Exploring the Twitter Myth: The Value of Twitter-generated Variables on Forecasting Tourist Arrivals

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**Abstract**

A growing body of research suggests that demand forecasts are efficient tools to help attractions formulate crowd management strategies and maintain competitiveness. Meanwhile, social media data are claimed to facilitate short-term and high-frequency demand forecasts quite well. However, only a handful of studies have explored the application of social media data in modeling tourism demand thus far. Applying Granger-causality analysis and dynamic modeling strategies to the case of the British Museum, this study aims to investigate if Twitter-generated variables can add value to accurate tourism demand forecasts. In this regard, we draw on research analyzing dynamics among Twitter-generated variables and various outcome variables from different disciplines to construct our potential predictors and further apply them in the practice of attraction-level tourism demand forecasts. Findings indicate a bidirectional relationship between the volume of tweets fetched under the name of the British Museum and tourist arrivals to the site. As regard model performance, the best fit is achieved with the autoregressive and distributed lag model that incorporates data from multisource (i.e., Twitter and Google Trends). This study contributes to tourism demand forecasting research by adding evidence to the value of dynamic models and multi-sourced high-frequency Internet data on accurate tourism demand forecasts at the attraction level and indicating directions for future research. Implications of this research for destination management are two-fold. First, an attraction can seek accurate forecasts of tourist arrivals through the utilization of Twitter data and especially the volume of tweets referred to the attraction's name. Second, attractions would benefit from engaging with individuals on Twitter on a broader level, that is, not only through content posted on an attraction's official account but also all related tweets that are publicly available.

**Keywords:** *tourism demand forecast; Twitter; dynamic models*

**Track:** Tourism Marketing

# 1. Introduction

A growing body of research suggests that short-term and high-frequency demand forecasts are efficient tools to help attractions formulate crowd management strategies and maintain competitiveness (X. Li, Law, Xie, & Wang, 2020). However, current tourism demand forecasting studies mainly focus on a large area (i.e. provinces, countries and regions) and base their forecasts on data sampled at low frequencies (i.e. monthly, quarterly and yearly tourists arrival data and search engine query data) (Song, Qiu, & Park, 2019). Through the lens of the least effort theory, empirical works confirmed that Facebook Likes are capable of representing tourists' visiting intent in the short term (Önder, Gunter, & Gindl, 2019). However, thus far, only a handful of studies have explored the application of social media data in modeling tourism demand (i.e., Gunter, Önder, and Gindl (2019); H. Li, Hu, and Li (2020); Önder et al. (2019)). And to the best of our knowledge, extremely limited studies are done in the attraction level (i.e., H. Li et al. (2020)). Therefore, this study aims to add into the literature on attraction-level tourism demand forecasts utilizing Twitter data and by doing so advance the literature and inform practice.

Applying the dynamic modeling approach with Twitter data in the case of the British Museum, this study demonstrate that high-frequency Twitter data (i.e., both monthly and daily volumes of tweets) can add value to the realization of accurate tourism demand forecasts. More specifically, results of the in- and pseudo-out-of-sample empirical analysis claim that: (1) there exists a bidirectional relationship among $Volumes_t$ (the volume of tweets fetched under the name of the British Museum at time $t$) and $Arrivalsa_t$ (volume of tourist arrivals to the British Museum at time $t$); (2) comparing to models based on past realizations of tourist arrivals only, alternative models incorporating past realizations of $Volumes_t$ as well as $GoogleTrends_t$ (index obtained from Google Trends with the query keyword 'the British Museum' under all categories at time $t$) perform much better; (3) $Volumes_t$ significantly outperforms $GoogleTrends_t$ in improving models' forecasting performance; and (4) dynamic models (the ARDL model class and the R-MIDAS-AR model class) incorporating lags of $Volumes_t$ significantly outperform the benchmark ARIMA model in the competition.

