

Forecasting Digital Public Interest in a Cultural Mega-Event: Evidence from the Untold Festival Using Google Trends and SARIMA

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Please cite this paper as:

Nicolescu, L., Barbu, A., Hamcerencu, M., & Gheorghită, A. (2026). Forecasting Digital Public Interest in a Cultural Mega-Event: Evidence from the Untold Festival Using Google Trends and SARIMA. In C. Vasiliu, D.-C. Dabița, A. Tziner, D. Pleșea, & V. Dinu (Eds.), *Proceedings of BASIQ International Conference on New Trends in Sustainable Business and Consumption, 12th Edition* (pp. 429-436). Editura ASE.

DOI 10.24818/BASIQ/2026/12/037

Abstract

The objective of the current paper is to analyze the temporal dynamics of the online public interest related to the Untold Festival, considered to be a cultural mega-event, using the seasonal forecasting methods on Google Trends data. The monthly time series with search intensity during the period from April 2021 to March 2026 were investigated for recurring patterns in public interest in the Untold Festival related to the festivals seasonality and the potential for forecasting the search interest related to the festival events.

The analysis demonstrates significant and stable annual seasonality, with a peak of search interest during the Untold Festival period followed by rapid fall in the interest level. Such seasonality shows that Untold Festival is a periodic temporal landmark related to the consumer interest in destination and the events taking place in the destination location. According to SARIMA analysis, the search interest is mainly driven by its seasonality without any trend component, as diagnosed residuals confirm the model adequacy in describing the dynamics of search interest in Untold events.

The contribution of the current work is relevant for both tourism forecasting literature and event management research and can be applied by destination marketers for managing promotion activities.

Keywords

Untold festival, google trends, SARIMA forecasting, digital public interest, cultural mega events, tourism.

DOI: 10.24818/BASIQ/2026/12/037

Introduction

In recent years, the rise of cultural and music festivals worldwide has led to a significant transformation in the manifestation of tourism demand, turning music festivals into important instruments for increasing destination visibility and strengthening international destination branding. Cultural mega-events not only generate substantial economic benefits for local economies, but also contribute to the long-term construction of destination image and reputation (Getz, 2008; Mair et al., 2023; Wang & Jin, 2019). In this context, events such as the Untold Festival may be viewed as powerful instruments for creating competitive advantage and attracting international tourism flows to emerging destinations in Eastern Europe.

At the same time, the digitization of consumer activities has significantly transformed the way tourism demand is analyzed and quantified. Traditionally, tourism demand has been measured through indicators such as tourist arrivals or overnight stays; however, online search activity has increasingly become an important source for measuring tourism-related interest in near real time. Google Trends, for example, provides researchers with access to large-scale and high-frequency datasets reflecting users' collective interests and intentions (Choi & Varian, 2012; Varian, 2014). Previous studies have demonstrated that search engine query data may serve as a reliable tool for forecasting tourism flows, identifying seasonality

patterns, and improving predictive modelling performance (Bangwayo-Skeete & Skeete, 2015; Pan et al., 2012; Önder & Gunter, 2016).

Moreover, recent advancements in tourism forecasting also imply that incorporating behavioral data from the digital environment could potentially help increase forecasting accuracy and enable dynamic analysis of tourism demand (Peng et al., 2014; Wen et al., 2019; Llewellyn et al., 2023; Wu et al., 2024). Some of the most widely used forecasting methods include autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) models, which are best suited for modelling time series with trend and seasonality components (Song & Li, 2008; Szostek et al., 2024). In addition, previous research indicated that the combination of forecasting models and online search engine data could considerably improve forecasting results (Li et al., 2018; Yang et al., 2015).

However, although a considerable amount of research was conducted in terms of tourism forecasting and digital analytics, only very little has been done in terms of developing forecasting models tailored specifically to festivals. Specifically, there is very limited research regarding forecasting cultural mega-events in emerging destinations located in Eastern Europe. Most existing research focuses primarily on tourism demand at the destination level and forecasting accuracy, whereas there is only a limited amount of research concerning digital search activity as a sign of tourist interest.

