SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 2900-2917
Open Access. Online & Print

DOI: 10.5281/zenodo.122.126223

TRACKING GENERATIVE AI ADOPTION IN A CULTURALLY DYNAMIC SETTING: DAILY GOOGLE TRENDS EVIDENCE FROM THE UAE

Mohammed Elseidi[1,2*]

[1]Umm Al Quwain University, Umm Al Quwain, UAE,
[2]Faculty of Commerce, Mansoura University, Mansoura, Egypt,
Email: drmohammed.elseidi@uaqu.ac.ae

Received: 20/10/2025
Accepted: 25/12/2025

Corresponding Author: Mohammed Elseidi (drmohammed.elseidi@uaqu.ac.ae)

ABSTRACT

Understanding the temporal dynamics and cultural determinants of generative AI adoption is essential for informed policymaking and effective deployment. This study presents a high-frequency, culture-aware analysis of public interest in ChatGPT within the United Arab Emirates (UAE), utilizing daily Google Trends data from April 2024 to May 2025. The objective is to dissect temporal patterns, assess volatility and event responsiveness, and benchmark predictive models for short-term forecasting. The methodology integrates time series decomposition (STL), volatility modeling (GARCH), anomaly detection, and autocorrelation analysis to uncover behavioral drivers. Special attention is given to cultural phenomena—particularly the effect of Ramadan—on usage patterns. A comparative forecasting experiment evaluates four models: SARIMA, Prophet, N-HiTS, and a feature-engineered Random Forest. The analysis reveals: (1) a sustained upward trend in ChatGPT interest; (2) a strong weekly cycle centered on the workweek; (3) event-driven volatility spikes linked to model releases and holidays; (4) a culturally induced drop in engagement during Ramadan; and (5) Random Forest outperforming all other models with a MAPE of 10.65%. This is the first empirical study to combine high-frequency trend analysis, cultural calendar effects, volatility modeling, and machine learning forecasting in the context of AI adoption in the MENA region. It introduces a novel, interpretable framework for real-time monitoring and forecasting of digital innovation diffusion, offering strategic insights for policymakers, educators, and AI developers operating in culturally dynamic settings.

KEYWORDS: Chatgpt Adoption; Google Trends; UAE; High-Frequency Time Series; GARCH; Cultural Analytics; Ramadan Effect; Machine Learning Forecasting; Random Forest; Digital Behavior Modeling; SARIMA; Prophet; N-Hits.

1. INTRODUCTION AND LITERATURE REVIEW

The unprecedented rise of generative artificial intelligence (AI), exemplified by OpenAI's ChatGPT, is fundamentally transforming policy-making, education, and commerce at an accelerated pace [1, 2, 3, 20, 27, 22]. Capturing the nuances of this rapid diffusion is imperative for multiple stakeholders: policymakers require timely and granular evidence to formulate responsive regulatory frameworks; educational institutions must adapt curricula and assessment methodologies to align with emerging AI capabilities; and businesses seek to harness AI-driven innovations to maintain competitiveness in fast-evolving markets [3, 4, 23, 37].

Empirical investigations have demonstrated ChatGPT's impact on lifelong learning paradigms, workforce upskilling, and the evolution of research practices in the social sciences [5, 6, 36, 20, 30]. Shifts in information-seeking behavior across linguistic and cultural contexts underscore the technology's integration into everyday life [4, 32, 39].

Tools like ChatGPT are becoming central to shaping public attention trajectories and digital engagement trends, further embedding themselves into the socio-technological fabric [21, 30].

High-frequency digital data sources—particularly Google Trends—offer a timely and scalable means of capturing behavioral signals related to technology adoption [8, 9, 10, 11, 34]. These data have been widely employed in domains such as economic forecasting [11, 12], health surveillance [10].

They have also been utilized to model commodity price fluctuations [34], monitor cybersecurity threats [38], and study behavioral trends during global crises [13]. In education, these tools inform pedagogical decisions and research into AI-assisted learning processes [5, 39, 23].

This study contributes a novel, high-resolution, and culturally informed exploration of generative AI adoption using daily Google Trends data for the United Arab Emirates (UAE)—a country recognized for its leadership in digital innovation and AI policy through initiatives such as the UAE National AI Strategy and the Falcon 40B model [14, 15, 29].

While studies on AI adoption are rapidly expanding, the UAE context offers a distinctive opportunity to observe the interplay between fast-paced digital transformation and culturally embedded temporal dynamics, such as those introduced by Ramadan and National Day observances [16, 17, 19]. These calendar-driven behaviors provide critical context for understanding nonlinear user engagement patterns [33] and underscore the importance of culturally attuned models for digital behavior forecasting [3, 17, 24, 31].

This research is the first to provide a high-frequency, culture-aware analysis of ChatGPT adoption dynamics in the UAE.

It advances the literature through the following four contributions:

1. **Daily-resolution adoption mapping:** The first empirical portrait of ChatGPT engagement in the UAE at a daily granularity, unveiling intra-week seasonal rhythms and growth trajectories often overlooked in coarser temporal analyses.
2. **Culture-aware behavioral analytics:** A novel methodology for detecting the influence of cultural calendars—specifically Ramadan—on search interest patterns, emphasizing the societal context of AI diffusion.
3. **Methodological integration:** A unified analytical pipeline incorporating STL decomposition, GARCH volatility modeling, anomaly detection, and both classical and machine learning forecasting techniques, offering a comprehensive understanding of trend, volatility, and predictability.
4. **Forecasting innovation:** Demonstration that a feature-engineered Random Forest model outperforms traditional (SARIMA), adaptive (Prophet), and deep learning (N-HiTS) approaches in short-term prediction of AI-related behavioral data.

By combining time series modeling, cultural insights, and machine learning benchmarks, this study establishes a pioneering framework for real-time analysis of digital technology adoption in a culturally dynamic and technologically progressive nation.

The overarching goals are to characterize the micro-dynamics of AI engagement, assess the role of cultural cycles, and set robust forecasting baselines that inform AI policy, education, and outreach in the Gulf region.

2. METHODS

This section outlines the methodological pipeline of the study, which progresses from data acquisition and pre-processing to advanced time series decomposition, volatility modeling, anomaly detection, and forecasting using both classical and machine learning models.

2.1. Data Acquisition and Pre-Processing

Daily Google Trends data for the search term "*ChatGPT*" in the United Arab Emirates were collected from April 1, 2024, to May 31, 2025. Google Trends normalizes search values to a scale of 0 to 100.

The data were pre-processed by:

- Removing duplicates by retaining only the first entry per date;
- Standardizing the index to a daily frequency to ensure completeness and temporal consistency;
- Dividing the dataset into:
  - **Training set:** April 1, 2024 – April 1, 2025;
  - **Test set:** April 2, 2025 – May 31, 2025 (60 days).

2.2. Time Series Decomposition and Volatility Modeling

2.2.1. Stl Decomposition

To extract trend and seasonal components, we applied STL (Seasonal-Trend-Loess) decomposition [25].

The additive form of STL decomposition is expressed as:

$$Y_t = T_t + S_t + R_t$$

where:

- $Y_t$is the observed value at time t,
- $T_t$is the smoothed trend,
- $S_t$is the seasonal component (weekly, period = 7),
- $R_t$is the residual component.

STL uses local regression to decompose the signal and is robust to outliers and missing values [45, 43, 46].

2.2.2. GARCH Model for Volatility

To model time-varying volatility in public attention, we applied a GARCH (1,1) model to the logarithmic returns of the series:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

The conditional variance is defined as:

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where:

- $\omega$is the constant term,
- $\alpha_1$captures reaction to new shocks,
- $\beta_1$captures volatility persistence.

A high $\alpha_1 + \beta_1$close to 1 indicates persistent volatility, reflecting clustering in public attention [26].

2.2.3. Anomaly Detection

We used Z-scores on residuals $R_t$from the STL decomposition to detect anomalies:

$$Z_t = \frac{R_t - \mu_R}{\sigma_R}$$

where $\mu_R$and $\sigma_R$are the mean and standard deviation of residuals. A threshold of $|Z_t| > 2.5$was used to flag significant deviations.

2.3. Forecasting Models

We evaluated four forecasting methods with different theoretical underpinnings to ensure diversity and robustness.

2.3.1. Sarima

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is denoted:

$$SARIMA(p, d, q)(P, D, Q)_m$$

where:

- p, d, q: non-seasonal AR, differencing, and MA orders,
- P, D, Q: seasonal AR, differencing, and MA orders,
- m: seasonal period (7 days for weekly seasonality).

Model orders were informed by Autocorrelation and Partial Autocorrelation plots (ACF/PACF).

2.3.2. Prophet

Prophet [28, 44] is a modular regression model with additive components:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

where:

- $g(t)$: trend (piecewise linear),
- $s(t)$: seasonality via Fourier terms,
- $h(t)$: effects of holidays (not used here),
- ε_t: residual error.

