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A Hybrid FinTech-Driven Framework for Volatility Forecasting: The Role of Digital Attention and Technical Indicators in the Dubai Financial Market

Nour Lababidi [1,*], Hasan Katalo [2] and Yahya Kamakhli [3]

[1] Teaching assistant at Damascus university, PhD student at Aleppo university, Damascus, Syria
[2] Professor at Aleppo university, Aleppo, Syria
[3] Lecturer at Aleppo university, Aleppo, Syria
* Correspondence: nour.lababidi@damascusuniversity.edu.sy

Abstract

Research Purpose: This study investigates the role of digital investor behavior, measured through Google Trends, alongside technical indicators such as RSI and Bollinger Bands, in forecasting volatility in the Dubai Financial Market. The aim is to develop a hybrid analytical framework that integrates behavioral and technical dimensions to enhance predictive accuracy in emerging markets. **Study Methodology**: Weekly data from 2020 to 2025 were collected, covering both crisis and post-crisis periods. Digital attention was quantified using Google Trends search indices, while technical indicators included RSI and Bollinger Bands calculated over a 7-day horizon. Volatility was modeled using ARCH, GARCH, and EGARCH frameworks, with Max Drawdown employed as a complementary risk metric to capture extreme market movements. **Findings**: The results reveal that digital investor attention significantly contributes to volatility forecasting, particularly when combined with technical indicators. Models incorporating both behavioral and technical variables demonstrated superior predictive performance compared to traditional approaches. The EGARCH model highlighted the asymmetric impact of negative shocks, while Max Drawdown provided additional insights into risk exposure during periods of heightened market stress. **Scientific value**: This study positions digital attention as a leading indicator in volatility modeling, moving beyond conventional approaches that treat behavioral signals as supplementary. By integrating Google Trends with technical analysis, the research introduces a hybrid forecasting framework that can be adapted to other emerging markets. **Practical Implications:** The findings offer practical value for policymakers and investors. Regulators can use digital attention measures as early-warning signals to anticipate instability, while investors can integrate behavioral and technical indicators to improve risk management and trading strategies. From a foresight perspective, the study contributes to building more resilient financial systems by embedding behavioral data into predictive tools.

Keywords: digital investor behavior; Google trends; volatility; technical indicators; volatility forecasting; risk prediction; emerging markets

1. Introduction and Literature Review

Previous research such as (Farrukh et al. 2017) has shown that online search activity can precede stock market movements. Financial markets experience frequent fluctuations that result in significant costs, affecting financial market indicators. Investor sentiment has been shown to significantly impact stock returns, as demonstrated by Smale (2017). Frequent price fluctuations are linked to a volatile pattern, resulting in a rise followed by a sharp decline. This is due to the interaction of a number of economic and psychological factors. Investors are increasingly interested in developing trading strategies to help them make informed investment decisions and limit losses. Trading strategies rely on technical analysis techniques based on historical price and volume data, as well as investor

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behavior analysis, which is a key tool used by traders to understand and analyze volatility (Celik, S.,2012). The aim of this research is to understand the volatility of financial markets and analyze their movements, especially in light of increasing volatility and uncertainty. This is achieved by providing early signals of potential fluctuations in the market return index, through which traders can use them to manage risks, determine the size of trades, and determine appropriate stop-loss points, reducing potential losses by using technical indicators such as moving averages, price patterns, and investor sentiment patterns and their relationship to fluctuations in financial markets (Smale, L., A.,2017). With the development of digital data, it has become possible to measure investor behavior online, particularly through tools such as Google Trends, which reflects collective mood and general interest. It provides real-time data on search volume related to specific topics. However, traditional tools, such as technical analysis and standard deviation are still widely used to measure momentum and volatility in financial markets (Keshavarz et al. 2022). There is a need for an analytical study that examines the role of these tools in understanding and analyzing patterns of volatility in financial markets, especially in light of rapidly changing economic conditions. Emerging financial markets, such as the Dubai Financial Market, are experiencing increased volatility driven by economic, political, and psychological factors.

Tabash et al. (2025) provided empirical evidence that global investor sentiment and financial stress significantly transmit to local market volatility in GCC countries, including the UAE. Their findings underscore the importance of incorporating behavioral variables into volatility models for regional markets. At the same time, digital attention measures such as Google Trends have emerged as promising tools for forecasting volatility, yet most prior studies have treated them as supplementary rather than central variables. Moreover, few studies have integrated behavioral signals with technical indicators in the context of emerging markets, where volatility is often driven by both economic shocks and collective psychology. This gap highlights the need for a hybrid framework that combines digital investor behavior with technical analysis to improve forecasting accuracy. Building on this gap, the present study develops and tests three hypotheses regarding the role of Google Trends and technical indicators in predicting volatility and risk in the Dubai Financial Market.

Since the seminal work of Engle (1982) on the ARCH model, volatility modeling has evolved into a wide spectrum of advanced approaches. Bollerslev (1986) extended ARCH into the GARCH framework, allowing for more flexible lag structures in conditional variance. Nelson (1991) introduced the EGARCH model to capture asymmetries in the impact of positive and negative shocks, while Glosten, Jagannathan, and Runkle (1993) proposed the GJR-GARCH model to account for leverage effects. Later, Baillie et al. (1996) developed the FIGARCH model to incorporate long memory in volatility processes. These extensions demonstrate that volatility is not only time-varying but also influenced by structural features such as persistence, asymmetry, and long-term dependence. Positioning the current study within this stream of research highlights the importance of integrating behavioral and technical indicators into advanced volatility models, especially in emerging markets where shocks tend to be more pronounced and persistent. It is not yet clear whether digital search data such as Google Trends provides reliable signals that can be used to predict volatility.

The primary objective of this study is to investigate the predictive power of digital investor behavior - measured through Google Trends- and technical indicators such as RSI and Bollinger Bands in forecasting market volatility within the Dubai Financial Market. By integrating behavioral data with traditional technical analysis, the research aims to develop a hybrid framework that enhances forecasting accuracy and risk assessment in emerging financial markets.

