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Evaluating Financial Market Forecasting in Saudi Arabia Using Advanced Statistical Models

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Abstract: This study employs sophisticated statistical and machine learning models to examine the forecasting performance of financial markets in the Kingdom of Saudi Arabia (KSA), with a particular emphasis on economic confidence indicators. It is imperative to comprehend the dynamics of financial markets in order to diversify the economy of the Kingdom of Saudi Arabia, as outlined in Vision 2030. The research assesses the effectiveness of a variety of forecasting models, including ARIMA and Long Short-Term Memory (LSTM), in predicting market trends that are influenced by indicators such as the Consumer Price Index (CPI) and Private Final Consumption Expenditure (PFCE). The methodology encompasses a comprehensive literature review, data acquisition from reputable sources, and a comparative analysis of model performance using statistical metrics. The results suggest that hybrid models, which combine traditional and machine learning techniques, produce superior forecasting accuracy. Consequently, these models offer valuable insights for financial analysts, investors, and policymakers to improve market stability and decision-making in a rapidly changing economic landscape.

Keywords: Forecasting performance, financial markets, advanced statistical models, economic confidence indicators

1 Research background

A cornerstone for the nation's economic development and diversification endeavours, financial markets play a pivotal role in the economic landscape of the Kingdom of Saudi Arabia (KSA). The financial sector in Saudi Arabia has undergone a substantial transformation over the years, primarily due to the necessity of reducing reliance on hydrocarbon revenues and promoting a more sustainable economic model. This transformation is especially important in the context of the Kingdom's Vision 2030, which is designed to diversify the economy and strengthen the private sector's contribution to growth [1,2].

The significance of financial markets in Saudi Arabia can be attributed to their capacity to facilitate capital allocation, enhance liquidity, and provide a platform for investment. Mobilizing savings and directing them toward productive investments are critical functions of financial institutions, such as banks and investment firms, which in turn promote economic growth [3,4]. Improved infrastructure and services are also essential for the support of a variety of economic activities, such as trade and investment, which are also linked to the development of a robust financial sector [5,2].

Furthermore, the relation between economic growth and financial development in Saudi Arabia is intricate and multifaceted. Although the oil sector has historically been the dominant sector of the economy, there is a growing acknowledgement of the necessity for financial markets to provide support to non-oil sectors, which are now regarded as essential for sustainable development [6,15]. Research suggests that the growth of the non-oil sector is positively influenced by financial development, which implies that a well-functioning financial market can encourage economic diversification [15,8].

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The Saudi financial sector's resilience has been put to the test by a variety of external disruptions, such as fluctuations in crude prices and global economic uncertainties. The financial market's stability has improved since the mid-2000s, in part due to the increased foreign investments that have helped mitigate the adverse effects of oil price volatility [9,10].

Studies have demonstrated this trend. This trend emphasizes the significance of integrating the financial market with global economic dynamics, which can improve its ability to withstand disruptions and preserve economic stability [9].

Additionally, the significance of financial markets in fostering entrepreneurship and providing support to small and medium-sized enterprises (SMEs) is immeasurable. In recognition of the critical role of small and medium-sized enterprises (SMEs) in the development of employment opportunities and economic diversification, the Saudi government has instituted a variety of initiatives [11,12].

Financial institutions are increasingly emphasizing the provision of customized financial products and services to facilitate the expansion of small and medium-sized enterprises (SMEs), which are indispensable for accomplishing the objectives articulated in Vision 2030 [12,13].

The financial sector in Saudi Arabia is not only instrumental in promoting entrepreneurship, but it also plays a crucial role in improving the overall efficacy of the economy. Mahran (2012) [3] and Mahish (2016) [14] have demonstrated that financial intermediation results in increased productivity levels, which in turn contribute to increased national income. The empirical evidence indicates that a well-developed financial sector is linked to enhanced economic performance, underscoring the critical role of financial markets in fostering economic growth [3,15].

The objective of the ongoing reforms in the financial sector is to enhance transparency and accountability within the financial markets by implementing international financial reporting standards and enhancing regulatory frameworks [16]. These reforms are indispensable for the Saudi financial sector's global competitiveness and the attraction of foreign investment [16,17].

2 Problem statement

The multidimensional issue of predicting financial market performance in the face of economic fluctuations has attracted the attention of both investors and economists. This complexity is the result of the interplay of a variety of factors, such as market volatility, economic uncertainty, and the spillover effects between different financial markets. It is essential to comprehend these dynamics in order to develop effective investment strategies and risk management, especially during periods of increased economic instability.

