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# Which search queries are more powerful in tourism demand forecasting: Searches via mobile device or PC?

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# Which search queries are more powerful in tourism demand forecasting: Searches via mobile device or PC?


## Abstract

**Purpose**: While relevant research has considered aggregated data from mobile devices and personal computers (PCs), tourists' search patterns on mobile devices and PCs differ significantly. This study aims to explore whether decomposing aggregated search queries based on the terminals from which these queries are generated can enhance tourism demand forecasting.

**Design/methodology/approach**: Mount Siguniang, a national geopark in China, is taken as a case study in this paper; another case, Kulangsu in China, is used as the robustness check. We decomposed the total Baidu search volume into searches from mobile devices and PCs. Weekly rolling forecasts were used to test the roles of decomposed and aggregated search queries in tourism demand forecasting.

**Findings**: Search queries generated from PCs can greatly improve forecasting performance compared to those from mobile devices and to aggregated search volumes from both terminals. Models incorporating search queries generated via multiple terminals did not necessarily outperform those incorporating search queries generated via a single type of terminal.

**Practical implications**: Major players in the tourism industry, including hotels, tourist attractions, and airlines, can benefit from identifying effective search terminals to forecast tourism demand. Industry managers can also leverage search indices generated through effective terminals for more accurate demand forecasting, which can in turn inform strategic decision making and operations management.

**Originality/Value**: This study represents one of the earliest attempts to apply decomposed search query data generated via different terminals in tourism demand forecasting. It also enriches the literature on tourism demand forecasting using search engine data.



**Keywords**: Tourism demand forecasting; Baidu Index; Search query; Mobile device; PC

## 1. Introduction

Tourist arrivals differ drastically between peak and non-peak seasons. The heads of destination management organizations thus face inherent challenges when striving to meet varying demand. Accurate tourism demand forecasting is crucial to helping managers strategize and allocate limited resources (Song *et al*., 2008). Traditional tourism demand forecasting methods rely on published statistical data, which can be constrained by delayed publication, small sample sizes, and low-frequency observations (Huang *et al*., 2017). By contrast, search engines record online search queries hourly; the queries that (potential) tourists enter into search engines can reflect trends in searchers' travel-related product preferences and guide predictions of tourists' travel behavior (Yang *et al*., 2015). The important role of search query volume in improving tourism demand forecasting performance has been demonstrated for both destinations and attractions (e.g., Pan *et al*., 2012; Bangwayo-Skeete and Skeete, 2015; Wu *et al*., 2017; Wen *et al*., 2019).

Travelers can access search engines via either personal computers (PCs) or internet-enabled mobile devices. Whereas mobile devices allow travelers to perform internet searches wherever and whenever a mobile signal is available (Ye *et al*., 2017), online searches via PCs are only possible in certain places. This perceived convenience from mobile devices enables users to search for relevant information and services without much effort (Chen *et al.*, 2019). Given the ubiquity of mobile devices, mobile search volumes have surpassed those of PCs (Murtagh, 2014). Furthermore, mobile search patterns are distinct from those executed via PCs (Church *et al*., 2008). Song *et al*. (2013) identified discrepancies in search behavior between mobile devices and PCs in terms of query categorization, query length, search time distribution, search location distribution, and user click patterns. Relatedly, Shin *et al*. (2016) divided search queries into queries from mobile devices and PCs when studying the National Influenza surveillance performance, and concluded that influenza surveillance performance based on search query volume data from PCs was less effective over time than that based on mobile device search queries. Sun *et al.* (2017) forecasted tourism demand for Mount Sanqingshan, China based on search query data from the year 2012 and found that the forecasting performance of searches on mobile devices outperformed that on PCs. Although Sun *et al.* (2017) compared the performance of PC and mobile device searches in 2012, mobile search volumes have exceeded those of PCs since 2014 (Murtagh, 2014). The traffic share of mobile devices also grew by 222% between 2013 and 2019 (Broadband Search, 2020). Accordingly, scholars have yet to differentiate search queries generated via different terminals since mobile search volumes have exceeded those of PCs. Researchers also have not yet compared the forecasting performance of search query volume data from multiple terminals versus a single type of terminal. This knowledge gap points to intriguing research questions: (1) Does applying search query volume data generated from different terminals help improve tourism demand forecasting accuracy compared to data aggregated from multiple terminals? (2) Does forecasting performance based on search query volume data generated from multiple terminals exceed performance based on data generated from a single terminal?

By decomposing aggregated search query data into mobile and PC queries, we aim to explore tourism demand forecasting performance based on search queries from mobile devices and PCs. This study represents one of the earliest attempts to apply decomposed search query data generated from different terminals to tourism demand forecasting. Specifically, this study is the first to compare the power of search query volumes generated from a single terminal (i.e., mobile devices *or* PCs), multiple terminals (i.e., mobile devices *and* PCs), and aggregated search query volumes from both terminals in tourism demand forecasting. The findings enrich the literature of search query data-based tourism demand forecasting.

## 2. Literature review

### *2.1 Search query–based tourism demand forecasting*

Traditional models for forecasting tourism demand can be categorized into time series models, econometric models, artificial intelligence models, judgmental methods, and hybrid models (Song *et al*., 2019). The popularity of internet big data, such as search engine data, continues to grow thanks to the advantages of high frequency and the potential sensitivity of such data in tracking consumer behavior (Yang *et al*., 2014). In this section, we review studies on tourism demand forecasting based on internet search queries and highlight corresponding research gaps.

Search engines process user queries and retrieve related documents online, affording travelers access to billions of webpages related to restaurants, hotels, transportation, attractions, shopping, and so forth (Pan *et al*., 2011). Advances in internet technology have led most tourists to use mobile devices or PCs to search for trip-related information before traveling (Fesenmaier *et al*., 2011). Tourism-related search keywords are sensitive to slight changes in visitor behavior and can reflect travelers' information needs, interests, and preferences (Pan *et al*., 2011; Yang *et al*., 2014; Yang *et al*., 2015). Therefore, search query data are frequently used to forecast tourist arrivals and hotel room demand (Dergiades *et al*., 2018; Wu *et al*., 2017; Yang *et al*., 2015).

Table 1 summarizes studies using search engine data to predict tourism demand. As indicated, search engine data are most often gathered from Google's and Baidu's search engines. Studies have shown that Google Trends and Baidu Index can reduce forecasting error and improve forecasting performance in tourism (Yang *et al*., 2015). In particular, search intensity index data on Google Trends are more effective in forecasting international tourist demand (Bangwayo-Skeete and Skeete, 2015; Li and Law, 2020), whereas Baidu index-based search volume data are more widely applied to forecast domestic tourist demand in China (Huang *et al*., 2017; Li *et al*., 2017; Li *et al*., 2018; Wen *et al*., 2019). Further, many scholars have used search engine data to forecast weekly or daily tourism demand given the high-frequency characteristics of such data (Huang *et al.*,2017; Volchek *et al.*, 2019).

In addition to applying pure search query data, researchers have simultaneously incorporated other data sources to forecast tourism demand; examples include social media data, causal variables, and other data types. Gunter *et al*. (2019) tested outcomes when integrating search intensity data on Google Trends and Facebook LIKES data to predict tourism demand. Li *et al*. (2020b) studied performance when incorporating search query data on Baidu Index and online review data to forecast weekly tourism demand. Hu and Song (2019) examined the utility of employing causal variables (e.g., historical data and traditional economic variables) and search volumes when forecasting short-haul tourism demand. In addition to the integrated use of search query data with social media and causal variables, other forms of data (e.g., weather, holidays, and seasonality) have also been included in search query–based forecasting models (Li *et al*., 2020b).

In terms of forecasting models, time-series models such as autoregressive with explanatory variables (ARX), autoregressive moving average with explanatory variables (ARMAX), and autoregressive integrated moving average with explanatory variables (ARIMAX) models are frequently employed to incorporate search queries while corresponding pure time-series models are taken as benchmarks (Pan *et al*., 2012; Yang *et al*., 2015; Law *et al*., 2019). In addition, the autoregressive distributed lag model (ADLM) and mixed data sampling (MIDAS) are two common econometric models. ADLM involves search query data at the same frequency as tourist arrival data (Önder, 2017; Gunter *et al*., 2019), whereas MIDAS uses higher-frequency search query data (Bangwayo-Skeete and Skeete, 2015; Gunter *et al*., 2019; Wen *et al*., 2020). Furthermore, based on the assumption of a non-linear relationship between search query volume and the number of tourist arrivals, several artificial intelligence models have already been used in tourism demand forecasting. Examples include the back propagation neural network (BPNN) (Li *et al*., 2018; Hu and Song, 2019), support vector regression (Sun *et al*., 2019; Li *et al*., 2020b), random forest (RF) (Li *et al*., 2020b), and deep learning model (Law *et al*., 2019). Hybrid artificial intelligence models in which search query volumes are taken as predictor variables have also been adopted to predict tourism demand (Li *et al*., 2018; Wen *et al*., 2019; Li and Law, 2020; Li *et al*., 2020a).

