

TOURISM DEMAND FORECASTING WITH ONLINE NEWS DATA MINING

ABSTRACT

This study empirically tests the role of news discourse in forecasting tourist arrivals by examining Hong Kong. It employs structural topic modeling to identify key topics and their meanings related to tourism demand. The impact of the extracted news topics on tourist arrivals is then examined to forecast tourism demand using the seasonal autoregressive integrated moving average with the selected news topic variables method. This study confirms that including news data significantly improves forecasting performance. Our forecasting model using news topics also outperformed the others when the destination was experiencing social unrest at the local level. These findings contribute to tourism demand forecasting research by incorporating discourse analysis and can help tourism destinations address various externalities related to news media.

Keywords: news discourse, topic modeling, tourism demand forecasting, Hong Kong

1. INTRODUCTION

Tourism demand fluctuates significantly due to internal and external volatilities (Song, Qiu, & Park, 2019), including today's frequent social, economic, political, and technological changes and a range of risks (Ritchie & Jiang, 2019). The factors affecting tourism demand exert both direct and indirect impacts; thus, modeling and forecasting must examine a diverse array of determinants in a broad context. The tourism demand model is traditionally based on economic theory (Song & Witt, 2000). However, researchers have expanded the economic framework by incorporating new determinants on a massive scale (Hu & Song, 2020; Wen, Liu, Song, & Liu, 2020). For example, amid the rapid advance of Internet technologies, web data have been acknowledged as a valuable indicator of tourism demand (Law, Li, Fong, & Han, 2019). Accordingly, numerous tourism demand forecasting studies have employed search query data to predict tourist arrivals accurately (Dergiades, Mavragani, & Pan, 2018; Law et al., 2019; Wen et al., 2020; Yang, Pan, Evans, & Lv, 2015).

These efforts have contributed to the development of tourism demand forecasting models that analyze tourists' web search behaviors by isolating their intentions and preferences. Researchers have tended to identify tourists' preferences and experiences by quantifying the volume and sentiments embedded in their social media posts (Li, Hu, & Li, 2020). Existing studies on big data and tourism demand forecasting have focused on the information tourists share. Empirical research on public discourse, formed by various forms of media at the structural level, has lagged behind in the tourism demand modeling and forecasting field. Examining public media discourse is critical for understanding how groups of people form collective images of the world beyond their borders.

The impact of news coverage on public perceptions has been studied extensively across the social sciences (Mainil, Platenkamp, & Meulemans, 2011; Mutz & Soss, 1997). News-

framing effects have been identified in the context of tourism destinations. For example, Kapuściński and Richards (2018) found that news media representations of travel sites had a powerful influence on the tourist decision-making process. This media influence has become even greater with the Internet streamlining media distribution and improving reader accessibility. In the online media environment, the delivery of news through increasingly personalized sources may cause homophily, the human tendency to construct echo chambers comprising compatible voices and beliefs (Dubois & Blank, 2018). This complex media environment and its many significant influences make tourism demand forecasting based on public discourse in online media essential. News media representations of tourism destinations allow tourists to link familiar locales with distant destinations across borders (Cai & Wang, 2018; Chilton, 2004). Online media provide images and descriptions that ultimately generate visits to a destination (Salazar, 2012). By layering this crucial phenomenon onto the concept of discourse, this study deepens the research on media discourse and its impact on tourist behaviors.