In this context, the Untold Festival represents a relevant case for examining the temporal evolution of digital public interest surrounding a large-scale cultural event. Therefore, this study aims to examine whether Google Trends data combined with SARIMA modelling can effectively forecast digital public interest in a cultural mega-event such as the Untold Festival. At the same time, the paper seeks to explore whether recurring search intensity patterns may reveal stable seasonal structures associated with festival-driven tourism demand.

The remainder of the paper is structured as follows. The next section reviews the literature on cultural mega-events, digital consumer behaviour, and tourism forecasting. The methodology section presents the data collection process and the SARIMA modelling approach. The following section discusses the empirical findings and forecasting results, while the final section outlines the conclusions, limitations, managerial implications, and directions for future research.

1. Review of the scientific literature

1.1. Cultural mega events and festival-driven tourism demand

Cultural mega events have increasingly gained importance in destination management for their ability to not only create short-term flows of tourists but also to generate visibility, symbolic significance, and destination differentiation (Getz, 2008; Mair et al., 2023; Wang & Jin, 2019). In the event tourism literature, mega events have been defined as drivers of tourism and strategic tools in destination marketing.

Specifically, within this broad category, music festivals occupy a particularly relevant position as they combine experiential consumption, destination branding, and a temporal clustering of tourism demand. Unlike other standard tourism products, festivals create intensive but temporary spikes in attention and consumption and thus become suitable for time-series analysis. Furthermore, the event tourism literature suggests that mega events are capable of adding value and competitiveness to destinations (Getz, 2008; Mair et al., 2023). Thus, from this perspective, Untold should be approached not only as a cultural mega event but also as a mechanism that structures tourists' attention in predictable time periods.

1.2. Digital consumer behavior and Google Trends as a proxy for public interest

The increasing digitization of tourists' behavior implies new ways of studying tourism demand. Tourists look up information about destinations online prior to making decisions, which implies that digital behavior can reveal patterns of interest, intent, and attention toward particular destinations (Varian, 2014). In this respect, the use of Google Trends as a proxy for public interest becomes particularly important since it provides normalized time-varying measures of search intensity rather than retrospective static estimates (Choi & Varian, 2012). Google Trends reports its measurements on a normalized 0–100 scale, reflecting search interest relative to selected time intervals and locations. Recent critical assessments also underline that, despite their predictive potential, search query datasets such as Google Trends may present methodological limitations related to normalization procedures, keyword selection, and behavioural interpretation, requiring careful contextualization in tourism forecasting studies (Mikulić & Baumgärtner, 2025).

In tourism forecasting, search queries have proven useful in improving forecasts of tourism outcomes, especially when other measures lagged in providing timely insights (Önder & Gunter, 2016; Pan et al., 2012). Bangwayo-Skeete and Skeete (2015) found that search data from Google could boost the predictive power of tourism-demand forecasts, while Mavragani and Ochoa (2019) showed that search indices can act as public-interest indicators, albeit limited by issues related to normalization and platform-specificity. Wen et

al.'s (2019) meta-analysis, in turn, confirmed the relevance of search queries in tourism forecasting, despite the variability in performance.

For festival tourism, the use of Google search indices represents a particular advantage. Contrary to other annual or quarterly measures like arrivals or revenue, Google Trends data capture the accumulation of public interest prior to the event taking place. Thus, Google Trends is informative not only because it reveals digital consumer behavior but also since it incorporates the timing of such behavior. It constitutes a suitable data source for analyzing how Untold impacts periodic fluctuations in public interest.

1.3. Time-series forecasting in tourism research

Tourism demand forecasting has long been recognized as an essential part of destination planning, marketing, investment timing, and resource allocation. Song and Li's (2008) extensive review shows that contemporary tourism forecasting research relies heavily on quantitative models aimed at anticipating future demand and supporting managerial decision-making. Simultaneously, the authors demonstrate that there is no universal optimal modeling approach in forecasting and that model choice is context-dependent, with consideration given to characteristics of available data such as seasonality and frequency.

