2024. The UNRATE column exhibited the unemployment rate as a percentage. In January 1974, the unemployment rate was 5.1%. By January 2024, the unemployment rate had declined to 3. Unlike the consistently increasing trends seen in CPI and GDP, the unemployment rate exhibited more variability. The unemployment rate fluctuated over time, reflecting economic cycles, recessions, and periods of growth.

The code snippet below showcases the setup for time series analysis and visualization. It entailed Importing specific time series analysis tools from statsmodels: seasonal_decompose for decomposing time series, particularly ARIMA for autoregressive consolidated moving average modeling, SARIMAX for seasonal ARIMA with exogenous regressors. Subsequently, it Created three DataFrames (df1, df2, df3) with sample data:df1: CPIAUCSL (Consumer Price Index) - monthly data, 601 periods, df2: GDP (Gross Domestic Product) - quarterly data, 201 periods, df3: UNRATE (Unemployment Rate) - monthly data, 601 periods.

```
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

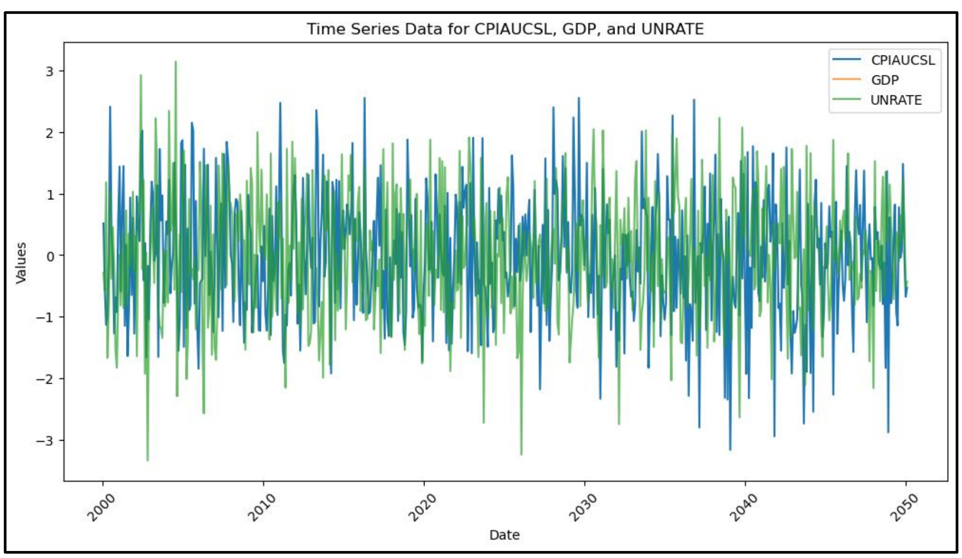
```
# Sample data setup (replace this with your actual data loading)
# Ensure 'DATE' columns are converted to datetime
df1 = pd.DataFrame({'DATE': pd.date_range(start='2000-01-01', periods=601, freq='M'),
'CPIAUCSL': np.random.randn(601)})
df2 = pd.DataFrame({'DATE': pd.date_range(start='2000-01-01', periods=201, freq='Q'),
'GDP': np.random.randn(201)})
df3 = pd.DataFrame({'DATE': pd.date_range(start='2000-01-01', periods=601, freq='M'),
'UNRATE': np.random.randn(601)})

# Convert DATE to datetime and merge datasets on DATE
df1['DATE'] = pd.to_datetime(df1['DATE'])
df2['DATE'] = pd.to_datetime(df2['DATE'])
df3['DATE'] = pd.to_datetime(df3['DATE'])

# Merge all datasets on DATE (left join to retain all CPIAUCSL and UNRATE data)
df = df1.merge(df2, on='DATE', how='left').merge(df3, on='DATE', how='left')
```