<Insert Table 1>

*2.2 Mobile devices versus PCs*

Mobile devices' far-reaching penetration has influenced consumers' online behavior. Due to these devices' inherent convenience and tailored features, the search volumes of mobile devices are growing and began to surpass those of PCs in 2014 (Murtagh, 2014). Search behavior differs via PCs and mobile devices and can be explained from two major aspects.

First, PCs have larger screens, a mechanical keyboard, and a generous storage capacity; these attributes make PCs heavy and limit their use to offices, homes, and other settings with internet access (Murphy *et al.*, 2016). In comparison, mobile devices offer unparalleled flexibility in time and space; they are portable and easily carried in one's pocket (Murphy *et al.*, 2016). Mobile devices also provide users internet access at nearly any time and place (Zou *et al.*, 2020). This convenience enables users to search for information about products/services with a low opportunity cost in terms of time (Chen *et al.*, 2019).

Second, when searching for information via PCs, users can easily enter information with a physical keyboard and use a mouse to scroll through search results on a large screen. These features allow users to locate desired information relatively quickly. Although tourists may bear a high opportunity cost of time when using PCs for information searches, they can benefit from more detailed information (Singh and Jang, 2020). On mobile devices, users must spend more time and effort entering search information and wading through results; these devices' small screen size also calls for greater cognitive effort than PCs, compromising users' global perspective on a task (Nunamaker *et al.*, 1988). Murphy *et al.* (2016) argued that tourists tend to search on several different terminals before making final hotel reservations, but most tourists still choose to complete their bookings on PCs.

Information economics theory posits that information searches are guided by a trade-off between the perceived costs of searching and the expected benefits of that search (Stigler, 1961). On one hand, the perceived search benefit of searching on PCs (vs. mobile devices) are reflected in the perceived quality and quantity of search results compared to mobile searches; it is easier to compare products, locate price information, and complete searches

(Singh and Jang, 2020). On the other hand, the perceived search costs of searching on PCs concern the user's perceived time (i.e., time cost) and difficulty gathering product/service information. The costs of searching on a mobile device may be lower than on a PC given mobile devices' flexibility in time and space (Singh and Jang, 2020). Ultimately, these disparate use patterns evoke differences in customer behavior: users' search patterns, query categorization, query length, time and location of searches, and click patterns tend to vary substantially by device type (Church *et al*., 2008; Song *et al*., 2013; Shin *et al*., 2016).

*2.3 Rationale for this study*

A comprehensive literature review suggests that most studies on tourism demand forecasting have not distinguished mobile and PC queries. A notable exception is Sun *et al*. (2017), who compared tourism demand forecasting performance using mobile and PC search query data based on a dataset from 2012. However, the search traffic share of mobile devices (vs. PCs) and tourists' search behavior have each changed substantially over time. It is therefore worthwhile to explore whether decomposing search queries into searches performed via mobile devices or PCs can enhance the accuracy of tourism demand forecasting using an updated search query dataset. Additionally, it will be useful to (1) investigate which type of query data is more powerful in forecasting tourism demand: data from mobile devices or PCs; and (2) compare the forecasting performance using search query volume data from multiple terminals versus a single terminal.

## 3. Methodology

An integrated framework (Figure 1) is proposed to evaluate the performance of search queries from mobile devices and PCs in tourism demand forecasting. Our approach consisted of four steps. First, two types of data were collected, namely search query data from Baidu as well as the number of weekly tourist arrivals to a tourist attraction. Search query data were then divided into three categories by terminal: (1) search queries via PCs, (2) search queries via mobile devices, and (3) their simple aggregate. Second, we adopted the feature selection method based on a Boruta algorithm (Kursa and Rudnicki, 2010) to choose search keywords with the most predictive power. Third, we developed several models to test the forecasting power of search query data via different terminals: (a) benchmark models, including the ARIMA model, autoregressive (AR) model, neural network (NN), RF, and NAÏVE; (b) one main forecasting model, an ARIMA model with search query data from mobile devices and PCs as explanatory variables (ARIMAX); and (c) robustness check forecasting models, including an autoregressive model with explanatory variables (ARX), NN with explanatory variables, and RF with explanatory variables. Fourth, the mean absolute percentage error (MAPE) and root mean square error (RMSE) were used to measure forecasting error, and the improvement ratio (IR) was used to compare forecasting model pairs.

<Insert Figure 1>

### *3.1 Data description*

Mount Siguniang, a UNESCO World Natural Heritage site as a giant panda habitat, is a national geopark in China. Due to the availability of high-frequency tourist arrival data, we selected Mount Siguniang as our focal case. We then forecasted weekly tourist arrivals of this attraction to investigate the roles of search queries generated via mobile devices and PCs in improving tourism demand forecasting performance. The number of tourist arrivals to Mount Siguniang from January 2, 2017 to July 21, 2019 were collected from the park's website at the weekly frequency level (https://www.sgns.cn/news/number). To reduce the effects of outliers, we performed a logarithmic transformation on weekly tourist arrivals in this study (Li *et al.*, 2017; Li *et al.*, 2020c).

Thanks to convenient internet access, most travelers use search engines to find tourism-related information when planning trips, such as details on hotels, food, traffic, recreation, and weather (Li *et al.*, 2017). As the most popular search engine across mainland China, Baidu's Index database (http://index.baidu.com) has been widely employed in tourism demand forecasting (Yang *et al.*, 2015; Li *et al.*, 2018; Li *et al.*, 2020b; Li *et al.*, 2020c). Therefore, we collected search query data from Baidu index.

In this paper, we sought to forecast tourist arrivals at an attraction level (i.e., Mount Siguniang). Search query selection differs from city- or country-level data in this case (Li *et al.*, 2017). Following Li *et al.* (2020b), we chose eight Chinese-language search keywords. The weekly search volume for each of these keywords on mobile devices and PCs was collected from January 2, 2017 to July 21, 2019 from Baidu Index. The description of weekly search volume of these keywords is shown in Table 2, and Figure 2 depicts the summative weekly volume of keywords via mobile device and PC searches. As illustrated, the search volume on mobile devices exceeded that on PCs during the study period; this pattern is consistent with that reported by Murtagh (2014).

<Insert Table 2>

<Insert Figure 2>

*3.2 Model specification*

To investigate tourism demand forecasting performance based on search queries generated through mobile devices and PCs, we employed an ARIMAX model as the main forecasting model, while an ARX model, NN model with explanatory variables, and RF model with explanatory variables served as robustness checks. We used an ARIMA model, AR model, NN model, RF model, and NAÏVE model without explanatory variables as benchmarks. These models are introduced briefly below.

***ARIMA/ARIMAX model***

The ARIMA model is an ARMA family model and a common benchmark model (Song *et al.*, 2019) owing to its flexibility and strong performance. An ARIMA (*p,d,q*) model is shown as follows

$$\Delta^d y_t = \mu + \sum_{i=1}^{p} \phi_i \Delta^d y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i},$$

where $\Delta$ is the difference function (i.e., $\Delta y_t = y_t - y_{t-1}$); $d$ indicates the rank of difference, determined by the unit roots testing of the arrival series; and $\varepsilon_t$ is the error term. $i$ denotes the $i$th lag; $\mu, \phi_i, \theta_i$ are coefficients. When incorporating explanatory variables (i.e., keyword search volume in our case), the ARIMA model becomes an ARIMAX model as follows:

$$\Delta^d y_t = \mu_t + \sum_{i=1}^{p} \phi_i \Delta^d y_{t-i} + \sum_{i=1}^{n} \sum_{j=1}^{r} \alpha_{ij} x_{i,t-j} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i},$$

where $x_{i,t-j}$ represents the lagged volume of different search keywords, and $j$ denotes the $j$th lag. These lagged time series were feature-selected using the Boruta algorithm (Kursa and Rudnicki, 2010). In this study, we used the "auto.arima" function in R's forecasting package to conduct forecast estimation (Hyndman and Khandakar, 2007).

### *AR/ARX model*

The ARX model incorporates the autoregressive component and lagged explanatory variables. The general ARX model is shown as follows

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{n} \sum_{j=1}^{q} \alpha_{ij} x_{i,t-j} + \varepsilon_t,$$

where $p$ is the maximum lag of dependent variable $y$, and $q$ is the maximum lag of explanatory variable $x$. Sun *et al*. (2019) used the Pearson correlation coefficient to determine the correlation between monthly search query volumes and tourist arrivals. They removed the coefficient below a certain threshold, resulting in a maximum lag of three months (roughly 12 weeks). Initially, the maximum lag of $x$ was set to 12, while the maximum lag of weekly tourist arrivals was determined by the partial autocorrelation function (PACF) test and set to 7. In the current study, these lagged time series were feature-selected using the Boruta algorithm (Kursa and Rudnicki, 2010).

