

# Enhancing Saudi Investment Decisions Using Artificial Intelligence (AI) and Market Cycles

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**Abstract:** The study investigates the integration between the advanced Arabic transformer-based sentiment models, namely: AraBERTv2, CAMEL- BERTDA, MARBERTv2 and market cycle detection (FFT, DPO, Hurst exponent). To enhance the predictive analytics of the Tadawul All Share Index (TASI) in Saudi Arabia, an important dataset of Arabic financial tweets and daily TASI price data are adopted to assess the effectiveness of ensemble sentiment models and cycle-based approaches for market timing and volatility forecasting. The results indicate that, while BERT-based sentiment models show robust in-sample classification accuracy, the predictive power of TASI returns is limited and unstable over time. In particular, the findings are in line with previous studies associated with the sentiment of the Saudi market. In contrast, cycle detection and Hurst exponent analysis consistently indicate actionable trading windows and confirm persistent, nonrandom market dynamics ( $H > 0.6$ ), challenging the efficient market hypothesis. In general, the findings highlight the superiority of hybrid cycle-based analytics over sentiment-only models for tactical investment strategies in the Saudi market. Furthermore, the results provide important insights for investors and policy makers and offer a novel and interesting framework for AI-driven financial analytics in emerging markets.

**Keywords:** Sentiment Analysis, Market Cycles, Artificial Intelligence, TASI, Tactical Trading

**JEL Classification:** G14, G15, G41, C45, C55

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## 1. Introduction

Financial forecasting has been reshaped by the growth of alternative data and natural language processing (NLP), with social media platforms— particularly Twitter/X—emerging as key sources of real-time investor sentiment signals [Xu et al., 2024, Zheng et al., 2024]. Such developments challenge traditional models that treat prices as purely fundamentally driven and instead emphasise the influence of mood, attention, and digital news flows in the formation of asset prices [Hung, 2021]. In this context, Saudi Arabian equity market, represented by the Tadawul All Share Index (TASI) [Tadawul All Share Index], is characterised by high retail participation, pronounced liquidity cycles, and the coexistence of conventional and Shariah-compliant indices [Hanif et al., 2025].

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Indeed, the rapid digital transformation and the strong adoption of Twitter in Saudi Arabia provide a particularly rich setting to study sentiment-driven price dynamics, yet the application of advanced transformer-based Arabic NLP models, such as AraBERT and MARBERTV2, to real-time sentiment prediction in this market remains limited. In the same vein, cycle and fractal-based methods, including the Fast Fourier Transform (FFT), the Hurst exponent, and the De-trended Price Oscillator (DPO), offer powerful frameworks for modeling the persistent, cyclical, and memory-driven nature of Saudi stock returns—features that traditional efficient market frameworks do not fully capture [Aslam et al., 2023].

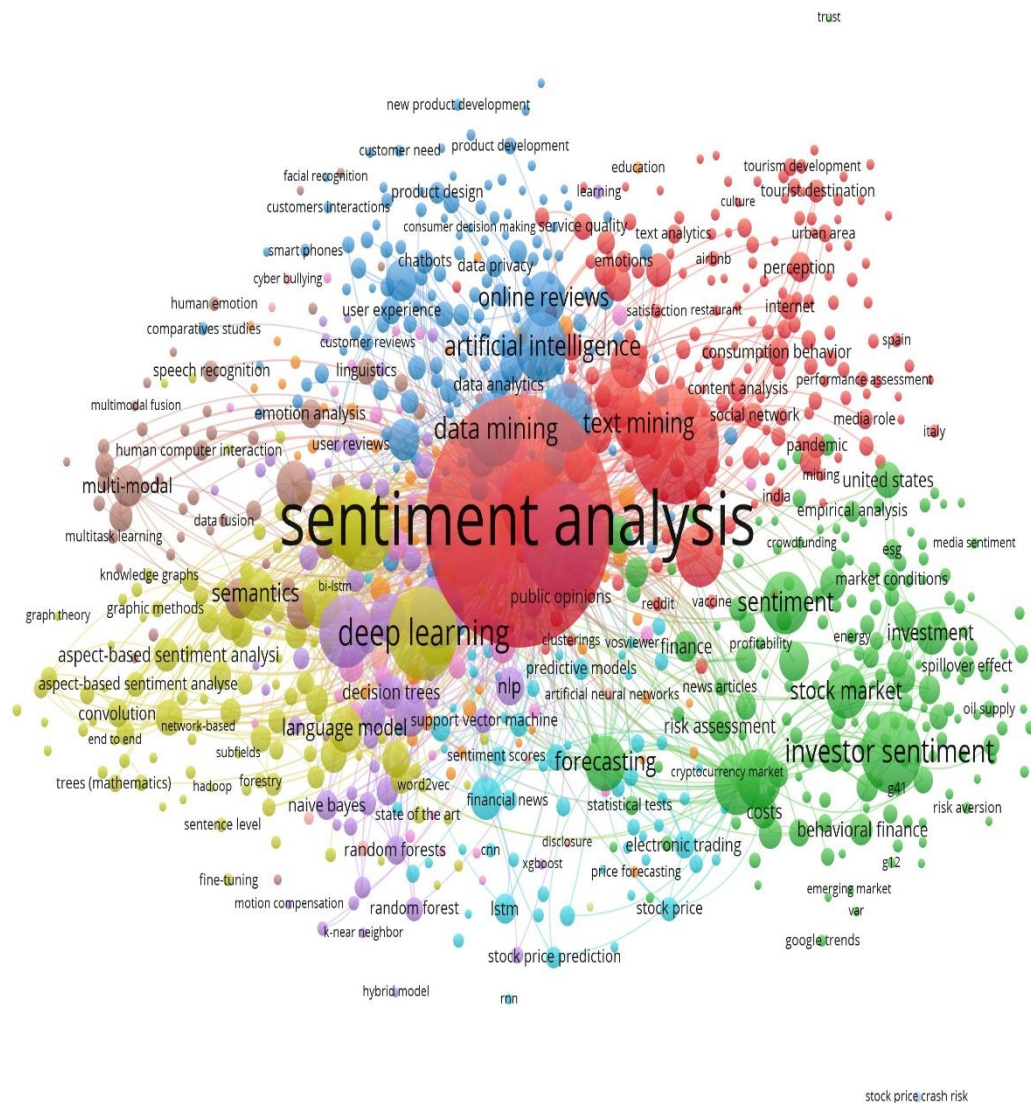
Despite the growing interest in these techniques, no existing research has systematically integrated Arabic BERT-based sentiment indicators with advanced cycle and fractal analytics for Saudi equities. This omission is striking given Saudi Arabia's economic prominence, deepening capital markets, and high levels of digital engagement, all of which underscore the need for more sophisticated forecasting tools that combine textual sentiment and market structure information at the market(index) and sectoral levels. The growing configuration of the Saudi market—driven by retail investors, influenced by oil-related macro-financial cycles, and segmented between conventional and Islamic finance—creates conditions in which both sentiment shocks and cyclical patterns can shape return dynamics in distinct ways. Nevertheless, there remains a major gap in the literature and in practice: existing models rarely join state-of-the-art Arabic sentiment analysis with cycle and fractal indicators to produce integrated forecasts for Saudi index returns. Addressing this gap requires a tailored hybrid modeling approach that unites deep-learning-based sentiment extraction with advanced time-series and spectral methods in a single empirical framework. Consequently, this study pursues two main objectives. Firstly, it tests whether Arabic Twitter sentiment, extracted using BERT-based models, significantly predicts daily returns on Saudi equity indices (**H1**). Secondly, it investigates the incremental forecasting value of the cycle and fractal features—specifically measures based on FFT, the Hurst exponent, the DPO, and the Future Line of delimitation (FLD)—to model and predict Saudi index returns (**H2**). By designing and estimating models that incorporate both sentiment and cyclical indicators, the study investigates whether a hybrid approach can deliver superior explanatory and predictive performance relative to sentiment-only or cycle-only specifications.