```
# Visualize the time series data
plt.figure(figsize=(12, 6))
plt.plot(df['DATE'], df['CPIAUCSL'], label='CPIAUCSL')
plt.plot(df['DATE'], df['GDP'], label='GDP', alpha=0.7)
plt.plot(df['DATE'], df['UNRATE'], label='UNRATE', alpha=0.7)
plt.legend()
plt.title('Time Series Data for CPIAUCSL, GDP, and UNRATE')
plt.xlabel('Date')
plt.ylabel('Values')
plt.xticks(rotation=45)
plt.show()
```

Output:



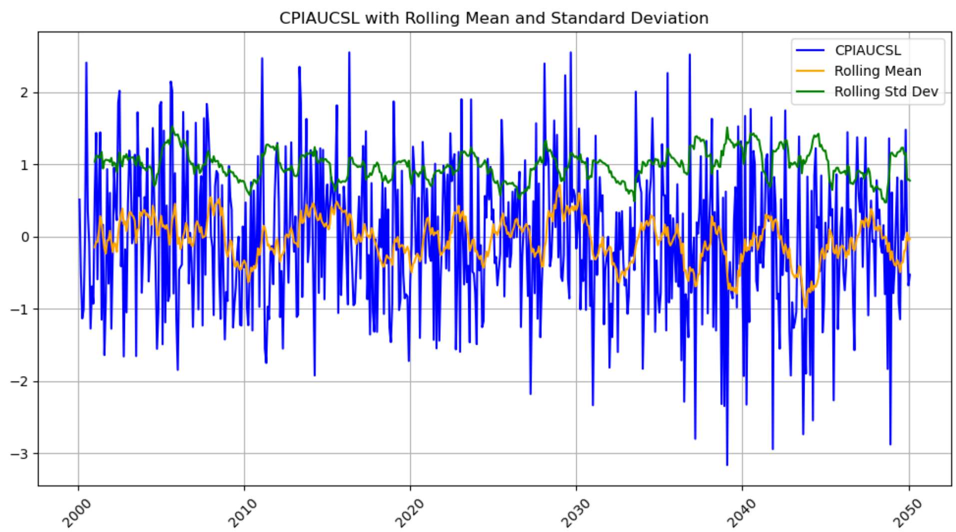
The graph above displays the time series data for the three economic indicators, notably CPIAUCS, GDP, and UNRATE, from 2000 to 2050. The data ranged from 2000 to 2050, offering historical data and future projections or simulations. UNRATE (green) appeared to have the most tremendous volatility, with frequent large swings; CPIAUCSL (blue) demonstrated moderate volatility, while GDP (orange) seemed to have the least volatility among the three.

```
# 3. Rolling Mean and Standard Deviation for CPIAUCSL
df['CPIAUCSL_rolling_mean'] = df['CPIAUCSL'].rolling(window=12).mean()
df['CPIAUCSL_rolling_std'] = df['CPIAUCSL'].rolling(window=12).std()

plt.figure(figsize=(12, 6))
plt.plot(df['DATE'], df['CPIAUCSL'], label='CPIAUCSL', color='blue')
plt.plot(df['DATE'], df['CPIAUCSL_rolling_mean'], label='Rolling Mean',
color='orange')
plt.plot(df['DATE'], df['CPIAUCSL_rolling_std'], label='Rolling Std Dev',
color='green')
plt.title('CPIAUCSL with Rolling Mean and Standard Deviation')
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

This code snippet sets up a visualization for the Consumer Price Index for All Urban Consumers (CPIAUCSL) data, along with its rolling mean and standard deviation. The code computed a 12-period rolling mean for CPIAUCSL and preserved it in a new column, 'CPIAUCSL_rolling_mean.' Successively, it Computed a 12-period rolling standard deviation for CPIAUCSL and preserved it in 'CPIAUCSL_rolling_std.'