### *NN model*

The NN model is an artificial intelligence model that has been broadly adopted for tourism demand forecasting throughout the past two decades (Law and Au, 1999; Wu *et al.*, 2017). Structurally, an NN consists of three parts (i.e., an input layer, hidden layer, and output layer), each of which contains respective nodes (Figure 3). Links exist between two nodes connecting two layers. The NN training process involves adjusting the weight of these links to fit the output (Law and Au, 1999). More details about NN models can be found in Law (2000). We adopted a three-layer simplified NN structure containing one hidden layer by using package ‘neuralnet’ in R, as shown in Figure 3 (Fritsch *et al.*, 2016). For our NN model with explanatory variables, lagged tourist arrivals and the lagged volume of different search keywords were taken as input in the input layer after feature selection of corresponding search keywords using the Boruta algorithm (Kursa and Rudnicki, 2010); only lagged tourist arrivals were used as input in the NN model without explanatory variables. Current tourist arrivals served as output for the output layer.

<Insert Figure 3>

***RF model***

RF (Breiman, 2001) combines classification, regression tree, and bagging. Specifically, by introducing the bagging method, it enhances CART learning algorithms on the stability and accuracy (Khaidem *et al.*, 2016). Using “randomForest” package in R, lagged tourist arrivals and lagged search queries were used as input for the RF model with explanatory variables, while only lagged tourist arrivals were included in the RF model without explanatory variables (RColorBrewer and Liaw, 2018). The current number of tourist arrivals served as the output variable.

*3.3 Forecasting evaluation*

We used MAPE and RMSE to measure forecasting error and referred to the IR to calculate improvement when comparing two forecasting models. Their respective formulas are as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$IR = \frac{MAPE(\mathrm{Model}_2) - MAPE(\mathrm{Model}_1)}{MAPE(\mathrm{Model}_2)} \times 100\%$$

where $y_i$ represents actual weekly tourist arrivals; $\hat{y}_i$ denotes the forecast value of weekly arrivals; and IR indicates the improvement of Model 1 compared with Model 2 when measuring forecast error based on MAPE.

## 4. Results

To answer the research questions presented earlier, we considered a main comparison model (i.e., ARIMAX) along with three group robustness checks (see Figure 4). Our main comparison, based on the ARIMAX model, was employed to test (1) whether including search queries generated via mobile devices or PCs in a tourism forecasting model could increase forecasting performance compared with a model including aggregated search volumes from both terminals; and (2) whether integrating both types of search query data simultaneously (i.e., generated via mobile devices *and* PCs) in a model could increase forecasting performance compared with including search queries generated from a single terminal (i.e., mobile devices *or* PCs). Comparisons with benchmark models were performed to examine the role of search query data in improving forecasting accuracy. The first group robustness check was conducted to test whether results generated in the main comparison (i.e., with ARIMAX) could be generated using other models (i.e., ARX, NN model with explanatory variables, and RF model with explanatory variables). The second group robustness check tested whether results from the main comparison based on weekly data could be produced using monthly data. The third group robustness check tested whether results from the main comparison could be generated using another case, Kulangsu in China.

<Insert Figure 4>

We used the Wilcoxon rank sum test (Wilcoxon *et al.*, 1970) to determine whether a significant difference existed between two time series. The test was conducted for each search query keyword generated via PCs, mobile devices, and their simple aggregate. Test results appear in Table 3, revealing significant differences in search volume patterns among keywords generated under these three conditions in most cases. This finding aligns with that of Church *et al*. (2008), who found that search patterns via mobile devices differed significantly from patterns via PCs. Accordingly, we considered search query volume data generated from different devices to forecast tourism demand and to compare relevant forecasting performance.

<Insert Table 3>

The dataset for our study spanned 133 weeks. The initial estimation applied data from the first 103 weeks of search queries and the number of tourist arrivals; then, we extended the estimation sample by another week each time. We therefore generated rolling forecasts of up to 12 weeks ahead until data for all time periods were included. In the forecasting process, different search keywords may possess distinct lag structures (Yang *et al.*, 2015). Thus, when incorporating search queries as forecasting indicators, we implemented the Boruta algorithm using the Boruta package in R to conduct feature selection for the ARIMAX, ARX, and NN models (Kursa and Rudnicki, 2010).

Table 4 lists comparison results for forecasting accuracy evaluations of the ARIMAX model when including search queries generated via PCs, mobile devices, their simple aggregate, and using separate search volumes from PCs and mobile devices simultaneously as forecasting indicators. Our findings showed several trends. First, our ARIMAX model incorporating search queries via PCs consistently and significantly outperformed queries generated via mobile devices. A potential explanation for this finding is that most tourists collect information on multiple terminals but make actual hotel reservations on PCs (Murphy *et al.*, 2016). That is, search data from PCs are more effective than data from mobile devices when forecasting tourism demand. Another possible reason is that tourists wish to obtain detailed information about alternative destinations before traveling, whereas simpler product comparisons constitute a perceived benefit of PC searches (Singh and Jang, 2020). This result contradicts that of Sun *et al.* (2017), presumably because their study involved datasets from the year 2012. The traffic share of mobile devices in 2012 was less than 20% (Broadband Search, 2020) but has increased sharply in recent years, exceeding 50% of all such traffic. Due to the low opportunity cost of time, random unrelated searches on mobile devices can produce noise when search queries generated on mobile devices are included in tourism demand forecasting.

Second, the ARIMAX model incorporating search queries generated via PCs consistently outperformed that incorporating aggregated search volumes generated via PCs and mobile devices. This phenomenon may have manifested for two reasons: (1) aggregated search volumes involved aforementioned noise from mobile searches; and (2) search patterns from mobile devices and PCs probably differ between weekdays and holidays. More specifically, individuals are likely to use search engines differently during their workdays and days off, such as by using PCs more during the workday and mobile devices more during holidays. Aggregated search volumes on mobile devices and PCs, with an equal weight distribution on holidays and workdays, would therefore introduce bias.

Third, the ARIMAX model including search queries generated on both terminals did not outperform that incorporating search queries generated via PCs alone; however, it outperformed that incorporating search queries generated on mobile devices alone. This pattern was possibly attributable to noise in mobile search volumes and to multicollinearity in forecasting models. The Pearson correlation coefficient between search volumes on PCs and mobile devices for each given keyword ranged from 0.4042 to 0.8286; therefore, integrating search volumes on PCs and mobile devices simultaneously in forecasting models may lead to multicollinearity, resulting in compromised forecasting performance. In addition, as mentioned, most tourists collect information on multiple terminals but make their ultimate hotel reservations on PCs (Murphy *et al.*, 2016). Search volumes on PCs would have included useful information hidden in results from mobile devices. Therefore, when incorporating search volumes from PCs and mobile devices, those on mobile devices cannot provide supplemental, useful information to improve forecasting performance. Overall, the ARIMAX model incorporating search queries generated via multiple terminals did not necessarily outperform those incorporating search queries generated via a single terminal type.

<Insert Table 4>

Table 5 lists forecasting improvements for the ARIMAX model using search queries generated via PCs as the leading indicator (vs. our benchmark models). Benchmark models included two time-series models (ARIMA and AR) and two artificial intelligence models (NN and RF). We noticed that, compared with ARIMA, AR, NN, RF, and NAÏVE, the models including search queries generated via PCs demonstrated significantly better forecasting accuracy. This finding echoes prior research (Bangwoyo-Skeete and Skeete, 2015; Yang *et al.*, 2015; Wen *et al.*, 2019; Li *et al.*, 2020b) suggesting that incorporating search queries into forecasting models can enhance tourism demand forecasting accuracy.

<Insert Table 5>

Tables 6 and 7 summarize the first robustness check results based on one time-series model (ARX) and two artificial intelligence models (NN and RF). Upon comparing the MAPE and RMSE of models incorporating search queries via PCs, mobile devices, aggregated volumes, and separate search volumes generated from PCs and mobile devices, we found that the forecasting performance of ARX, NN, and RF models with explanatory variables produced the same results as the ARIMAX model in Table 4. Figure 5 presents the average improvement in forecasting models incorporating search queries generated via PCs over different forecasting horizons. Compared with forecasting models involving search queries generated via mobile devices, aggregated search volumes, and separate search volumes generated from PCs and mobile devices, the models that included search queries generated via PCs as the leading indicator demonstrated significantly better tourism demand forecasting accuracy.