We configured Prophet to use multiplicative seasonality to capture growing oscillations.

2.3.3. N-Hits

N-HiTS (Neural Hierarchical Interpolation for Time Series) is a deep learning model designed for multiscale forecasting [41, 42, 40].

It decomposes a signal using a hierarchical block architecture:

$$\hat{y}_{t+h} = \sum_{i=1}^{K} f_i(x_t) \cdot \phi_i(h)$$

where:

- $f_i(x_t)$: learned block-specific transformations,
- $\phi_i(h)$: basis functions for forecasting horizon h,
- K: number of blocks.

It implicitly captures multi-frequency patterns and leverages attention mechanisms for long-range dependencies [18].

2.3.4. Random Forest with Feature Engineering

The Random Forest regressor builds an ensemble of decision trees, each trained on bootstrapped samples. For time series use, we created an engineered feature set:

- **Calendar Features:** Day of week, month, day of year;
- **Lag Features:** Lags of 1, 7, 14, 30, 60 days;
- **Rolling Statistics:** 7-day rolling mean and standard deviation.

The model prediction is the mean of all decision trees:

$$\hat{y}_t = \frac{1}{B}\sum_{b=1}^{B} T_b\,(x_t)$$

where T_b is the b-th tree and B is the total number of trees.

2.4. Evaluation Metrics

We used three standard forecasting accuracy metrics:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\, y_i - \hat{y}_i| RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\,y_i - \hat{y}_i)^2} MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)$$

MAPE was the primary comparison criterion due to its interpretability and scale-independence.

2.5. Implementation Details

All analyses were conducted in Python 3.10 and R 4.3. Time series decomposition used the statsmodels STL implementation (v0.14) with default robustness settings. GARCH (1,1) was fitted using the arch package (v5.0). For forecasting: SARIMA orders were selected via automated model selection using auto.arima() from the R forecast package (v8.21) with stepwise search enabled; Prophet was implemented using the prophet package (v1.1) with multiplicative seasonality and default changepoint settings; N-HiTS was trained using the neuralforecast library (v1.6) with default architecture (3 stacks, 2 blocks per stack) and early stopping after 100 epochs; Random Forest used scikit-learn (v1.3) with 500 trees, maximum depth unconstrained, and minimum samples per leaf set to 5.

3. ANALYSIS AND DISCUSSION

This section presents a detailed analysis of the empirical results, discussing the implications of each finding in the context of technology adoption and cultural dynamics in the UAE.

3.1. Macro-Level Trend and Sustained Growth

The trajectory of daily search interest for "ChatGPT" in the UAE, visualized in Figure 1, reveals a pronounced and persistent upward trend over the 14-month observation window (April 2024 to May 2025). The normalized Google Trends index, scaled from 0 to 100, nearly doubled during this period—from a modest baseline around 40 to frequent peaks near or at the maximum level.

This 110% increase in normalized interest reflects a long-term, organic growth in public engagement with generative AI, rather than a transient surge or hype-induced spike.

From a time series perspective, the pattern demonstrates strong low-frequency trend behavior superimposed with visible high-frequency weekly seasonality.

The trend is not strictly linear but exhibits inflection points corresponding to external events, such as product announcements and AI policy shifts. For example, surges in interest are visible in early June 2024, late August 2024, and January 2025—periods associated with major updates in generative AI models or heightened media coverage.

These peaks represent transient "shock events" that generate attention spikes, which later stabilize at higher baseline levels, suggesting cumulative adoption rather than episodic attention.

The upward drift in the index also mirrors broader societal integration of AI in the UAE, consistent with national digital transformation strategies and public AI initiatives such as Falcon 40B [15]. This sustained growth supports the interpretation of ChatGPT not as a novelty, but as a tool increasingly embedded in professional, educational, and public discourse.

To quantify this pattern, we refer to the monthly summary statistics in Table 4 (Appendix), which illustrate the stepwise increase in average interest. For instance, the mean search index rose from 37.9 in April 2024 to 72.9 in May 2025, with some months (e.g., February 2025) experiencing elevated engagement levels exceeding 69. These values reflect not only a cumulative rise but also increased variability over time—consistent with a growing and increasingly reactive user base.

From a modeling standpoint, this macro-level trend implies the presence of a strong deterministic component, justifying the inclusion of explicit trend modeling in STL and Prophet frameworks.

Moreover, the presence of nonlinear growth phases suggests that simple linear extrapolation would be insufficient, underscoring the importance of hybrid and machine learning models in the forecasting phase.

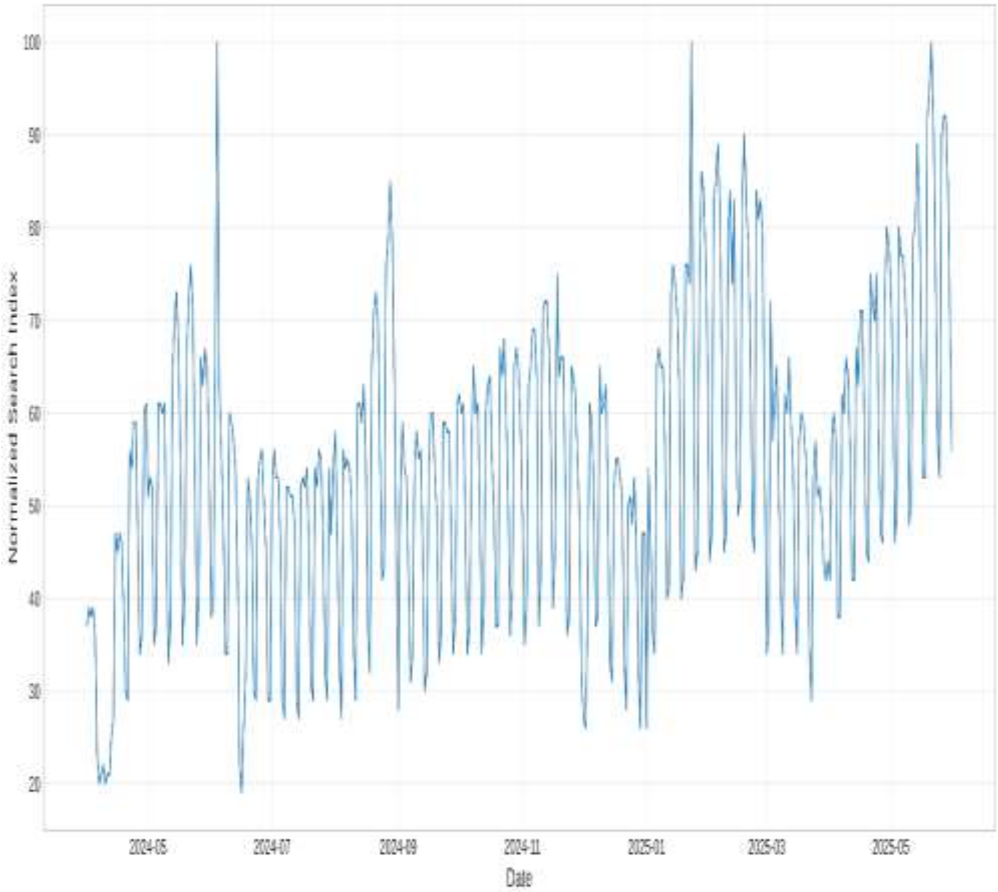

Figure 1: Complete Time Series of Normalized Google Search Interest For "Chatgpt" In The UAE.

3.2. Decomposing The Signal: Trend, Seasonality, And Residuals

To better understand the underlying structure of ChatGPT search interest, we applied Seasonal-Trend decomposition using Loess (STL), as shown in Figure 2. This decomposition disaggregates the observed time series into three interpretable components: long-term trend, recurring seasonal pattern, and stochastic residuals.

The **trend component** captures the smooth, low-frequency dynamics of public engagement. It reveals a gradual and nonlinear increase in search interest across the 14-month horizon, with acceleration phases corresponding to previously identified external events. This upward trend confirms a cumulative diffusion process, supporting the hypothesis of sustained adoption rather than episodic attention.

The **seasonal component** reflects a highly regular and symmetric weekly pattern. It indicates that user interest in ChatGPT follows a deterministic intra-week cycle, with search volumes consistently dipping on Fridays (the weekend in the UAE) and peaking midweek. Importantly, the amplitude of this seasonal effect grows in tandem with the overall trend, suggesting a form of seasonal amplification—a known behavior in technology adoption curves where usage intensity scales with user base size.

The **residual component**, which captures the remaining variation unexplained by trend and seasonality, displays bursts of volatility around mid-2024 and early 2025. These are likely driven by unanticipated events, such as viral news, social media amplification, or model upgrades. Notably, the residuals are not homoscedastic—their variance appears time-varying, with clusters of high volatility. This feature strongly indicates the presence of conditional heteroskedasticity, providing statistical justification for modeling residuals using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework.