Output:



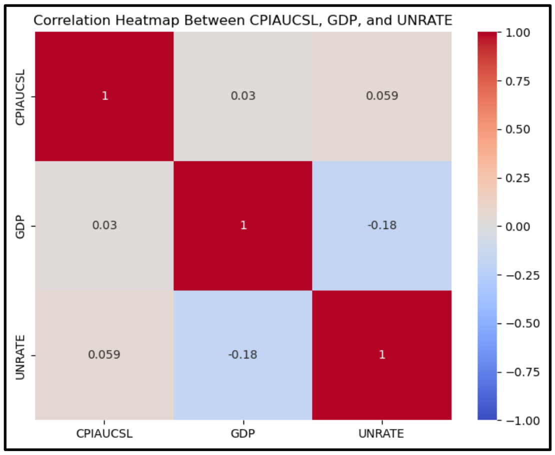
The graph above portrays the Consumer Price Index for All Urban Consumers (CPIAUCSL) data, its 12-period rolling mean, and standard deviation from 2000 to 2050. CPIAUCSL (Blue Line) demonstrated relatively high volatility with frequent large swings, with Values ranging from -3 to 2.5. No clear long-term pattern was visible, which is unusual for accurate CPI data. As expected, the Rolling Mean (Orange Line) was Smoother than the raw data, mainly fluctuating between -0.5 and 0.5. Rolling Standard Deviation (Green Line) Generally stayed between 0.5 and 1.5.

The code snippet below sets up a correlation analysis and visualization of the three economic indicators: CPIAUCS, GDP, and UNRATE (Unemployment Rate). Correlation Computation comprised: df_corr = df[['CPIAUCSL,' 'GDP,' 'UNRATE']].corr(), which computed the pairwise correlations between CPIAUCSL, GDP, and UNRATE. Subsequently,
the result was preserved in a new data frame called df_corr.

```
# 4. Correlation Heatmap Between CPIAUCSL, GDP, and UNRATE
df_corr = df[['CPIAUCSL', 'GDP', 'UNRATE']].corr()

plt.figure(figsize=(8, 6))
sns.heatmap(df_corr, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Heatmap Between CPIAUCSL, GDP, and UNRATE')
plt.show()
```

Output:



The correlation heatmap above exhibits the relationships between three economic indicators: CPIAUCS, GDP, and UNRATE (Unemployment Rate). Here is an interpretation of the results. All diagonal values were 1, which was anticipated because they represent the correlation of each variable with itself. Regarding CPIAUCSL and GDP, the correlation was 0.03, indicating a fragile positive relationship. This showed that alterations in CPI were barely associated with changes in GDP in this dataset. Concerning CPIAUCSL and UNRATE Correlation, the correlation was 0.059, again indicating a weak positive relationship. This outcome suggested that alterations in CPI had little association with changes in the unemployment rate. On the other hand, for GDP and UNRATE, the correlation was -0.18, indicating a weak negative association. This outcome was the strongest correlation among the three pairs, suggesting that as GDP increases, there is a slight tendency for unemployment to decrease or vice versa.

The following code snippet from the Python script performed a seasonal evaluation of data related to two variables: "CPIAUSL" and "UNRATE." The line df['Month'] = df['DATE'].dt.month extracted the month from a date column in a DataFrame df created a new column called "Month." To Calculate Monthly Averages,

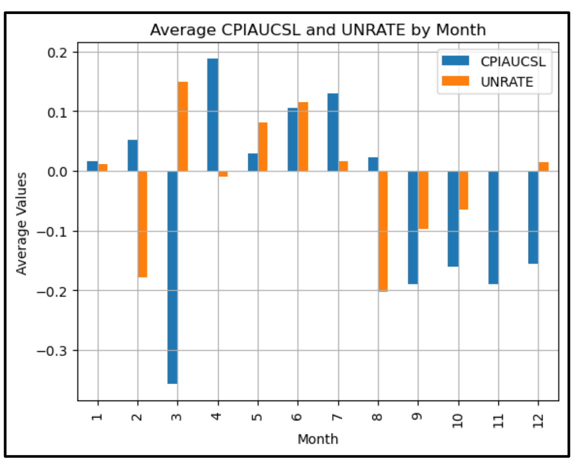
monthly_avg = df. group by ('Month').mean()[['CPIAUSL,' 'UNRATE']]: This command grouped the data by the "Month" column and computed the mean values for the "CPIAUSL" and "UNRATE" columns. The result is stored in the monthly_avg variable.

```
# 5. Seasonality Check - Monthly Average for CPIAUCSL and UNRATE
df['Month'] = df['DATE'].dt.month

monthly_avg = df.groupby('Month').mean()[['CPIAUCSL', 'UNRATE']]

plt.figure(figsize=(12, 6))
monthly_avg.plot(kind='bar')
plt.title('Average CPIAUCSL and UNRATE by Month')
plt.ylabel('Average Values')
plt.grid(True)
plt.show()
```