<Insert Table 6>

<Insert Table 7>

<Insert Figure 5>

Table 8 lists the second group of robustness check results for monthly tourism demand forecasting. The forecasting accuracy of the ARIMAX model, incorporating search query data generated from different terminals as predicting indicators, was compared along a 1- to 3-month forecasting horizon. Comparison results based on MAPE and RMSE were consistent with those of weekly tourism demand forecasting.

<Insert Table 8>

Table 9 and 10 include the third group of robustness check results based on another tourist attraction in China, Kulangsu. We compared the forecasting accuracy of the ARIMAX model incorporating search query data generated from different terminals as predicting indicators along weekly and monthly forecasting horizons, and with our benchmark models. The MAPE and RMSE results were similar to those generated for Mount Siguniang. In summary, the forecasting results based on our ARIMAX model incorporating search queries via PCs consistently and significantly outperformed those incorporating queries generated via mobile devices, aggregated search volumes, and separate search volumes generated from PCs and mobile devices.

<Insert Table 9>

<Insert Table 10>

## 5. Conclusion and implications

### *5.1 Conclusions*

Mobile devices have revolutionized travelers' online search behavior (Church *et al.*, 2008). Based on two national park cases in China, our empirical results showed that patterns of tourism-related search queries differed significantly across mobile devices and PCs. We also found that, compared with models incorporating search queries generated via mobile devices or via both terminals (whether aggregated or separate), tourism demand forecasting can improve significantly when using PC data. We further confirmed that models incorporating search query from PC can greatly improve the accuracy of tourism demand forecasting compared with models without these search queries.

### *5.2 Theoretical implications*

This study is one of the first to identify and decompose aggregated search query volumes into queries generated via mobile devices and PCs to improve tourism demand forecasting. Most prior studies only examined the role of aggregated search queries in improving tourism demand forecasting performance, with the exception of work by Sun *et al.* (2017) which compared performance using search query data from mobile devices and PCs in tourism demand forecasting. Our study extends that of Sun *et al.* (2017) by comparing forecasting performance based on mobile search query data and PC data and by comparing forecasting performance based on search query data generated via a single terminal type (either mobile devices *or* PCs) and multiple terminals (mobile devices *and* PCs).

### *5.3 Practical implications*

Our study provides practical implications for industry managers. Compared with mobile devices, our research shows that search queries generated via PCs should provide more accurate tourism demand forecasts. This finding holds particular value for the tourism industry, including hotels, tourist attractions, and airlines, in identifying effective search terminals to predict tourism demand. Instead of using aggregated search query data for forecasting, industry managers should consider search indices generated by effective terminals for more accurate prediction. These data can inform their strategic decisions as well as operations management. Our insights collectively highlight the importance of identifying effective search terminal–generated data within aggregated search volumes.

### *5.4 Limitations and future research*

Despite its utility, this study is not without limitations. First, we mainly used search query volumes in our forecasting models to predict tourism demand. In the future, other variables (e.g., weather, holidays, and social media data) should be combined with search engine data in forecasting models to achieve higher forecasting accuracy. Second, we simply compared the performance of aggregated search volumes by adding search volumes from PCs to those from mobile devices; our approach to aggregating search queries generated via both terminals may have influenced forecasting performance. The aggregation rule should be examined further to promote accurate tourism demand predictions. Third, we conducted forecasting based on two specific tourist attractions in China due to the unavailability of the number of tourist arrivals for other attractions. Findings from this study are not intended to be generalized to all other attractions but to demonstrate the potential of using decomposed search queries to increase forecasting accuracy. This initiative is inherently exploratory, and more extensive investigations are recommended that include additional cases.

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**Table 1**. Selected tourism forecasting studies using search query data

| References | Predicted Variable | Search Data Frequency | Data sources | Forecasting Models |
|---|---|---|---|---|
| Pan *et al.* (2012) | Hotel rooms in Charleston, South Carolina, USA | Weekly | SQ | TS, E |
| Bangwayo-Skeete and Skeete (2015) | Tourist arrivals to the Caribbean | Weekly | SQ | TS, E |
| Yang *et al.* (2015) | Tourist arrivals to Hainan, China | Monthly | SQ | TS |
| Huang *et al.* (2017) | Tourist arrivals to the Forbidden City, China | Daily | SQ | TS, E |
| Li *et al.* (2017) | Tourist arrivals to Beijing, China | Weekly | SQ | TS |
| Önder (2017) | Tourist arrivals to cities (Vienna, Barcelona) and countries (Austria and Belgium) | Monthly | SQ | TS, E |
| Sun *et al.* (2017) | Tourist arrivals to Mount Sanqingshan | Daily | SQ | TS |
| Dergiades *et al.* (2018) | Tourist arrivals to Cyprus | Monthly | SQ | E |
| Li *et al.* (2018) | Tourist arrivals to Beijing & Hainan, China | Monthly | SQ | TS, E, AI |
| Bokelmann and Lessmann (2019) | Tourist arrival to German | Monthly | SQ | TS, E |
| Gunter *et al.* (2019) | Tourist arrivals to four Austrian cities | Monthly | SQ + Facebook Likes | E |
| Hu and Song (2019) | Tourist arrivals from Hong Kong to Macau | Monthly | SQ + Econometric variables | TS, E, AI |
| Law *et al.* (2019) | Tourist arrivals to Macau | Monthly | SQ | TS, E, AI |
| Sun *et al.* (2019) | Tourist arrivals to Beijing, China | Monthly | SQ | TS, AI |
| Volchek *et al.* (2019) | Tourist arrivals to five London museums | Monthly & Weekly | SQ | TS, AI |
| Wen *et al.* (2019) | Tourist arrivals to Hong Kong | Monthly | SQ | TS, AI |
| Li and Law (2020) | Tourist arrivals to Hong Kong | Monthly | SQ | TS, AI |
| Bi *et al.* (2020) | Tourist arrivals to Jiuzhaigou and Huangshan Mountain Area, China | Daily | SQ + Weather | AI, TS |
| Höpken *et al.* (2020) | Tourist arrivals to Sweden | Monthly | SQ | AI, TS |
| Li *et al.* (2020a) | Tourist arrivals to Jiuzhai Valley and Kulangsu | Daily | SQ + Weather + Holiday + Seasonality | TS, AI |
| Li *et al.* (2020b) | Tourist arrivals to Mount Siguniang, China | Weekly | SQ + Online review data | TS, AI |
| Li *et al.* (2020c) | Tourist arrivals in Beijing, China and hotel occupancy in the city of Charleston, South Carolina, USA | Monthly | SQ | TS |

| | | | | |
|---|---|---|---|---|
| Tang *et al.* (2020) | Tourist arrivals to Hainan, China | Monthly | SQ | AI, TS |
| Wen *et al.* (2020) | Tourist arrivals in Hong Kong from mainland China | Daily | SQ | TS, E |
| Xie *et al.* (2020) | Tourist arrivals to Hong Kong | Monthly | SQ | TS, AI |
| Zhang *et al.* (2020) | Tourist arrivals to Hong Kong | Monthly | SQ | TS, E, AI |

Note: AI: artificial intelligent model; E: econometric model; SQ: search query index; TS: time series model.