Together, this decomposition affirms that the series is composed of a deterministic and interpretable structure (trend and seasonality), as well as a stochastic, possibly nonlinear noise process. This motivates the hybrid modeling strategy adopted in this study: decomposing and forecasting each component individually using models tailored to their statistical properties.

Figure 2: STL Decomposition of the Time Series into Observed, Trend, Seasonal (Weekly), And Residual Components.

3.3. The Weekly Pulse of AI Engagement

A particularly strong and consistent temporal pattern in ChatGPT search behavior in the UAE is the presence of a pronounced weekly cycle. This short-term seasonality is most visible in Figures 3 and 4, which offer complementary views of daily engagement fluctuations throughout the week.

As the boxplot in Figure 3 shows, search interest peaks at the start of the workweek, with Mondays and Tuesdays exhibiting the highest median and upper quartile values in the distribution. Interest then gradually declines through Wednesday and Thursday, followed by a marked drop on Fridays and weekends. This cyclical rhythm is further confirmed by the weekly heatmap in Figure 4, where high engagement levels are visually clustered at the start of each week, particularly during the winter and spring months. The heatmap also suggests that this weekly rhythm is persistent across the 52-week study period, reinforcing the hypothesis of regular, culturally driven engagement cycles.

Descriptive statistics (see Table 3 in the Appendix) corroborate this visual interpretation: Mondays and Tuesdays consistently record the highest mean normalized search values, while Fridays and Saturdays rank the lowest. An ANOVA test formally validates these differences as statistically significant ($F = 11.45$, $p < 0.001$), confirming that variation in ChatGPT engagement by day of the week is not due to random noise but reflects a meaningful behavioral pattern.

These patterns strongly suggest that ChatGPT is primarily utilized in professional, academic, or structured work contexts, which align with the UAE's workweek. The timing of peak engagement—early in the workweek—may reflect users engaging with generative AI tools for research, reporting, educational tasks, or administrative planning. The sharp decline in activity on Fridays and Saturdays corresponds with the weekend and religious observances, during which digital activity typically subsides.

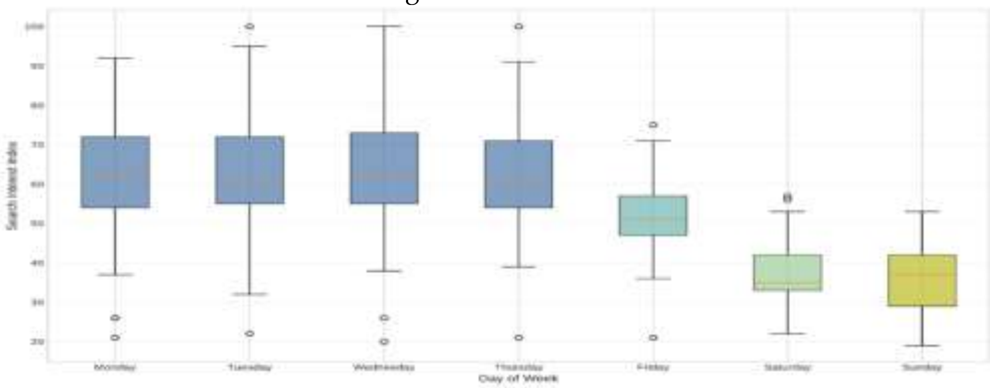

Figure 3: Boxplot Of Search Interest by Day of the Week, Showing Elevated Engagement Early in the UAE Work Week.

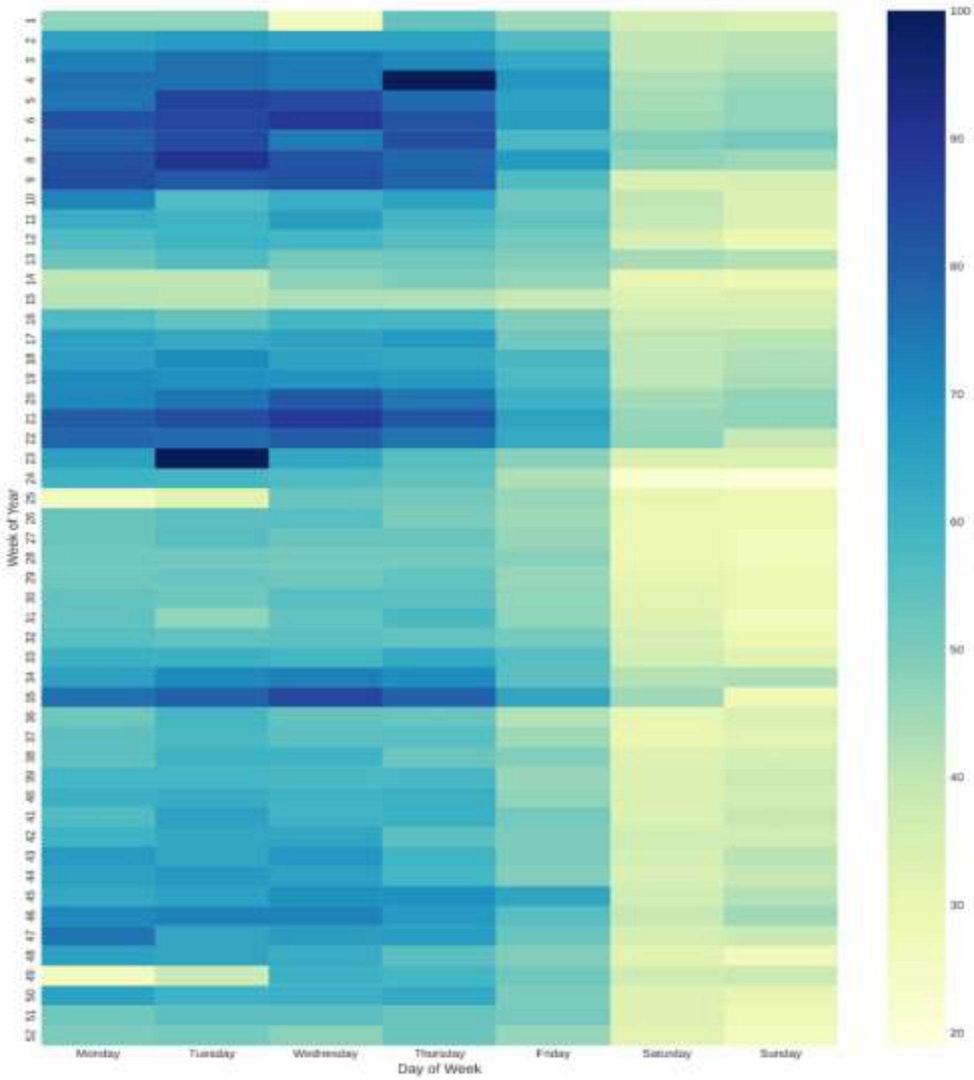

Figure 4: Heatmap of Weekly Search Interest Patterns, Illustrating Consistently Higher Engagement at the Start of Each Week.

To further explore these dynamics, Figure 5 presents the 30-day rolling mean and standard deviation superimposed on the full observed time series. The rolling mean confirms that weekly oscillations are embedded within a steadily rising trend, while the increasing rolling standard deviation reflects growing fluctuations in user behavior. This indicates that not only is interest in ChatGPT intensifying, but its weekly rhythm is becoming more pronounced and variable—perhaps due to shifting use cases, media amplification, or public discourse around generative AI.