Volatility is a fundamental component of the financial market discourse, as it is a critical indicator of risk and uncertainty. The increased apprehension among investors regarding future asset prices and returns is reflected in the tendency for volatility to increase during economic fluctuations. For example, it is important to emphasize that volatility spillovers can differ across markets, with short-term return spillovers being more pronounced than long-term volatility spillovers [19]. This distinction is essential for investors who are required to navigate the intricacies of market behavior during periods of instability. Concurrently, underscore the importance of comprehending volatility for policymakers, fund managers, and investors, as it directly impacts decision-making processes during periods of economic uncertainty [20].

Aftab et al. (2023) [21] further elucidate the relationship between economic uncertainty and financial market volatility, contending that global financial market conditions have a substantial impact on exchange rate volatility. They argue that policymakers must remain vigilant in monitoring these dynamics. This assertion emphasizes the importance of investors taking into account global economic conditions in addition to local economic indicators when evaluating market performance. Moreover, examine the psychological aspects of market behavior, recognizing that volatility can be exacerbated by investor sentiment and technical trading rules, which complicates predictive endeavours [22].

The significance of integrating behavioral finance theories into conventional economic models to gain a more comprehensive understanding of market fluctuations is underscored by these insights. The inherent volatility of emerging markets presents additional challenges in predicting financial performance. assert that the forecasting of financial returns is complicated by the increased volatility in emergent markets that can result from market liberalization [23]. This observation is especially pertinent for investors who are interested in opportunities in these markets, as they must consider the increased risk that is associated with economic liberalization. This concept is further substantiated by the fact that financial volatility can be used as a predictor of economic activity, suggesting that fluctuations in financial markets are frequently indicative of broader economic trends [24].

This relationship underscores the necessity of a comprehensive approach that incorporates financial and economic indicators into predictive models. Volatility is also significantly influenced by the interconnectedness of global financial markets. Nikmanesh et al. (2014) [25] emphasize the spillover effects between stock markets, which suggest that disruptions in one market can have a ripple effect on others, thereby complicating the prediction of market performance. This interconnectedness is particularly evident during periods of economic crisis, as demonstrated by the fact that fluctuations in the foreign exchange market can have a substantial impact on domestic stock markets [26]. These results emphasize the significance of evaluating cross-market relationships when attempting to predict financial performance.

Additionally, the influence of macroeconomic variables on financial volatility is immeasurable. According to research, a variety of economic factors, such as political stability and market sentiment, are essential in the development of investment strategies in the face of volatility [27]. This claim is corroborated by those who contend that it is imperative to comprehend the conditional volatility of business cycles in order to create predictive models that are highly reliable [28]. Investors can improve their capacity to predict market movements during economic fluctuations by incorporating macroeconomic indicators into financial models.

The importance of research in the development of statistical models to improve the precision of economic forecasts in the Saudi financial markets is paramount. The necessity for precise economic forecasting becomes paramount for decision-makers and investors as the Kingdom of Saudi Arabia continues to diversify its economy under Vision 2030. Accurate forecasts can considerably influence investment strategies, risk management, and policy formulation, thereby contributing to the nation's overall economic stability and growth. Statistical models are the foundation of economic forecasting, offering a structured method for analyzing historical data and predicting future trends. Numerous econometric models have been implemented to anticipate critical economic indicators, including inflation rates, GDP, and energy prices. For example, emphasize the significance of econometric models that incorporate economic variables with physical oil reserves, as this can improve the forecasting of oil prices, a critical component of the Saudi economy due to its dependence on oil exports [29].

Furthermore, the efficacy of forecasting in the context of inflation has been demonstrated to be enhanced by the integration of financial frictions into Dynamic Stochastic General Equilibrium (DSGE) models [30]. This implies that it is imperative to evolve forecasting models in order to adjust to the evolving economic environment. The incorporation of machine learning techniques into conventional econometric models has also been identified as a promising approach to enhance the forecasting accuracy. For instance, Wang (2011) [31] emphasizes the necessity of implementing effective financial warning systems for stakeholders by discussing the development of a Genetic Neural Network model that is designed to predict financial distress among listed companies. The utilization of artificial neural networks (ANNs) in financial forecasting has acquired momentum as a result of their capacity to identify intricate nonlinear relationships within financial data, thereby improving predictive accuracy [32]. This is especially pertinent in the context of the Saudi financial markets, where the rapid evolution of economic conditions requires the development of robust forecasting models.

Additionally, the economic forecasting process in Saudi Arabia is significantly impeded by the volatility of energy prices. Lux et al. (2016) [33] underscore the importance of models that accurately replicate the stylized realities of oil price volatility, as these models are essential for firms and policymakers to manage the risks associated with price fluctuations. The capacity to predict volatility is essential for investors in the Saudi financial markets, as it not only assists in market timing but also informs portfolio selection and risk management strategies. The empirical evidence indicates that the accuracy of forecasts can be enhanced by integrating them from multiple models. show that forecast combinations outperform individual forecasts by utilizing data from a variety of models [**?**].