# 2. Related Literature

## *2.1. Social media data in tourism demand forecasting*

Academics increasingly acknowledge the predictive power of social media data in the tourism domain (X. Li et al., 2020). Tourism products can be characterized as intangible, experiential, and perishable (Xiang, Magnini, & Fesenmaier, 2015) and hence are not easily verified and controlled in advance. While providing more focused, up-to-date and credible information, social media are used by tourists as an information source to reduce perceived risks (Luo & Zhong, 2015). According to the least effort theory, least-effort individuals tend to use the most convenient search method while trying to find information with the most familiar tools available (Zipf, 2016). Notably, for regular Facebook users, it is easier to look for the destination or attraction's Facebook homepage rather than to go to the actual website for information regarding events and other destination-related news (Enter & Michopoulou, 2013). Underpinned by the least effort theory, it has been examined at various destinations that Facebook Likes obtained from destination management organization's (DMO's) Facebook homepage can be used as one of expedient leading indicators for tourism demand (Gunter et al., 2019). More recently, H. Li et al. (2020) examined the predictive ability of reviews data fetched from attractions' homepage in online tourism agencies' platforms and proved its efficiency in improving model's forecasting accuracy in comparison with models utilizing search engine query data. These early studies show the potential of social media data in explaining tourism demand and encourage efforts to include more social media platforms (e.g., Twitter and Facebook) and diverse data types (e.g., reactive data such as retweets and likes) in the future research.

### *2.2. Twitter-generated variables and predictive analysis*

Regarding Twitter's ability to fulfil individuals' information searching needs, evidence shows that major search engines have long started to include appropriate tweets as separate verticals in their search results (Xiang & Gretzel, 2010). Similar to search engines, Twitter offers an interface for individuals to search for publicly available tweets (Lin & Mishne, 2012), and it has been claimed that many tweets are questions that can be answered in a Twittersphere (Morris, Teevan, & Panovich, 2010). Twitter, therefore, is a valuable and user-driven information source with unprecedented volumes (Boyd, Golder, & Lotan, 2010) for users to search for travel-related information (Leung, Bai, & Stahura, 2015). Recent studies have shown the influence of Twitter-generated variables on various outcome variables in different research contexts. In the finance domain, the volume of tweets referring to a financial product (e.g., stocks and cryptocurrencies) has been recognized as a good measure of attention of both uninformed individuals (Behrendt & Schmidt, 2018) and well-informed investors (Shen, Urquhart, & Wang, 2019) as well as an efficient predictor to the trading volume, return (Behrendt & Schmidt, 2018) and volatility of a financial product (Shen et al., 2019). While in the tourism context, well-informed individuals who have the knowledge and/or experience of an attraction would not only be searching for it in the search engines but also be tweeting about it (Bigne, Oltra, & Andreu, 2019). These tweets may involve commenting on news posts related to the attraction or making travel-related suggestions about the attraction based on their experience (Chung & Koo, 2015). In alignment with this stream of research, it is of necessity to investigate whether the volume of tweets referred to the name of an attraction can serve as an efficient explanatory variable in modeling tourist arrivals. On DMO's Facebook homepage, Facebook Statistics includes reactions[1], comments, shares, and other interactions. Among all these interactions, Önder et al. (2019) emphasize 'likes' because of its prevalence. While for each tweet, 'likes' is the only type of reaction an individual can give. Therefore, it is worth investigating if Twitter likes can also serve as an efficient predictor in the scenario of demand forecasting for attractions. While for each public tweet, retweeting is another type of interaction worth investigating. Structurally, retweeting behaviour can be seen as 'the Twitter-equivalent of email forwarding where users post messages initially posted by others'(Boyd et al., 2010) (p.1). Consequently, retweeting behaviour can bring new participants into a particular thread (or a conversation) through information diffusion, inviting them to engage in this conversation however not address them directly. Considering the important role of retweeting behaviour in the information diffusion process in micro-blog platforms like Twitter (Hou, Huang, & Zhang, 2015), it is of value to investigate if the volume of retweeting activities can serve as an efficient predictor in the scenario of demand forecasting for attraction.