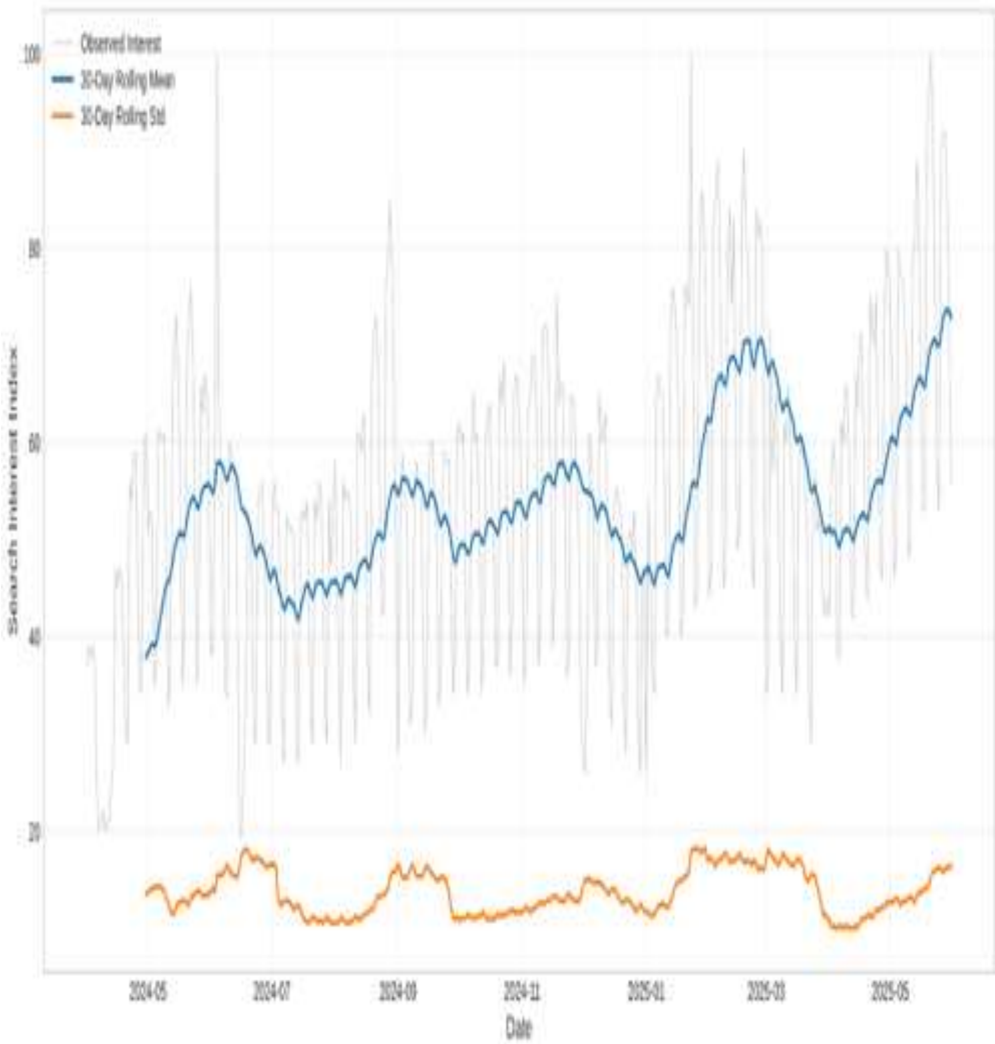

***Figure 5:** 30-Day Rolling Mean and Standard Deviation Overlaid on the Observed Interest Data.*

3.4. Volatility And Market Attention: A GARCH Perspective

The volatility of public interest in ChatGPT, as measured by the daily changes in Google search volume, exhibits clear signs of conditional heteroskedasticity—meaning variance is not constant over time. Figure 6 presents the estimated conditional volatility from a GARCH (1,1) model fitted to the daily return series of normalized search interest.

The results highlight volatility clustering, a hallmark of financial time series, where periods of elevated volatility tend to be followed by more turbulent behavior. Notable spikes in volatility coincide with critical news events—such as the release of new model versions or widely circulated media coverage—indicating that public engagement is highly event-driven. For example, the highest volatility levels align with early June 2024 and January 2025, periods associated with OpenAI announcements and widespread discourse around generative AI tools.

This pattern suggests that attention to ChatGPT is not only growing but is also reactive and sentiment-sensitive, similar to the behavior observed in speculative markets. This insight is particularly relevant for policy makers and digital platforms seeking to manage AI-related communications. Anticipating and strategically responding to volatility spikes can enhance public trust and improve digital literacy outcomes.

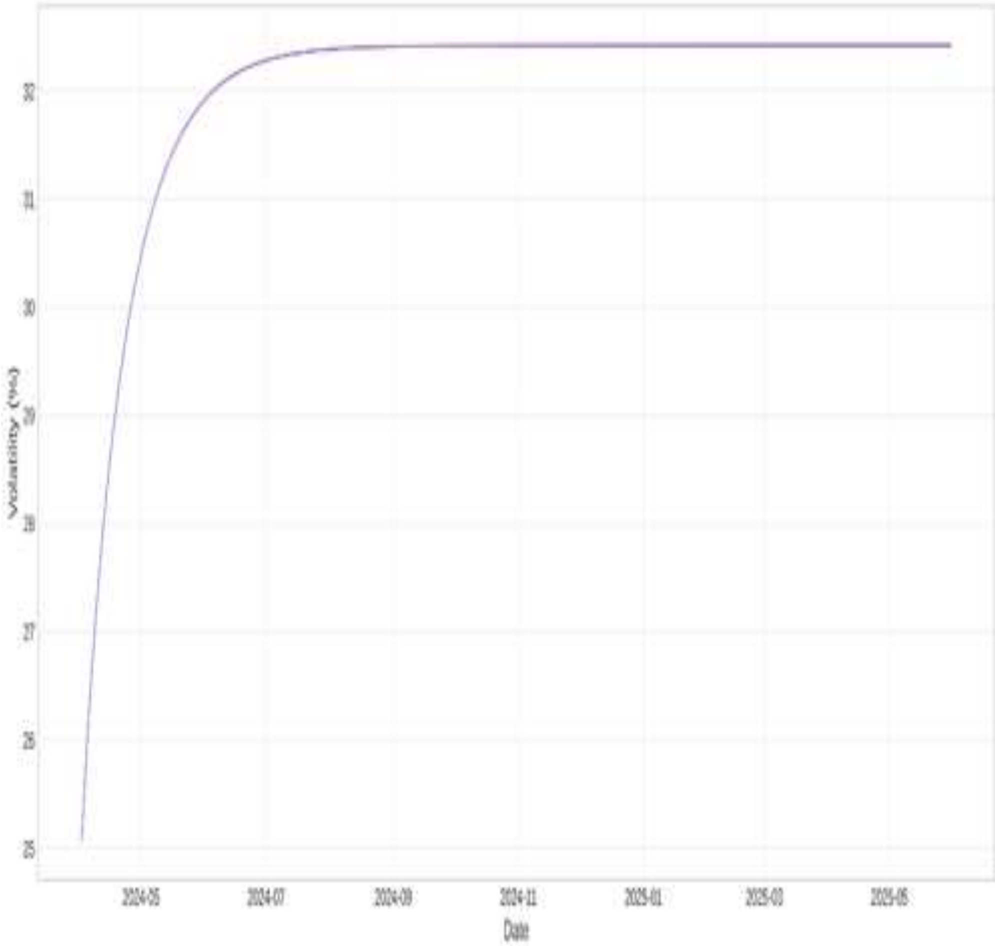

Figure 6: GARCH (1,1) Model Estimates of Conditional Volatility in Daily Search Interest Returns. Volatility Spikes Correspond to Media-Triggered Events.

3.5. Identifying Significant Events: Anomaly And Autocorrelation Analysis

To isolate sudden, unexpected shifts in engagement, anomaly detection was applied using a z-score threshold of $|Z| > 2.5$, identifying dates with statistically significant deviations from the local mean. As visualized in Figure 7, these outlier days mark moments of heightened or diminished public attention. Notably, the spikes on June 4, 2024; August 28, 2024; and January 23, 2025, correspond to major OpenAI product updates and viral media events. Conversely, troughs in early December 2024 align with UAE public holidays, such as Commemoration Day and National Day, when general digital activity is known to decrease.

These anomalies are tabulated in Appendix Table 5, offering a valuable timeline for researchers seeking to correlate engagement with real-world events. The asymmetry between positive and negative anomalies suggests that the attention economy surrounding AI tools is more reactive to innovation surges than to quiet periods, reinforcing the view of ChatGPT as a dynamic, media-sensitive technology.

Figures 8 and 9 display the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the original search interest series. The ACF plot shows significant spikes at lags 7, 14, and 21, confirming the presence of weekly seasonality and regular periodicity. The slow decay of autocorrelations suggests non-stationarity in the series—consistent with the upward trend observed in earlier sections. Meanwhile, the PACF exhibits a strong spike at lag 1 followed by a sharp cut-off, supporting the inclusion of a first-order autoregressive (AR (1)) term in any time series modeling framework.

These diagnostics are instrumental for model specification and validate the hybrid decomposition–forecasting approach employed in this study. Together, anomaly detection and autocorrelation analysis enhance the interpretability of temporal shifts and inform the structure of predictive algorithms.