Among existing forecasting techniques, ARIMA-family models have remained especially popular since they are well-suited to modeling univariate time series with temporal dependency and seasonal pattern repetitions (Arumugam & Natarajan, 2023; Szostek et al., 2024). Hyndman and Khandakar's (2008) research on selecting automatic ARIMA models has become widely recognized and used, introducing a systematic approach based on information criteria such as AIC, AICc, and BIC for selecting models. ARMA- and ARIMA-family approaches have seen widespread application in tourism for forecasting various indicators, especially those exhibiting pronounced seasonal components (Song & Li, 2008). Further research in tourism forecasting has emphasized integrating big data sources and advanced analytics techniques, including search query data to enhance forecasts (Li et al., 2017; Peng et al., 2014; Yang et al., 2015; Wen et al., 2019 (Mikulić & Baumgärtner, 2025)).

This approach becomes especially relevant to festivals as their demand patterns tend to be strongly seasonal and connected to recurring annual cycles. Therefore, seasonal ARIMA-like models would be appropriate. Rather than revealing a robust long-run growth, however, such patterns reflect the repetitive structure of seasonal public interest. A good forecast would capture spikes, show no evidence of residual autocorrelation, and allow managers to make short-term projections.

Even though existing research has proved that Google Trends is a reliable predictor of in tourism forecasting, the literature has primarily focused on predicting either a particular destination, total tourists' arrival numbers, or overall tourism demand (Li et al., 2017; Önder & Gunter, 2016). Notably, far fewer studies have analyzed cultural mega-events in terms of forecasting and even fewer have been dedicated to music festivals held in Eastern Europe. Moreover, in most of the literature, the emphasis has been placed on forecasting accuracy rather than on interpreting digital search patterns as expressions of consumer behavior and concentration of demand around an event (Wen et al., 2019; Peng et al., 2014).

In such a context, the Untold Festival provides an appropriate case study in investigating the role played by a mega cultural event in the formation of public attention, its modeling through the use of Google Trends, and generating managerial implications based on forecasting tools. The present study thus contributes to the existing literature in two ways. Firstly, it extends the concept of tourism forecasting by analyzing an individual event instead of a tourism destination. Secondly, it adds to our knowledge of consumer dynamics by conceptualizing search intensity as a measure of attention and thus demand.

2. Research methodology

The quantitative time-series analysis is employed in this study to investigate and predict the digital public interest in the Untold Festival based on data provided by Google Trends. The monthly search data for the search term "Untold Festival" was collected during April 2021 and March 2026, which resulted in 60 data points measured on a scale from 0 to 100.

The keyword "Untold Festival" was chosen for its specificity, which reduces ambiguity and unrelated results generated by more general search terms like "Untold". The selected query matches the official branding and allows direct extraction of search behavior tied to the festival itself. Google Trends data were collected in April 2026, using the "Web Search" category and monthly frequency settings. Global search interest was analyzed to capture the festival's international digital visibility. Google Trends scores range from 0 to 100, with 100 representing the highest observed search interest during the selected period.

The dataset is considered to be a univariate time series with an annual seasonality of 12 data points per year, allowing the discovery of any repeated tendencies linked with the festival cycle. To explore the internal structure of the series, a Seasonal and Trend decomposition using Loess (STL) was applied, which expresses the time series as:

$$y_t = T_t + S_t + R_t$$

where T_t represents the trend, S_t the seasonal component, and R_t the irregular component.

To predict the public interest in the Untold Festival, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is employed. SARIMA modelling was selected due to its suitability for analysing seasonal univariate time series characterized by recurring annual patterns. Compared to more complex machine learning approaches, SARIMA models provide a higher degree of interpretability and are effective when applied to relatively short datasets exhibiting strong seasonal structures. Since festival-related tourism demand is typically concentrated around recurring annual cycles, the use of SARIMA models is considered appropriate for capturing temporal dependencies and seasonal fluctuations in digital public interest. In simpler words, the SARIMA model can be formulated as follows:

$$y_t = y_{t-12} + \varepsilon_t$$

which means that the current observation mainly depends on the last year's observation at the same time point plus a random error term.