## 3. Methodology

To investigate the dynamics among tourist arrivals and potential predictors, we first estimate a vector autoregressive (VAR) model. A classic VAR(k) model is expressed as equation (1)[2]:

$$x_t = \mathrm{c} + \sum_{j=i}^{k} \beta_j x_{t-j} + \varepsilon_t \tag{1}$$

The lag length is determined by the Schwarz Bayesian information criterion, and we estimate three separate models examining whether the volume of tweets can help predict tourist arrivals. From these VAR models, we employ the linear Granger causality test (Granger, 1969) as it has a greater sensitivity to the selection of lags determined by the Schwarz Information Criterion

[1] Reactions include angry, haha, like, love, sad, and wow.

[2] In equation (1), $x_t$ denotes a vector that contains the variables of interest, including (in our case $Volumes_t$, $Volumes_t$, $Likes_t$ and $Retweets_t$), c is a vector of constants and $\varepsilon_t$ is a vector of independent white noise innovations.

(SC). The linear Granger causality test can be expressed as equations (2) and (3)[3]:

$$\Delta x_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta x_{t-j} + \sum_{j=1}^{m} \beta_{2i} \Delta y_{t-i} + \varepsilon_{1t} \quad (2)$$

$$\Delta y_t = \delta_0 + \sum_{i=1}^{n} \delta_{1i} \Delta y_{t-i} + \sum_{j=1}^{m} \delta_{2j} \Delta x_{t-j} + \varepsilon_{2t} \quad (3)$$

To test whether the Granger causality runs from $x_t$ to $y_t$, the null hypothesis ($H_0$) is: $H_0$: $\delta_{2j}$ = 0, $j$ = 1, 2, ......... q. If at least one of $\delta_{2j}$ is not equal to zero, then $H_0$is rejected and it suggests that $x_t$ Granger causes $y_t$. It means that the past value of $x_t$ has a significant linear predictive power on the current value of $y_t$, and vice versa.

Researchers have yet to reach a consensus on an optimal method for modeling tourism demand when using social media data. However, it is clear that the autoregressive integrated moving average model (ARIMA) has been widely used in a diverse research context and proved to perform well (Song et al., 2019). Therefore, the ARIMA model class is firstly employed as the benchmark. A general ARIMA model takes the form of equation (4)[4]:

$$\varphi^*(L^j) y_t^j = a^j + \theta(L^j) \varepsilon_t^j \quad (4)$$

To examine the explanatory power of Twitter-generated variables, two dynamic model classes: the autoregressive distributive lag (ARDL) model class and a restricted mixed data sampling auto-regression (R-MIDAS-AR) model class are further employed. A general ARDL and R-MIDAS-AR model takes the form of equation (5)[5] and equation (6)[6]:

$$y_t^j = a^j + \sum_{i=1}^{12} b_i^j \cdot y_{t-i}^j + \sum_{i=1}^{12} c_i^j \cdot x_{t-i}^j + \varepsilon_t^j \quad (5)$$

$$y_t^j = a^j + \sum_{i=1}^{12} b_i^j \cdot y_{t-i}^j + c^j \cdot \sum_{k=1}^{m} \omega(k^j, \theta) L_{HF}^{kj} x_t^j + \varepsilon_t^j \quad (6)$$

With the ability to incorporate lags of the dependent variable as additional explanatory variables, the ARDL model class has been used quite frequently in the tourism demand modeling literature (Gunter et al., 2019; Narayan, 2004; Önder et al., 2019). While being able to accommodate high-frequency explanatory variables in addition to a low-frequency dependent variable and other low-frequency explanatory variables, the MIDAS model class

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[3] In equation (2) and (3), $\Delta$ is the difference operator, $m$ and $n$ are lag orders for $x_t$ and $y_t$ respectively ($m$ and $n$ are determined by AIC), $\beta$ and $\delta$ are parameters for estimation, and $\varepsilon_{1t}$ is the error term.

[4] In equation (4), $y_t^j$ denotes the volume of tourists demand in period t to attraction j; $a^j$ denotes the attraction-specific intercept; $\varepsilon_t^j$ represents the attraction-specific error term in period $t. \varphi^*(L^j)$ and $\theta(L^j)$ are attraction-specific lag polynomials of finite orders $p$ and $q$ with d unit-roots ($\varphi^*(L^j) = \varphi(L^j)(1 - L^j)^d$).