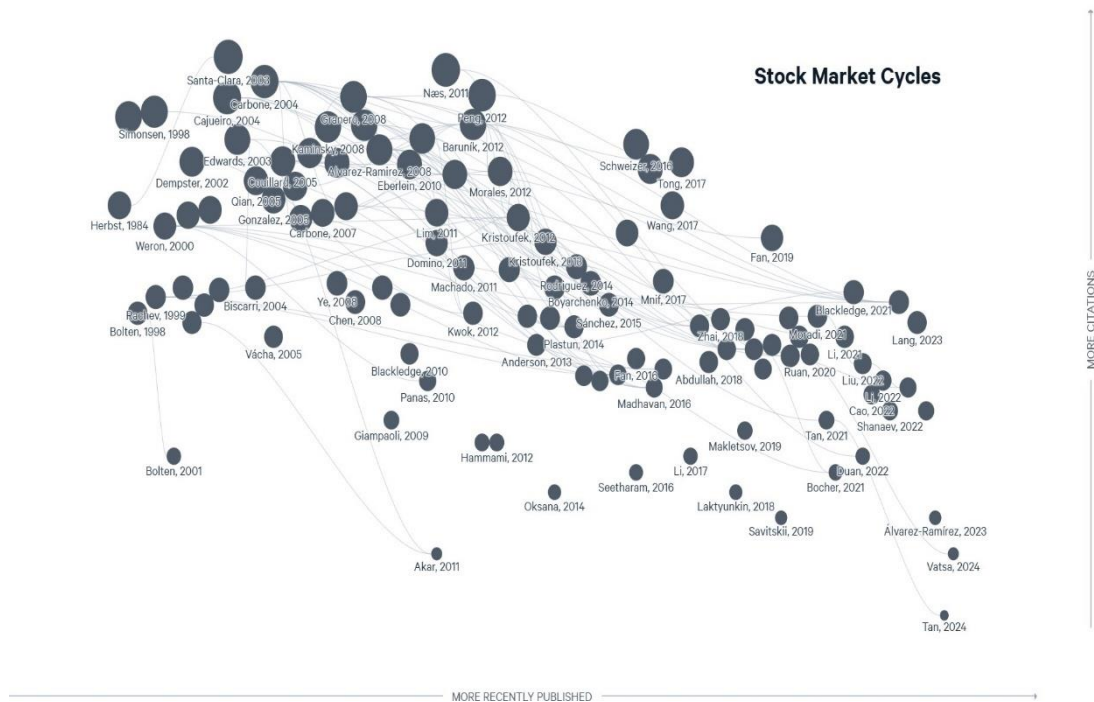
This study thus proposes the first comprehensive predictive framework that combines deep-learning-based Arabic sentiment extraction with advanced cycle and fractal analysis, benchmarked in conventional and Shariah-compliant indices in Saudi Arabia during the period 2023–2024. This, in turn, fills an important gap at the intersection of financial econometrics and Arabic NLP and offers new practical tools for investors, asset managers, and policy makers seeking to understand and anticipate Saudi market movements in an era of digital finance. The remainder of the study proceeds by setting out theoretical motivation and research questions, then detailing the methodological innovations and empirical design, before presenting the main results and describing the implications for academic research and policy in the Saudi context.

## 2. Literature Review and Hypotheses Development

Recent literature highlights the growing importance of Arabic Twitter sentiment analysis, particularly when implemented using advanced BERT-based models, for forecasting equity returns in Saudi Arabia's conventional and Islamic indices [Alqurashi, 2023, Yadav, 2024]. Although classical Efficient Market Hypothesis (EMH) frameworks remain a standard reference, behavioural finance and the Fractal Market Hypothesis (FMH) are increasingly invoked to explain observed

return dynamics, with numerous studies documenting market cycles, memory effects, and persistent non-linear patterns in emerging and Islamic markets [Aslam et al., 2023]. Hence, deep learning models such as BERT and its Arabic variants have been successfully applied to Twitter data to infer investor mood and short-term market direction, despite persistent challenges related to dialectal variation, data sparsity, and annotation quality in Arabic sentiment analysis [Antoun et al., 2020]. In the same line, cycle and fractal-based tools, including the Hurst exponent, the fast Fourier Transform (FFT), and the trended price oscillator (DPO), have been adopted to show that Saudi and regional indices are structured by multi-scale cycles and long-memory behaviour, features that traditional linear or purely random-walk models systematically overlook [Aslam et al., 2023]. Comparative studies of Islamic versus conventional benchmarks further indicate that, although both types of index share exposure to common macroeconomic and regional shocks, Islamic indices tend to exhibit smoother cycles, somewhat lower volatility, and slightly more stable sentiment effects, reflecting differences in sectoral composition, leverage constraints, and Shariah screening [Raza et al., 2024, Aslam et al., 2023].





**Fig. 1:** VOS viewer and Lightmaps citation network for "Investor Sentiment" and "Price Cycles"

Turning focus to bibliometric analyses using tools such as VOSviewer and Litmaps, figure 1 shows that research on Arabic sentiment analysis and financial cycles has expanded rapidly in recent years, but also reveal that these two strands are rarely integrated, particularly in relation to Saudi equities and Islamic finance [Donthu et al., 2021, Nyakurukwa and Seetharam, 2023]. Existing contributions typically focus either on improving Arabic NLP models for financial sentiment or on characterising cyclical and fractal properties of regional markets, without embedding both types of information in unified predictive architectures for Saudi indices. To date, no published study has comprehensively combined real-time Arabic Twitter sentiment, detailed cycle and fractal indicators, and hybrid forecasting models in the specific context of Saudi Arabia. This synstudy underscores both the originality and the necessity of the present research: it systematically unites transformer-based Arabic sentiment analytics, cycle and fractal features, and comparative analysis of conventional and Shariah-compliant Saudi stock indices within a robust methodological framework tailored to the structural and behavioural characteristics of the Saudi market.

## 2.1. Theoretical Paradigms Underpinning Saudi Financial Prediction

The dynamics of Saudi equity prices are anchored in, yet frequently deviate from, the classical Efficient Market Hypothesis (EMH), which posits that asset prices immediately and fully reflect all available information [Fama, 1970]. Although EMH remains a benchmark, empirical evidence for Saudi Arabia documents persistent return predictability, long memory, and anomalies that are inconsistent with a purely random-walk environment, indicating that informational efficiency is at best partial. Behavioural finance provides a complementary lens by highlighting the role of sentiment, cognitive biases, and heuristics, which are particularly salient in the Saudi market given its strong participation in retail, the widespread flow of local news and the extensive use of social

media, all of which amplify deviations from fully rational pricing [Barberis, 2018]. The fractal market hypostudy (FMH) further extends this view by modelling prices as the result of heterogeneous agents interacting across multiple horizons, generating persistent, multi-scale cycles; in the MENA region, including Saudi Arabia, long-memory behaviour and Hurst exponents above 0.5 offer support for FMH-style dynamics [Aslam et al., 2023, Peters, 1994]. Taken together, these strands motivate a hybrid theoretical rationale in which Saudi market predictability arises jointly from sentiment-driven mispricing and cycle/fractal effects, justifying the study's dual focus on behavioural and cyclical explanations.