What distinguishes this study is its focus on digital attention as a leading indicator, moving beyond conventional price-based models. Unlike previous research that often treats behavioral signals as supplementary, this study positions them as central components in volatility modeling. Furthermore, the use of Max Drawdown as a risk metric adds depth to the analysis by capturing extreme market movements, offering practical insights for investors and analysts operating in volatile environments. A relationship between financial decision-making and human digital behavior was demonstrated by analyzing the correlation between online searches related to political or business events and subsequent stock market movements, and it was found that (Farrukh et al .2017) increased searches for these topics may lead to a rise or fall in the stock market. The researchers (Dimpfl & Jank, 2016) conducted a study on the relationship between online search queries and financial market volatility; which relied on search data as an indicator of investor sentiment. The results indicated that a high volume of searches for information related to financial markets is an indicator of future price fluctuations. These results can be used to improve the models for predicting financial market volatility in our study, and the researchers found that (Michele, Matteo, & Carlo, 2021) found a relationship between the volume of search queries in Italy, Germany, France, Britain, Spain, and the United States and the stock markets fluctuations. The Italian Google Trends index was found to be the main driver of the financial markets. Researchers believe (Ranco et al. 2015) there is was a relationship between news sentiment and reader behavior on financial platforms (Yahoo! Finance). The analysis relied on the number of clicks and the number of views, which are useful in predicting price trends. The study noted that news alone is not sufficient for prediction, but when combined with the interest of digital readers, it becomes a powerful tool for predicting movements in financial markets. Digital behavioral tools may be insufficient for accurate forecasting, indicating a need for additional methods to improve prediction accuracy.

The researcher found (Ramona, Silvia, & Raluca,2024) that Google Trends is a good indicator of public interest in the cryptocurrency market, which drives prices and affects trading volumes. This interest is particularly evident in periods of volatility, and these findings may help investors understand the dynamics of cryptocurrencies and build their trading strategies. Based on the above findings, digital behavior can be used as early warning signals for the future. The researchers (Deveikyte et al. 2022) analyzed sentiment extracted from news and tweets on Twitter to predict the future volatility of the FTSE-100 index. The results showed a relationship between positive sentiment and market volatility on the following day. News articles were modeled using Latent Dirichlet Allocation. (Phuong & Nhung, 2021) used the technical indicator RSI (Relative Strength Index) to study the impact of investment sentiment on the returns of the Vietnamese market. They relied on analytical methods such as (GLS) Generalized Least Squares and Fama-MacBeth regression. The results showed that a high RSI reflects a degree of optimism or overbought among investors, but this study did not rely on any variable that indicates public behavior and assumed that prices reflect these sentiments. The researcher suggested (Yuri, Sujin & Seongbin, 2025) a proposed a system that combines sentiment analysis of publicly available news with the (RSI) to identify overbought and oversold conditions for buy/sell decisions. The results demonstrated the system's ability to adapt to different market sectors and its ability to improve trading results. The system provides a practical and executable investment strategy.) Markus, Qian, & Min, 2024) confirmed the importance of investor sentiment in technical analysis, examining the effectiveness of technical analysis when combined with market sentiment on news in derived from the US and Chinese stock markets, where the combination yields a profitable portfolio strategy. In summary, the literature demonstrates that advanced volatility models such as GARCH, EGARCH, and FIGARCH have been widely applied to capture the dynamics of financial market risk, while technical indicators like RSI and Bollinger Bands provide valuable signals of investor sentiment and momentum. At the same time, digital attention measures such as Google Trends have emerged as promising tools for forecasting volatility, yet most prior studies have treated them as supplementary rather than central variables. Moreover, few studies have integrated behavioral signals with technical indicators in the context of emerging markets, where volatility is often driven by both economic shocks and collective psychology. This gap highlights the need for a hybrid framework that combines digital investor behavior with technical analysis to improve forecasting accuracy. Building on this gap, the present study develops and tests three hypotheses regarding the role of Google Trends and technical indicators in predicting volatility and risk in the Dubai Financial Market.

In summary, the literature demonstrates that advanced volatility models such as GARCH, EGARCH, and FIGARCH have been widely applied to capture the dynamics of financial market risk,

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while technical indicators like RSI and Bollinger Bands provide valuable signals of investor sentiment and momentum. In this context, a recent study by Deep et al. (2025) emphasized the importance of technical indicators in risk management, suggesting that these indicators may be more useful for hedging risks than for predicting returns themselves. At the same time, digital attention measures such as Google Trends have emerged as promising tools for forecasting volatility, yet most prior studies have treated them as supplementary rather than central variables. Moreover, few studies have integrated behavioral signals with technical indicators in the context of emerging markets, where volatility is often driven by both economic shocks and collective psychology. This gap highlights the need for a hybrid framework that combines digital investor behavior with technical analysis to improve forecasting accuracy. Building on this gap, the present study develops and tests three hypotheses regarding the role of Google Trends and technical indicators in predicting volatility and risk in the Dubai Financial Market (Deep et all 2025).

The objective of this research is to examine of digital investor behavior, by integrating technical analysis indicators, and predicting volatility using two methods: standard deviation (volatility) and maximum loss over a period of time. To achieve this goal, three research hypotheses were proposed:

H1: People search more online when technical indicators are overbought or oversold.

H2: There is effectiveness in using Google Trends data and technical analysis indicators (Bollinger RSI) in predicting volatility in the Dubai market.

H3: Google trends data and technical indicators are effective for help to reduce investment risks by anticipating market volatility early.