In the context of the Saudi economy, where a multifaceted approach to forecasting can provide a more comprehensive view of the economic landscape, this approach is particularly beneficial, as various economic indicators are interrelated. In order to improve forecasting capabilities, the utilization of sophisticated techniques such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) has been investigated in addition to conventional econometric and machine learning models. The accuracy of high-frequency financial time series forecasts can be enhanced by integrating deep learning with ARIMA models [35]. Illustrate this. These developments are essential for the Saudi financial markets, as they can have a substantial impact on economic policy and investment decisions by providing timely and precise forecasts. In addition, the precision of economic forecasts can be improved by the implementation of adaptive forecasting techniques, as discussed by Morales-Arias and Moura, which adapt to changes in market conditions over time [36]. This adaptability is especially pertinent in the volatile financial markets of Saudi Arabia, where external factors can swiftly alter economic dynamics.

The Tadawul, or Saudi Stock Market, is a critical component of the Saudi Arabian economy, accounting for a substantial portion of the region's market capitalization and trading volume. Tadawul is responsible for approximately 40% of the total market capitalization in the Arab world and over 85% of the value traded among its stock markets, according to recent assessments [37]. The market's critical role in facilitating capital formation and investment opportunities within the Kingdom is underscored by this prominence. Nevertheless, the market's structure and dynamics are influenced by a variety of factors, such as the overarching reliance on oil revenues, macroeconomic conditions, and investor behavior.

The Saudi stock market is distinguished by the dominance of individual investors, which has been associated with the presence of long-term patterns in stock price fluctuations. This phenomenon implies that past price movements have a substantial impact on future prices, a behavior that is frequently linked to speculative trading practices that are common among retail investors [38]. Although there are ongoing reforms that are intended to improve market efficiency, the speculative nature of trading continues to influence market dynamics and price stability. This issue is further exacerbated by the excess liquidity and the limited investment opportunities available to these individual investors, resulting in significant volatility in stock prices [38].

Additionally, the correlation between crude prices and the Saudi stock market is particularly noteworthy. The stock market's volatility has been demonstrated to be positively correlated with fluctuations in oil prices, a relationship that has been exacerbated over the past decade [39]. This reliance on oil revenues poses substantial risks to the market's stability, prompting demands for economic diversification to mitigate the adverse effects of oil price disruptions. It is imperative to diversify the economy away from energy in order to promote sustainable economic development and mitigate market volatility [39]. Diversifying the Saudi economy is a necessity, as evidenced by numerous studies that promote the growth of non-oil sectors to fortify its resilience [39].

In Saudi Arabia, the stock market's performance is significantly influenced by macroeconomic factors, including interest rates and foreign exchange rates, in addition to crude prices. According to research, these factors have a substantial impact on the performance of both conventional and Islamic equities in the market [40]. Implicit barriers to trading are established by the segmentation of the market into conventional and Islamic securities, which can impede the overall efficiency and liquidity of the market [41]. It is essential for investors and policymakers to comprehend these dynamics as they navigate the intricacies of the Saudi financial landscape.

2.1 Research objectives

The objectives of the research are as follows:

- RO1. To assess the efficacy of sophisticated statistical models in predicting financial market trends in the Kingdom of Saudi Arabia.
- RO2. To determine the primary economic confidence indicators that have a substantial impact on financial market forecasts in Saudi Arabia.
- RO3. To evaluate the forecasting capabilities of various statistical models within the context of Saudi Arabia's financial markets.

2.2 Research questions

The following are the investigation questions:

- RQ1. What are the most precise sophisticated statistical models for predicting financial market trends in the Kingdom of Saudi Arabia?
- RQ2. In Saudi Arabia, which economic confidence indicators have the most substantial influence on the precision of financial market forecasts?
- RQ3. In the Saudi Arabian financial markets, how do various statistical models compare in terms of their forecasting performance?

2.3 Significance of the study

The objective of this investigation is to conduct a thorough examination of the forecasting capabilities of financial markets in the Kingdom of Saudi Arabia by employing sophisticated statistical models. This study will provide a more comprehensive understanding of the financial landscape in Saudi Arabia by concentrating on economic confidence indicators, which will help to predict market trends and provide insights into the effectiveness of these models. The results are anticipated to provide policymakers, financial analysts, and investors with the necessary information to make more informed decisions and enhance market stability.