## **2.2. *Investor Sentiment Literature (H1)***

Within this hybrid framework, investor sentiment is defined as an emotion- or bias-driven assessment of financial prospects that is not fully justified by fundamentals, and is especially powerful in the Saudi market, where retail investors are digitally active and prone to herding behavior [Alqurashi, 2023, Albahli et al., 2022]. Recent advances in Arabic natural language processing, particularly BERT-based transformer models, have enabled real-time extraction of rich sentiment signals from Arabic Twitter posts, consistently outperforming lexicon-based and classical machine learning methods in classification accuracy and stability [Boulanouar et al., 2024, Alasmari et al., 2023]. However, applications that directly link transformer-derived Arabic sentiment to return predictability in Saudi equities remain scarce, as well as a notable absence of studies that systematically test the predictive power of such sentiment measures across both Islamic and conventional indices within unified hybrid modelling architectures. Equipped by the previous analysis, the first hypothesis is derived from behavioural finance, market cycles, and NLP-based sentiment measurement [Salloum and Almustafa, 2023, Bordoloi and Biswas, 2023, Alshaikhmubarek, 2024, Liu et al., 2024, MSCI, 2024] and identified as Investor sentiment scores have a statistically significant effect on Saudi index returns.

## **2.3. *Cycles and Fractal Methods in Financial Modelling (H2)***

Parallel to the sentiment literature, modern cycle and fractal methods have revealed that Saudi equity prices display strong periodicities, phase structure, and persistent volatility patterns that are not captured by standard linear models [Aslam et al., 2023, Blackledge and Lamphiere, 2021]. Techniques such as Fast Fourier Transform (FFT), De-trended Price Oscillator (DPO), and Future Line of Demarcation (FLD) provide a spectral and phase-based characterisation of these dynamics, while Hurst exponent estimates above 0.5 confirm the non-random, trend-reinforcing nature of returns over various horizons. From an FMH perspective, volatility clustering and fractal measures offer a more nuanced understanding of market stability and liquidity, particularly for segmental and Islamic indices that may respond differently to shocks. However, despite the maturity of these tools, no existing study has integrated detailed cycle features with advanced Arabic sentiment or NLP-based indicators in a single joint predictive framework for Saudi equities, leaving an important methodological and empirical gap. Hence, the second hypothesis which is based on research linking cycles, market structure, and regime clustering to medium-term predictability [Kaur et al., 2021, Borgioli et al., 2024, Pereverzin, 2020, Hung, 2021] is identified as Cycle strength indicators (FFT amplitude, Hurst exponent, FLD phase) significantly explain the variation in Saudi index returns.

## **2.4. *Saudi Market Structure and Islamic vs Conventional Index Evidence***

The Saudi market structure reinforces the relevance of this dual perspective. The Tadawul All Share Index (TASI) and major Islamic indices such as those provided by FTSE and MSCI differ

systematically in sectoral composition, leverage exposure, and volatility characteristics, with Islamic benchmarks generally showing lower volatility and more persistent return patterns [Hanif et al., 2025, Alamgir and Cheng, 2023]. Hence, such structural distinctions, rooted in Shariah screening and sectoral tilts, imply that the transmission of sentiment and the manifestation of cycles may not be homogeneous across index types. Despite this, empirical work that compares the cycle and fractal properties between Saudi Islamic and conventional indices, and links these differences to predictability and sentiment sensitivity, remains limited, suggesting that the interaction between index design, volatility structure, and behavioural forces is under-explored.

In sum, the existing literature provides separate but incomplete treatments of Arabic BERT-based sentiment modelling, cycle and fractal analysis, and Saudi market microstructure, without integrating these dimensions into a unified predictive architecture. To date, there has been no comprehensive study that combines transformer-derived Arabic Twitter sentiment with advanced cycle/fractal indicators to forecast Saudi index returns, while explicitly contrasting Islamic and conventional benchmarks [Boulanouar et al., 2024, Aslam et al., 2023]. Hence the absence of integrated and KSA-specific evidence motivates the present study, which adopts a novel dual-method approach to examine how sentiment and cyclical structure jointly shape return dynamics in the Saudi equity market.

### 3. Model, Data and Methodology

#### 3.1 Model

The analysis in this study is based on the employed regression model, which has the following functional form:

$$MR_t = [\alpha + \beta_1 ICI_t + \beta_2 CYCL_t + \beta_3 \sum_i^3 CONT_i + \epsilon_{it}] \quad (1)$$

where  $t$  is the time period (2023 - 2024);  $ICI_t$  is the Investor sentiment indicator,  $CYCL_t$  is the Cycle Strength indicator of the period  $t - i$ , and  $CONT$  refers to the control variables of the study.

#### 3.2 Independent and Dependent Variables

Starting with Investor sentiment, scores are the core independent variables, extracted from Arabic financial tweets related to the Saudi market using a multi-model ensemble of fine-tuned BERT-based transformers: AraBERT, MARBERTV2, and CAMELBERT. These models excel in capturing deep contextual and dialectical variation, enabling robust sentiment extraction from Saudi Twitter discourse. Sentiment scores are computed for each tweet and then aggregated daily (or weekly) by index. The resulting measures include: (i) discrete classifications (positive, neutral, or negative on an ordinal scale); and (ii) continuous probability-weighted averages on a normalized scale (e.g.,  $-1$  for completely negative,  $0$  for neutral,  $+1$  for completely positive, or using mean model outputs per sentiment class).

As for Cycle Strength Indicators, Cyclical dynamics are represented by multiple cycle strength indicators constructed from Saudi market price series using spectral (Fourier) and fractal (Hurst/FLD) analyses. These include:

(i) **FFT amplitude**, the magnitude of the dominant cycle components identified by fast Fourier Transform decomposition of the return series, reflecting the relative strength of underlying

periodicities or market regimes [Song et al., 2021]; (ii) the **Hurst exponent** ( $H$ ), a real-valued measure typically in  $[0, 1]$  that quantifies long memory, persistence, or anti-persistence in returns ( $H > 0.5$  signals trending or long-memory regimes,  $H < 0.5$  indicates mean reversion,  $H = 0.5$  suggests randomness) [Borgioli et al., 2024, Xie et al., 2023, Gospodinova, 2022, Moradi et al., 2021]; and (iii) **FLD indicators**, denoting the cycle phase (e.g., crest, trough) and the magnitude of market oscillations, derived from Future Line of Demarcation algorithms [Kaur et al., 2021, Salloum and Almustafa, 2023]. Cycle indicators are computed for each Saudi index on a daily basis, capturing latent cyclical effects that inform market timing and the interplay with aggregate sentiment flows [Kaur et al., 2021, Gospodinova, 2022]. Moving into Index Returns, the main dependent variable is market return, defined as the percentage change in the

Saudi conventional and Islamic index levels. Formally:

$$Return_t = \frac{Index_i - Index_{i-1}}{Index_{i-1}} \times$$

Returns are computed on daily and, where relevant, weekly frequencies for TASI and FTSE Saudi Arabia All Cap Islamic. The data set is rich and granular: daily closing prices for Saudi conventional indices (Tadawul All Share Index—TASI) and Islamic indices (e.g., FTSE or MSCI Saudi Islamic) are analysed alongside high-frequency Arabic financial sentiment harvested from Twitter using the Twitter API. Data are expressed both in SAR and USD when a comparison with global benchmarks is warranted, with all series spanning a sufficiently long horizon for out-of-sample validation.

### 3.3 Methodology

Our study adopts a *mixed-methods* research design to address the complexities of predicting the behaviour of the Saudi stock market, integrating both **quantitative** and **qualitative** strands within a coherent pragmatic framework. Mixed-method designs are increasingly endorsed in contemporary finance and behavioural research because they enable triangulation, complementarity, and expansion of findings, thereby mitigating the limitations of single-method approaches [Dewasiri et al., 2018, Lorenz et al., 2025, Creswell, 2024]. In this study, the quantitative component applies advanced time-series econometrics, including regression models and cycle- detection techniques such as the Hurst exponent, fast Fourier transform (FFT), de-trended price oscillator (DPO), and future line of demarcation (FLD), to analyse historical price data from both conventional and Islamic- compliant Saudi indices, thereby offering statistical rigour in modelling market cycles, volatility, and risk–return characteristics [Kaur et al., 2021, Corzo et al., 2020]. The qualitative component is operationalised through fine-tuned BERT-based sentiment extraction from Arabic Twitter data, capturing the real-time pulse of investor mood, expectations, and behavioural biases specific to the Saudi market [Du et al., 2024, Lu et al., 2023b]. Using state- of-the-art transformer language models, this analysis moves beyond simple text counts to generate context-aware, nuanced indicators of sentiment polarity and thematic shifts that are often absent from structured financial datasets [Bordoloi and Biswas, 2023]. Integrating subjective social signals with objective market data aligns with current calls for holistic approaches in financial research, where the psychological states of investors and online discourse can materially influence market outcomes [Zhao et al., 2025].