Output:



As per the graph above, it was evident that the average values of CPIAUCSL fluctuated throughout the year, with some months showing positive values and others showing negative values. The highest average value was seen in April, while the lowest average value was recorded in March. Still, on the average plot, UNRATE reaches higher values at the beginning of the year and lower values towards the end. The highest average value is realized in January, whereas the lowest average occurs in September.

4.3 Model Evaluation

4.3.1 ARIMA Model

```
                               SARIMAX Results
==============================================================================
Dep. Variable:               CPIAUCSL   No. Observations:                  601
Model:                 ARIMA(1, 1, 1)   Log Likelihood                -859.892
Date:                Thu, 26 Sep 2024   AIC                           1725.784
Time:                        15:53:59   BIC                           1738.974
Sample:                             0   HQIC                          1730.919
                                - 601
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0351      0.042     -0.834      0.404      -0.117       0.047
ma.L1         -0.9927      0.006   -160.603      0.000      -1.005      -0.981
sigma2         1.0215      0.065     15.837      0.000       0.895       1.148
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 1.54
Prob(Q):                              1.00   Prob(JB):                         0.46
Heteroskedasticity (H):               1.09   Skew:                             0.01
Prob(H) (two-sided):                  0.52   Kurtosis:                         2.75
===================================================================================
```

The ARIMA model was fitted using 601 observations. The log-likelihood value was -859.892. This component measured the model's goodness of fit. A higher log-likelihood indicated a better fit. AR coefficient [ar.L1: -0.0351] This outcome indicated a small negative autoregressive effect at lag 1. It implied that the CPI's current value was slightly negative to its value one period ago. MA Coefficients [ma.L1: -0.9927]: This outcome suggested a solid negative moving average effect at lag 1. This implied that the value of CPI in the present period strongly negatively relates to the error term of the previous period.

Ljung-Box (L1) (Q): 0.00, Prob. (Q): 1.00 indicated no residual autocorrelation at lag 1. Jarque-Bera (JB): 1.54, Prob (JB): 0.46 implied that the residuals were normally distributed around zero. Heteroskedasticity (H) result of 1.09, Prob(H) (two-sided): 0.52, indicated that there was no evidence of heteroskedasticity. Skewness and Kurtosis: The distribution was considered symmetric with a very low skewness of 0.01. A kurtosis value of 2.75 also reflects a heavier-tailed distribution. The diagnostic tests suggest that the current model fits the data reasonably well. Nevertheless, further refinements may be required depending on the specific application and the relative importance of having accurate predictions or inferences.