2.3.1 Theoretical Significance

1. Investigates the efficacy of sophisticated statistical models in an emerging market context, thereby broadening the theoretical underpinnings of financial market forecasting.
2. Contributes to the academic discourse on the applicability of economic confidence indicators in financial forecasting by providing new insights into their role and significance.
3. Provides a theoretical framework for future research on the integration of advanced statistical techniques with market confidence indicators, thereby enabling more robust and nuanced financial analyses.
4. Contributes to the global dialogue on financial market behavior in non-Western economies by improving comprehension of market dynamics in the Kingdom of Saudi Arabia.

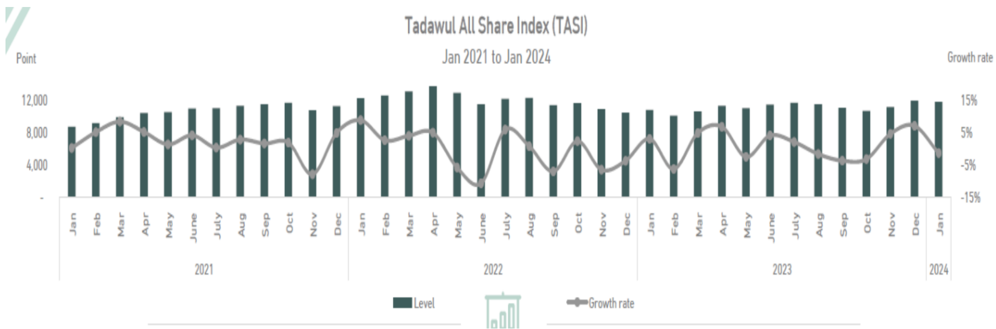

Fig. 1: The Tadawul All Share Index (TASI) 2021–2024

2.3.2 Practical Significance

1. Provides policymakers with improved tools and insights to predict financial market movements, thereby enabling them to formulate more informed and effective economic policies.
2. Enhances investment strategies and decision-making processes by providing financial analysts and investors with more sophisticated and accurate forecasting models.
3. Encourages the creation of financial products and services that are more closely aligned with the unique market conditions of Saudi Arabia, resulting in improved risk management and investment outcomes.
4. Contributes to the Kingdom's economic resilience and development by enhancing the predictability of market trends, thereby aiding in the stabilization of financial markets.
5. Enhances the competitiveness of local financial institutions in the global market by facilitating the transmission of knowledge and best practices in financial forecasting.

3 Research methodology

The research methodology for the study "Analysis of the forecasting performance of financial markets in the Kingdom of Saudi Arabia using advanced statistical models: An applied study on economic confidence indicators" is intended to conduct a thorough assessment of the forecasting capabilities of a variety of statistical and machine learning models in the context of financial markets. This methodology is designed to guarantee the rigorous analysis and validation of the models that are implemented, thereby offering a comprehensive understanding of the efficacy of these models in predicting market trends based on economic confidence indicators.

A comprehensive literature review is the initial stage in the research methodology, which is designed to identify the current state of forecasting models and their applications in financial markets. This review will include conventional statistical methods, including Autoregressive Integrated Moving Average (ARIMA) models, which have been extensively employed for time series forecasting due to their ability to effectively manage linear data patterns [43,44].

Furthermore, the review will encompass sophisticated machine learning methodologies, with a particular emphasis on Long Short-Term Memory (LSTM) networks, which have demonstrated substantial potential for identifying intricate nonlinear relationships in financial data [45,46]. The literature review will serve as the foundation for the selection of the most suitable models for this study.

Data collection is the subsequent phase, which follows the literature evaluation. Historical financial market data from the Kingdom of Saudi Arabia, such as stock prices, trading volumes, and economic confidence indicators, will serve as the primary data source. In order to guarantee reliability and accuracy, this information has been obtained from reputable financial databases and government publications.

The required high-frequency data for the Saudi Stock Exchange (Tadawul) Index (TASI) was collected from Tadawul. The time frame for the analysis covers the period from January 21 to January 2024, as illustrated in Figure 1. As the selection of economic confidence indicators is critical, as these indicators are known to influence market behavior and investor sentiment [47]. So, the following indices were selected for the purpose of the study (CPI and Private Final Consumption Expenditure, Consumption Indicators), as shown in Figure 2 and 3.