#### 4. Empirical Findings

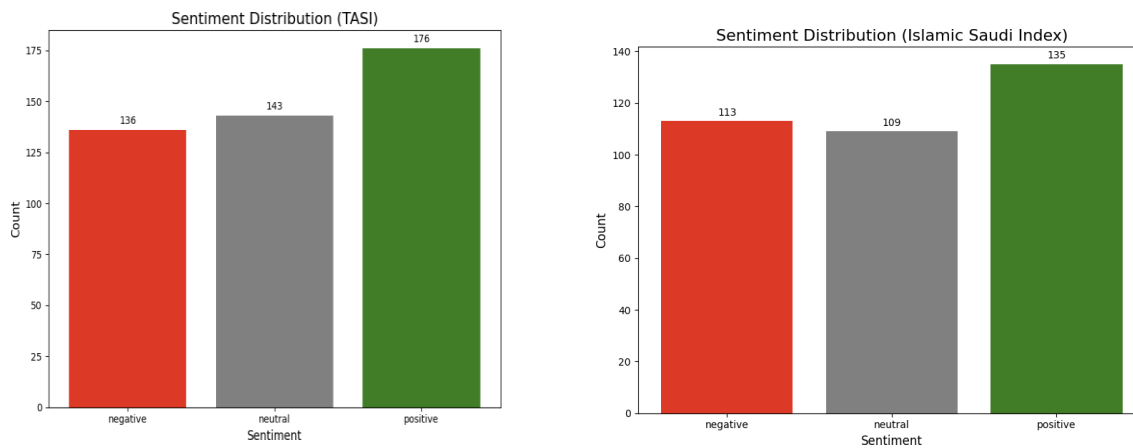
We start our analysis with the descriptive statistics of sentiment scores. Table 1 Shows that both indices exhibit a remarkably small mean daily return ( $\approx 0.03\%$ ), with standard deviations for daily change below 1% (0.71% for TASI, 0.78% for FTSE Islamic), confirming a predominantly calm, liquid and mature market for the sample. Furthermore, event-driven volatility is present, as the worst daily losses and gains occasionally exceed  $\pm 2.5\%$  on the TASI and  $\pm 3\%$  for the Islamic FTSE, but such extremes are rare. Finally, FTSE Islamic shows steady growth (from 425 to 544 over two years), while

TASI also trends upward, with typical price swings confined within tight interquartile ranges. Thus, both indices display stability characteristics but remain responsive to shocks. Interestingly, Median and quartile statistics are close to means for both indices, indicating a near-normal distribution of daily closes and returns—a favourable property for regression and time-series modelling.

**Table 1:** Descriptive Statistics: TASI vs. FTSE Saudi Arabia Islamic Index (Jan 2023–Dec 2024)

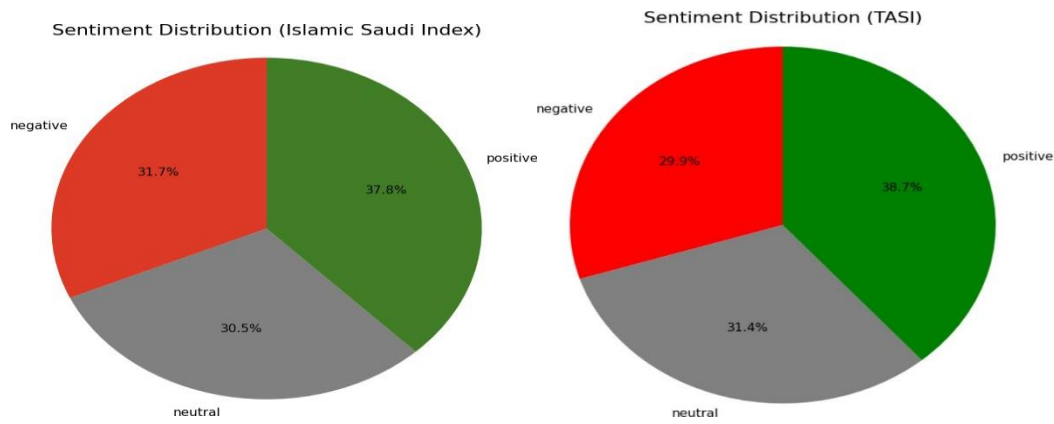
Index	N	Mean Close	Std Dev	Min Close	Max Close	Mean %Chg
TASI	498	3084.25	175.33	2656.26	3422.66	0.03%
FTSE Saudi Islamic	505	491.97	29.20	425.27	543.63	0.03%

Overall, both indices signal a resilient market environment, less prone to persistent speculative bubbles or panics compared to some emerging peers. In line with previous studies, the slightly smaller standard deviation of the FTSE Islamic supports that Islamic indices tend to be marginally less volatile due to Shariah-compliance screens.



**Fig. 2:** Sentiment class distributions for TASI (left) and FTSE Islamic (right).

Figures 2 and 3 show that both indices are slightly optimistic overall. For TASI, positive sentiment accounts for 39%, with neutral at 31% and negative at 30%. The Islamic FTSE profile is nearly identical: 38% positive, 31% neutral, and 31% negative. Such strong similarity shows that the Saudi market sentiment is generally balanced, with no persistent dominance of bullish or bearish mood for either index. Additionally, both indices began in 2023 with more negative-dominant sentiment and shifted towards positive by the end of 2024, indicating synchronised responses to positive macroeconomic or market developments along with mood distribution.