This study quantifies the key topics in news media discourse and their impact on tourist arrivals through an empirical investigation of news discourse on and tourism demand in Hong Kong. Hong Kong, as a global destination, derives great benefit from its tourism-related industries, but its extremely high population density (6,940 people per square kilometer) can lead to conflicts between residents and tourists (Cramer, Torgersen, & Kringlen, 2004; Qiu, Park, Li, & Song, 2020). The asymmetric market structure of tourism in Hong Kong also generates social discourses in and outside Hong Kong. Specifically, among Hong Kong's tourist arrivals in 2019, those from Mainland China accounted for 78.3%, 61.2% of whom were same-day visitors (HKTG, 2020). Large-scale and frequent visitation from a single source market can generate hostility toward tourism and tourists from Hong Kong residents (Chen, Hsu, & Li, 2018; Tse & Qiu, 2016; Zhang, Wong, & Lai, 2018). However, this phenomenon is difficult to pin down, as its prevalence may be exaggerated by hostile media and political interests. As Yu, McManus, Yen, and Li (2020) indicated, political animosity may be exemplified in the Hong Kong protests, which have caused a significant decline in tourism. However, little is known about how social and political discourse influences tourism revenues, particularly the impact on tourist arrivals in Hong Kong. This study performs tourism demand forecasting based on online news data mining to answer three questions. First, what are the relevant topics in major market news discourse? Second, are there positive or negative associations between key topics and tourist arrivals? Third, does the inclusion of news data significantly improve forecasting performance?

The study answered these questions by identifying relevant topics in major market news discourse using structural topic modeling (STM). The study used news data mining to identify topics related to Hong Kong as a tourism destination and compared them between two major markets: Mainland China and the United States (US). Second, the study explored the positive and negative associations between the key topics and tourist arrivals. The study then quantified the topic weights and interpreted the meanings behind the topics discussed by public media in tourist origin areas. Finally, the study employed selected news topics and tourist arrival data to forecast tourism demand using the seasonal autoregressive integrated moving average with exogenous variables (SARIMAX) method. The study assessed the value

of the news topic data for tourism demand forecasting by comparing the SARIMAX models under two scenarios: with and without news data used as explanatory variables. The SARIMAX model was then compared with basic time series models such as the seasonal autoregressive integrated moving average (SARIMA), exponential smoothing state space (ETS), and seasonal Naïve models.

The remainder of this paper is organized as follows. The second section provides an academic foundation. The third section presents the study's data collection and methods such as topic modeling and tourism demand forecasting. The fourth section outlines the empirical results and the fifth section concludes.

2. LITERATURE REVIEW

2.1 Discourse analysis in tourism

Discourse is an analytical concept that reflects power, knowledge, and changes through text and representation (Livholts & Tamboukou, 2015). The goal of discourse analysis is to identify topics and segments of discourse conveying a coherent aggregate of thoughts (Chafe, 2001). Discourse analysis in tourism is a complex and evolving topic that is playing an increasingly significant role in broader social science research (Ateljevic & Doorne, 2002; Pritchard & Jaworski, 2005). Discourse studies in tourism examine how distant places and people look at and interact with one another beyond their borders. As Chilton (2004) noted, discourse in the global context involves great complexity and enormous changes, with increasing information, capital, and human flows. Beyond the conventional hegemonic business-centered research paradigm, discourse analysis also examines more decentralized and multi-actor tourism phenomena (Fazito, Scott, & Russell, 2016). By aligning this complex interplay with multilayer representations, various social discourses may show how tourism development affects and has been affected by society at large (Jordan, Moran, & Godwyll, 2019).

Media representations of a tourism destination can be linked to the social construction of places and images (Fusté-Forné, 2020). Salazar (2012) conceptualized tourism imaginaries and their diffusion in the form of images and discourse. His study found that tourism imaginaries derived from various information sources reduce the uncertainty and risk of tourism in spaces apart from the mundane world of average tourists (Salazar, 2012). Beyond destination spaces, collective sentiments and perceptions of tourism itself (i.e., pro- or anti-tourism) have also emerged. As tourism is an interactive process between guests and hosts, discourse in tourism also resonates with host communities' responses to tourism and tourists (Gustafson, 2002). Public sentiment is influenced by positive and negative media coverage, which reinforces or mitigates responses to the environmental, societal, and economic impacts of tourism on local systems (Milano, Novelli, & Cheer, 2019; Seraphin, Sheeran, & Pilato, 2018). This study examined the former case to identify what leading media in local markets were discussing and how those discussions may have influenced actual and future visitation to the destination.