[5] In equation (5), $b_i^j$ and $c_i^j$j are the attraction-specific regression coefficients on past realizations of tourists' arrivals and current and past realizations of the monthly aggregated Twitter-generated variables, respectively. The remainder of the notation in equation (6) has the same interpretation as equation (4).

[6] In equation (6), $L_{HF}^{kj}$ represents the attraction-specific high-frequency lag operator with $k^j$ daily lags, which are automatically selected in a general-to-specific approach out of a maximum of m = 60. $\omega(k^j, \theta)$ denotes the weighting function of high-frequency Twitter-generated variables. The remainder of the notation in equation (6) has the same interpretation as equations (4) and (5).

has been suggested as an efficient tool in modeling search engine query data (Bangwayo-Skeete & Skeete, 2015; Havranek & Zeynalov, 2021; Wen, Liu, Song, & Liu, 2021). Following Gunter et al. (2019), we applied a non-exponential Almon function with four shapes for the specification of $\theta$ in the R-MIDAS-AR model as it is suggested to demonstrate the best overall in-sample model fit. To verify the forecasting performance of different models, four criteria that are frequently used in related research (Song et al., 2019) are adopted, including: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and symmetric mean absolute percentage error (SMAPE). The model with the lowest values on these four criteria can be considered as the best forecasting model.

## 4. Empirical analysis

We use the British Museum as the case of study and obtain data from the UK government's website[7] to construct the dependent variable $Arrivals_t$. $Arrivals_t$ spans from *1st January 2014 to 31st December 2019* and is reported in a monthly frequency. To preclude any potential distortions to the subsequent analyses stemming from the seasonal patterns, tourist arrivals are seasonally adjusted through a moving average filter to form the series $Arrivalsa_t$. Using the selected query keyword 'British Museum', tweets are continuously obtained and stored in real time between the period of *1st January 2014 to 31st December 2019* through a live stream crawler Twint, resulting in a dataset with a total of 722,717 public Tweets[8]. Based on the dataset, series including $Volumes_t$, $Likes_t$ and $Retweets_t$ are then constructed through simple temporal aggregation[9]. For comparison purposes, we include search engine query data gathered from Google Trends under the query 'the British Museum' within the same period. The series $GoogleTrends_t$ is structured time series data and is automatically aggregated in a monthly frequency. To ensure stability and avoid spurious regression sequence, the Augmented Dickey-Fuller (ADF) test allowing for trends and intercept are implemented to evaluate if unit-roots exist in our dataset. The test results conclude that the null hypothesis of the ADF test is rejected

[7] Obtained from: https://www.gov.uk/government/statistical-data-sets/

[8] To eliminate the effect of tweets criticizing the stolen artefacts exhibited in the British Museum, we further exclude tweets with keywords including 'stolen' (and its synonyms 'stole' and 'steal'), 'return', 'slave', 'racist', 'racism', and 'colony' (and its synonyms 'colonial' and 'colonies') based on the results of text analysis to the top 50 tweets with most likes. Additionally, non-English tweets are filtered out, considering the need for convenient data computing. The designed adjustment results in a dataset with *604,185* public tweets spanning from *1st January 2014* to *31st December 2019*.

[9] Since the ARDL model class requires the frequency of both dependent and explanatory variables to be in accordance (Gunter et al., 2019), tweets data are then aggregated to a monthly frequency by simple summation.

at least at the 5% significance level for each variable[10]. From **Table 1**, it can be concluded that there exists bidirectional causality between $Volumes_t$ and $Arrivalsa_t$ with a lag order of 1 at the 5% significance level. Moreover, the null hypothesis that '$GoogleTrends_t$ does not Granger cause $Arrivalsa_t$' has been refused at the 10% significance level with a lag order of 1. In the meantime, Granger causality has not been examined among $Arrivalsa_t$, $Likes_t$ and $Retweets_t$. Consequently, it is worth further investigating if the incorporation of past realizations of $GoogleTrends_t$ (aggregated in a monthly frequency) and $Volumes_t$ (aggregated in both monthly and daily frequencies) can help realize more accurate forecasts of $Arrivalsa_t$ compared to models only utilizing past realizations of $Arrivalsa_t$.