4.3.2 SARIMAX

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                           CPIAUCSL   No. Observations:                  601
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood                -864.720
Date:                            Thu, 26 Sep 2024   AIC                           1739.440
Time:                                    15:54:06   BIC                           1761.324
Sample:                                         0   HQIC                          1747.967
                                            - 601
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0313      0.042     -0.748      0.455      -0.113       0.051
ma.L1         -0.9997      0.290     -3.445      0.001      -1.569      -0.431
ar.S.L12       0.0725      0.045      1.621      0.105      -0.015       0.160
ma.S.L12      -0.9998      3.972     -0.252      0.801      -8.784       6.785
sigma2         1.0069      3.998      0.252      0.801      -6.829       8.842
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 1.39
Prob(Q):                              0.99   Prob(JB):                         0.50
Heteroskedasticity (H):               1.09   Skew:                            -0.08
Prob(H) (two-sided):                  0.54   Kurtosis:                         2.82
===================================================================================
```

As showcased above, the log-likelihood of -864.720 provides a baseline for model fit. It suggests that this particular SARIMAX specification offers a certain level of fit to the data. As regards the Coefficient ar.L1 [-0.0313], the negative coefficient indicated a slight negative correlation with the previous period's value—coefficient ma. L1 (-0.9997) indicates a strong negative relationship with the last period's error term. Concerning the Coefficient ar.S.L12 (0.0725), the positive coefficient indicated a slight positive correlation with the same period from the previous year. Regarding sigma2 (1.0069), it was close to 1, which implied that it was a well-specified model. Ljung-Box (L1) (Q): 0.00. This value suggested no significant autocorrelation at lag 1, which was a good sign, indicating that the model captured the time series dependencies well—heteroskedasticity (H)of 1.09 tested for constant variance in the residuals. The 1.09 was close to 1, indicating mild heteroskedasticity. The Jarque-Bera (JB): 1.39, tested for normality of the residuals. A lower value suggested closer alignment with a normal distribution. 1.39 was relatively low, indicating the residuals were reasonably close to normally distributed.

4.4 Feature Importance Analysis

Feature importance analysis is critical in models, especially in time-series forecasting, as it depicts which economic indicators bear more influence on the predictive outcomes. Having dealt with datasets such as the Consumer Price Index, Gross Domestic Product, and Unemployment Rate, determine which variable importance will contribute most to the model's predictions. These, therefore, go a long way to help arrive at better accuracy of the models; at the same time, they also contribute significantly toward valuable economic insights for decision-makers.

SHAP [(Shapley Additive exPlanations] values are a game-theoretic approach that assigns an importance score to each feature for interpreting the output of machine learning models. SHAP explains the contribution each economic feature makes, such as inflation, rates of interest, or government spending, toward predicting a target variable in GDP growth or changes in the consumer price index. The SHAP values will allow insight into which indicators have the most significant influence on forecasted economic outcomes through the calculation of the marginal contribution of each feature to the model's predictions. For instance, SHAP might indicate that unemployment rates influence the future GDP more than the CPI at specific periods, hence underlining how labor market conditions drive economic growth.

Granger causality is a statistical hypothesis test determining whether one-time series can predict another. It can be used in economic forecasting to determine which one of two economic indicators, say CPI and UNRATE, could have predictive power over the target variable like GDP. The purpose of Granger's casualty test is to check whether one indicator consistently improves the forecast accuracy of another upon analyzing lag values for different economic indicators. The test may indicate, for instance, that changes in the unemployment rate Cause changes in GDP, which can be interpreted as using changes in labor market conditions to predict economic growth in periods close to the present.