Many information sources such as mass and social media, news articles, and word of mouth have a great effect on tourism markets, especially in shaping images of tourism

destinations and their associated visit intentions (Cai & Wang, 2018; Chaulagain, Wiitala, & Fu, 2019). Destination images formed by various sources mediate tourists' decision making by raising awareness of potential destinations (Jalilvand, 2017). Thus, tourism destination organizations should focus on media discourse about destination images and narratives relating to tourism (McLennan, Becken, & Moyle, 2017). Cai and Wang (2018) argued that news articles were more carefully considered than other sources and had more credibility. Identifying how news coverage intentionally or unintentionally influences public perceptions and behaviors has been a longstanding concern in the social sciences (Mainil et al., 2011; Mutz & Soss, 1997). However, tourism studies tend to use social media to capture a representation of tourists' experiences (Giglio, Bertacchini, Bilotta, & Pantano, 2019; Månsson, 2011; Tussyadiah & Fesenmaier, 2009).

Although news coverage may deliver an overamplified frame (Oliver & Maney, 2000), considerable attention has been paid to the media in tourism and its leading role in promoting tourism destinations (Kim, Lee, Mjelde, & Lee, 2014). As Viken (2016) emphasized, discourse in media involves power relations not only in politics but also in tourism studies that address spaces and people. Hannam and Knox (2005) underlined that discourse from various sources can show how people interpret their own and other parts of the world. Hence, tourism researchers need to utilize discourse analysis to investigate image formation, representations of tourism experiences, sentiment, and behavioral intentions (Hannam & Knox, 2005). However, this requires further efforts toward a rigorous methodological approach to an interdisciplinary perspective on discourse analysis (Pritchard & Jaworski, 2005). For instance, in the recent econometrics literature, Shapiro, Sudhof, and Wilson (2020) provided a valid application of news-based sentiment analysis to nowcasting models of economic indices. Their study argued that to improve predictive accuracy, nowcasting and forecasting should rely on not only objective and quantifiable variables (e.g., employment and income) but also more subjective variables.

2.2 Big data and online news media in tourism demand forecasting

Big data analytics can extract new information with which to measure and forecast tourist arrivals (Colladon, Guardabascio, & Innarella, 2019). Numerous tourism scholars and practitioners have acknowledged that a macro perspective is needed to address tourism demand modeling and forecasting, urging the collection of new indicators beyond traditional economic variables, such as search engine data from the Google and Baidu indices (Dergiades et al., 2018; Wen et al., 2020; Yang et al., 2015), user-generated content, and reviews from online travel forums (Colladon et al., 2019; Li, Law, Vu, Rong, & Zhao, 2015). Law et al. (2019) conceptually and empirically demonstrated that using the most popular search engine data in a major market can make tourism demand forecasting more precise and timelier.

Given the benefits of big data, a growing body of the literature is examining the use of text- and news-based measures as sources of information for forecasting and assessing the economy (Ardia, Bluteau, & Boudt, 2019; Shapiro et al., 2020; Thorsrud, 2018). Several researchers have examined their use in opinion forecasting in the social and political sciences (Lerman, Gilder, Dredze, & Pereira, 2008). Soft (as opposed to hard) information from texts,

opinions, and expressions of sentiment can improve predictive power (Shapiro et al., 2020). In particular, in the knowledge domains of economics and computer science, topic mining from large-scale online news data has been widely employed (Hurtado, Agarwal, & Zhu, 2016; Schumaker & Chen, 2009). For instance, applying a dynamic topic model, Morimoto and Kawasaki (2017) extracted topics from financial news that helped improve the accuracy of market volatility forecasting. Tobback, Naudts, Daelemans, de Fortuny, and Martens (2018) argued that a forecasting model combining news article data has greater accuracy, especially when addressing significant uncertainty and risk during tumultuous periods.