The selection relied on automatic parameter identification using the `auto.arima()` function available in R, following the methodology proposed by Hyndman and Khandakar (2008). The optimal model specification was selected based on the minimization of the Akaike Information Criterion (AIC), while additional criteria such as AICc and BIC were also considered to ensure model stability. Residual diagnostics, including autocorrelation analysis and the Ljung–Box test, were subsequently employed to validate the adequacy of the selected model. The best-fitting model obtained is $ARIMA(0, 0, 0)(0, 1, 0)_{12}$, capturing the seasonal component in the dataset. To check the validity of the model, the Ljung–Box test was conducted and demonstrated that the residuals could be assumed to be white noise. Based on this model, the forecast values were calculated for the next 12 months.

Although the selected methodological approach is suitable for identifying seasonal dynamics in digital public interest, there are several limitations. The analysis is based on a short time series and on normalized Google Trends data, which reflect relative search intensity rather than actual tourism flows. Therefore, the findings should be interpreted primarily as indicators of digital public attention associated with the festival.

3. Analysis and Results

3.1 Temporal evolution of search interest

The time series for the search interest regarding the Untold Festival exhibits a pronounced seasonal effect with peaks recurring every year. This is illustrated in Figure no. 1 (time series plot) below. The search intensity is fairly low most of the year, with the numbers lying within the range of 5 and 20. However, there is a sudden spike during the summer season, especially in the month of August, when the peaks have reached 93 (2022), 100 (2023), 65 (2024), and 70 (2025).

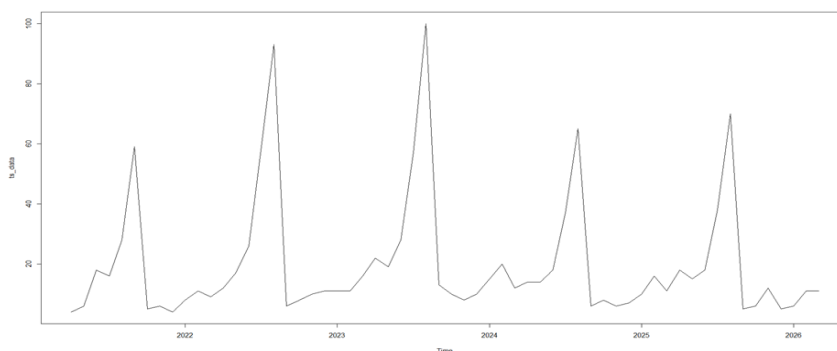


Figure no. 1. Monthly Google Trends search interest for the Untold Festival (2021-2026)

Additionally, a seasonal decomposition was applied in order to gain a clearer understanding of the structural elements of the time series. As it can be seen from the Figure no. 2 below, the seasonal component presents

a very stable and repetitive pattern for each year, which means that the identified peaks are no coincidences and indicate a consistent connection with the yearly festival. In other words, the level of public interest is consistently synchronized with the calendar of the event.

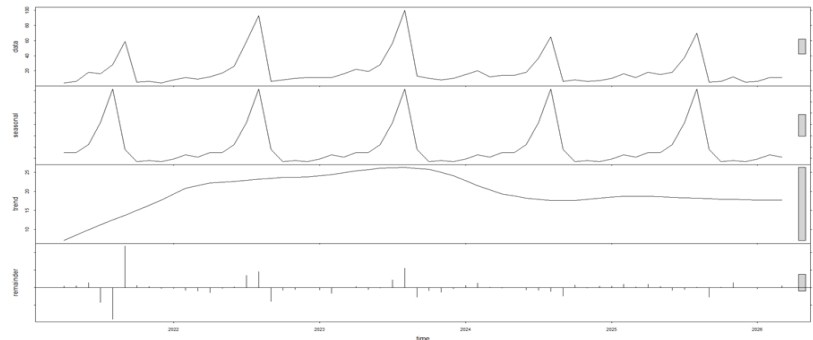


Figure no. 2. STL decomposition of the time series: trend, seasonal, and remainder components

The trend component demonstrates a slow growth trend between 2021 and 2023 and then shows a minor reduction before leveling off in later years. This implies that the festival had an initial growth period in terms of its online presence and reached its peak in 2023. Afterward, there was a period of stability. The remainder component illustrates minimal variation in the data, suggesting that the fluctuations are mostly caused by the seasonal pattern rather than unexpected changes.