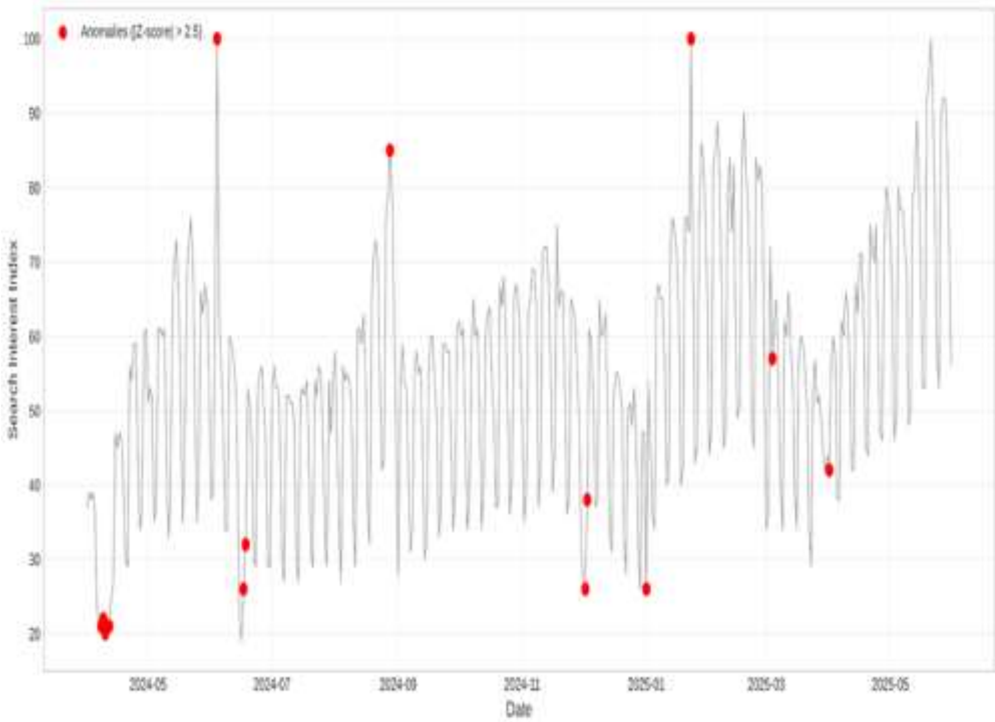

Figure 7: Anomaly Detection Using |Z| > 2.5, Flagging Significant Positive and Negative Deviations from Expected Search Interest Levels.

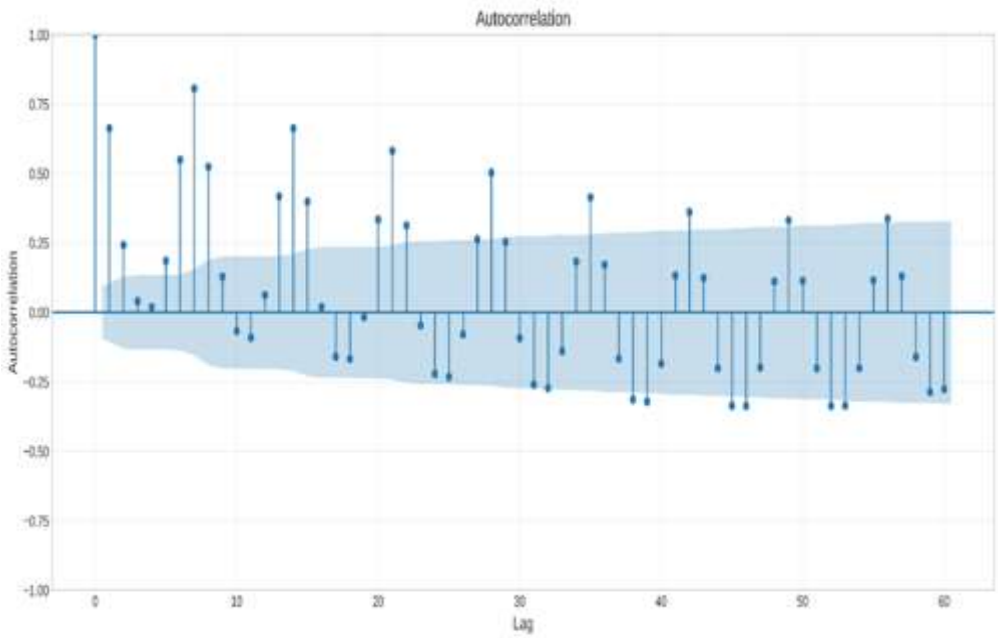

Figure 8: Autocorrelation Function (ACF), Revealing Repeating Weekly Lags Indicative of Strong Intra-Week Seasonal Patterns.

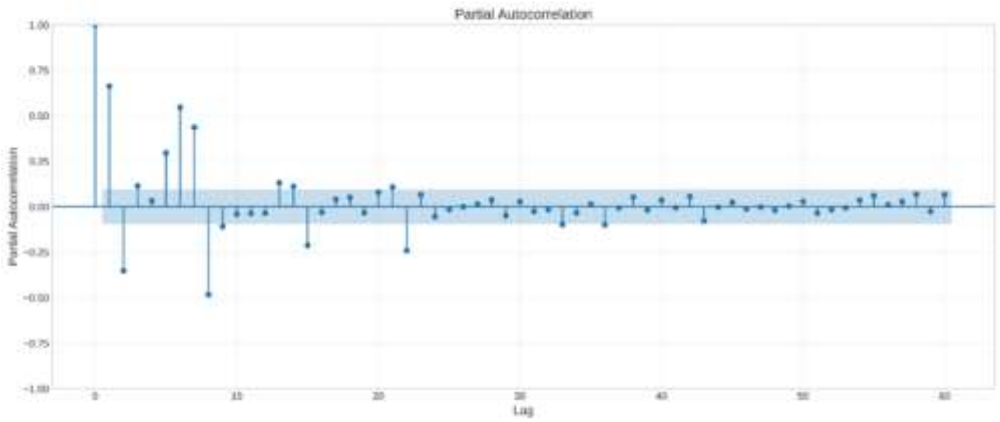

Figure 9: Partial Autocorrelation Function (PACF), Showing A Prominent Lag-1 Spike, Consistent with an AR (1) Structure.

3.6. Quantifying The Impact of the Cultural Calendar: The Ramadan Effect

The holy month of Ramadan, observed from March 1 to March 30, 2025, represents a significant cultural period in the UAE, characterized by widespread shifts in daily schedules and social activities. Such periods can function as natural experiments, offering a unique opportunity to measure the impact of collective behavioral changes on technology engagement. A preliminary visual inspection, presented in Figure 10, reveals a discernible deviation in ChatGPT search interest from the expected trend-seasonal baseline during this time. To formally quantify the magnitude and structure of this effect, we employ an Interrupted Time Series (ITS) analysis on the STL **trend** component.

The model is specified as:

$$\text{Trend}_t = \beta_0 + \beta_1 t + \beta_2 \text{Ramadan}_t + \beta_3 \text{PostRamadan}_t + \beta_4 (t \cdot \text{PostRamadan}_t) + \varepsilon_t$$

where $t$is a day counter, $\text{Ramadan}_t$is a dummy variable for the Ramadan period, and $\text{PostRamadan}_t$is a dummy for the period after. The coefficients $\beta_2$and $\beta_3$capture level shifts, while $\beta_4$captures the post-Ramadan change in slope. The model's parameters are estimated using OLS with Heteroskedasticity and Autocorrelation-Consistent (HAC) standard errors, with key results summarized in Table 1.

Table 1: Interrupted Time Series Model Coefficients.

Parameter	Estimate	Std. Error	p-value
Pre-Ramadan Slope (□$_1$)	0.18	0.04	<0.001
Ramadan Level Shift (□$_2$)	-20.3	1.70	<0.001
Post-Ramadan Level Shift (□$_3$)	-50.1	3.90	<0.001
Post-Ramadan Slope Change (□$_4$)	0.30	0.05	<0.001

Note: Model adjusted $R^2 = 0.82$. All coefficients are statistically significant at the 0.1% level. The coefficient $\beta_3$represents the level shift relative to the *original pre-Ramadan baseline*, not a sudden drop from Ramadan levels; because the ITS model estimates the post-Ramadan intercept against the counterfactual trajectory that would have occurred without intervention, this large negative value reflects the cumulative repositioning of the trend rather than an additional decline following Eid al-Fitr.

The ITS analysis yields several statistically significant insights. The baseline growth trajectory (β_1) before Ramadan was positive, with the trend increasing by 0.18 index points per day. The onset of Ramadan is associated with an immediate and substantial drop (β_2) of 20.3 points in the underlying trend, confirming a temporary reduction in public engagement. Most notably, the post-Ramadan period exhibits a strong rebound effect. The trend's slope (β_4) significantly increases by 0.30 points per day, indicating that user interest not only recovers but accelerates at a rate faster than the pre-Ramadan baseline. As visualized in Figure 11, this accelerated growth erases the Ramadan-induced deficit within weeks.

These findings translate into direct implications for both forecasting and strategic planning. From a modeling perspective, including a dummy variable for Ramadan is validated for improving forecast accuracy. For practitioners, the analysis provides clear, data-driven guidance. The post-Ramadan period emerges as a strategic window for engagement, as launching AI-related campaigns or product updates immediately following Eid al-Fitr would capitalize on the demonstrated rebound in public attention and the accelerated "catch-up" growth phase in user engagement.