**Fig. 3:** Sentiment proportions for TASI (left) and FTSE Islamic (right).

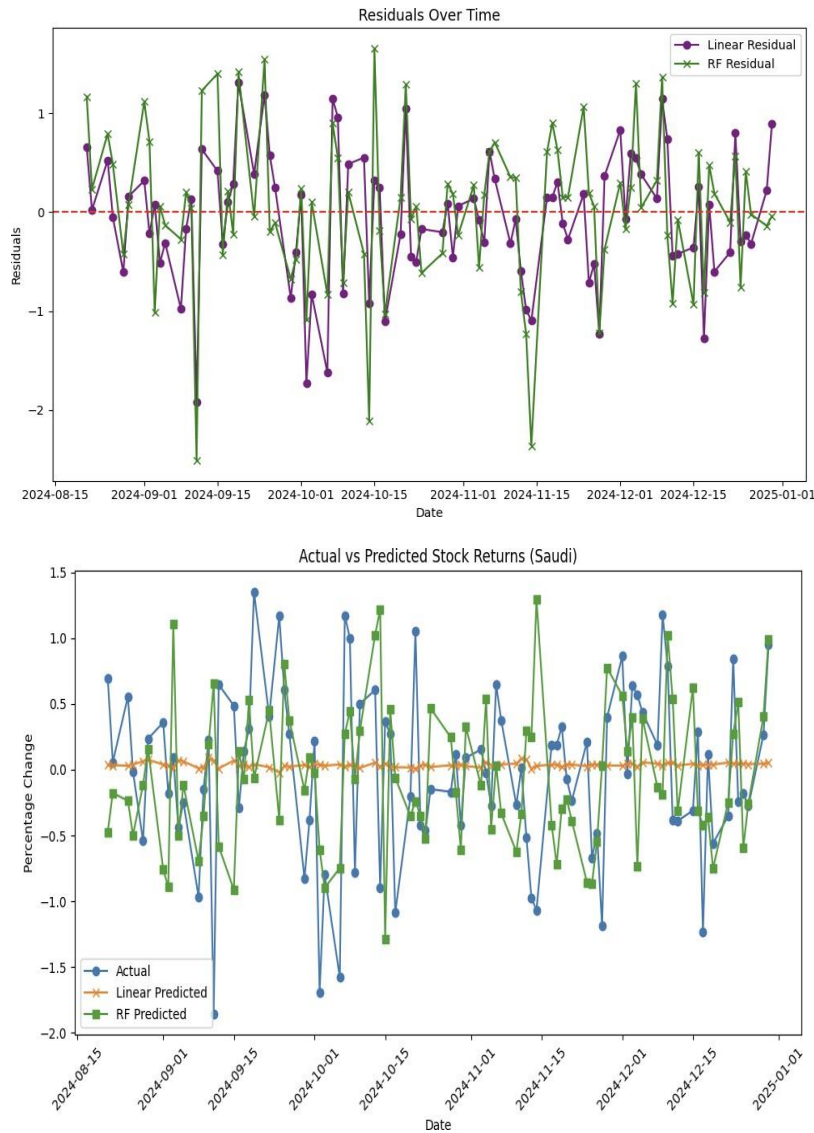
Overall, the figure indicates that the sentiment-based predictors are relevant in both the conventional and Islamic segments of the Saudi market. Strong cross-index alignment implying that religious or structural segmentation immunizes a market against behavioral feedback, providing a strong empirical basis for the joint modelling of sentiment-return relationships— essential for hypothesis testing and practical knowledge of trading or risk management.

Moving our attention to regression and correlation between indices, Table 2 and 2 show that for: Firstly, both indices, linear regression outperforms random forest, indicating that the relationship between average daily sentiment and stock returns is well described by a simple linear model. Secondly, TASI model errors (0.52% MAE) are larger than those for the FTSE Islamic index (< 0.01), due to differences in price units or underlying index volatility, but in both, prediction errors remain low and stable. Finally, both indices show positive, but modest, correlations between Twitter sentiment and returns. The FTSE Islamic index exhibits a somewhat stronger sentiment-return link (0.195) than TASI (0.117), suggesting that even in Shariah-compliant segments, mood in Arabic tweets nudges prices in the same direction. Positive online mood predicts slightly higher chances of market gains for both indices, but many days move independently of social sentiment.

**Table 2:** Predicting Daily Returns from Sentiment (TASI vs. FTSE Saudi Arabia Islamic Index)

Index	Model	MAE	RMSE
TASI	Linear Regression	0.518	0.657
TASI	Random Forest	0.586	0.790
FTSE Saudi Islamic	Linear Regression	0.0073	0.0089
FTSE Saudi Islamic	Random Forest	0.0085	0.0107

Regarding the stock return prediction, we found that both models predict small/moderate moves well, but frequently underestimate large, one-off shocks. The linear model is more stable but less responsive to big swings; the random forest captures more variation but also makes significant errors. Notably, residuals (prediction errors) often cluster close to zero, with rare larger spikes on event-driven market days and the random forest model produces more extreme errors than linear regression, particularly during exceptional volatility.



**Fig. 4:** Model Diagnostics for TASI: Actual vs. Predicted (left) and Residuals Over Time (right).

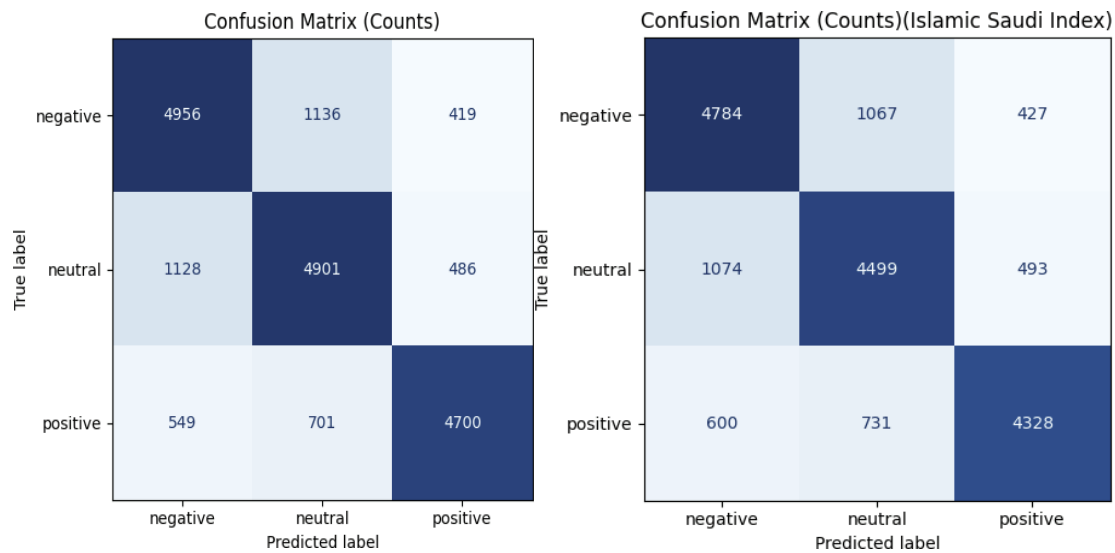
Next is the performance of forecasting models using TASI and FTSE Saudi Arabia Islamic Index. Table 3 shows that logistic regression with TF-IDF features is the clear winner for both indices, delivering around 67% accuracy and the highest F1 scores. However, both models outperform random guessing by a wide margin. TF-IDF features (which weigh word importance) slightly outperform simple count-based features everywhere. All classes are classified well; “positive” is the easiest (F1 0.79), and neutral/negative is sometimes mixed but still strong (F1 0.73 to 0.75).

**Table 3:** Sentiment Classification Performance: TASI vs. FTSE Saudi Islamic

Index	Model/Feature	Accuracy	F1-w	F1-m	Support
TASI	Logistic (TF-IDF)	0.673	0.674	0.674	40,000+
TASI	Naive Bayes (TF-IDF)	0.646	0.645	0.644	40,000+
FTSE Islamic	Logistic (TF-IDF)	0.673	0.674	0.674	18,003
FTSE Islamic	Naive Bayes (TF-IDF)	0.643	0.641	0.640	18,003

**Table 4:** FTSE Saudi Islamic: Best Logistic Model Class Break- down

Class	Precision	Recall	F1	Support
Negative	0.74	0.76	0.75	6,278
Neutral	0.71	0.74	0.73	6,066
Positive	0.83	0.77	0.79	5,659



**Fig. 5:** Confusion matrices (raw counts) for TASI (left) and FTSE Saudi Arabia Islamic Index (right): Both show strong diagonal patterns with most errors in the negative/neutral border

In the same line, Table 3, Table 4, and Figure 5 show that most tweets in both indices are well classified; Sentiment identification works reliably for Saudi financial tweets with these models and features (accuracy/F1 ~67%). Furthermore, positive tweets are detected with notably high precision, negatives and neutrals are a bit harder, but the model’s errors are well-behaved and understandable for social-financial data. Interestingly, Reliable tweet identification reinforces that the sentiment signal itself is robust, which underpins all further sentiment-return modelling and market forecasting.