3.2 SARIMA Model Results

As seen in Table no. 1 below, the results summarize the main estimation outputs of the SARIMA model. The selected specification, $ARIMA(0,0,0)(0,1,0)_{[12]}$, indicates that the series is driven entirely by seasonal differencing, with no autoregressive or moving average components, highlighting the dominance of annual patterns. The log-likelihood value reflects the overall goodness-of-fit of the model, while the AIC, AICc, and BIC values confirm a parsimonious specification with an appropriate balance between model fit and complexity. The relatively close values of these information criteria suggest model stability and robustness. Finally, the estimated variance of the residuals ($\sigma^2 = 242.6$) captures the inherent variability of the series, which is largely influenced by the pronounced peak values observed during the festival period.

Table no. 1. SARIMA model estimation results

Indicator	Value
Model	$ARIMA(0,0,0)(0,1,0)_{[12]}$
Log Likelihood	-199.91
AIC	401.82
AICc	401.90
BIC	403.69
Sigma ²	242.6

Furthermore, the forecast accuracy was measured in Table no. 2 and it shows how well the SARIMA model predicts the data. The relatively low MAE (6.620) and RMSE (13.933) indicate that the model captures the general pattern of the series reasonably well. The MASE value below 1 (0.800) suggests that the model performs better than a simple baseline model. However, the higher MAPE (42.358%) and the negative MPE (-14.939%) show that the model has some difficulty predicting the exact size of the peaks, which are very sharp and irregular. Finally, the low ACF1 value (0.104) indicates that there is little remaining pattern in the errors, meaning the model has captured most of the important information in the data.

Table no 2. Forecast accuracy measures of the SARIMA model

Metric	Value
ME	0.686
RMSE	13.933
MAE	6.620
MPE	-14.939
MAPE	42.358
MASE	0.800
ACF1	0.104

Table no. 3 below presents the results of the Ljung-Box test used to evaluate the independence of the model residuals. The high p-value (0.9921) strongly supports the null hypothesis of no autocorrelation, showing that the residuals behave as white noise and that the model successfully captures the underlying temporal structure, therefore confirming the adequacy of the SARIMA model.

Table no. 3. Ljung-Box Test Results for Residual Diagnostics

Statistic	Value
Q*	3.3878
Df	12
p-value	0.9921

3.3 Forecasting results

The forecast results indicate that the observed seasonal pattern is expected to persist in the future. The model predicts a continuation of cyclical behaviour, with gradual increases in search interest leading up to the festival period, followed by sharp peaks and rapid declines, Figure no. 3.

The confidence intervals widen around peak periods, reflecting increased uncertainty associated with extreme values. This suggests that while the timing of peaks is highly predictable, their exact magnitude remains subject to variability.

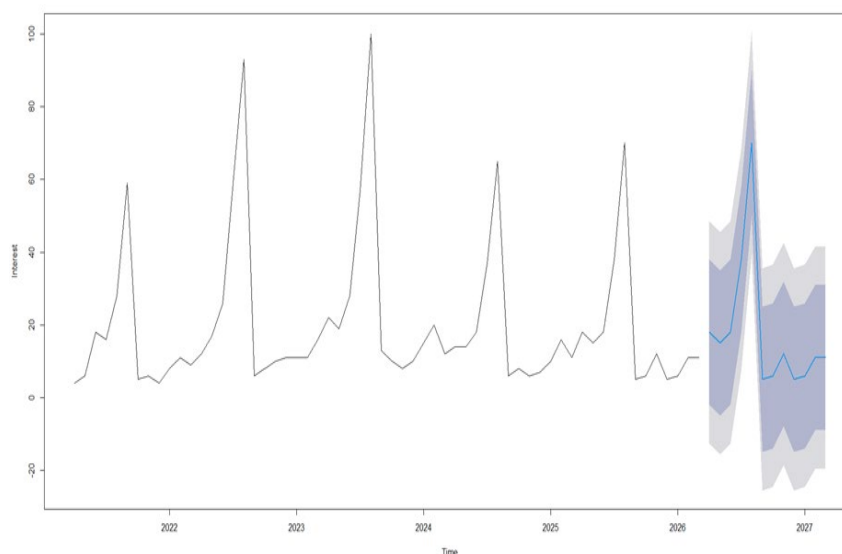


Figure no. 3. SARIMA forecast of search interest for the Untold Festival (for the next 12 months)