**Table 2**. Variable descriptions

| Keywords | Search terminal | Max | Min | Mean | Median | Std. |
|---|---|---|---|---|---|---|
| Mount Siguniang Travel Guide | Mobile devices | 3353 | 0 | 383.6 | 375 | 376.2 |
| Mount Siguniang's weather | Mobile devices | 12932 | 1047 | 3939.0 | 3946 | 2165.7 |
| Mount Siguniang's altitude | Mobile devices | 5047 | 360 | 1545.0 | 1308 | 873.3 |
| Where is Mount Siguniang | Mobile devices | 5942 | 773 | 2019.0 | 1651 | 958.9 |
| Tourist attractions in Mount Siguniang | Mobile devices | 931 | 0 | 296.4 | 260 | 229.5 |
| Tickets to Mount Siguniang | Mobile devices | 2465 | 187 | 724.1 | 654 | 332.0 |
| Travel at Mount Siguniang | Mobile devices | 894 | 0 | 315.2 | 323 | 205.3 |
| Hotel at Mount Siguniang | Mobile devices | 1114 | 0 | 403.6 | 474 | 241.0 |
| Mount Siguniang Travel Guide | PCs | 599 | 0 | 242.7 | 238 | 143.6 |
| Mount Siguniang's weather | PCs | 1751 | 451 | 814.5 | 786 | 267.6 |
| Mount Siguniang's altitude | PCs | 676 | 64 | 462.4 | 476 | 106.3 |
| Where is Mount Siguniang | PCs | 564 | 0 | 208.9 | 190 | 131.6 |
| Tourist attractions in Mount Siguniang | PCs | 581 | 0 | 255.1 | 248 | 136.4 |
| Tickets to Mount Siguniang | PCs | 570 | 59 | 337.9 | 335 | 117.4 |
| Travel at Mount Siguniang | PCs | 647 | 0 | 252.2 | 246 | 142.4 |
| Hotel at Mount Siguniang | PCs | 648 | 0 | 225.3 | 191 | 144.6 |
| Mount Siguniang Travel Guide | Mobile devices & PCs | 3726 | 0 | 626.3 | 581 | 466.4 |
| Mount Siguniang's weather | Mobile devices & PCs | 13848 | 1551 | 4753.0 | 4694 | 2392.1 |
| Mount Siguniang's altitude | Mobile devices & PCs | 5542 | 650 | 2007.0 | 1762 | 947.5 |
| Where is Mount Siguniang | Mobile devices & PCs | 6128 | 773 | 2228.0 | 1880 | 1026.5 |
| Tourist attractions in Mount Siguniang | Mobile devices & PCs | 1326 | 0 | 551.6 | 509 | 331.3 |
| Tickets to Mount Siguniang | Mobile devices & PCs | 2786 | 373 | 1062 | 988 | 399.6 |
| Travel at Mount Siguniang | Mobile devices & PCs | 1264 | 0 | 567.4 | 555 | 293.3 |
| Hotel at Mount Siguniang | Mobile devices & PCs | 1632 | 0 | 628.9 | 628 | 343.3 |

**Table 3**. Wilcoxon rank sum test between search query volumes from different devices

| *Terminal 1* | PCs | | PCs | | Mobile devices | |
|---|---|---|---|---|---|---|
| *Terminal 2* | Mobile devices | | Aggregated | | Aggregated | |
| Statistics | **W value** | ***p*-value** | **W value** | ***p*-value** | **W value** | **P.value** |
| Mount Siguniang Travel Guide | 5785.0 | 0.0000 | 3202.0 | 0.0000 | 5047.0 | 0.0000 |
| Mount Siguniang's weather | 197.5 | 0.0000 | 8.0 | 0.0000 | 6499.5 | 0.0024 |
| Mount Siguniang's altitude | 598.0 | 0.0000 | 3.5 | 0.0000 | 5371.0 | 0.0000 |
| Where is Mount Siguniang | 0.0 | 0.0000 | 0.0 | 0.0000 | 6946.0 | 0.0219 |
| Tourist attractions in Mount Siguniang | 7650.5 | 0.2636 | 3956.0 | 0.0000 | 4735.0 | 0.0000 |
| Tickets to Mount Siguniang | 1172.0 | 0.0000 | 193.0 | 0.0000 | 3728.5 | 0.0000 |
| Travel at Mount Siguniang | 6696.0 | 0.0067 | 3067.5 | 0.0000 | 4426.0 | 0.0000 |
| Hotel at Mount Siguniang | 4603.5 | 0.0000 | 2589.5 | 0.0000 | 5036.5 | 0.0000 |

Note: W value indicates statistics from the Wilcoxon rank sum test.

**Table 4**. Forecasting performance and comparison of ARIMAX

| Horizon | PCs | Mobile | IR_P_M | Aggregated | IR_P_A | IR_M_A | P&M | IR_P&M_P | IR_P&M_M |
|---|---|---|---|---|---|---|---|---|---|
| **MAPE** | | | | | | | | | |
| 1 | 0.2982 | 0.4329 | *31.12%* | 0.3471 | *14.08%* | *-24.74%* | 0.3378 | *-13.26%* | *21.98%* |
| 2 | 0.3358 | 0.5471 | *38.63%* | 0.4159 | *19.27%* | *-31.53%* | 0.3531 | *-5.17%* | *35.45%* |
| 3 | 0.3219 | 0.5458 | *41.02%* | 0.4397 | *26.79%* | *-24.13%* | 0.3312 | *-2.89%* | *39.31%* |
| 6 | 0.2643 | 0.5448 | *51.49%* | 0.3868 | *31.68%* | *-40.86%* | 0.2901 | *-9.79%* | *46.74%* |
| 9 | 0.2771 | 0.4877 | *43.19%* | 0.3960 | *30.04%* | *-23.15%* | 0.2907 | *-4.91%* | *40.40%* |
| 12 | 0.1898 | 0.2935 | *35.35%* | 0.2482 | *23.55%* | *-18.26%* | 0.2223 | *-17.14%* | *24.27%* |
| **RMSE** | | | | | | | | | |
| 1 | 3271.39 | 4980.59 | *34.32%* | 4778.20 | *31.54%* | *-4.24%* | 4189.67 | *-28.07%* | *15.88%* |
| 2 | 3297.07 | 5568.49 | *40.79%* | 4906.58 | *32.80%* | *-13.49%* | 4073.42 | *-23.55%* | *26.85%* |
| 3 | 3418.42 | 5357.98 | *36.20%* | 5076.82 | *32.67%* | *-5.54%* | 4031.57 | *-17.94%* | *24.76%* |
| 6 | 3439.91 | 6465.47 | *46.80%* | 5008.39 | *31.32%* | *-29.09%* | 4344.13 | *-26.29%* | *32.81%* |
| 9 | 3291.31 | 6265.26 | *47.47%* | 5962.55 | *44.80%* | *-5.08%* | 4179.74 | *-26.99%* | *33.29%* |
| 12 | 3041.90 | 6220.09 | *51.10%* | 5558.63 | *45.28%* | *-11.90%* | 4320.89 | *-42.05%* | *30.53%* |

Note: MAPE: mean absolute percentage error; RMSE: root mean square error; IR_P_M: improvement ratio of models with search queries generated via PCs compared to those generated via mobile devices; IR_P_A: improvement ratio of models with search queries generated via PCs compared with models with aggregated search volumes generated via PCs and mobile devices; IR_M_A: improvement ratio of models with search queries generated via mobile devices compared with models with aggregated search volumes generated via PCs and mobile devices; P&M: model incorporating search queries generated via PCs and mobile devices simultaneously; IR_P&M_P: improvement ratio of models incorporating search queries generated via PCs and mobile devices simultaneously compared with models with search volumes generated via PCs; IR_P&M_M: improvement ratio of models incorporating search queries generated via PCs and mobile devices simultaneously compared with models with search volumes generated on mobile devices; IR_P&M_A: improvement ratio of models incorporating search queries generated via PCs and mobile devices simultaneously compared with models with aggregated search volumes generated via PCs and mobile devices.

**Table 5**. Forecasting comparison with benchmark models

| Horizon | ARIMAX | ARIMA | AR | NAÏVE | NN | RF | Improvement of ARIMAX comparing to | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| X | (PCs) | \ | \ | \ | \ | \ | ARIMA | AR | NAÏVE | NN | RF |
| **MAPE** | | | | | | | | | | | |
| 1 | 0.2982 | 0.4881 | 0.4899 | 0.5493 | 0.6790 | 0.4819 | *38.91%* | *39.13%* | *45.71%* | *56.08%* | *38.11%* |
| 2 | 0.3358 | 0.6957 | 0.7077 | 0.7978 | 0.7386 | 0.6231 | *51.74%* | *52.55%* | *57.91%* | *54.54%* | *46.12%* |
| 3 | 0.3219 | 0.7560 | 0.7755 | 0.8623 | 0.6657 | 0.6565 | *57.42%* | *58.49%* | *62.67%* | *51.64%* | *50.97%* |
| 6 | 0.2643 | 0.5471 | 0.6052 | 0.5179 | 0.5592 | 0.5227 | *51.70%* | *56.33%* | *48.97%* | *52.74%* | *49.44%* |
| 9 | 0.2771 | 0.6472 | 0.7057 | 0.6693 | 0.6275 | 0.4772 | *57.19%* | *60.74%* | *58.61%* | *55.85%* | *41.94%* |
| 12 | 0.1898 | 0.3716 | 0.3688 | 0.5648 | 0.4000 | 0.5356 | *48.93%* | *48.55%* | *66.40%* | *52.57%* | *64.57%* |
| **RMSE** | | | | | | | | | | | |
| 1 | 3271.39 | 7063.67 | 6971.66 | 8231.96 | 6610.68 | 6354.70 | *53.69%* | *53.08%* | *60.26%* | *50.51%* | *48.52%* |
| 2 | 3297.07 | 6795.71 | 6714.26 | 8328.38 | 6706.59 | 7069.19 | *51.48%* | *50.89%* | *60.41%* | *50.84%* | *53.36%* |
| 3 | 3418.42 | 6897.29 | 6820.96 | 8729.20 | 6666.29 | 7487.51 | *50.44%* | *49.88%* | *60.84%* | *48.72%* | *54.35%* |
| 6 | 3439.91 | 6991.99 | 6943.57 | 8998.37 | 7272.16 | 8109.74 | *50.80%* | *50.46%* | *61.77%* | *52.70%* | *57.58%* |
| 9 | 3291.31 | 7527.17 | 7414.35 | 10089.99 | 7136.48 | 8292.58 | *56.27%* | *55.61%* | *67.38%* | *53.88%* | *60.31%* |
| 12 | 3041.90 | 7606.29 | 7500.18 | 7540.98 | 7925.08 | 8348.19 | *60.01%* | *59.44%* | *59.66%* | *61.62%* | *63.56%* |