**Table 1.** Results of Granger causality test

| *Lag* | *Null hypothesis* | *F-Statistics* | *Prob.* | *Conclusion* |
|---|---|---|---|---|
| 1 | $GoogleTrends_t$ does not Granger Cause $Arrivalsa_t$ | 2.867 | 0.095 | ***Refuse*** |
| 1 | $Arrivalsa_t$ does not Granger Cause $GoogleTrends_t$ | 2.098 | 0.152 | Accept |
| 1 | $Volumes_t$ does not Granger Cause $Arrivalsa_t$ | 3.968 | 0.050 | ***Refuse*** |
| 1 | $Arrivalsa_t$ does not Granger Cause $Volumes_t$ | 4.578 | 0.036 | ***Refuse*** |
| 5 | $Likes_t$ does not Granger Cause $Arrivalsa_t$ | 1.286 | 0.283 | Accept |
| 5 | $Arrivalsa_t$ does not Granger Cause $Likes_t$ | 1.687 | 0.153 | Accept |
| 3 | $Retweets_t$ does not Granger Cause $Arrivalsa_t$ | 1.558 | 0.209 | Accept |
| 3 | $Arrivalsa_t$ does not Granger Cause $Retweets_t$ | 1.600 | 0.199 | Accept |

For all models, we use the full dataset spanning from *1st January 2014* to *31st December 2019* in the estimation process. In total, six models are estimated, including one ARMIA model as the benchmark and five rival models including three ARDL models and two R-MIDAS-AR models. Estimates for the two dynamic model classes feature an adequate in-sample model fit as judged by higher adjusted R squared values and lower AIC values as well as an overall statistical significance as indicated by high model F-statistics that are statistically significantly different from zero at the 1% significance level[11]. Judged by the adjusted R-squared value and the AIC value, it can be concluded from **Table 2** that dynamic models (model 2 to 6) beat the benchmark ARIMA model (model 1) in the competition of in-sample model fit. Comparing

[10] Detailed results of the ADF test are available from the authors on request.
[11] Details results of estimations (e.g., F-statistics and coefficient estimates) for each model are available from the authors on request. While not all individual coefficients of estimated models are significantly different from zero, a large majority of them are statistically significant at conventional significance levels (1% and 5% significance level), which also holds for all coefficient estimates of the four-shapes parameter θ.

model 2, model 3 and model 5, it is clear that $Volumes_t$ provides more explanatory power to $Arrivalsa_t$ than $GoogleTrends_t$ (model 2 and model 5 provide more considerable adjusted R-squared value and smaller AIC value than model 3). In addition, between the two classes of dynamic models, the ARDL model class provides a slightly better in-sample model fit and potentially results in a slightly better out-of-sample forecast accuracy (model 5 provides a more considerable adjusted R-squared value and smaller AIC value than model 2). Furthermore, although $Volumes_t$ provides more explanatory power to $Arrivalsa_t$ than $GoogleTrends_t$, models incorporated both $GoogleTrends_t$ (as fixed regressors) and $Volumes$ (model 4 and model 6) present improvement in in-sample model fit compared to models only adopted $GoogleTrends_t$ or $Volumes_t$ as the explanatory variable (model 2, model 3 and model 5). Last, model 4 provides the most significant adjusted R-squared value and smallest AIC value and hence ranks 1st among all rival models in the in-sample model-fit competition.