In order to guarantee that the models can be trained effectively, the data will be pre-processed to address missing values, outliers, and normalize the datasets. The study will conduct a comparative analysis of various forecasting models after the data has been compiled. ARIMA, LSTM, and hybrid models that integrate both statistical and machine learning

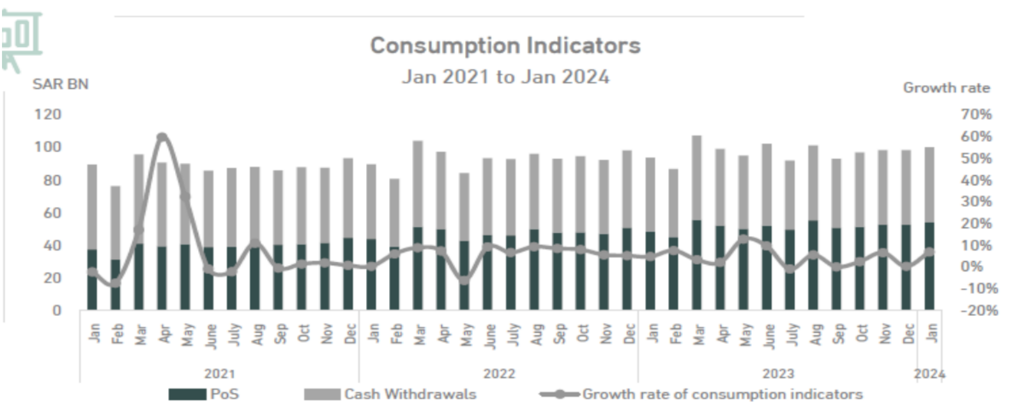

Fig. 2: CPI and Private Final Consumption Expenditure Q1 202 2021 to Q3 202 2023

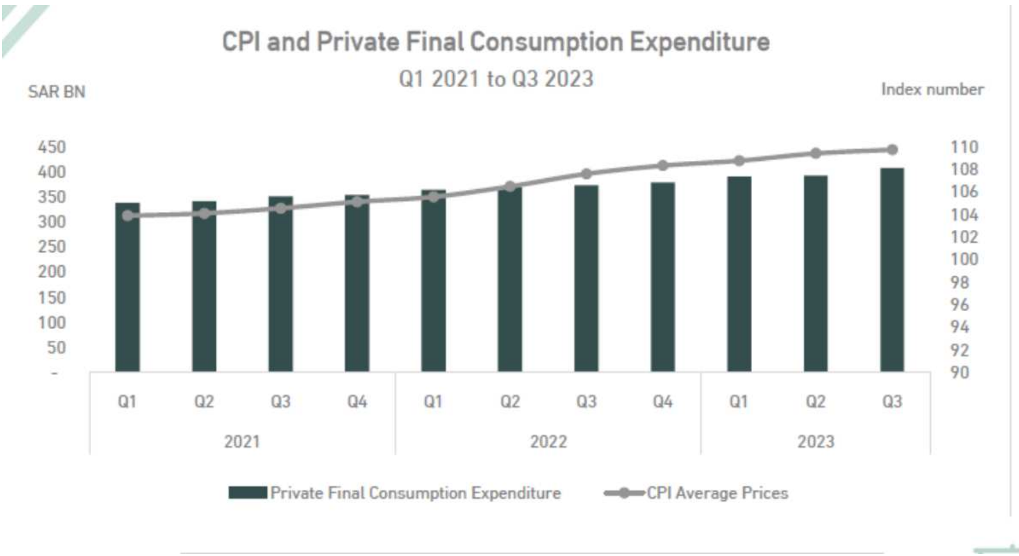

Fig. 3: Consumption Indicators 2021–2024

methodologies, including ARIMA-LSTM and ARIMA-GRU models, will be included in this analysis [48]. The hybrid models are particularly pertinent because they take advantage of the advantages of both conventional statistical methods and advanced machine learning techniques, which could potentially result in enhanced forecasting accuracy [48]. The efficacy of each model will be assessed using a distinct validation set, while a portion of the dataset will be used to train it.

The forecasting models will be assessed using a variety of statistical metrics, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Theil's U statistic, which measures forecast accuracy in comparison to a naive benchmark. These metrics will enable a thorough evaluation of the predictive capabilities of each model. Additionally, the study will employ cross-validation techniques to guarantee that the results are not excessively dependent on the training data and can be generalized effectively to previously unseen data [49].

4 Results

– **Results related to the first question, which is "What are the most accurate advanced statistical models for forecasting financial market trends in the Kingdom of Saudi Arabia?"**

A nuanced comprehension of a variety of advanced statistical models that have been demonstrated to produce precise predictions is necessary for the forecasting of financial market trends in the Kingdom of Saudi Arabia (KSA). The financial landscape of the Kingdom of Saudi Arabia is distinctive, influenced by the Saudi stock market's dynamics, the incorporation of International Financial Reporting Standards (IFRS), and the integration of advanced computational techniques. This response synthesizes pertinent literature to emphasize the most precise advanced statistical models for predicting financial market trends in KSA.