Demand forecasting studies within the tourism context have integrated analyses of tourism-related big data and new sets of variables into traditional models to improve their accuracy (Song et al., 2019). Web data from search engines and online review platforms have become valuable predictors because they represent tourists' intentions and preferences (Wen et al., 2020; Yang et al., 2015). User-generated content from online travel communities such as TripAdvisor also works for tourism demand forecasting when coupled with search query data (Colladon et al., 2019). Li et al. (2020) indicated that Internet big data have significantly improved forecasting performance and that tourism demand forecasting based on multiple sources outperforms other single-source models. While many tourism demand forecasting studies have utilized web data to improve accuracy, only a handful have used news media data to create forecasting models.

By reviewing 165 publications on big data applications in tourism studies, Li, Xu, Tang, Wang, and Li (2018) concluded that online news and opinions should be incorporated into tourism research and practices more deeply because they uniquely identify various externalities impacting tourism market fluctuations and policy responses. Examining tourism demand modeling and forecasting, Stepchenkova and Eales (2011) found that news coverage was a significant factor in destination demand, with online versions of newspapers making media even more influential for potential tourists. Önder, Gunter, and Scharl (2019) capitalized on online news media coverage to predict tourist arrivals to European cities. Stepchenkova and Eales (2011) quantified the volume, topic, and favorability of news media messages and their significant impact on destination choice (i.e., tourist arrivals). However, the quantification of media discourse was criticized by Colladon et al. (2019), who warned about integrating online discourse into forecasting models without explaining how the new data influenced the forecasts. Going beyond quantifying the volumes of reviews or search queries, identifying topics in media discourse may also explain particular variations in destination choice.

This study brings together two distinctive methodological approaches: discourse analysis and tourism demand forecasting. Combining them allows this study to adopt a broader view and identify both *what* the news media in relevant major markets (China and the US) are saying about the target destination (Hong Kong) and *how* such knowledge could improve forecasting demand in the target destination.

2.3 Topic modeling in tourism

Recent tourism and hospitality studies have used topic modeling to analyze online customer reviews of various tourism-related service settings such as hotels (Hu, Zhang, Gao, & Bose,

2019), restaurants (Park, Chae, & Kwon, 2020), and accommodation sharing (Ding, Choo, Ng, & Ng, 2020). Going beyond its dominant use for online review data from the demand sides, Wang, Li, Wu, and Wang (2020) applied latent Dirichlet allocation (LDA) to examine tourism destination image. Unlike a structured or item-based survey used to compare image changes before, during, and after travel, LDA enabled the researchers to explore the transformed representations of a tourism destination image from the content (Wang et al., 2020). Stamolampros, Korfiatis, Chalvatzis, and Buhalis (2020) applied STM, a topic modeling algorithm, to identify employee feedback in tourism and hospitality firms. These novel methods are becoming critical tools in tourism studies for the analysis of text data that convey rich information on the perceptions and sentiments of the supply and demand sides.

Among various topic modeling algorithms, STM has several advantages over other topic-modeling algorithms. First, STM can generate models that have a predictive power greater than that of competing algorithms such as LDA (Roberts, Stewart, & Airoidi, 2016). In addition to improving predictive performance, STM is designed to generate readily interpretable topic models and offer quantitative metrics for evaluating the interpretability of topics such as semantic coherence and topic exclusivity (Roberts et al., 2016). In the tourism literature, text mining has typically been applied to user-generated content from social media or online review sites (Jia, 2020; Vu, Li, & Law, 2019); few attempts have been made to use news as a text-mining data source. Therefore, there is little understanding on the value of this technique. Hence, this study applied STM to infer information from online news sources to discover the hidden thematic structure with less subjective biases to improve tourism demand forecasting.