Essential correlation and autocorrelation analyses are frequently applied at the preliminary stage to establish which economic indicators move with or in advance of target variables such as GDP or CPI. The correlation matrix underlined the relationships between interest rates, inflation, and unemployment rates in features showing how each factor drives economic outcomes. In particular, autocorrelation is a measure of how, at each point in time, the current value of a variable is related to its past values, such as last quarter's GDP; thus, it provides information regarding the persistence of trends in economic variables. For instance, in an application that is forecasting GDP growth, the analysis of feature importance returns, for example:

- Unemployment rate- UNRATE: the most critical predictor factor, especially during an economic recession, because this is a significant indicator of labor market conditions.
- The CPI, in this case CPIAUCSL, is a leading indicator of inflationary pressure; this is a gauge for central banks, which eventually trickles down to affecting GDP growth.

Consumer spending and industrial production might be strong predictors during economic expansion. It will also allow policymakers and analysts to find out which variables carry the most weight so that they can focus on these indicators for economic projections or formulating responses to potential downturns.

5. Discussion

One of the most cutting-edge innovations in AI-driven economic forecasting is curating advanced machine learning techniques, such as deep learning, reinforcement learning, and ensemble methods. These algorithms have outperformed the traditional econometric models with greater accuracy and flexibility while handling large and complex datasets.

Deep learning, primarily RNNs and LSTM networks has revolutionized the prediction of temporal economic variables. Unlike conventional models that treat the relationship between variables as linear, deep learning models can learn nonlinear patterns and interactions inherent in many economic data. For example, LSTM networks were exceptionally good at time-series forecasting due to remembering long-term dependencies in data, which makes them ideal for predicting some economic indicators, such as GDP growth or inflation trends over extended periods.

Reinforcement learning has also emerged as an intensely sought-after approach to optimally making economic policy and financial market decisions. The reinforcement learning algorithms learn from interacting with the environment through feedback while adapting to ever-changing economic conditions. These algorithms have been applied to portfolio management, trading strategies, and even monetary policy, where the return is optimized for the long term based on evolving economic data.

Ensemble techniques, such as Random Forests and XGBoost, consolidate the predictions of multiple models to enhance overall forecasting accuracy. These algorithms have been specifically efficient in economic prediction, where consolidating the strengths of distinct models can yield more robust and reliable predictions. For instance, an ensemble of models might predict inflation by incorporating inputs from GDP, unemployment rates, and consumer spending trends. This results in a more comprehensive prediction than any single model could provide.

Hybrid models, which integrate traditional econometric algorithms with AI and machine learning methodologies, represent another instrumental innovation in economic forecasting. Such models leverage the relative strengths of the two approaches: they conserve the interpretability and theoretical foundation typical of the previous approach while gaining from the predictive power of AI. In the case of time-series forecasting, there has been an improvement in the use of ARIMA-LSTM hybrid models. While ARIMA may capture the linear components, LSTM models nonlinear and longer-term dependencies, thus allowing them a better forecast than a single model. Similarly, factor models combined with machine learning can extract latent factors out of big data and use AI to predict future trends based on these factors.

5.1 Implication for Policymakers and Economists:

Better Accuracy and Timeliness in Economic Forecasts: One of the most immediate benefits for policymakers is the significant improvement in the accuracy and timeliness of economic forecasts enabled by AI-driven models. Traditional econometric methods of multiple regressions falter in handling complexities and nonlinear relationships inherent in financial data. They depend on limited leading or lagging indicators such as quarterly GDP reports or unemployment figures. By contrast, AI can handle vast volumes of data with complexities and intricacies and process real-time data from social media, satellite imagery, and financial transactions.

Informed Policy Formulation and Scenario Simulation: Another vital implication of AI-driven economic forecasting is improving policy formulation based on more sophisticated scenario analysis and simulations. Based on historical data, traditional policy analysis models are usually static and build predictions about the effect of interventions, such as tax rate cuts or interest rate changes. Such models may not be capable of predicting rapid changes in conditions or considering more complex nonlinear interactions among economic variables. In particular, AI can precisely model various scenarios using reinforcement learning and machine learning-driven simulations. These models allow policymakers to contextualize the many policy measures in real-time, factoring in dynamic feedback loops and changing conditions. For example, it can generate a simulated version of a fiscal stimulus package's results under varying scenarios of high inflation or supply chain crises worldwide; policymakers may want to weigh the trade-offs before the policy.