**Table 5:** Most Common Classification Outcomes (True → Predicted)

Index	True → Predicted	Count
TASI	negative → negative	4956
TASI	neutral → negative	1128
TASI	positive → neutral	701
FTSE Islamic	negative → negative	4784
FTSE Islamic	neutral → negative	1074
FTSE Islamic	positive → neutral	731

**Table 6:** Class-level Precision and Recall (Selected)

Index	Precision	Recall	F1	Class
TASI		Negative	0.76	0.78 0.77
TASI		Neutral	0.57	0.62 0.59
TASI		Positive	0.72	0.64 0.68
FTSE Islamic		Negative	0.71	0.64 0.67
FTSE Islamic		Neutral	0.64	0.68 0.66
FTSE Islamic		Positive	0.69	0.72 0.70

To conclude, most predictions are accurate (diagonal counts are the highest). The most common misclassifications are between “neutral” and “negative,” or between “neutral” and “positive,”—not extreme opposites. This pattern is consistent across both indices, showing the universal challenge of interpreting mild or nuanced online market sentiment. Both models are strongest for clear negative or positive sentiment, with the most misclassifications found in the neutral category. Precision and recall show balanced performance: around 0.70 for easy-to-read tweets, but lower for ambiguous/neutral.

**Table 7:** 5-Fold Cross-Validation Performance: TASI and FTSE Saudi Arabia Islamic Index

Metric	TASI (Mean $\pm$ Std)	FTSE Islamic (Mean $\pm$ Std)
Accuracy	0.7608 $\pm$ 0.0033	0.7597 $\pm$ 0.0039
F1 Macro	0.7627 $\pm$ 0.0034	0.7613 $\pm$ 0.0038
F1 Weighted	0.7614 $\pm$ 0.0033	0.7603 $\pm$ 0.0038
Balanced Accuracy	0.7613 $\pm$ 0.0033	0.7600 $\pm$ 0.0039
Precision Macro	0.7648 $\pm$ 0.0035	0.7635 $\pm$ 0.0037
Recall Macro	0.7613 $\pm$ 0.0033	0.7600 $\pm$ 0.0039

Table 7 implies that the sentiment classifiers for both the TASI and the FTSE Saudi Arabia All Cap Islamic indices are consistent and generalizable, providing a strong empirical foundation for their deployment in subsequent sentiment-based forecasting and analytical applications, as well as for future tests of adaptability to evolving language usage and market conditions. Table 8 shows that both models become more accurate as the training sample expands, with scores plateauing near 0.75–0.76, confirming robust learning from added data.

**Table 8:** Walk-Forward Validation (Sample Months, Key Metrics)

Index	Test Month	n_train	n_test	Balanced Acc.	Accuracy
TASI	2023-07	36,186	10,998	0.729	0.728
TASI	2023-11	70,735	8,231	0.754	0.754
FTSE Islamic	2023-07	36,133	10,151	0.726	0.725
FTSE Islamic	2023-11	68,189	8,040	0.755	0.757

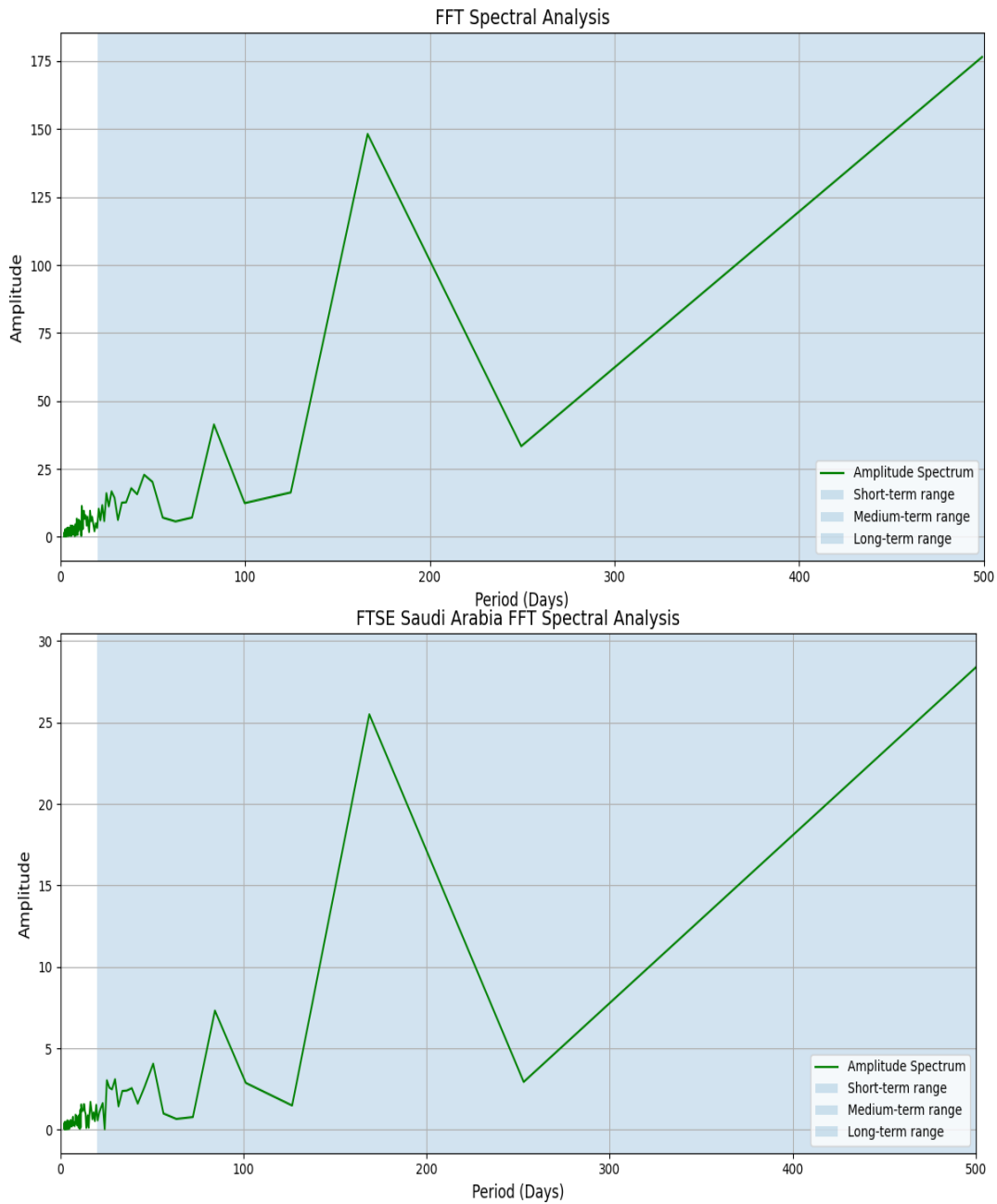
In sum, walk-forward and time-based validation confirms that sentiment classification performance is strong and stable for both index types, making these models well suited for ongoing, real-time behavioral finance research or decision support.

It is worth noting that the indices are examined and analyzed using the Fast Fourier Transform (FFT) and the De-trended Price Oscillator (DPO) to highlight the core cycles in daily prices for 2023–2024. Cycles are identified as short-term (20–60 days), medium-term (60–200 days), and long-term (200–500 days).

With regards to dominant Cycles and Forecasted Turning Points (2023–2024), table 9 shows that indices present nearly identical short- and medium- term cycle durations (45/50 days and 166/168 days), with notable phase alignment across recent peaks. In addition, spectra from FFT (Figure 6) and DPO visualizations confirm strong and persistent oscillatory signals at these horizons for both indices, supporting consistent cycle behavior across the Saudi market. Interestingly, short- and medium-term cycles shape both the price action of both indices, confirming a “nested” cyclical market structure (fractal-like) that is stable during the study window

**Table 9: Dominant Cycles and Forecasted Turning Points (2023– 2024)**

Index	Cycle Type (Days)	Period	Last Trough	Next Trough	Next Peak
TASI	Short	45	2024-11-27	2025-01-11	2025-02-02
TASI	Medium	166	2024-08-05	2025-01-18	2025-04-11
TASI	Long	499	2023-12-31	2026-09-24	2027-05-31
FTSE Islamic	Short	50	2024-11-14	2025-01-03	2025-01-28
FTSE Islamic	Medium	168	2024-05-31	2025-05-02	2025-07-25
FTSE Islamic	Long	253	2024-05-31	2025-10-19	2026-02-22



**Fig. 6: FFT Comparison: TASI vs FTSE Saudi Arabia Islamic (Key Peaks Highlighted)**

In summary, both conventional and Islamic Saudi equity indices are governed by persistent and synchronized short- and medium-term cycles, as revealed by FFT and DPO. This structural regularity lays a powerful foundation for hybrid technical, fractal, and behavioral models in GCC market analytics.