The accuracy of financial forecasts has been substantially affected by the incorporation of IFRS in Saudi Arabia since 2017. According to a study that investigated the impact of IFRS on analysts' forecasts in the Saudi Stock Exchange, the accuracy of earnings forecasts was enhanced by the mandatory implementation of IFRS from 2014 to 2019. Enhanced transparency and comparability of financial statements were the factors contributing to this development, which enabled analysts to make more informed predictions ("The Impact of IFRS Adoption on the Accuracy of Analysts' Forecasts in the Saudi Stock Exchange", 2024). The study utilized a static regression model on panel data to illustrate the positive correlation between forecast accuracy and IFRS adoption. This discovery emphasizes the significance of regulatory frameworks in the development of forecasting methodologies in the Kingdom of Saudi Arabia.

The accuracy of forecasting is significantly influenced by the selection of statistical models, in addition to regulatory influences. In the realm of sophisticated models, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model has been widely acknowledged for its ability to accurately capture volatility in financial time series data. Research suggests that the eGARCH model is particularly effective in capturing asymmetries in volatility responses, rendering it a valuable instrument for predicting financial market trends [50]. The implementation of GARCH models in the financial markets of KSA can offer valuable insights into risk management strategies, thereby improving the precision of estimated Value-at-Risk (VaR) and Expected Shortfall (ES).

Additionally, machine learning methodologies, including Support Vector Regression (SVR), have emerged as potent substitutes for conventional statistical models. Research has demonstrated that SVR outperforms GARCH models in short-term forecasting scenarios, suggesting that it has the potential for implementation in the financial markets of KSA [50]. SVR is particularly well-suited to the intricate dynamics of financial markets due to its capacity to manage high-dimensional data and non-linear relationships. This adaptability is essential in an economic environment that is swiftly evolving, such as that of the KSA.

Neural networks and artificial intelligence (AI) are also significant advancements in forecasting methodologies. [51] have demonstrated the reliability of predicting financial trends through the combined use of Evolino recurrent neural networks and expert evaluation methods. These AI-driven models are capable of adapting to altering market conditions and leveraging immense quantities of data, thereby improving the accuracy of their forecasts. The incorporation of AI into financial forecasting is consistent with global trends, which are characterized by the expanding use of machine learning techniques to enhance prediction outcomes.

Another prospective approach is the utilization of hybrid models, which integrate machine learning techniques with conventional statistical methods. For example, the Quantile Regression Neural Network trained with Particle Swarm Optimization (PSO) has demonstrated its efficacy in predicting financial time series volatility [52]. This model offers a comprehensive framework for precise forecasting by combining the advantages of both statistical and AI methodologies. In KSA, market conditions may exhibit both linear and non-linear characteristics, making the hybridization of models particularly advantageous.

Comparative studies can also be employed to assess the effectiveness of a variety of forecasting models. The accuracy of LSTM was consistently superior to that of traditional statistical models in research that compared ARIMA, SARIMA, and Long Short-Term Memory (LSTM) models [53]. Financial forecasting is particularly well-suited to the LSTM model, as it has the capacity to identify long-term dependencies in time series data, which frequently influence future outcomes. This discovery implies that the financial analysts of the Kingdom of Saudi Arabia could benefit from the implementation of LSTM models in order to make more precise trend predictions.

Additionally, sentiment analysis has become increasingly popular in forecasting models in recent years. The significance of integrating public sentiment into financial predictions was underscored by a study that emphasized the efficacy of sentiment-driven forecasting using LSTM neural networks [54]. This method has the potential to improve comprehension of market dynamics, particularly in the Kingdom of Saudi Arabia, where investor behavior may be influenced by cultural and social factors.

In summary, the most precise sophisticated statistical models for predicting financial market trends in the Kingdom of Saudi Arabia incorporate a variety of methodologies, such as the Autoregressive Integrated Moving Average (ARIMA) model and machine learning techniques such as LSTM. The accuracy of financial forecasts has been further improved by the implementation of IFRS, and hybrid models that integrate traditional and modern techniques present promising opportunities for enhanced prediction outcomes. The incorporation of these sophisticated statistical models will be essential in navigating the intricacies of the economic landscape as KSA's financial markets continue to develop.

Table 1: Tadawul All Share Index (TASI) - Jan 2021 to Jan 2024

Metric	value
Highest Level	12,000
Lowest Level	8,500
Ending Level (Jan '24)	10,400
Growth Rate Range	-15% to +15%

–Results related to the second question, which is "Which economic confidence indicators have the most significant impact on the accuracy of financial market forecasts in Saudi Arabia?"