2. Materials and Methods

2.1. Critique of the Theory of Financial Market Efficiency

The Efficient Market Hypothesis, as formalized by Fama (1970), posits that asset prices fully reflect all available information. Critics of market efficiency, such as Lo & Mackinlay (1999), argue that price movements are not entirely random. The random walk theory, popularized by Malkiel (2019), has been increasingly questioned in light of behavioral finance evidence. Early theoretical foundations of market efficiency can be traced back to Samuelson (1965), who argued that properly anticipated prices fluctuate randomly the study period from 2020 to 2025 was deliberately chosen to capture a wide range of market conditions and shocks that are particularly relevant to emerging markets. This timeframe includes the outbreak of the COVID-19 pandemic, fluctuations in global oil prices, and subsequent recovery phases, all of which had significant impacts on the Dubai Financial Market. By covering both crisis and post-crisis periods, the dataset provides a robust environment to test the predictive power of digital attention and technical indicators under varying levels of volatility and uncertainty. This choice ensures that the proposed hybrid framework is evaluated in a context that reflects real-world challenges faced by investors and policymakers in emerging economies. While the methodology provides a comprehensive framework by integrating digital attention and technical indicators, several limitations should be acknowledged. First, Google Trends data may not fully capture institutional investor behavior or private information flows, which can also drive volatility. Second, technical indicators such as RSI and Bollinger Bands are sensitive to parameter choices and may generate false signals under extreme market conditions. Finally, the study focuses on a single emerging market (Dubai), which limits the generalizability of the findings to other contexts. These limitations, however, open avenues for future research to extend the framework to multiple markets and incorporate additional behavioral data sources such as social media sentiment.

The efficient market hypothesis states that the price of a financial asset is random and cannot be predicted using technical analysis or other methods. This challenges the claim of effectiveness of technical analysis methods that are able to predict what will happen to the price in the future (Murphy, J. ,1999). Many studies conducted in recent years question the validity of the efficient market theory, emphasizing that the price of a financial asset has a specific behavior that it follows, thus opposing the idea of a random walk of price movement. Opposing the idea of random walk of price movement, this study focuses on how technical analysis tools use past price changes to detect patterns that help investors predict future movements. In addition, recent studies in the field known as "Behavioral Finance" (Antony, A.,2019) have emerged, indicating that investment decisions made to buy or sell a financial asset are not entirely rational, and that there are a large number of investors who can influence price movement in unpredictable ways. Future price movements may be influenced based on public psychology, which ranges between panic, fear, and pessimism on the one hand, and confidence and optimism on the other. This indicates that prices do not reflect what they are actually worth, but rather what people think they are. This helps explain the rapid declines and rises in financial markets during certain periods, driven by emotions that may take time to stabilize. There are several important indicators to explain most of the behavior of financial market participants, who follow the herd behavior of rising and falling according to their psychological state. This research attempts to study the impact of digital behavior on predicting fluctuations in financial markets.

2.2. Digital Attention Hypothesis - Alternative Indicators such as Google Trends

Recent studies, including Ramona et al. (2024), have shown that Google Trends can reflect public interest in financial assets, influencing prices and trading volumes. Research such as Ranco et al. (2015) indicates that digital reader behavior on financial platforms can enhance price trend predictions. Yang et al. (2020) studied the effect of investor attention on trading volume and returns, using search engine data as a proxy for interest. Some investors have limited cognitive capacity and can process all the information available in the market, cannot process all the information available in the market. This focus on high-profile news sometimes causes investors to ignore more important but less exciting or less clear data. This behavior leads to price distortions because supply and demand are influenced by the amount of attention and interest of investors more than the actual value. This explanation for why stock prices often move sharply after important news and later revert to stability. The Researchers (Yang, Ma, & Wang ,2020) studied the effect of attention on trading volume and returns in the Chinese financial market. They relied on the appearance of the stock and related financial market news in the (Baidu) search engine, as the increase in the number of searches is an indicator of increased investor interest (Yang, D., Ma, T., Wang, Y., & Wang, G. ,2020). In our study, we use Google Trends data to capture investors digital behavior and apply the attention hypothesis. There is clear evidence that excessive investor attention creates temporary biases in financial markets. This supports behavioral finance theory and completely contradicts the efficiency of financial markets.

A growing body of literature has utilized Google Trends to capture investor attention and predict market dynamics. In a comprehensive international study, Said and Slim (2022) examined the dynamic relationship between investor attention—measured via Google Search Volume Index (GSVI)—and stock market volatility across 14 developed and emerging markets. Using an empirical similarity model enhanced with Google Trends data, they found that increased investor attention significantly predicts short-term realized volatility, with the effect being more pronounced during periods of market stress. Their findings support the attention hypothesis, which posits that limited cognitive capacity leads investors to focus on attention-grabbing information, thereby influencing price dynamics and volatility. This study provides strong empirical justification for incorporating Google Trends data as a leading indicator in volatility forecasting models, particularly in markets where retail investor behavior plays a significant role.

2.2. Theories Related to Technical Indicators

Technical indicators are widely used in investment valuation and management, as discussed in foundational texts like Jordan & Miller (2009). Traditional tools such as technical analysis remain relevant in volatility measurement, as noted by Keshavarz et al. (2022). Both fundamental and technical analysis play complementary roles in market analysis, as discussed by Suresh (2013).

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2.2.1. Relative Strength Index (RSI)

The Relative Strength Index (RSI) was developed by Wilder (1978) to measure the speed and change of price movements.

Recent empirical studies have emphasized that technical indicators such as RSI and Bollinger Bands are not only mechanical tools but also reflect underlying investor sentiment. For instance, Phuong and Nhung (2021) showed that high RSI values in the Vietnamese market are associated with investor optimism and overbought conditions, while low RSI values indicate pessimism and oversold states. Similarly, Markus, Qian, and Min (2024) demonstrated that combining Bollinger Band signals with market sentiment extracted from news in the US and Chinese markets yields superior forecasting performance compared to technical analysis alone. These findings suggest that RSI and Bollinger Bands can serve as proxies for collective psychology, capturing herd behavior and emotional extremes. Integrating these indicators with digital attention measures such as Google Trends therefore provides a richer framework for understanding volatility in emerging markets like Dubai, where investor sentiment plays a critical role in driving short-term fluctuations.