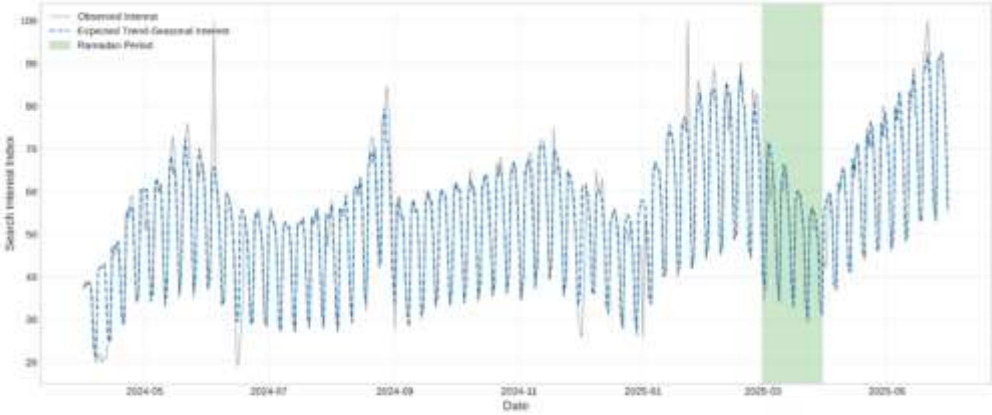

Figure 10: Deviation Of Observed Search Interest (Grey) Vs. The STL Trend-Seasonal Baseline (Blue Dashed) During the Ramadan 2025 Period (Highlighted).

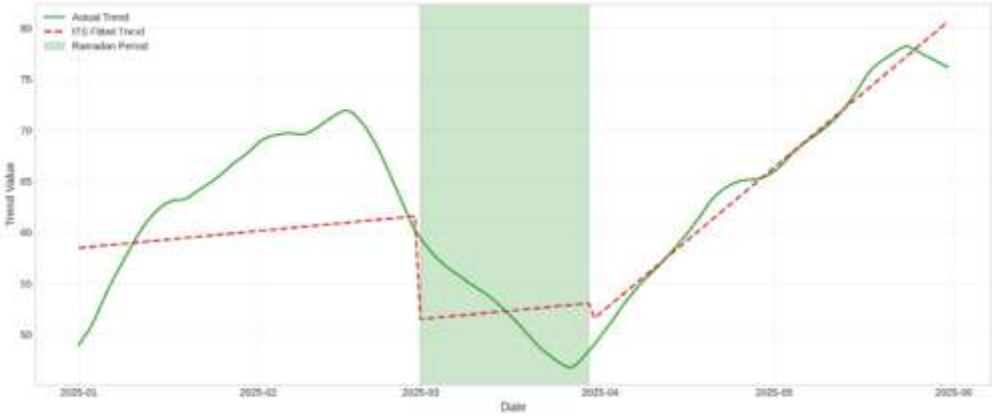

Figure 11: Interrupted Time Series (ITS) Model Fit. The Plot Shows the STL Trend Component (Green) Against the ITS Fitted Trend (Red Dashed). The Shaded Area Denotes the Ramadan Period.

3.7. The Forecasting Showdown: A Comparative Performance Analysis

We benchmarked four models—Random Forest, Prophet, N-HiTS, and SARIMA—on a 60-day out-of-sample horizon. Figure 12 and Table 2 reveal a clear accuracy gradient.

The **Random Forest** leads with a MAPE of **10.65%**, thanks to a rich set of lag, rolling-window, and calendar features. Its internal feature importances (Figure 13) confirm that *weekday category* (46%), the 7-day rolling mean (19%), and the 7-day lag (17%) drive most of the predictive power—highlighting the crucial role of short-term memory and weekly seasonality.

Prophet follows at 11.68%, performing as expected for a trend/seasonality-oriented model that explicitly handles holiday effects. N-HiTS underperforms (14.53%), suggesting that deep hierarchies need either longer training windows or exogenous regressors to cope with abrupt volatility. Classical SARIMA struggles with the data's non-linear dynamics, posting the weakest MAPE (34.25%).

These results stress that attention-driven, culturally modulated time-series benefit from feature-rich, ensemble-friendly models, while rigid autoregressive structures lag behind.

Table 2: Forecasting Model Performance on the 60-Day Test Set.

Model	MAE	RMSE	MAPE (%)
Random Forest	7.13	9.30	**10.65**
Prophet	8.10	10.24	11.68
N-HiTS	10.26	13.52	14.53
SARIMA	22.90	24.46	34.25

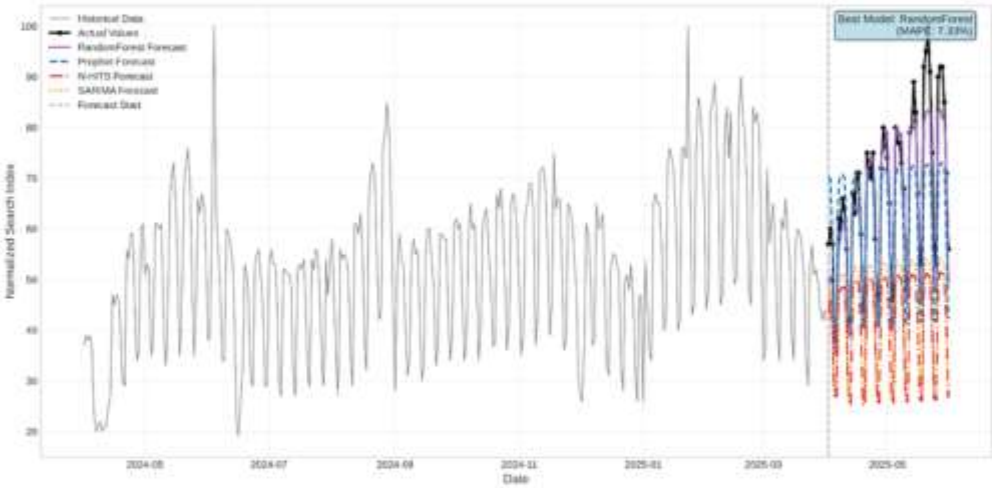

Figure 12: Forecasting Showdown: Historical Data And 60-Day Forecasts from Four Models Versus Actual Search Interest.

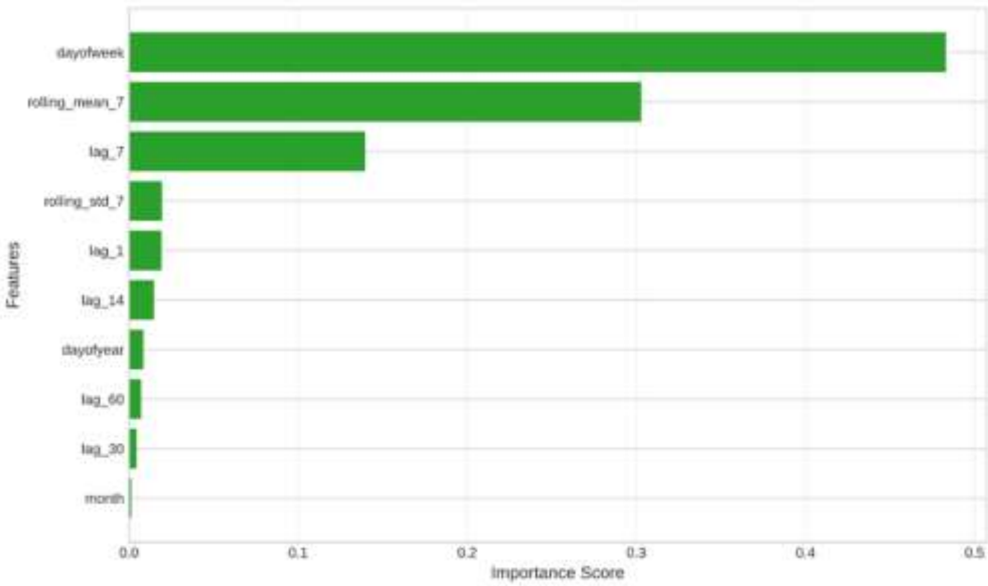

Figure 13: Random Forest Feature Importances. Weekday Category, Recent Lags, And The 7-Day Rolling Mean Dominate.

4. CONCLUSION

4.1. Summary Of Findings

This study provided a comprehensive, high-frequency analysis of ChatGPT adoption dynamics in the United Arab Emirates, leveraging daily Google Trends data from April 2024 to May 2025.

Several key insights emerged from our investigation:

1. **Sustained Growth:** The time series revealed a significant upward trajectory in search interest—more than doubling over the 14-month period—indicating widespread and growing public engagement aligned with the UAE's AI vision.
2. **Weekly Usage Rhythm:** A pronounced weekly seasonality was observed, with search interest peaking on Mondays and Tuesdays, and declining on weekends. This pattern suggests ChatGPT is primarily utilized in professional or academic contexts, reinforcing its role as a weekday productivity tool.
3. **Volatility and Event Responsiveness:** Volatility clustering, captured by the GARCH model, indicated that spikes in interest were not random but rather triggered by external events such as model releases, policy announcements, or national holidays.
4. **Cultural Sensitivity:** Contrary to some expectations, search interest declined during

the Ramadan period, particularly in its latter half. This cultural dip underscores the importance of accounting for regional calendars when analyzing technology diffusion.