**Table 2.** In-sample model fit and Pseudo-out-of-sample One-step-ahead forecasts evaluation

| *No* | *Model* | *Exogenous predictors* | *Fixed regressors* | *Adjusted $R^2$* | *AIC* | *RMSE* | *MAE* | *MAPE* | *SMAPE* |
|---|---|---|---|---|---|---|---|---|---|
| **1** | ARIMA (1, 0, 7) | / | / | 0.635 | 23.351 | 41368.6 | 35155.55 | 7.3 | 6.96 |
| **2** | ARDL(1, 4) | $Volumes_t$ | / | 0.648 | 23.086 | 30510.6 | 25003.87 | 5.14 | 5.02 |
| **3** | ARDL(1, 0) | $Google\ Trends_t$ | / | 0.620 | 23.221 | 34312.49 | 29652.32 | 6.07 | 5.88 |
| **4** | ARDL(1, 4) | $Volumes_t$ | $Google\ Trends_t$ | ***0.671*** | ***23.031*** | ***26817.82*** | ***21967.49*** | ***4.48*** | ***4.41*** |
| **5** | R-MIDAS-AR (1, 50) | $Volumes_t$ | / | 0.634 | 23.237 | 30928.18 | 24804.00 | 5.12 | 4.97 |
| **6** | R-MIDAS-AR (1, 50) | $Volumes_t$ | $Google\ Trends_t$ | 0.658 | 23.183 | 29142.74 | 24614.25 | 5.03 | 4.91 |

**Table 2** also presents evaluations to the accuracy of the one-step-ahead pseudo-out-of-sample forecasts for seasonally adjusted monthly tourist arrivals at the British Museum based on our estimations. As can be seen from the results, the two classes of dynamic models (model 2 to 6) are able to mimic the historical observations of seasonally adjusted tourist arrivals to the British Museum much better than the benchmark ARIMA model (model 1). While for the comparison of these two dynamic model classes, the RMSE, MAE, MAPE and SMAPE criteria all suggest that model 4 performs best. Given that model 4 already presents the best in-sample model fit, the results meet our expectations. The results again confirm the value of dynamic models (Önder et al., 2019) and multisource Internet data in forecasting tourism demand (H. Li et al., 2020). Taking the effects of $GoogleTrends_t$ aside, among model 1, model 2, and model 5, model 5 presents a slightly better forecasting performance than model 1 and model 2 according

to the MAE, MAPE and SMAPE criteria. It confirms the value of high-frequency data in improving models' forecasting performance.

## 5. Conclusion and Directions for Future Research

In summary, it can be concluded that there exists a bidirectional causal relationship between seasonally adjusted tourist arrivals and the monthly aggregated volume of tweets referred to the British Museum. Through the model estimating process, it can further be concluded that dynamic models significantly outperform the pure time series model in the forecasting practice. Subsequently, the estimates suggest that the one ARDL model with explanatory variables generated from multiple sources (i.e., Twitter and Google Trends) produces both the best in-sample model fit and the most accurate forecasts, and hence provide more evidence on the value of dynamic models (Önder et al., 2019) and multisource Internet data in forecasting tourism demand (Li et al., 2020b). Implications of this research for destination management are two-fold. First, an attraction can seek accurate forecasts of tourist arrivals through the utilization of Twitter data and especially the volume of tweets referred to the attraction's name. Second, attractions would benefit from engaging with individuals on Twitter on a broader level, that is, not only through content posted on an attraction's official account but also all related tweets that are publicly available.

There are a few limitations in the present research. First and foremost, current preprocessing procedures of Twitter data limit our ability to omit irrelevant information (e.g., tweets criticizing stolen artefacts in the British Museum). And consequently, it raises the question that if a more sophisticated data cleaning process is implemented, would $Likes_t$ and $Retweets_t$ present causal relationships with $Arrivalsa_t$? Second, the value of abundant information contained in each tweet (e.g., sentiment) have not been fully exploited, and it may weaken the argument on the advantage of Twitter data in comparison to search engine query data. Third, models employed in this study do not consider characteristics of museums different to other types of attractions. Upcoming research could consider museums-specific indicators such as holidays and special exhibitions as dummy variables to achieve higher model fit. Forth, this study mainly considered and investigated dynamics between Twitter data and tourist arrivals in the modeling process. A comparison with social media data from other sources such as Facebook statistics would benefit future research. Last, the purpose of this study is to examine if it is necessary to incorporate Twitter data in the modeling and estimating process of tourism demand forecasts at the attraction level. By nature, it is explorative. The results of this study are case-based and hence cannot be simply generalized. It is worth investigating in future research if the findings of this study are valid in other cases or research settings.

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