The revealed periodicity of digital attention implies that the associated demand for tourism services during festivals is highly synchronized with specific experiential consumption practices, which occur within certain temporal intervals. The recurring peaks recorded in the Google Trends data imply that consumers conduct online searches ahead of time before participating in the festival, thereby corroborating the hypothesis that digital attention may act as a predictor of tourism intention.

With regard to destination branding, the results highlight the function of cultural mega-events as tools for enhancing visibility through the digital space. In light of the seasonal patterns discovered in connection with the Untold Festival, the events can be viewed as more than just entertainment products. Instead, festivals contribute to destination branding by increasing digital visibility of Cluj-Napoca and Romania as festival tourism destinations.

The findings are also consistent with previous tourism forecasting studies that emphasized the usefulness of Google Trends data in capturing tourism-related behavioural dynamics and improving predictive modelling performance (Bangwayo-Skeete & Skeete, 2015; Wen et al., 2019). However, unlike many previous studies focusing primarily on destination-level tourism demand, the present research highlights the applicability of digital forecasting approaches to festival-specific tourism phenomena and cultural mega-events.

Conclusion

It can be seen from the results that public interest in the Untold Festival is characterized by a high level of stability in terms of seasonality. This is supported by the presence of annual peaks in the time series (for instance, 93 in 2022 and 100 in 2023). The STL decomposition also confirms this conclusion, demonstrating the existence of a strong and stable seasonal component and a weak trend that stabilizes after 2023. Based on this, it can be assumed that the event has already entered its maturity stage. The estimated model $ARIMA(0,0,0)(0,1,0)[12]$ demonstrates that the process under consideration is solely driven by seasonal differencing, i.e., the current observation is influenced primarily by observations made in the same period of the previous year.

From the statistical point of view, the proposed $ARIMA(0,0,0)(0,1,0)[12]$ model demonstrates good adequacy, with relatively small error rates ($MAE = 6.620$; $RMSE = 13.933$) and the lowest Mean Absolute Scaled Error ($MASE = 0.800$). Although the relatively high $MAPE$ (42.358%) implies some problems with capturing extreme peaks, which is normal for a volatile dataset of festivals, the model's diagnostics suggest its adequacy: the Ljung–Box test p-value equals 0.9921, while $ACF1 = 0.104$.

Overall, the obtained results contribute to the existing scientific literature by proving that the interest of users in events is characterized by stable seasonality, indicating the importance of using mega-events as anchors in the temporal organization of consumption behavior. From a methodological perspective, the research reveals the benefits of integrating Google Trends data and applying the SARIMA model for forecasting tourism interest. Finally, the strong seasonality of the data allows marketers and event organizers to plan promotions during high consumer interest periods.

Despite its contributions, this study is subject to several limitations. Firstly, the time-series contains a relatively small sample size that can affect the accuracy of the forecast in the long term. Secondly, since Google Trends gives data on the popularity of keywords and not real visits, it shows changes in digital attention, not tourist behaviour. Lastly, while the SARIMA model was able to effectively capture seasonal components, it may be overly simplistic when dealing with behavioural components affected by other factors like media coverage or macroeconomics conditions.

Further studies may extend this methodological approach by incorporating a combination of several types of datasets such as social media performance indicators or ticket sales data. In addition, comparisons between other festivals or geographical regions can provide insight into seasonality differences and improve the applicability of results.

Generative Artificial Intelligence (GenAI) usage statement:

No GenAI tool was used in the development of this paper.

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