**Table 6**. Robustness check results measured by MAPE

| Horizon | PCs | Mobile | IR_P_M | Aggregated | IR_P_A | IR_M_A | P&M | IR_P&M_P | IR_P&M_M |
|---|---|---|---|---|---|---|---|---|---|
| **ARX** | | | | | | | | | |
| 1 | 0.3616 | 0.5766 | *37.28%* | 0.4289 | *15.67%* | *-34.45%* | 0.3919 | *-8.35%* | *32.04%* |
| 2 | 0.3683 | 0.4879 | *24.52%* | 0.4260 | *13.55%* | *-14.53%* | 0.3943 | *-7.05%* | *19.20%* |
| 3 | 0.3940 | 0.5469 | *27.95%* | 0.4357 | *9.56%* | *-25.53%* | 0.4090 | *-3.80%* | *25.21%* |
| 6 | 0.3212 | 0.4485 | *28.40%* | 0.3890 | *17.45%* | *-15.30%* | 0.3732 | *-16.20%* | *16.80%* |
| 9 | 0.3180 | 0.4551 | *30.12%* | 0.3908 | *18.62%* | *-16.46%* | 0.3463 | *-8.90%* | *23.90%* |
| 12 | 0.2753 | 0.3934 | *30.00%* | 0.3226 | *14.65%* | *-21.93%* | 0.3048 | *-10.69%* | *22.52%* |
| **NN** | | | | | | | | | |
| 1 | 0.6362 | 0.7445 | *14.54%* | 0.6841 | *7.00%* | *-8.82%* | 0.7152 | *-12.42%* | *3.92%* |
| 2 | 0.6064 | 0.7411 | *18.18%* | 0.6820 | *11.08%* | *-8.67%* | 0.6836 | *-12.72%* | *7.77%* |
| 3 | 0.4419 | 0.5780 | *23.54%* | 0.5440 | *18.77%* | *-6.23%* | 0.5073 | *-14.80%* | *12.22%* |
| 6 | 0.4441 | 0.6078 | *26.93%* | 0.5618 | *20.94%* | *-8.20%* | 0.5137 | *-15.67%* | *15.48%* |
| 9 | 0.3631 | 0.5359 | *32.25%* | 0.4240 | *14.36%* | *-26.41%* | 0.4535 | *-24.89%* | *15.39%* |
| 12 | 0.3450 | 0.4392 | *21.44%* | 0.3392 | *-1.73%* | *-29.49%* | 0.4454 | *-29.08%* | *-1.40%* |
| **RF** | | | | | | | | | |
| 1 | 0.3643 | 0.5405 | *32.61%* | 0.4915 | *25.89%* | *-9.96%* | 0.3917 | *-7.55%* | *27.52%* |
| 2 | 0.3483 | 0.5843 | *40.38%* | 0.5249 | *33.64%* | *-11.32%* | 0.3903 | *-12.04%* | *33.21%* |
| 3 | 0.3893 | 0.5986 | *34.96%* | 0.5293 | *26.44%* | *-13.10%* | 0.4254 | *-9.26%* | *28.94%* |
| 6 | 0.3441 | 0.5316 | *35.27%* | 0.4638 | *25.80%* | *-14.63%* | 0.3880 | *-12.74%* | *27.02%* |
| 9 | 0.3515 | 0.5926 | *40.69%* | 0.4907 | *28.38%* | *-20.75%* | 0.4233 | *-20.44%* | *28.56%* |
| 12 | 0.3258 | 0.4905 | *33.58%* | 0.4256 | *23.45%* | *-15.24%* | 0.4049 | *-24.28%* | *17.45%* |

Note: The meaning of parameters are the same as the note on Table 4.

**Table 7**. Robustness check results measured by RMSE

| Horizon | PCs | Mobile | IR_P_M | Aggregated | IR_P_A | IR_M_A | P&M | IR_P&M_P | IR_P&M_M |
|---|---|---|---|---|---|---|---|---|---|
| **ARX** | | | | | | | | | |
| 1 | 4948.10 | 7495.88 | *33.99%* | 6580.52 | *24.81%* | *-13.91%* | 5246.75 | *-6.04%* | *30.00%* |
| 2 | 4663.26 | 6752.24 | *30.94%* | 6152.38 | *24.20%* | *-9.75%* | 5050.07 | *-8.29%* | *25.21%* |
| 3 | 4740.75 | 6933.00 | *31.62%* | 6288.48 | *24.61%* | *-10.25%* | 5163.67 | *-8.92%* | *25.52%* |
| 6 | 4904.43 | 7291.70 | *32.74%* | 6637.07 | *26.11%* | *-9.86%* | 5785.38 | *-17.96%* | *20.66%* |
| 9 | 4527.56 | 7150.09 | *36.68%* | 6474.31 | *30.07%* | *-10.44%* | 5482.80 | *-21.10%* | *23.32%* |
| 12 | 4725.64 | 8027.05 | *41.13%* | 7045.69 | *32.93%* | *-13.93%* | 5892.30 | *-24.69%* | *26.59%* |
| **NN** | | | | | | | | | |
| 1 | 6574.65 | 6582.68 | *0.12%* | 6637.36 | *0.94%* | *0.82%* | 6743.81 | *-2.57%* | *-2.45%* |
| 2 | 6628.50 | 6683.20 | *0.82%* | 6679.86 | *0.77%* | *-0.05%* | 6686.98 | *-0.88%* | *-0.06%* |
| 3 | 6539.70 | 6586.15 | *0.71%* | 6639.76 | *1.51%* | *0.81%* | 6617.53 | *-1.19%* | *-0.48%* |
| 6 | 6983.34 | 7255.12 | *3.75%* | 7125.68 | *2.00%* | *-1.82%* | 7208.36 | *-3.22%* | *0.64%* |
| 9 | 6814.62 | 6869.08 | *0.79%* | 6633.83 | *-2.73%* | *-3.55%* | 6930.36 | *-1.70%* | *-0.89%* |
| 12 | 7257.80 | 7306.52 | *0.67%* | 7062.42 | *-2.77%* | *-3.46%* | 7324.49 | *-0.92%* | *-0.25%* |
| **RF** | | | | | | | | | |
| 1 | 5407.60 | 6615.94 | *18.26%* | 5848.96 | *7.55%* | *-13.11%* | 5613.21 | *-3.80%* | *15.16%* |
| 2 | 4943.67 | 6461.44 | *23.49%* | 5595.13 | *11.64%* | *-15.48%* | 5430.30 | *-9.84%* | *15.96%* |
| 3 | 4845.15 | 6420.13 | *24.53%* | 5556.17 | *12.80%* | *-15.55%* | 5630.33 | *-16.21%* | *12.30%* |
| 6 | 5326.66 | 6456.15 | *17.49%* | 5990.00 | *11.07%* | *-7.78%* | 5945.97 | *-11.63%* | *7.90%* |
| 9 | 5229.11 | 6463.84 | *19.10%* | 5675.76 | *7.87%* | *-13.88%* | 5612.56 | *-7.33%* | *13.17%* |
| 12 | 5674.13 | 7058.03 | *19.61%* | 6258.02 | *9.33%* | *-12.78%* | 6249.50 | *-10.14%* | *11.46%* |

**Table 8**. Robustness check results using monthly datasets

| Horizon (Months) | PC | Mobile | IR_P_M | Aggregated | IR_P_A | IR_M_A | P&M | IR_P&M_P | IR_P&M_M |
|---|---|---|---|---|---|---|---|---|---|
| **MAPE** | | | | | | | | | |
| 1 | 0.2699 | 0.4436 | *39.16%* | 0.8349 | *67.67%* | *46.87%* | 0.2931 | *-8.62%* | *33.91%* |
| 2 | 0.2287 | 0.3204 | *28.61%* | 0.3355 | *31.84%* | *4.52%* | 0.2377 | *-3.95%* | *25.79%* |
| 3 | 0.1640 | 0.3661 | *55.21%* | 0.3229 | *49.23%* | *-13.36%* | 0.1931 | *-17.75%* | *47.26%* |
| **RMSE** | | | | | | | | | |
| 1 | 13164.83 | 15338.32 | *14.17%* | 19537.08 | *32.62%* | *21.49%* | 13360.40 | *-1.49%* | *12.90%* |
| 2 | 8486.84 | 22438.23 | *62.18%* | 19448.37 | *56.36%* | *-15.37%* | 8545.66 | *-0.69%* | *61.91%* |
| 3 | 8246.08 | 19653.63 | *58.04%* | 13963.55 | *40.95%* | *-40.75%* | 8869.67 | *-7.56%* | *54.87%* |