The Relative Strength Index (RSI) measures the strength and speed of price change over a specific period of time. It was developed by (Welles Wilder ,1978). Overbought levels are above 70, while oversold levels are below 30. These points will indicate future upward and downward movements in the financial markets. (RSI) is derived from the average upward price changes over a specified period, and the average downward price changes over the same period. The average loss is calculated as a positive number, ensuring that the Relative Strength Index (RSI) is always greater than or equal to zero. The RSI ranges from 0 to 100

$$\boldsymbol{RSI} = \mathbf{100} - \frac{\mathbf{100}}{\mathbf{1}+\boldsymbol{RS_t}} \quad (1)$$

$$\boldsymbol{RS_t} = \frac{\boldsymbol{AVG(Gains)}}{\boldsymbol{AVG(Losses)}} \quad (2)$$

The choice of a 7-day horizon was selected for calculating RSI and Bollinger Bands to enhance sensitivity to short-term fluctuations, which are characteristic of emerging markets like Dubai. Which are often subject to higher volatility and shorter cycles of investor sentiment compared to developed markets. While previous studies commonly adopt 14-day or 20-day windows, these longer horizons may smooth out short-term fluctuations and fail to capture rapid reversals that are typical in highly volatile environments. By using a shorter 7-day period, the indicators become more sensitive to sudden changes in price dynamics, allowing for earlier detection of overbought and oversold conditions as well as short-term volatility spikes. This adjustment enhances the responsiveness of the technical signals and aligns the methodology with the fast-moving nature of emerging financial markets.

2.2.2. Bollinger Bands Technical Analysis Tool

Bollinger Bands were developed by **Bollinger (2001**) as a tool to measure volatility and identify breakout signals. This tool was invented by (John Bollinger,2001). This tool helps in identifying saturation areas, measuring volatility, and breakout signals (breakouts). This tool is suitable for measuring volatility and the ability to identify market breakouts by using the standard deviation with price averages in its model, while the RSI measures the strength and weakness of the price movement to identify overbought and oversold conditions. the time period of 7 days was used instead of 20 days to calculate the averages because of the highly volatility markets such as emerging markets (Dubai Financial Market) long periods, such as 20 days, can mask significant short-term changes. This allows for the identification of short-term volatility spikes and the capture of short-term trend reversals. The shorter the time period, the narrower and more dynamic the bands, reflecting changes more quickly. This can be done as follows:

$$\text{Upper Band}(UB) = \text{MB} + \text{k}.\sigma_n \quad (3)$$

$$\text{Lower Band}(LB) = \text{MB} - \text{k}.\sigma_n \quad (4)$$

Technical analysis tools seek to identify trading opportunities, i.e., they can explain the reasons for price movements. However, using this strategy alone is not sufficient. This analysis can be further

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developed by incorporating sentiment and public trends to account for external market influences and investor sentiment. This is the goal of this research, aiming to achieve the highest degree of accuracy in predicting future market trends.

2.3. Theories of Risk Measurement

Understanding volatility is crucial for investment decision-making, as highlighted in studies such as Dhanker (2019). Measuring volatility (standard deviation) and risk is an important method used to understand the behavior of financial markets and make investment decisions. Volatility expresses the fluctuation of stock prices around their average over a specific period of time. Theoretical and practical methods for measuring volatility vary, and these methods have been used in research:

Historical Volatility: It is based on calculating the standard deviation of stock or asset returns over a specified period of time, and is used to estimate past risks and actual market volatility.

$$\text{Volatility} = \sigma_t = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\left(R_{t-i} - \overline{R}\right)} \quad (5)$$

2.3.1. Risk Indicator (Max Drawdown)

This definition aligns with the risk measurement framework proposed by Chekhlov et al. (2005) the maximum potential loss in an investment portfolio, a risk management tool for investors. In our study, we will rely on a simple Max Drawdown equation as a dynamic measure of risk, representing the maximum decline from the peak to the trough (drawdown) of the Dubai Financial Market Index's return over a seven-days period. It is as follows:

$$MDD = MaX_{t\epsilon[1,T]}\left(\frac{MaX_{s\epsilon[1,t]}P_s - P_t}{MaX_{s\epsilon[1,t]}P_s}\right) \quad (6)$$

2.3.2. Conditional Volatility Regression Models for (GARCH/ARCH Models):

It is used to estimate time-varying volatility. This type of model allows for prediction of volatility during periods of high volatility or potentially low risk, and is common in empirical studies of financial markets. This study relied on the autoregressive conditional variance (ARCH) models and its generalized extension (GARCH) to measure and analyze the dynamics of return volatility in the Dubai Financial Market.

These models are based on the hypothesis that the conditional variance of returns is not constant over time, but rather is affected by the degree of previous shocks, making them one of the most widely used statistical tools in analyzing financial market volatility.

- ARCH(q) model: One of the early attempts to model volatility was formulated by (Engle ,1982) and is as follows:

$$\boldsymbol{r_t = \mu + \epsilon_t} \quad \mathbf{(7)}$$

Since the previous squared error terms determine the current value of the model's error variance, the ARCH(q) model can be defined as the variance of the series σt2, it is being modeled:

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p} \sigma_i \varepsilon_{t-i}^2 \quad (8)$$

- **GARCH(p,q) model:** It is an extension of the ARCH model, and was developed by (Bollerslev ,1986) and is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (9)$$

Using a combination of these methods allows analysts and investors to more accurately assess risk and volatility, contributing to improved investment strategies and informed decision-making, especially when studying the impact of behavioral factors on stock prices.