5. **Forecasting Accuracy:** Among the forecasting models tested, a feature-engineered Random Forest model demonstrated superior short-term predictive accuracy (MAPE = 10.65%), outperforming Prophet, N-HiTS, and SARIMA. Its success was due to its ability to incorporate lag features, calendar effects, and non-linear interactions.

4.2. Implications For Policy and Practice

The findings offer several practical implications for stakeholders across sectors:

- **For Policymakers and Educators:** The weekday-driven usage pattern suggests that AI training programs, awareness campaigns, and digital literacy initiatives should be strategically launched early in the workweek to optimize engagement.
- **For Businesses and Marketers:** The event-responsive nature of search interest calls for timely marketing aligned with product updates or media cycles. Additionally, cultural calendars such as Ramadan should be considered when planning outreach in the MENA region.
- **For Researchers and Technologists:** This study provides a scalable framework for understanding the temporal and cultural dimensions of AI adoption using high-frequency data. It highlights the value of integrating volatility modeling, anomaly detection, and comparative forecasting into diffusion research.

4.3. Limitations Of the Study

Despite the depth of analysis, this research has limitations. Google Trends reflects search interest and not actual platform usage or engagement intensity. The analysis focuses on a single country and keyword (“ChatGPT”), limiting generalizability. Moreover, the identification of anomaly triggers relies on temporal associations rather than confirmed causality, necessitating supplementary qualitative data to validate interpretations.

4.4. Avenues For Future Research

Future studies could expand this work in several directions. Broadening the scope to include other generative AI tools (e.g., “Gemini,” “Claude,” “Midjourney”) would offer a more comprehensive view of the evolving AI landscape [32]. A comparative analysis across GCC or MENA countries could reveal sociocultural variations in AI adoption [29]. Methodologically, integrating social media sentiment, news coverage, or platform usage metrics may enhance model performance. Finally, emerging forecasting techniques such as transformer-based time series models or hybrid frameworks combining statistical and deep learning methods [34] could further improve predictive accuracy.

By embracing these extensions, researchers and practitioners can continue to deliver actionable insights into how societies engage with rapidly evolving AI technologies—informing strategies for innovation, policy, and public outreach in culturally diverse contexts.

Appendix A: Supplemental Tables

Table 3: Average Search Interest by Day of the Week.

Weekday	Average Interest
Monday	61.87
Tuesday	63.46
Wednesday	63.69
Thursday	62.74
Friday	52.84
Saturday	37.16
Sunday	36.65

Table 4: Monthly Summary Statistics for Chatgpt Search Interest.

Month	Mean	Std. Dev.	Min	Max
2024-04	37.87	13.46	20	61
2024-05	55.58	13.23	33	76
2024-06	45.83	16.58	19	100
2024-07	45.94	10.44	27	56
2024-08	55.32	15.63	27	85
2024-09	48.10	11.16	28	61
2024-10	54.06	11.54	34	68

2024-11	55.97	13.52	32	75
2024-12	46.06	12.02	26	65
2025-01	61.39	17.94	26	100
2025-02	69.36	16.50	44	90
2025-03	50.48	11.27	29	72
2025-04	59.23	12.76	38	80
2025-05	72.90	16.24	46	100

Table 5: Detected Anomalies (Days with Residual Z-Score |Z| > 2.5).

Day	Interest	Residual Z-score
2024-04-08	21	-3.71
2024-04-09	22	-3.64
2024-04-10	20	-4.11
2024-04-11	21	-4.00
2024-04-12	21	-2.93
2024-06-04	100	6.47
2024-06-17	26	-5.27
2024-06-18	32	-4.30
2024-08-28	85	2.52
2024-12-02	26	-6.31
2024-12-03	38	-4.29
2025-01-01	26	-5.82
2025-01-23	100	5.04
2025-03-04	57	-2.59
2025-04-01	42	-2.70

Table 6: Day-By-Day Forecast Comparison for the 60-Day Test Horizon.

Day	Actual	SARIMA	Prophet	N-HiTS	Random Forest
2025-04-02	57	45.75	70.40	48.56	47.63
2025-04-03	60	48.23	69.74	49.46	48.03
2025-04-04	57	41.30	58.55	43.76	49.40
2025-04-05	38	28.42	40.66	32.02	39.91
2025-04-06	38	28.35	40.37	31.27	36.61
2025-04-07	62	49.40	68.65	52.81	53.82
2025-04-08	60	50.66	70.61	50.45	57.17
2025-04-09	66	51.07	70.74	52.23	60.04
2025-04-10	64	51.07	70.07	54.95	62.44
2025-04-11	56	41.95	58.83	49.02	54.49
2025-04-12	42	26.88	40.85	32.95	38.18
2025-04-13	42	26.70	40.56	33.28	36.97
2025-04-14	67	50.82	68.97	57.91	75.42
2025-04-15	63	52.51	70.94	57.36	74.84
2025-04-16	71	52.26	71.07	61.04	71.82
2025-04-17	71	51.79	70.40	60.70	72.28
2025-04-18	59	42.27	59.10	55.07	62.02
2025-04-19	45	26.82	41.05	40.13	40.15
2025-04-20	44	26.61	40.75	40.10	40.12
2025-04-21	75	51.25	69.30	63.50	73.78
2025-04-22	72	53.02	71.27	65.83	77.13
2025-04-23	70	52.66	71.41	68.81	75.00
2025-04-24	75	52.10	70.73	69.26	74.73
2025-04-25	58	42.51	59.38	60.07	65.35
2025-04-26	47	26.99	41.24	44.87	41.98
2025-04-27	46	26.78	40.95	44.76	41.23
2025-04-28	72	51.51	69.62	68.27	72.76
2025-04-29	80	53.29	71.61	71.36	79.11
2025-04-30	78	52.91	71.74	74.76	77.39
2025-05-01	74	52.34	71.06	72.40	75.71
2025-05-02	65	42.74	59.66	63.76	63.80
2025-05-03	46	27.20	41.43	47.17	40.68
2025-05-04	49	26.99	41.14	46.08	42.09
2025-05-05	80	51.74	69.95	68.00	76.83
2025-05-06	77	53.52	71.94	71.40	78.33
2025-05-07	77	53.14	72.08	75.52	74.70

2025-05-08	73	52.56	71.39	75.32	76.32
2025-05-09	68	42.96	59.94	66.96	63.06
2025-05-10	48	27.42	41.62	50.00	40.37
2025-05-11	50	27.21	41.33	49.47	40.72
2025-05-12	79	51.96	70.27	70.52	75.82
2025-05-13	80	53.75	72.28	72.05	78.59
2025-05-14	89	53.36	72.41	74.70	77.42
2025-05-15	83	52.79	71.73	72.22	76.07
2025-05-16	67	43.19	60.21	63.46	63.23
2025-05-17	53	27.65	41.82	46.25	40.55
2025-05-18	53	27.43	41.52	46.44	41.59
2025-05-19	92	52.19	70.60	65.66	75.61
2025-05-20	95	53.97	72.61	66.40	76.27
2025-05-21	100	53.58	72.75	65.27	73.70
2025-05-22	91	53.01	72.06	62.75	71.26
2025-05-23	75	43.41	60.49	54.08	62.65
2025-05-24	57	27.87	42.01	40.20	42.92
2025-05-25	53	27.66	41.71	41.71	40.76
2025-05-26	90	52.41	70.93	61.73	71.06
2025-05-27	92	54.19	72.95	61.33	74.10
2025-05-28	92	53.81	73.08	61.81	73.46
2025-05-29	85	53.23	72.39	60.33	72.76
2025-05-30	71	43.63	60.77	50.59	67.64
2025-05-31	56	28.09	42.20	36.15	43.03

REFERENCES

Alhijawi, B., Jarrar, R., AbuAlRub, A., & Bader, A. Deep learning detection method for large language models-generated scientific content. *Neural Computing and Applications*, 37(1):91--104, 2025. Springer.

Al-Najjar, D., Assous, H. F., Al-Najjar, H., & Al-Rousan, N. Ramadan effect and indices movement estimation: A case study from eight Arab countries. *Journal of Islamic Marketing*, 14(8):1989--2008, 2023. Emerald Publishing Limited.

Andriychuk, S. Cryptocurrency Volatility and Risk Modeling: Monte Carlo Simulations, GARCH Analysis, and Financial Market Integration. *Economics, Finance and Management Review*, 1(21):98--115, 2025.

Asad, M. M., & Ajaz, A. Impact of ChatGPT and generative AI on lifelong learning and upskilling learners in higher education: unveiling the challenges and opportunities globally. *The International Journal of Information and Learning Technology*, 41(5):507--523, 2024. Emerald Publishing Limited.