**Table 9**. Forecasting performance and comparison on Kulangsu

| Frequency | Horizon | PC | Mobile | IR_P_M | Aggregated | IR_P_A | IR_M_A | P&M | IR_P&M_P | IR_P&M_M |
|---|---|---|---|---|---|---|---|---|---|---|
| **Weekly** | **MAPE** | | | | | | | | | |
| | 1 | 0.0795 | 0.0931 | *14.62%* | 0.0907 | *12.29%* | *-2.72%* | 0.0897 | *-12.79%* | *3.69%* |
| | 2 | 0.0797 | 0.0950 | *16.11%* | 0.0910 | *12.47%* | *-4.33%* | 0.0922 | *-15.71%* | *2.93%* |
| | 3 | 0.0774 | 0.0841 | *7.89%* | 0.0816 | *5.03%* | *-3.10%* | 0.0873 | *-12.72%* | *-3.82%* |
| | 6 | 0.0680 | 0.0846 | *19.64%* | 0.0819 | *16.94%* | *-3.35%* | 0.0801 | *-17.78%* | *5.35%* |
| | 9 | 0.0572 | 0.0792 | *27.84%* | 0.0794 | *28.03%* | *0.27%* | 0.0683 | *-19.43%* | *13.81%* |
| | 12 | 0.0626 | 0.0895 | *30.06%* | 0.0895 | *30.07%* | *0.02%* | 0.0761 | *-21.64%* | *14.92%* |
| | **RMSE** | | | | | | | | | |
| | 1 | 27001.55 | 34031.29 | *20.66%* | 33199.56 | *18.67%* | *-2.51%* | 30176.09 | *-11.76%* | *11.33%* |
| | 2 | 27547.65 | 34581.86 | *20.34%* | 33373.30 | *17.46%* | *-3.62%* | 29709.01 | *-7.85%* | *14.09%* |
| | 3 | 26161.66 | 29479.95 | *11.26%* | 28720.58 | *8.91%* | *-2.64%* | 27079.61 | *-3.51%* | *8.14%* |
| | 6 | 21939.04 | 28688.84 | *23.53%* | 28014.20 | *21.69%* | *-2.41%* | 24692.99 | *-12.55%* | *13.93%* |
| | 9 | 19788.67 | 27353.36 | *27.66%* | 27110.43 | *27.01%* | *-0.90%* | 21990.68 | *-11.13%* | *19.61%* |
| | 12 | 21181.87 | 29599.95 | *28.44%* | 29501.03 | *28.20%* | *-0.34%* | 23985.50 | *-13.24%* | *18.97%* |
| **Monthly** | **MAPE** | | | | | | | | | |
| | 1 | 0.0524 | 0.0786 | *33.36%* | 0.0640 | *18.20%* | *-22.75%* | 0.0709 | *-35.37%* | *9.79%* |
| | 2 | 0.0534 | 0.0648 | *17.61%* | 0.0692 | *22.82%* | *6.33%* | 0.0754 | *-41.21%* | *-16.35%* |
| | 3 | 0.0634 | 0.0794 | *20.14%* | 0.0848 | *25.17%* | *6.30%* | 0.0832 | *-31.14%* | *-4.73%* |
| | **RMSE** | | | | | | | | | |
| | 1 | 96724.99 | 125837.24 | *23.13%* | 112005.45 | *13.64%* | *-12.35%* | 106283.78 | *-9.88%* | *15.54%* |
| | 2 | 102180.74 | 105299.90 | *2.96%* | 119566.85 | *14.54%* | *11.93%* | 113469.51 | *-11.05%* | *-7.76%* |
| | 3 | 114166.29 | 120974.50 | *5.63%* | 134856.01 | *15.34%* | *10.29%* | 126500.42 | *-10.80%* | *-4.57%* |

**Table 10**. Forecasting comparison with benchmark models on Kulangsu

| Horizon | ARIMAX | ARIMA | AR | Naïve | NN | RF | Improvement of ARIMAX comparing to | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| X | (PCs) | \ | \ | \ | \ | \ | ARIMA | AR | Naïve | NN | RF |
| **MAPE** | | | | | | | | | | | |
| 1 | 0.0795 | 0.0971 | 0.0972 | 0.0963 | 0.1007 | 0.1326 | *18.13%* | *18.16%* | *17.46%* | *21.04%* | *40.02%* |
| 2 | 0.0797 | 0.1092 | 0.1091 | 0.1304 | 0.1106 | 0.1220 | *27.08%* | *27.00%* | *38.91%* | *28.00%* | *34.68%* |
| 3 | 0.0774 | 0.1078 | 0.1075 | 0.1722 | 0.1089 | 0.1878 | *28.16%* | *27.96%* | *55.03%* | *28.86%* | *58.76%* |
| 6 | 0.0680 | 0.0963 | 0.0964 | 0.1534 | 0.0993 | 0.1533 | *29.37%* | *29.42%* | *55.66%* | *31.47%* | *55.63%* |
| 9 | 0.0572 | 0.0855 | 0.0859 | 0.1503 | 0.0887 | 0.1766 | *33.10%* | *33.46%* | *61.97%* | *35.55%* | *67.63%* |
| 12 | 0.0626 | 0.0911 | 0.0913 | 0.1218 | 0.0932 | 0.1359 | *31.30%* | *31.45%* | *48.62%* | *32.86%* | *53.96%* |
| **RMSE** | | | | | | | | | | | |
| 1 | 27001.55 | 33563.56 | 33571.40 | 36535.44 | 34552.87 | 44103.44 | *19.55%* | *19.57%* | *26.09%* | *21.85%* | *38.78%* |
| 2 | 27547.65 | 37806.35 | 37805.48 | 45998.34 | 38644.34 | 38191.46 | *27.13%* | *27.13%* | *40.11%* | *28.71%* | *27.87%* |
| 3 | 26161.66 | 36854.59 | 36802.36 | 56001.32 | 37380.97 | 64980.88 | *29.01%* | *28.91%* | *53.28%* | *30.01%* | *59.74%* |
| 6 | 21939.04 | 33038.89 | 33070.97 | 48583.69 | 34049.89 | 52876.42 | *33.60%* | *33.66%* | *54.84%* | *35.57%* | *58.51%* |
| 9 | 19788.67 | 31952.63 | 32027.89 | 45961.37 | 33278.81 | 60364.37 | *38.07%* | *38.21%* | *56.94%* | *40.54%* | *67.22%* |
| 12 | 21181.87 | 34095.78 | 34282.32 | 36199.34 | 35436.30 | 48476.51 | *37.88%* | *38.21%* | *41.49%* | *40.23%* | *56.30%* |