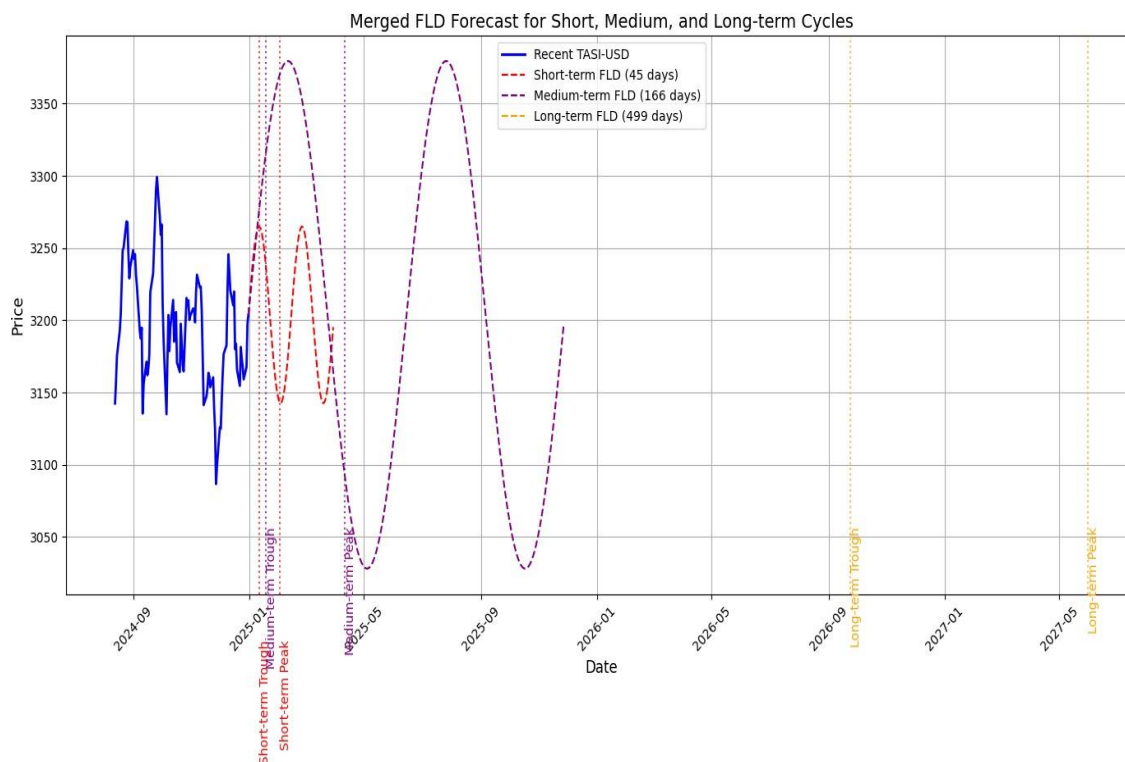
**Table 10:** FLD Predicted Turning Points and Amplitude (2025+) – TASI vs FTSE Saudi Arabia Islamic

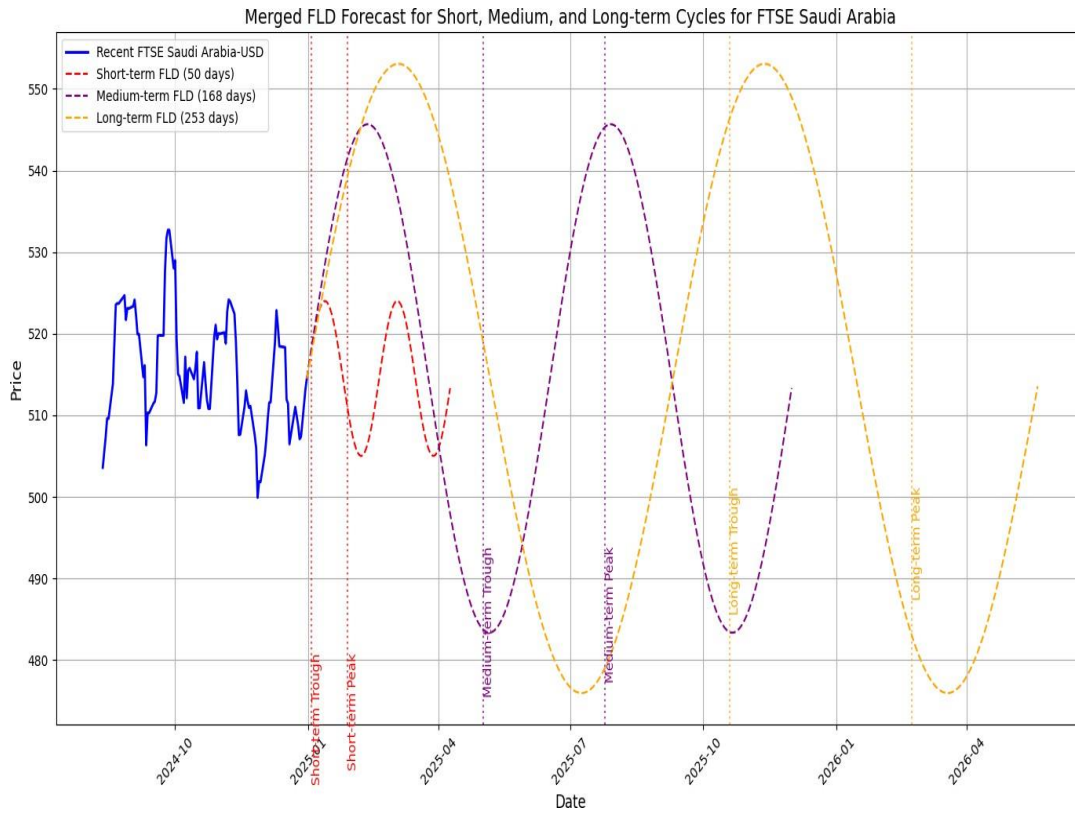
Index	Cycle	Next Trough	Next Peak	Forecast Range
TASI	Short	2025-01-11	2025-02-02	3143–3265 USD
TASI	Medium	2025-01-18	2025-04-11	3028–3379 USD
FTSE Islamic	Short	2025-01-03	2025-01-28	505–524 USD
FTSE Islamic	Medium	2025-05-02	2025-07-25	483–546 USD

Next is FLD Forecasting and Turning Points. Table 10 indicates that both’ FLD forecasts for both indices align well, with the conventional index (TASI) showing slightly earlier and stronger moves, and the FTSE Islamic index showing a lower amplitude and a brief lag; major confluence (close alignment of short/medium cycle troughs) appears in TASI in early January 2025—an actionable window for tactical rebalancing.