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In the context of volatility modeling, the choice of appropriate model specifications and error distributions is critical for accurate estimation. Samuel et al. (2023) developed a comprehensive simulation framework to evaluate the performance of GARCH-family models under different innovation distributions, including normal, Student-t, and skewed Student-t. Their findings suggest that mis specifying the innovation distribution can lead to biased volatility persistence estimates, particularly in emerging markets characterized by fat tails and asymmetry. This highlights the importance of selecting appropriate GARCH specifications—such as the EGARCH model used in the present study—to capture asymmetric volatility dynamics and ensure robust forecasting performance (Samuel et al . 2023).

3. Data

3.1. Google Trends

Data was collected from the official website during the period 2020-2025 (from the beginning of November 2020 until the beginning of August 2025). The data was extracted every three months of each year and then collected daily for five years to obtain accurate data. The data was extracted for the keywords related to the financial markets, which are: "stock market, investment." The average data for the two mentioned words was taken to obtain the Google Trends index, and the data is scored from (0-100) based on the audience's interest during the time period. Keywords were selected based on their relevance to general investor attention in the Dubai financial context. As for the technical indicators, they are: the Relative Strength Index (RSI), which was calculated for a period of 7 days, but in the research, a period of 7 days was used instead of 14 days to quickly capture short-term reversals, allowing the indicator to react quickly to recent changes (increasing the indicator's sensitivity).

3.2. The Bollinger Bands

Technical analysis tool was calculated for a period of seven in line with the RSI indicator to capture fluctuations and fluctuations in the short term, while the dependent variable of Volatility was calculated as the standard deviation of the Dubai Financial Market Index return for of seven days period, which will help understand the state of instability and uncertainty.

3.3. The Max Drawdown Risk

Indicator was calculated over a seven-days period based on the closing prices of the Dubai Financial Market Index to measure the true risk and collapse, and compared to periods of falling/rising RSI and Bollinger Bands, in addition to the psychological variable Google Trends, to identify periods of collapse.

Despite the comprehensive design of the methodology, several limitations should be acknowledged. First, Google Trends data may not fully capture the behavior of institutional investors or private information flows, which can also influence market volatility. Second, technical indicators such as RSI and Bollinger Bands are sensitive to parameter choices and may generate misleading signals during extreme market conditions. Third, the study focuses exclusively on the Dubai Financial Market, which limits the generalizability of the findings to other emerging or developed markets. Finally, the reliance on a single data source for digital attention may overlook complementary behavioral signals from social media platforms or news sentiment. These limitations, however, provide opportunities for future research to extend the framework by incorporating additional behavioral datasets and applying the model to a broader set of markets.

4. Results

The following section presents the empirical results derived from the models described above, beginning with descriptive statistics and proceeding to hypothesis testing.

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics of all variables. The average volatility of the Dubai market was 0.8%, with a maximum of 6%, indicating relatively low volatility during the study period. The structural market risk index (maximum drawdown) ranged between -1 and -0.018 with an arithmetic mean of -0.47. While the market momentum index (RSI) ranged between 1.4 (the market is oversold) and 98 (the market is overbought) with an arithmetic mean of 56.5 (the market is relatively stable).

The Bollinger Band ranged between 13.8 and 787, with an arithmetic mean of 125.

On the other hand, for the Google Trends index, the lowest index was 8.8 and the highest index was 82.8, with an average of 29.8 and a standard deviation of 8, while the Google Trends share index ranged between 0 and 100 with an arithmetic mean of 43.4 and a standard deviation of 20.7, while the Google Trends investment index ranged between 35 and 100 with an arithmetic mean of 71.6 and a standard deviation of 12.

Figure 1 shows that the study period witnessed acceptable fluctuations in the Dubai Market Index, and severe fluctuations in the other variables during the study period, especially at the beginning of the study period, which coincided with the spread of the coronavirus, which indicates that selling operations took place for a limited period, leading to declines in the market, followed by buying operations leading to increases in the market.

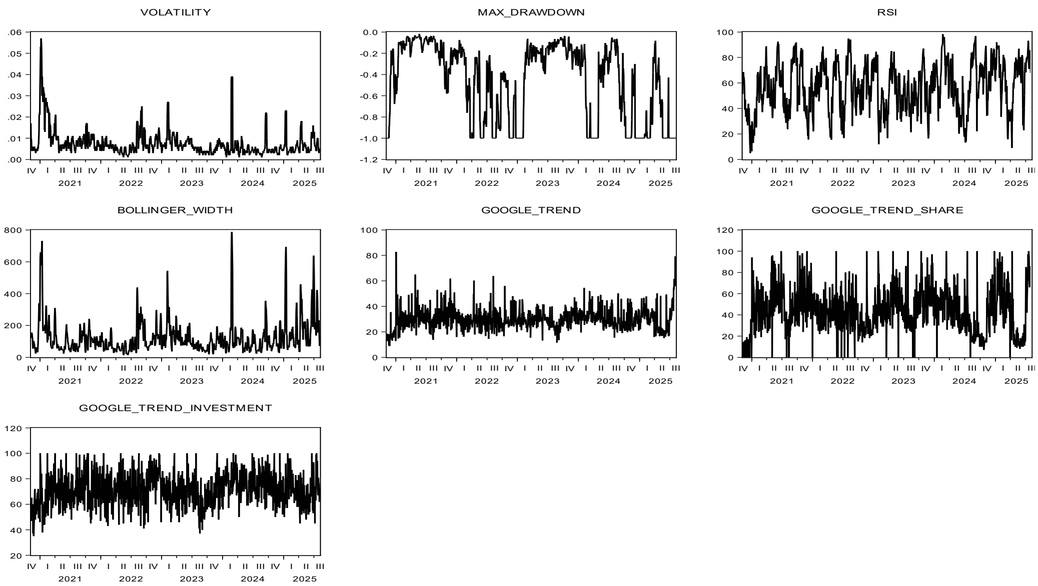

Figure 1. Time-series Plot of Variable. Source: Eviews statistical program outputs.