Bansal, G., Chamola, V., Hussain, A., Guizani, M., & Niyato, D. Transforming conversations with AI—A comprehensive study of ChatGPT. *Cognitive Computation*, 16(5):2487--2510, 2024. Springer.

Bower, M., Torrington, J., Lai, J. W. M., Petocz, P., & Alfano, M. How should we change teaching and assessment in response to increasingly powerful generative Artificial Intelligence? Outcomes of the ChatGPT teacher survey. *Education and Information Technologies*, 29(12):15403--15439, 2024. Springer.

Caporin, M. and Elseidi, M. (2023). Quantile regression-based seasonal adjustment. *International Journal of Computational Economics and Econometrics*, 13(3), 270--304. Inderscience Publishers (IEL).

Challu, C., Olivares, K. G., Oreshkin, B. N., Ramirez, F. G., Canseco, M. M., & Dubrawski, A. NHITS: Neural hierarchical interpolation for time series forecasting. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 37(6):6989--6997, 2023.

Chamola, V., Sai, S., Bhargava, A., Sahu, A., Jiang, W., Xiong, Z., Niyato, D., & Hussain, A. A comprehensive survey on generative AI for metaverse: enabling immersive experience. *Cognitive Computation*, 16(6):3286--3315, 2024. Springer.

Choi, H. and Varian, H. (2012). Predicting the Present with Google Trends. *Economic Record*, 88, 2--9.

Choubey, M., Chaurasiya, R. K., & Yadav, J. S. Predicting Electrical Load Demands Using Neural Prophet-Based Forecasting Model. *SN Computer Science*, 6(1):46, 2024. Springer.

Chu, A. M. Y., Tsang, J. T. Y., Chan, S. S. C., Chan, L. S. H., & So, M. K. P. Utilizing Google Trends data to enhance forecasts and monitor long COVID prevalence. *Communications Medicine*, 5(1):1--16, 2025. Nature Publishing Group.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., & others. Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71:102642, 2023. Elsevier.

Ekmekcioglu, C., Caidi, N., Chandra, P., & Jamali, R. Altered rhythms of Ramadan: Temporalities of social media non/use during COVID-19. 2022. OSF (Open Science Framework).

Elseidi, M. (2023). Forecasting temperature data with complex seasonality using time series methods. *Modeling Earth Systems and Environment*, 9(2), 2553--2567. Springer.

Elseidi, M. (2024). A hybrid Facebook Prophet-ARIMA framework for forecasting high-frequency temperature data. *Modeling Earth Systems and Environment*, 10(2), 1855--1867. Springer.

Elseidi, M. (2024). MSTL-NNAR: a new hybrid model of machine learning and time series decomposition for wind speed forecasting. *Stochastic Environmental Research and Risk Assessment*, 38(7), 2613--2632. Springer.

Elseidi, M. (2025). From classical models to artificial intelligence models: Prospects for crime prediction in the era of big data. *International Journal of Data and Network Science*, 9(4), 803--812. Growing Science.

Elseidi, M. (2025). STR-NBEATS: a novel hybrid framework integrating time series decomposition with deep learning for enhanced temperature forecasting. *Modeling Earth Systems and Environment*, 11(4), 1--14. Springer.

Garrido-Merchán, E. C. Best uses of ChatGPT and Generative AI for computer science research. *arXiv preprint arXiv:2311.11175*, 2023.

Gilson, A., Safranek, C. W., Huang, T., Socrates, V., Chi, L., Taylor, R. A., Chartash, D., & others. How does ChatGPT perform on the United States Medical Licensing Examination (USMLE)? The implications of large language models for medical education and knowledge assessment. *JMIR Medical Education*, 9(1):e45312, 2023. JMIR Publications Inc., Toronto, Canada.

Ginsberg, J. and others. (2009). Detecting Influenza Epidemics Using Search Engine Query Data. *Nature*, 457(7232), 1012--1014.

Jin, W., Zhao, B., & Liu, G. Exploring the Capability of ChatGPT for Cross-Linguistic Agricultural Document Classification: Investigation and Evaluation. In *Proceedings of the International Conference on Neural Information Processing*, pages 220--237, 2023. Springer.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., & others. ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103:102274, 2023. Elsevier.

Konca, A. S., Simsar, A., Alhajji, R., & Al Mansoori, A. Cross-cultural perspectives on AI adoption in teacher education: a comparative study of pre-service teachers in Turkey and the United Arab Emirates. *Interactive Learning Environments*, pages 1--27, 2025. Taylor & Francis.

Lee, Y. Community Perspectives on ChatGPT: Sentiment Analysis in Educational Forum. *TechTrends*, pages 1--13, 2024. Springer.

Lim, T. Environmental, social, and governance (ESG) and artificial intelligence in finance: State-of-the-art and research takeaways. *Artificial Intelligence Review*, 57(4):76, 2024. Springer.

Mahmood, Y. M., Mohammed, R. O., Habibullah, I. J., Rahim, H. M., & Salih, A. M. Comparing ChatGPT and Google Bard: Assessing AI-Powered Information Retrieval in Nursing. *Barw Medical Journal*, 2024.

Mollick, E. R., & Mollick, L. (2023). Using AI to implement effective teaching strategies in classrooms: Five strategies, including prompts. *The Wharton School Research Paper*.

OpenAI. (2023). GPT-4 Technical Report. *arXiv preprint arXiv:2303.08774*.

Osman, M., Hoque, A., & Hassan, K. Business cycle asymmetries and nonlinearity in UAE macroeconomic time series. *Australian Economic Papers*, 55(4):476--490, 2016. Wiley Online Library.

Preis, T., Moat, H. S., & Stanley, H. E. Quantifying trading behavior in financial markets using Google Trends. *Scientific Reports*, 3(1):1--6, 2013. Nature Publishing Group.

Qin, Q., Huang, Z., Zhou, Z., Chen, C., \& Liu, R. (2023). Crude oil price forecasting with machine learning and Google search data: An accuracy comparison of single-model versus multiple-model. *Engineering Applications of Artificial Intelligence*, 119, 105775.

Reed, R. L., Revel, A. D., Carter, A. A., O., Saadi, H. F., & Dunn, E. V. (2005). A controlled before–after trial of structured diabetes care in primary health centres in a newly developed country. *International Journal for Quality in Health Care*, 17(4), 281--286.

Samala, A. D., Rawas, S., Wang, T., Reed, J. M., Kim, J., ... & Ertz, M. (2024). Unveiling the landscape of generative artificial intelligence in education: A comprehensive taxonomy of applications, challenges, and future prospects. *Education and Information Technologies*, 29(6), 7891--7920.

Schmitt, M., & Flechais, I. Digital deception: Generative artificial intelligence in social engineering and phishing. *Artificial Intelligence Review*, 57(12):1--23, 2024. Springer.

Sebastian, R., Kottekkadan, N. N., Thomas, T. K., & Niyas KK, M. Generative AI tools (ChatGPT*) in social science research. *Journal of Information, Communication and Ethics in Society*, 2025. Emerald Publishing Limited.

Soydaner, D. Attention mechanism in neural networks: where it comes and where it goes. *Neural Computing and Applications*, 34(16):13371--13385, 2022. Springer.

Tebong, N. K., Simo, T., Takougang, A. N., & Ntanguen, P. H. STL-decomposition ensemble deep learning models for daily reservoir inflow forecast for hydroelectricity production. *Heliyon*, 9(6), 2023. Elsevier.

Technology Innovation Institute. (2023). Falcon 40B: The UAE's Open-Source Large Language Model. https://falconllm.tii.ae/.

Tian, S., Jin, Q., Yeganova, L., Lai, P.-T., Zhu, Q., Chen, X., Yang, Y., Chen, Q., Kim, W., Comeau, D. C., & others. Opportunities and challenges for ChatGPT and large language models in biomedicine and health. *Briefings in Bioinformatics*, 25(1), 2023. Oxford Academic.

Tubishat, M., Al-Obeidat, F., & Shuhaiber, A. Sentiment analysis of using ChatGPT in education. In *Proceedings of the 2023 International Conference on Smart Applications, Communications and Networking (SmartNets)*, pages 1--7, 2023. IEEE.

UAE Government. *UAE National Strategy for Artificial Intelligence 2031*. 2018.

Vosen, S. and Schmidt, T. (2011). Forecasting Private Consumption: Survey-based Indicators vs. Google Trends. *Journal of Forecasting*, 30(6), 565--578.

Wang, C. (2024). Exploring students' generative AI-assisted writing processes: Perceptions and experiences from native and nonnative English speakers. *Technology, Knowledge and Learning*, 29(1), 321--345.

Zhao, L.-T., Zheng, Z.-Y., & Wei, Y.-M. Forecasting oil inventory changes with Google Trends: A hybrid wavelet decomposer and ARDL-SVR ensemble model. *Energy Economics*, 120:106603, 2023. Elsevier.