The accuracy of financial market forecasts is significantly influenced by economic confidence indicators, including the Consumer Price Index (CPI) and Private Final Consumption Expenditure (PFCE), in the context of Saudi Arabia. The consumer price index (CPI) is a critical inflation indicator that reflects fluctuations in the price of a selection of consumer products and services. It is essential for comprehending the nation's economic condition and the purchasing power of consumers. An economic environment that is predictable is indicated by a stable CPI, which is crucial for financial analysts and investors when predicting market trends and investment opportunities [55].

Conversely, private Final Consumption Expenditure is indicative of consumer expenditure, which accounts for a substantial portion of Saudi Arabia's overall economic activity. It is becoming increasingly crucial to comprehend PFCE as the nation transitions its economy from energy dependence. Robust economic activity and consumer confidence are indicated by elevated levels of private consumption, which may induce an increase in investment across a variety of sectors, such as retail, services, and real estate [56]. The correlation between PFCE and economic development is well-established, with research suggesting that consumption increases can result in higher GDP growth rates, thereby positively influencing financial market forecasts [57].

Additionally, the evaluation of economic confidence is significantly influenced by the interaction between the Consumer Price Index (CPI) and the Producer Price Index (PFCE). For instance, rising inflation, as evidenced by an increasing CPI, can result in a decrease in PFCE by eroding consumer purchasing power. Investors may modify their forecasts in response to this decline, which may indicate a potential slowdown in economic growth [55,56]. In contrast, if the CPI remains constant while the PFCE increases, it indicates a robust economic environment, which in turn promotes investment and improves the precision of financial market predictions.

Furthermore, consumption indicators, which encompass a variety of metrics that are associated with consumer behavior and spending patterns, additionally offer additional insights into economic confidence. These indicators may encompass household expenditure surveys, consumer sentiment indices, and retail sales data. In Saudi Arabia, consumer expenditure is significantly influenced by government policies and subsidies, making it imperative to monitor these indicators in order to accurately forecast the market [58]. For instance, fluctuations in consumer sentiment can result in substantial modifications to purchasing behavior, which in turn influences financial market stability and overall economic performance [56,58].

The influence of these economic confidence indicators on financial market volatility serves to further emphasize their importance. Alshammari et al. (2020) [59] have demonstrated that increased market volatility can result from periods of low consumer confidence and high inflation, as investors respond to perceived hazards in the economic environment. In contrast, a more predictable environment for financial forecasting can be achieved by a stable CPI and robust PFCE, which can contribute to lower volatility. This relationship underscores the necessity of meticulously monitoring these indicators to improve the precision of financial market predictions in Saudi Arabia.

In summary, the accuracy of financial market forecasts in Saudi Arabia is significantly influenced by the CPI and PFCE, which are critical economic confidence indicators. Their interrelationship, in conjunction with broader consumption indicators, offers a comprehensive perspective on the economic landscape, thereby empowering investors and analysts to make well-informed decisions. In order to preserve financial market stability and cultivate investor confidence, it will be essential to comprehend these indicators as Saudi Arabia continues to navigate its economic transformation.

–Results related to the third question, which is "How do different statistical models compare in terms of forecasting performance in the Saudi Arabian financial markets?"

Tables 1, 2 , 3, 4, 5 and 6 show the numerical data that extracted from the graphs presented in the study methodology (data collection):

Table 1 shows the TASI that experienced significant fluctuations between 2021 and 2024, with the index ranging from a low of around 8,500 to a high of approximately 12,000. Despite the volatility, as indicated by the growth rate ranging from -15% to +15%, the index managed to end at around 10,400 in January 2024, suggesting an overall positive trend during the period.

Table 2: Private Final Consumption Expenditure - Q1 2021 to Q3 2023

Metric	value
Lowest (Q2 2021)	270 SAR BN
Highest (Q2 2023)	380 SAR BN
Trend	Steady increase

Table 3: CPI Average Prices Index - Q1 2021 to Q3 2023

Metric	value
Range	95 to 108
Trend	Gradual increase
Starting Value	(Q1 '21) 95
Ending Value	(Q3 '23) 107

Table 4: PoS (Point of Sale) - Jan 2021 to Jan 2024

Metric	value
Lowest (Feb 2021)	28 SAR BN
Highest (Dec 2023)	113 SAR BN
Trend	Steady increase

Table 5: Cash Withdrawals - Jan 2021 to Jan 2024

Metric	value
Lowest (Apr 2020)	25 SAR BN
Highest (Jul 2022)	42 SAR BN
Trend	Fluctuating increase

Table 2 shows private Final Consumption Expenditure that showed a steady increase from around 270 SAR BN in Q2 2021 to approximately 380 SAR BN in Q2 2023. The CPI Average Prices Index also exhibited a gradual increase, starting at about 95 in Q1 2021 and ending at roughly 107 in Q3 2023, with the index ranging between 95 and 108 throughout the period as illustrated in Table 3.