We note from the Table 1 although the variables volatility and maximum drawdown are indicators of risk in financial markets, the relationship between them is insignificant and almost non-existent, which indicates the difference in the nature of each of them in measuring risk. We note from the table that the variables that have a significant relationship with the market volatility variable (VOLATILITY) are the RSI variable, and it is an inverse relationship, meaning that a decrease in RSI is associated with an increase in market volatility due to market tension and increased uncertainty in it, and it is a direct relationship with the BOLLINGER variable. That is, bandwidth is associated with increased market volatility. This makes sense, given that bandwidth is directly derived from the standard deviation of market prices, and is directly related to both the Google Trend SHAR and the

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average Google Trend shar. This means that increased interest in the stock market often coincides with higher market volatility. As we note from the table, the variables that have a significant relationship with the market risk index variable (max drawdown) are the RSI variable, and it is an inverse relationship, meaning that a decrease in the RSI to less than 30 is associated with an increase in market risks and the occurrence of large losses, and an inverse relationship with the BOLLINGER variable, meaning that the width of the bands is associated with a greater market collapse, meaning that periods of high volatility may not necessarily be associated with a long-term decline. We also note from the table that the variables that have a significant relationship with the (RSI) variable are the BOLLINGER variable, which is a direct relationship, meaning that the width of the bands is associated with an increase in market momentum, and this means that the two indicators complement each other in prediction.

4.2. Hypothesis 1: Digital Attention and Technical Indicators

There is a direct relationship between Google Trend, volatility, and Max Drawdown. This means that the more interest in the word "stock market" in Google, the more likely the market will decline the following week. Furthermore, increased investment interest is associated with lower maximum drawdowns, meaning the market will decline less the following week. As a result, digital behavior can be used to improve the accuracy of forecasting volatility in emerging financial markets.

There is a direct relationship between Google Trend and RSI, which means people search more online when technical indicators are in overbought/oversold states, which supports early signals for predicting market volatility.

These relationships confirm that combining traditional technical indicators such as Bollinger Width and RSI with behavioral indicators extracted from Google Trends search data can enrich risk prediction models in emerging markets, by providing a more comprehensive reading of market and investor behavior.

Table 3 reports the unit root test results. All variables are stationary at level, satisfying the prerequisite for time-series modeling. The probability values are below 0.05, confirming stationarity.

4.3. Hypothesis 2: Volatility Forecasting Using GARCH/EGARCH

Arch Effect model

Arch Effect Model Terms:

The first condition: the condition of the existence of low and high volatility for short and long periods, and for that we conduct a regression model between the dependent variable “market volatility” and each of the variables, Google Trends data and technical analysis indicators (BOLLINGER & RSI), and Table 4 shows the results of this model.

concerns us in this model is the trend of the model’s regression residuals over time, as Figure 2 shows this trend.

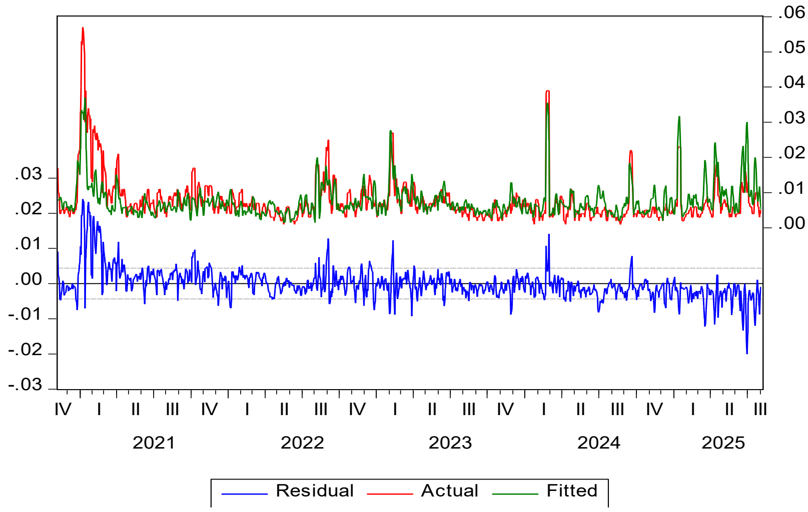

Figure 2. Volatility Trends. Source: Eviews statistical program outputs

We notice from the figure that there are low oscillations and high oscillations for different periods, so the first condition for applying the Arch Effect model is met.

The second condition: the condition of the existence of the Arch Effect. This condition is tested through the Heteroskedasticity Test: Arch, where we obtain Table 5.

Table 5 shows the ARCH effect test results. The significant ARCH effect ($p < 0.05$) confirms the presence of time-varying volatility, justifying the use of GARCH-family models.

Estimation of the (GARCH) model

In order to study the effectiveness of Google Trend data and technical analysis indicators (Bollinger Band, RSI) in predicting volatility in the Dubai market (VOLATILITY), the researchers used the Generalized Autoregressive Conditional Variance (GARCH) model, which assumes that the variance of the residuals (random errors) is a function of the previous values of the variance and the square of the random errors according to the mean equation (after adding appropriate lag terms to the equation): Arch Effect.

$$VOLATILTY_t = C + \vartheta_t\, VOLATILTY_{t-1} + e_t \quad (10)$$

The GARCH model after adding the GOOGLE TREND variable and the BOLLINGER and RSI variables, according to the following variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \theta\ GOOGLE\ TREND + \delta\ \mathrm{BOLLINGER\ WIDTH} + \varphi\ \mathrm{RSI} + e_t \quad (11)$$

And the following TARCH model:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \theta\ GOOGLE\ TREND + \delta\ BOLLINGER\ WIDTH + \varphi\ RSI + e_t \quad (12)$$

where I_(t-1)is equal to one if the random error of the first lag is less than zero and zero otherwise.

According to the EGARCH model to address the asymmetric impact of positive and negative shocks, the equation becomes as follows:

$$\ln(\sigma_t^2) = \omega + \alpha\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta\ GOOGLE\ TREND + \delta\ BOLLINGER\ WIDTH + \varphi\ RSI + e_t \quad (13)$$

Since the coefficient γ considers the asymmetry in the impact of shocks, if negative shocks are followed by more fluctuations, the value of the coefficient will be negative.