Targeted and Proactive Interventions in Policy: AI-driven forecasting facilitates more targeted and proactive policy intervention, which is helpful in such sector-specific issues or regional disparities in economic performance. Working out the granular data of the situation at the industry, regional, or household level, AI can pinpoint specific areas of weakness or growth that might go unnoticed through broader economic metrics. For instance, during a recession, AI models can help policymakers identify sectors or regions more likely to experience widespread job losses and concomitant drops in consumer spending. Rather than pursuing across-the-board national policies, governments might adopt targeted interventions, tax relief targeted to particularly vulnerable areas, or sector-specific stimulus packages to those most in need. AI can probably identify inflationary pressures on specific sectors, like housing or energy, so the monetary authorities may use monetary policy with a scope to take care of inflation without stifling growth in other sectors.

5.2 Case Studies

5.2.1 AI-Driven Predictions during the 2008 Global Financial Crisis

The 2008 global financial crisis undoubtedly ranks among the worst modern crises in the USA. Traditional economic models failed to anticipate the magnitude and pace of the situation that would lead to such a deep recession, extreme turbulence in global markets, and unparalleled government interventions. In the aftermath of the crisis, Machine Learning Modes were used retroactively to determine how sophisticated algorithms could have enhanced early warnings and decision-making.

The salient application of these technologies was to analyze volumes of financial data on housing market trends, bank lending patterns, and consumer debt levels using machine learning algorithms. Machine learning algorithms such as Support Vector

Machines and Random Forests provided the valuation of the property and concentrative risk in subprime high-risk credits not valued by traditional systems. Retrospectively, If AI models such as ARIMA and SARIMAX existed before 2008, they would have served as early warnings signaling the housing market burst with ample time for regulators and policymakers to take preventive action.

More importantly, AI-powered network analytics probed the interconnectedness of global financial institutions, creating systemic risks characteristic of the economic crisis. By mapping the complex relationships of banks to financial markets, the AI models highlighted contagion potential and the collapse of the interbank lending networks that would not be readily perceivable from traditional models. It is another AI-based approach that purposely shows the importance of real-time systemic risk monitoring in financial markets and shapes regulative policies to inhibit future economic crises. While these AI models have been applied post-crisis, understandings have been developed that call for including machine learning tools within the financial risk management system. This has, in turn, resulted in the cosmos of many financial institutions and central banks adopting AI-driven methods for forecasting to realize better detection and management of risk factors, with early warnings in a better position to flag similar vulnerabilities in the future.

5.2.2 AI in Economic Forecasting during COVID-19

The COVID-19 pandemic became one of the most disruptive events since the Great Depression, in which consumer behavior, labor markets, and global supply chains underwent rapid changes. Central banks and governments had to project the economic consequences of this pandemic and implement policies to limit the damage. In such a period of uncertainty, AI models were crucial in generating real-time insights. Undoubtedly, one of the most significant applications of AI in the pandemic was to track consumer spending and mobility data to anticipate economic activity. Traditional economic indicators, such as GDP or unemployment reports, were issued with significant delays and thus difficult to handle with swift policymaking. AI models used real-time data from various sources, including Google Mobility Reports, credit card transactions, or online retail sales, to estimate the immediate effects of lockdowns and social distancing measures on economic activity. For instance, AI-driven analytics over transactional data showcased acute shrinkage in consumer spending and travel, thus providing real-time insight into the economic contraction much earlier than official reports.