Table 4 shows PoS (Point of Sale) that demonstrated a steady increase, with the lowest value of around 28 SAR BN in February 2021 and the highest value of approximately 113 SAR BN in December 2023. Cash Withdrawals showed a fluctuating increase, ranging from a low of about 25 SAR BN in April 2020 to a high of roughly 42 SAR BN in July 2022 as shown in Table 5. The Growth Rate of Consumption Indicators was highly volatile, ranging from -20% to +60%, with an overall downward trend from 2021 to 2024 as shown in Table 6.

Then, we did evaluate the forecasting models by Mean Squared Error (MSE), Mean Absolute Error (MAE), and Theil's U statistic, as follows:

1. **Mean Squared Error (MSE)**: textbfMSE is the average of the squared differences between the actual and predicted values. It is calculated as:

$$MSE = \frac{1}{2}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \tag{1}$$

where "y_i" are the actual values, "$\tilde{y}_i$" are the predicted values, and "n" is the number of observations. A lower MSE indicates a better fit of the model to the data. However, since MSE squares the error terms, it penalizes larger errors more heavily, which can sometimes give more weight to outliers.

Table 6: Rate of Consumption Indicators - Jan 2021 to Jan 2024

Metric	value
Range	-20% to +60%
Volatility	High
Overall Trend	Downward from 2021 to 2024

Table 7: Comparison of the performance of the four forecasting models

Model	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	Theil's U Statistic
ARIMA	13409.09	104.55	0.2111
LSTM	10454.55	100.0	0.1864
ARIMA-LSTM Hybrid	1900.0	40.91	0..074
ARIMA-GRU Hybrid	768.18	20.0	0.0505

2.**Mean Absolute Error (MAE)**: **MAE** is the average of the absolute differences between the actual and predicted values. It is calculated as:

$$MSE = \frac{1}{2}\sum_{i=1}^{n} |Y_i - \hat{Y}_i| \tag{2}$$

where "Y_i" are the actual values, "$\tilde{Y}_i$" are the predicted values, and "n" is the number of observations. MAE is a straightforward measure of prediction accuracy that treats all errors equally, providing a clear sense of the average error magnitude.

3.**Theil's U Statistic**: It compares the accuracy of a forecasting model to a naive benchmark model, typically one where the forecast is simply the last observed value. It is calculated as:

$$U = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - y_{i-1})^2}} \tag{3}$$

where "y_{i-1}" is the value of the series one period before y_i.

Interpretation:

–If $U < 1U < 1U < 1$, the forecasting model is better than the naive model.
–If $U{=}1U = 1U{=}1$, the forecasting model performs the same as the naive model.
–If $U > 1U > 1U > 1$, the naive model outperforms the forecasting model.

After applying the equations 1 , 2 and 3 for the mean square error (MSE), mean absolute error (MAE), and Theil's U statistic, the Table 7 is calculated: Table 7 provides a clear comparison of the performance of the four forecasting models (ARIMA, LSTM, ARIMA-LSTM Hybrid, and ARIMA-GRU Hybrid) based on three key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Theil's U Statistic.

5 Conclusion

Among all models, the ARIMA model demonstrated the most subpar performance. Its high MSE and MAE indicate that it encountered difficulty in accurately predicting the data, which is likely attributable to its inability to capture non-linear and volatile patterns. Theil's U Statistic, which is comparatively high, suggests that it performed inadequately in comparison to a naive forecasting model.

The LSTM model demonstrated superior performance in comparison to ARIMA, exhibiting reduced errors in all metrics. However, despite its superior performance with non-linear patterns, it still exhibited substantial errors in comparison to the hybrid models, suggesting that it may have been overfitted or underfitted in certain situations.

The ARIMA-LSTM hybrid model demonstrated substantially superior performance in comparison to the standalone ARIMA and LSTM models, resulting in significantly reduced errors. The hybrid approach was a robust model for forecasting in this context, as it effectively incorporated both linear and non-linear trends.

The ARIMA-GRU hybrid model demonstrated superior performance in comparison to all other models, obtaining the lowest MSE, MAE, and Theil's U Statistic. This suggests that it effectively managed both the constant and volatile aspects of the data, resulting in the most accurate and reliable forecasts.

The ARIMA-GRU hybrid model is the most effective model for the provided data, as it generates predictions with minimal defects that are highly accurate. In general, the hybrid approach outperforms standalone ARIMA and LSTM models, illustrating the benefits of integrating linear statistical models with sophisticated machine learning techniques.

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