Tables 6–8 presents the GARCH model estimation results. The one-period lag coefficients are statistically significant and positive, indicating that volatility persists from one day to the next.

It is evident from the top part of the three tables that the one-period lag coefficients are statistically significant in all models and their positive sign indicates that any day's volatility is positively affected by the previous day's volatility.

It is clear from the lower part of Tables No. (6), (7) and (8) that the coefficient β is positive and statistically significant, meaning that the variance of the previous period has a positive effect on the variance of the current period, and that the coefficient α is statistically significant. However, in the

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third model (EGARCH model), it was positive and statistically significant, and the sum of the coefficients α and β in this model is less than one, which means that the shocks to which the conditional variance is exposed do not have a continuous effect.

We also note in the EGARCH model that the coefficient γ is negative and statistically significant, indicating that negative shocks are followed by more volatility (random error variance) in the Dubai market.

Table 9 summarizes the EGARCH model results. Unlike the GARCH and TARCH models, the Google Trends and technical indicators coefficients become statistically significant in this specification, explaining 83% of volatility variations. According to the three criteria (AIC, SCH, H-Q), the best model is the EGARCH model, which confirms our above result that we reached regarding the γ coefficient, and the value of the Log likelihood test also indicates that the coefficients of the independent variables combined are not equal to zero, which indicates the suitability of the tested models in terms of the number of independent variables. The value of the Durbin-Watson test close to 2 in the three models indicates the absence of autocorrelation between the residuals, and confirms the validity of the estimate of random errors and thus the statistical significance of the estimated coefficients.

We note that Table 9 the probability value corresponding to the F and Chi-Square statistics is greater than the statistical significance level of 0.05, and therefore we accept the null hypothesis that the variance of the residuals of the estimated model is constant, and we note that Table 10 the corresponding probability value of the chi-square statistic is greater than the statistical significance level of 0.05, and therefore we accept the null hypothesis that there is no serial correlation between the residuals of the estimated model.

4.4. Hypothesis 3: Risk Reduction Using Max Drawdown

Arch Effect Model

Arch Effect Model Terms:

The first condition: the condition of the presence of low and high fluctuations for short and long periods. For this, we conduct a regression model between the dependent variable “maximum drawdown” and each of the different data variables from Google Trends and technical analysis indicators (BOLLINGER & RSI). Table 1 shows the results of this model.

What interests us in this model is the direction of the residuals of the model's regression over time, as the following figure illustrates this direction:

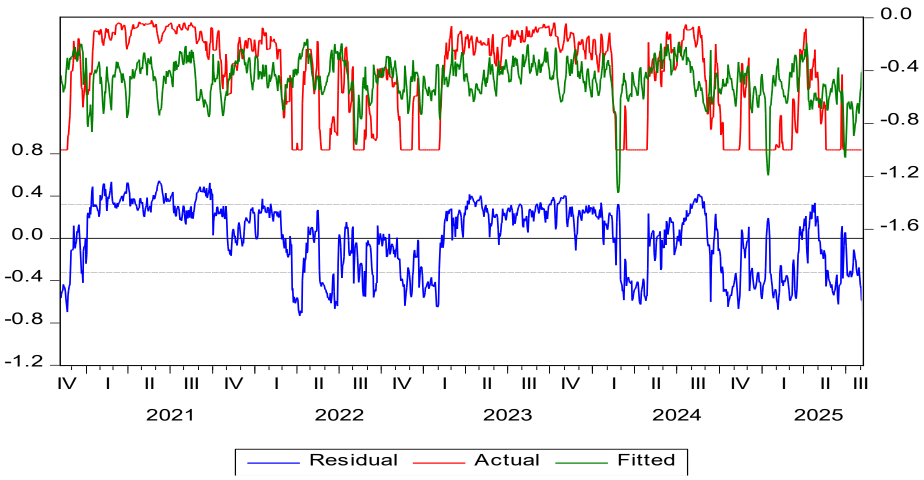

Figure 3. Residual Plot for Max Drawdown Model. Source: Eviews statistical program outputs.

We notice from the figure that there are low oscillations and high oscillations for different periods, so the first condition for applying the Arch Effect model is met.

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The second condition: the condition of the existence of the Arch Effect. This condition is tested through the Heteroskedasticity Test: Arch, where we obtain Table 2 it is clear from the table that the probability value corresponding to the F and Chi-Square statistics is less than the statistical significance level of 0.05, and thus we have verified the two conditions for applying the Arch Effect model.

Estimating the (GARCH) model:

In order to study the contribution of Google Trend data and technical analysis indicators (BOLLINGER & RSI) in reducing risks in the Dubai market (MAX DRAWDOWN), the researchers estimated the models presented above but by changing the dependent variable to MAX DRAWDOWN, as Tables 13–15 show the results of the required regression equations.

$$MAX\ DRAWDON_t = C + \vartheta_t\ MAX\ DRAWDON_{t-1} + e_t \quad (14)$$

The GARCH model after adding the Google Trend variable and the BOLLINGER and RSI variables, according to the following variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \theta\ GOOGLE\ TREND + \delta\ \text{BOLLINGER WIDTH} + \varphi\ \text{RSI} + e_t \quad (15)$$

The (TARCH) model is shown in Table No. (14).

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \theta\ GOOGLE\ TREND + \delta\ BOLLINGER\ WIDTH + \varphi\ RSI + e_t \quad (16)$$

where I_(t-1)is equal to one if the random error of the first lag is less than zero and zero otherwise.

According to the (EGARCH) model to address the asymmetric impact of positive and negative shocks, the equation becomes as shown in Table No. (15).5. Conclusions

$$\ln(\sigma_t^2) = \omega + \alpha\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta\ GOOGLE\ TREND + \delta\ BOLLINGER\ WIDTH + \varphi\ RSI + e_t \quad (17)$$

The following tables (13), (14), (15) show the results of the required regression equations.