AI models predicted the recovery trajectory of various industries. For instance, Deep learning models would be trained on historical economic data using LSTM networks, predicting how quickly different hospitality and retail sectors would recover once the lockdown measures were eased. These AI-driven forecasts helped governments decide which sectors to focus their financial support on and assisted businesses in formulating their post-pandemic strategy. Besides, AI-driven economic forecasting played a vital role in the healthcare sector in predicting the demand at various levels for medical supplies, hospital capacity, and financial costs for various public health interventions, such as vaccine rollouts. AI models integrated epidemiological data with economic models to run different recovery scenarios based on vaccination rates so governments could allocate resources better.

6. Conclusion

The prime objective of this research project was to explore the efficacy of AI-driven predictive modeling in forecasting US economic trends. This research project involved a time series analysis of three key financial indicators: Most notably, the Consumer Price Index (CPIAUCSL), the Gross Domestic Product (GDP), and the Unemployment Rate (UNRATE). Datasets entailed the Consumer Price Index for All Urban Consumers (CPI) from 1950 to the present, GDP: U.S. Gross Domestic Product (GDP) quarterly, and UNRATE: US Unemployment Rate (UNRATE) from 1950 to the present. These datasets provided valuable insights into the US economy, and this analysis aims to explore trends, seasonality, and relationships between these variables over time. One of the most immediate benefits for policymakers and the U.S. government is the significant improvement in the accuracy and timeliness of economic forecasts enabled by AI-driven models such as the ARIMA and SARIMAX. Another vital implication of AI-driven economic forecasting is improving policy formulation based on more sophisticated scenario analysis and simulations. AI-driven forecasting facilitates more targeted and proactive policy intervention, which is helpful in such sector-specific issues or regional disparities in economic performance.

References

[1] Abu-Jamie, T. N., & Al-Absy, M. S. M. (2024). Advances in AI and Their Effects on Finance and Economic Analysis. The AI Revolution: Driving Business Innovation and Research: 1, 507-523.

[2] Dadhich, M., Pahwa, M. S., Jain, V., & Doshi, R. (2021). Predictive models for stock market index using stochastic time series ARIMA modeling in an emerging economy. In *Advances in Mechanical Engineering: Select Proceedings of CAMSE 2020* (281–290). Springer Singapore.

[3] HASAN, M. R. (2021). The Contribution of Foreign Direct Investment and Its Impact on Economic Growth and Inflation in Bangladesh. *PalArch's Journal of Archaeology of Egypt/Egyptology*, *18*(08), 4070-4088.

[4] Jain, A., Sukhdeve, T., Gadia, H., Sahu, S. P., & Verma, S. (2021, March). COVID-19 prediction using time series analysis. In *2021 International Conference on artificial intelligence and intelligent systems (ICAIS)* (1599-1606). IEEE.

[5] Khan, M. A., Debnath, P., Al Sayeed, A., Sumon, M. F. I., Rahman, A., Khan, M. T., & Pant, L. (2024). Explainable AI and Machine Learning Model for California House Price Predictions: Intelligent Model for Homebuyers and Policymakers. *Journal of Business and Management Studies*, *6*(5), 73-84.

[6] Okeleke, P. A., Ajiga, D., Folorunsho, S. O., & Ezeigweneme, C. (2024). Predictive analytics for market trends using AI: A study in consumer behavior.

[7] Pro-AI-Rokibul. (2024). *-AI-Driven-Predictive-Modeling-of-U.S.-Economic-Trends-Insights-and-Innovations/models/main.ipynb at main · proAIrokibul/-AI-Driven-Predictive-Modeling-of-U.S.-Economic-Trends-Insights-and-Innovations*. GitHub. https://github.com/proAIrokibul/-AI-Driven-Predictive-Modeling-of-U.S.-Economic-Trends-Insights-and-Innovations/blob/main/models/main.ipynb

[8] Manigandan, P., Alam, M. S., Alharthi, M., Khan, U., Alagirisamy, K., Pachiyappan, D., & Rehman, A. (2022). Forecasting natural gas production and consumption in the United States-evidence from SARIMA and SARIMAX models. *Energies*, *14*(19), 6021.

[9] Mehra, S., Aggarwal, S., & Mitra, P. (2024, July). Predictive Analytics and AI-Driven Strategies for Enhanced Cash Flow Forecasting. In Intelligent Systems Conference (pp. 296–315). Cham: Springer Nature Switzerland.

[10] Siami-Namini, S., & Namin, A. S. (2020). Forecasting economics and financial time series: ARIMA vs. LSTM. *arXiv preprint arXiv:1803.06386*.

[11] Zeeshan, M. A. F., Sumsuzoha, M., Chowdhury, F. R., Buiya, M. R., Mohaimin, M. R., Pant, L., & Shawon, R. E. R. (2024). Artificial Intelligence in Socioeconomic Research: Identifying Key Drivers of Unemployment Inequality in the US. *Journal of Economics, Finance and Accounting Studies*, *6*(5), 54-65.

[12] Zong, Z., & Guan, Y. (2024). AI-Driven Intelligent Data Analytics and Predictive Analysis in Industry 4.0: Transforming Knowledge, Innovation, and Efficiency. *Journal of the Knowledge Economy*, 1-40.