**Table 11:** Hurst Exponent, Amplitude Stability, and Cycle Con- fluence

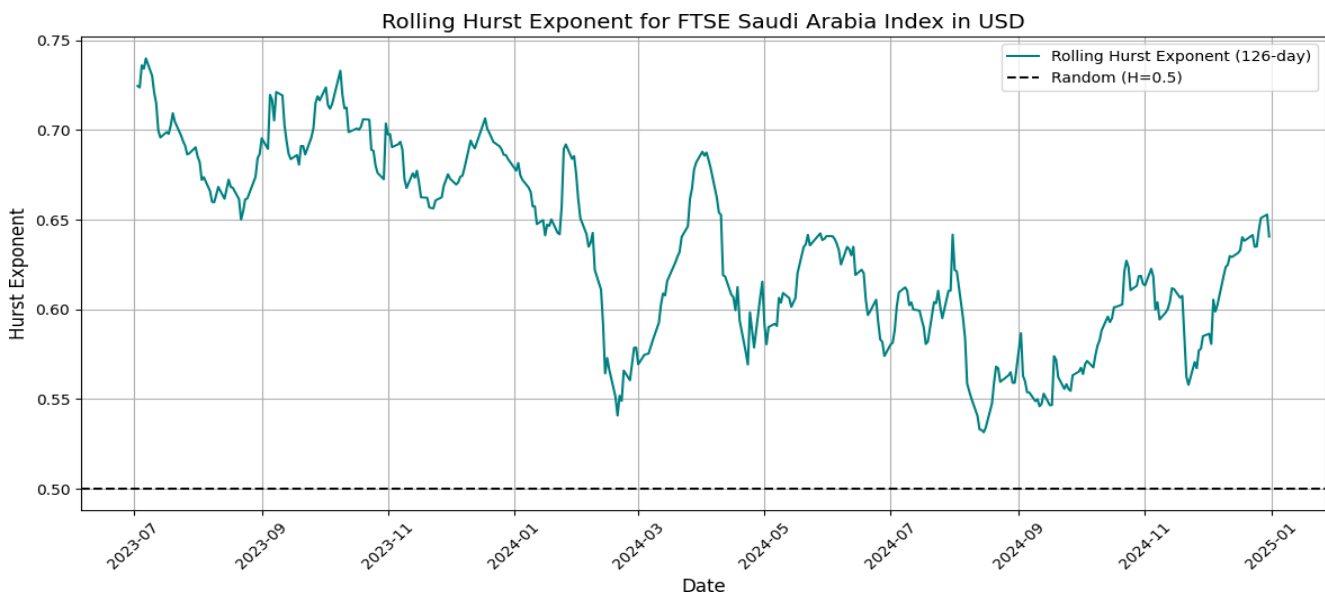
Index	Metric	Short-term	Medium-term	Long-term
TASI	Hurst ( $H$ )	0.64		
FTSE Islamic	Hurst ( $H$ )	0.62		
TASI	Stability Ratio ( $S$ )	0.33	0.25	0.10
FTSE Islamic	Stability Ratio	0.29	0.22	0.08

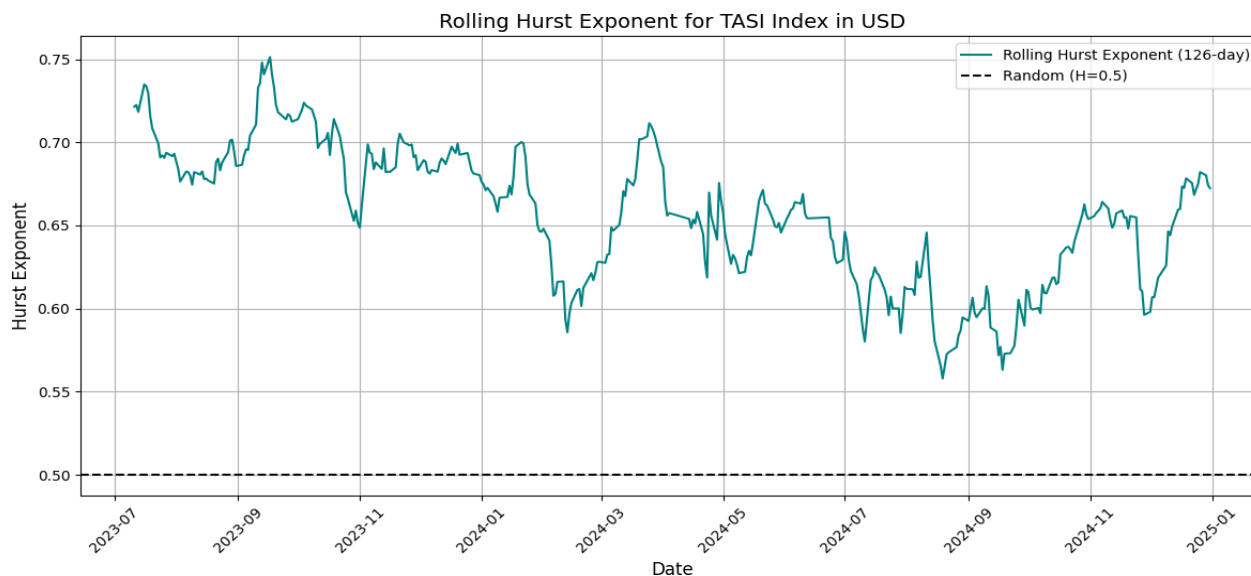




**Fig. 7:** Merged FLD Cycles: TASI (top) and FTSE Islamic (bottom) – note lag and smoother profiles for FTSE Islamic.

For Hurst Exponent and FMH Dynamics, Table 11 indicates that both indices exhibit  $H > 0.6$ , indicating the persistence of the trend and supporting the viability of momentum or cycle-aligned strategies; and long-term cycles are most stable (lowest  $S$ , suggesting the highest predictability for long-term investors, especially in the Islamic segment of the FTSE.





**Fig. 8:** Rolling Hurst Exponent: TASI and FTSE Islamic (over-laid) Trending and regime shifts visible

Moving attention to multi-horizon cyclicity, Figure 7 and 8 show that: (i) both markets have a strong multi-horizon cyclicity, with FLD and rolling Hurst confirming persistent, semi-predictable rhythms; the FTSE Islamic is smoother, with lower forecast amplitude and delayed cycles, likely due to sectoral screens and lower leverage. This, in turn, makes its timing signals marginally more conservative but less volatile and Cycle confluence (tight alignment of troughs/peaks) in TASI (absent in FTSE during this period) highlights windows of high regime-change probability—ideal for tactical long or short exposures. Overall, we found evidence supporting the cycle and fractal signals, implying that behavioral and technical feedback are consistent across both indices but slightly dampened/lagged in the Islamic segment.

## 5. Conclusion

The study examined the impact of investor sentiment and market cycles jointly on equity return dynamics in Saudi Arabia using the Tadawul All Share Index (TASI) and Shariah-compliant indices during the period 2023–2024. The study integrated Arabic Twitter-based sentiment—extracted through an ensemble of AraBERT, MARBERTV2 and CAMELBERT models—with advanced cycle and fractal indicators, including FFT, DPO, FLD and Hurst exponent, within novel econometric approach. We found a significant relationship between investor sentiment and stock returns. The pattern of results holds for both conventional and Islamic indices, with slightly a stronger sentiment–stock return correlation for Shariah-compliant indices, indicating that sentiment effects are not confined to speculative segments of the market.

Additionally, the analysis shows that spectral and fractal analyses reveal persistent short- and medium-term cycles, Hurst exponents well above 0.5, and stable FLD turning points across both index types, confirming that Saudi equity prices deviate from pure random walks and are structured by multi-scale, partially predictable regimes. The interaction between When sentiment and cycle indicators has a powerful forecasting impact implying that behavioral and cyclical information is jointly informative for return prediction and risk assessment.

This study is the first to examine the relationship between investor sentiment, cycle indicators and the changes and prediction of stock returns in the KSA market. It, therefore, provides insights to investors, managers, and policymakers on the importance of both AI and investor sentiment over different economic cycles, and their role in the KSA economy. The study results are also important for regulators to understand how investor mood can affect market behavior and stock returns. Furthermore, the study findings reveal new information on the long and short-run dynamics in the relationships between sentiment, AI-driven financial analytics in Arab markets and market policy orientation.

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