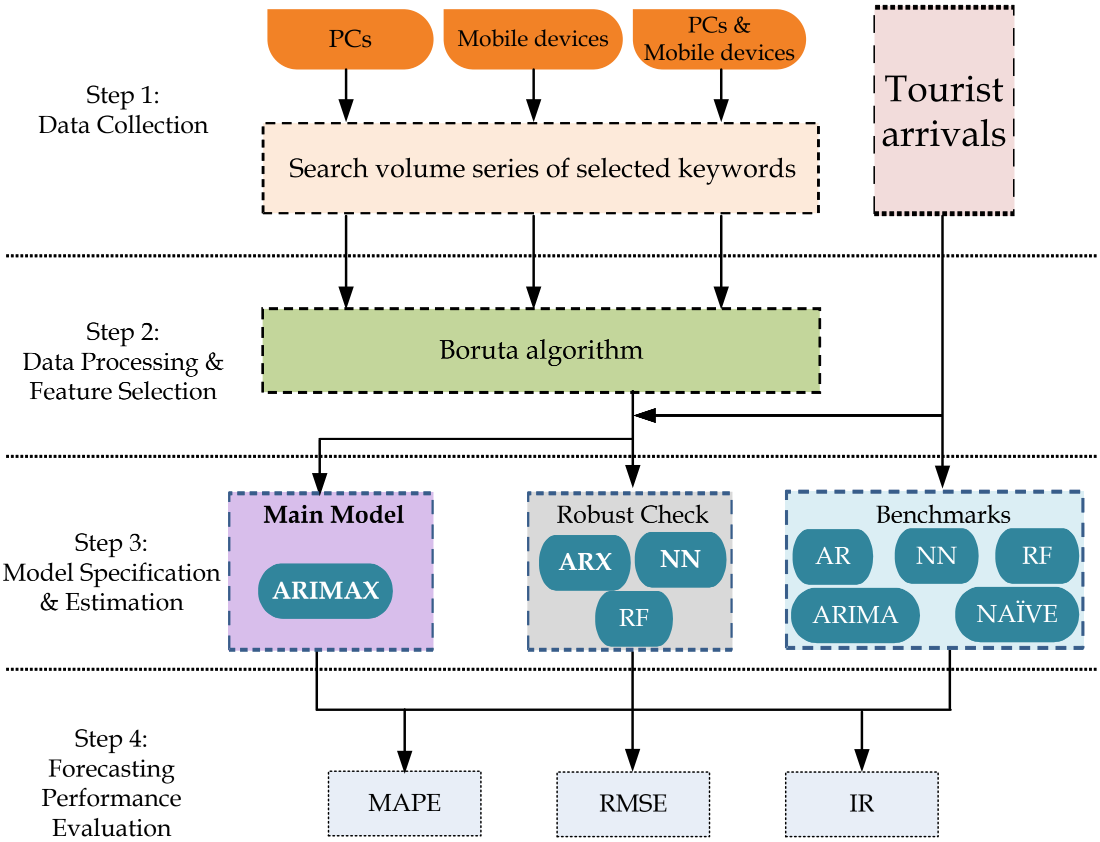


**Figure 1**. Research framework

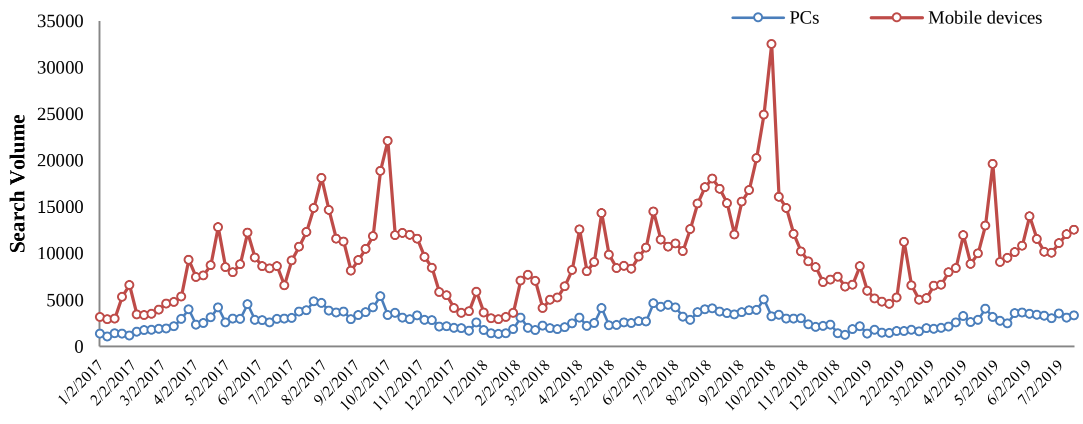


**Figure 2**. Weekly search volumes on PCs and mobile devices

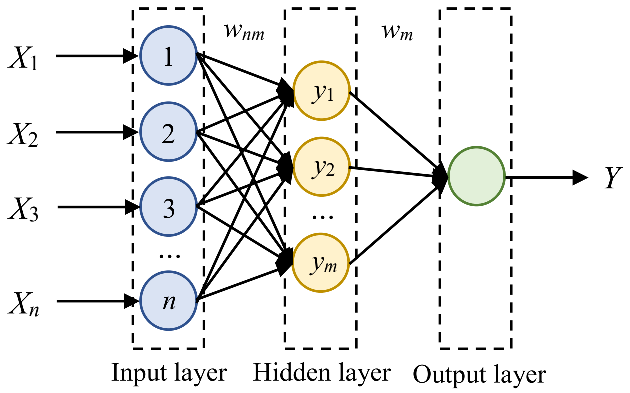


**Figure 3**. Neural network model

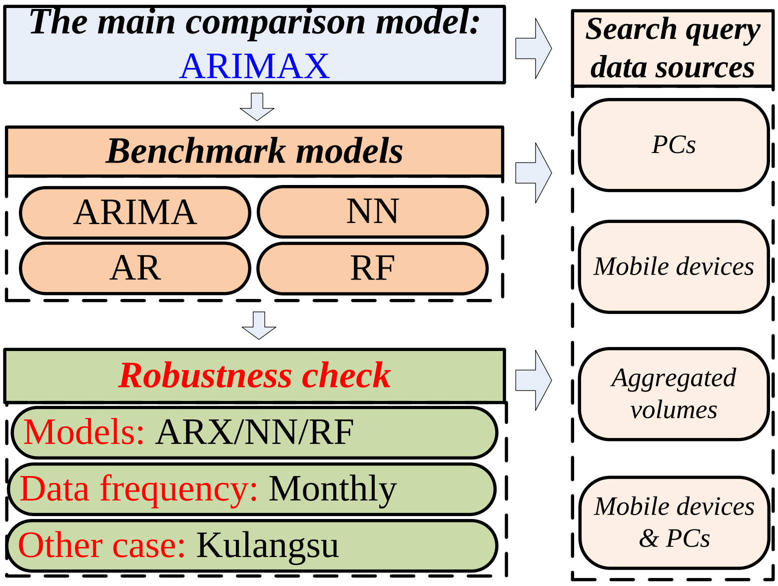


**Figure 4**. The results structure

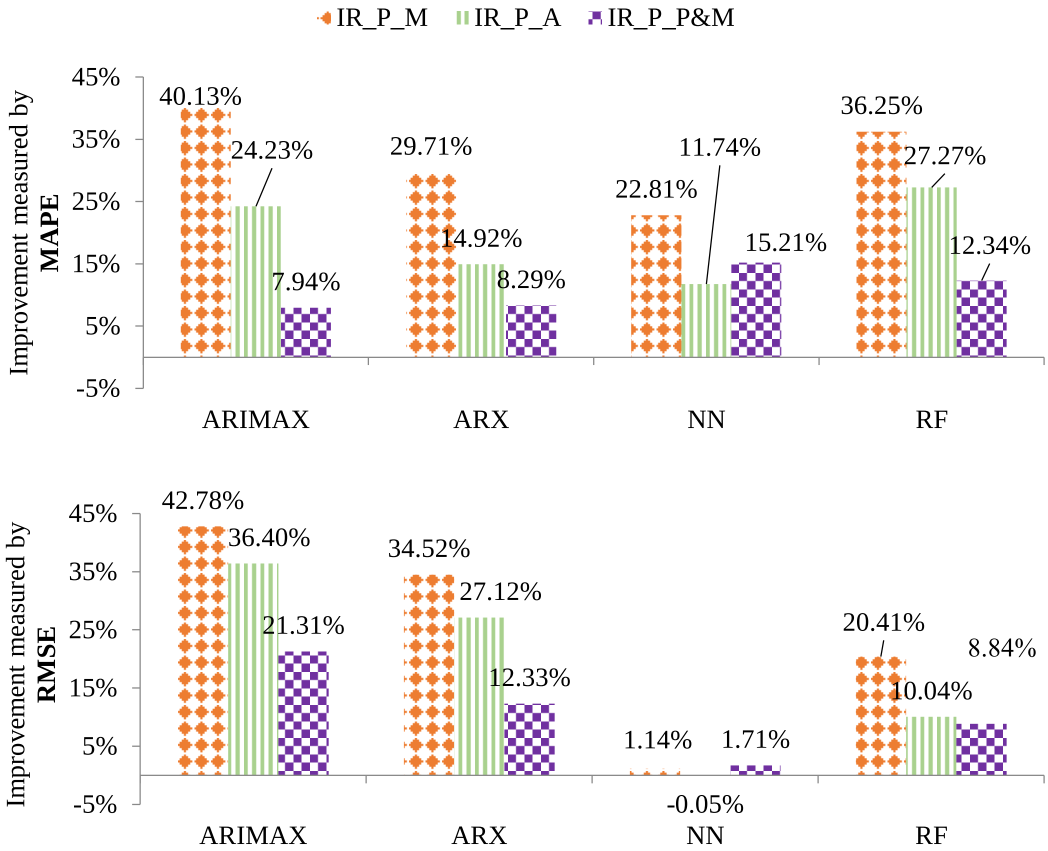


**Figure 5**. Average IR of models incorporating search queries via PCs