It is clear from the upper part of Tables No. (13), (14), and (15) that the lag coefficients for one period and two periods are statistically significant in all models, and the sign of their coefficients indicates that the maximum decline on any day is positively affected by the maximum decline of the previous day, and turns into a negative effect after two days.

It is clear from the lower part of Tables No. (13), (14), and (15) that the coefficient β is positive and statistically significant, meaning that the variance of the previous period has a positive effect on the variance of the current period, and that the coefficient α is statistically significant. However, in the third model (EGARCH model), it was positive and statistically significant, and the sum of the coefficients α and β in this model is greater than one, which means that the shocks to the conditional variance have a continuous effect. We also note in the EGARCH model that the coefficient γ is positive and statistically significant, which indicates that negative shocks are followed by greater declines (maximum decline) in the Dubai market.

We note in Tables No. (13), (14), (15) that the coefficients that measure the contribution of each of the independent variables GOOGLE TREND and BOLLINGER & RSI in reducing investment risks in the Dubai market are statistically significant at a significance level of 0.05.

This indicates that increased interest in searching for market-related keywords on Google often coincides with reduced investment risk in the market, that wider BOLLINGER bands are associated with greater market crashes, and that a lower RSI is associated with significant market losses.

We note that the adjusted coefficient of determination in the third model constitutes a large explanation percentage of 95% of the fluctuations, and according to the three criteria (AIC, SCH, H-Q), the best model is the EGARCH model, which confirms our result above that we reached about the γ coefficient. The value of the Log likelihood test also indicates that the coefficients of the independent variables combined are not equal to zero. This indicates the suitability of the tested models in terms of the number of independent variables, and the Durbin-Watson test value close to

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2 in the three models indicates the absence of autocorrelation between the residuals, confirming the validity of the random error estimate and thus the statistical significance of the estimated coefficients

5.5. Diagnostic Tests

Variance stability test for residuals:

We note from the table No. (16) probability value corresponding to the F and Chi-Square statistics is greater than the statistical significance level of 0.05, and thus there is stability of the variance of the residuals of the estimated model, and we note from the table No. (17) corresponding probability value of the chi-square statistic is greater than the statistical significance level of 0.05, and therefore we accept the null hypothesis that there is no serial correlation between the residuals of the estimated model.

5.6 Results Interpretation

The findings of this study contribute to the growing literature on forecasting volatility by demonstrating the value of integrating digital attention with technical indicators in an emerging market context. Consistent with Dimpfl and Jank (2016), the results confirm that search activity captured by Google Trends provides meaningful signals of investor sentiment and market stress. Moreover, the significant role of RSI and Bollinger Bands aligns with Phuong and Nhung (2021) and Markus et al. (2024), who emphasized the importance of combining technical analysis with behavioral factors.

Beyond statistical validation, the results have important strategic implications. In markets such as Dubai, where volatility is often driven by both economic shocks and collective psychology, the hybrid framework developed here offers policymakers and regulators an early-warning system to anticipate instability. For investors, the integration of digital behavior into forecasting models enhances risk management by identifying periods of heightened uncertainty before they materialize. This aligns with the foresight perspective of designing predictive tools that support resilience in financial systems.

Importantly, the study positions digital attention not as a supplementary variable but as a leading indicator of volatility. This reframing opens new avenues for foresight research, suggesting that behavioral data sources—such as search queries, social media sentiment, and digital news engagement—can be systematically incorporated into forecasting models to strengthen market preparedness. Future research could extend this framework to other emerging markets or integrate additional behavioral datasets, thereby contributing to the development of more adaptive and anticipatory financial systems.

5.7. Practical Implications

The hybrid framework developed in this study offers practical value for both policymakers and investors. For regulators, integrating digital attention into volatility models can serve as an early-warning system, enabling proactive measures to stabilize markets during periods of heightened uncertainty. For investors, the combined use of Google Trends, RSI, and Bollinger Bands provides more accurate signals to anticipate risk exposure and adjust trading strategies accordingly. In the broader foresight perspective, the model contributes to building more resilient financial systems by embedding behavioral data into predictive tools, supporting adaptive and anticipatory decision-making in emerging markets.

6. Conclusion

It is noteworthy that some coefficients in the GARCH model were statistically insignificant. This may be attributed to potential multicollinearity among predictors, or to the fact that asymmetric effects—captured more effectively by the EGARCH model—dominate the volatility process in the Dubai market during the study period. The superiority of the EGARCH model in capturing asymmetric shocks aligns with the foundational work of Nelson (1991), who introduced EGARCH to model the differential impact of positive and negative news on volatility.

This study demonstrates that integrating digital attention with technical indicators provides a powerful framework for forecasting volatility in emerging markets. By positioning Google Trends as a leading indicator rather than a supplementary variable, the research highlights the importance of behavioral signals in shaping market dynamics. The results confirm that combining RSI and Bollinger Bands with digital search activity improves predictive accuracy and offers practical tools for investors and policymakers to anticipate risk.

Beyond the Dubai Financial Market, the proposed hybrid approach has broader implications for foresight research, suggesting that digital behavior can be systematically incorporated into volatility models to strengthen resilience in financial systems. Future studies may extend this framework to other emerging markets or integrate additional behavioral datasets such as social media sentiment and news analytics. In doing so, the predictive capacity of financial models can be enhanced, supporting more adaptive and anticipatory strategies in the face of uncertainty.

7. Future Research

Future studies could extend this framework by incorporating machine learning models such as Long Short-Term Memory (LSTM) networks to compare predictive accuracy with the hybrid approach proposed here. Additionally, testing the model in other emerging markets would enhance its generalizability. Furthermore, incorporating alternative behavioral data sources, such as sentiment from financial news or social media platforms, could provide a more comprehensive measure of investor attention.

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