3. METHODOLOGY

3.1 Data and preprocessing

This study focused on forecasting tourist arrivals in Hong Kong from two tourism markets: the largest short-haul market, Mainland China (78.29% of all arrivals in 2019), and the largest long-haul market, the US (28.09% of the long-haul market in 2019). Data on monthly tourist arrivals from Mainland China and the US between January 2011 and November 2019 were collected from the Hong Kong Tourism Board (see Figure 1). This study posits that information related to a destination published in a tourism market's news creates associations and images of the destination among the locals, affecting tourists' choices. Although not all travelers read newspapers or online news, the news addresses pressing economic, cultural, political, and social issues (Dehler-Holland, Schumacher, & Fichtner, 2021; Schudson, 2002). Studies have found that mainstream news media in different countries reported on the same event using different vocabulary and with different tones, indicating that news content tends to reflect each country's prevailing culture and interests (Roberts et al., 2016; Schudson, 2002).

One mainstream online news source was selected from each tourism market to explore how trending events and topics were depicted and disseminated. The study chose *China Daily* as the online news source with which to forecast tourist arrivals from Mainland China for two reasons. The first was to avoid language bias. *China Daily* is published in English, allowing

an unbiased comparison with US news sources. Second, *China Daily* enjoys the largest circulation among English-language online news in Mainland China (He, Zhang, & Chen, 2020). To forecast tourist arrivals from the US, the study chose CNN, a widely known mainstream US news source that covers global issues (Zhang & Hellmueller, 2017). The keyword “Hong Kong” was used to search for destination-related online news articles from online news sources. This generated 163,571 related news items from *China Daily* and 9,886 CNN news items published between January 2011 and November 2019. The distribution of news in *China Daily* and CNN is shown in Figure 2.

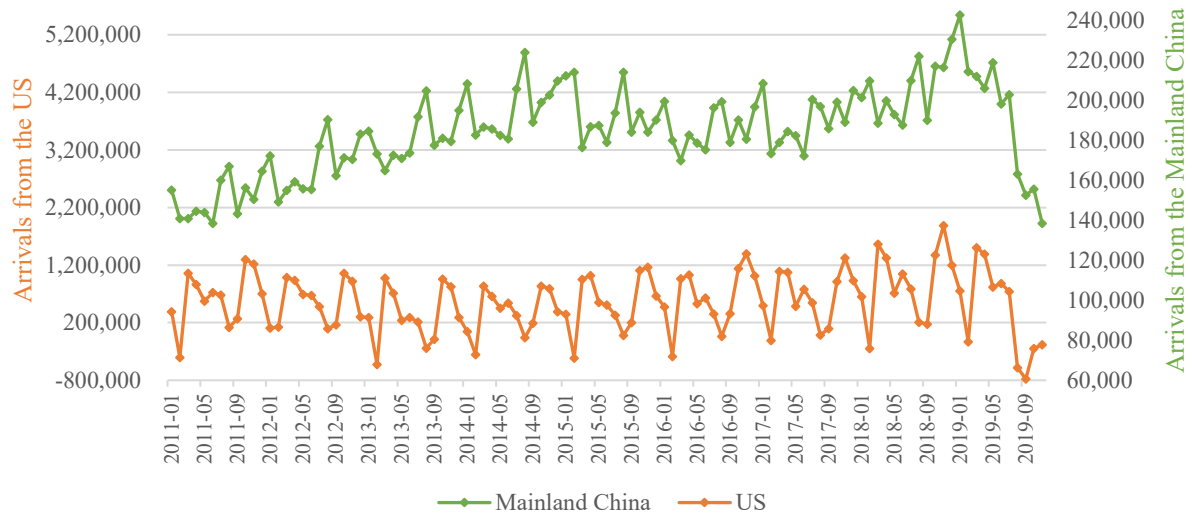


Figure 1. Monthly tourist arrivals from Mainland China and the US

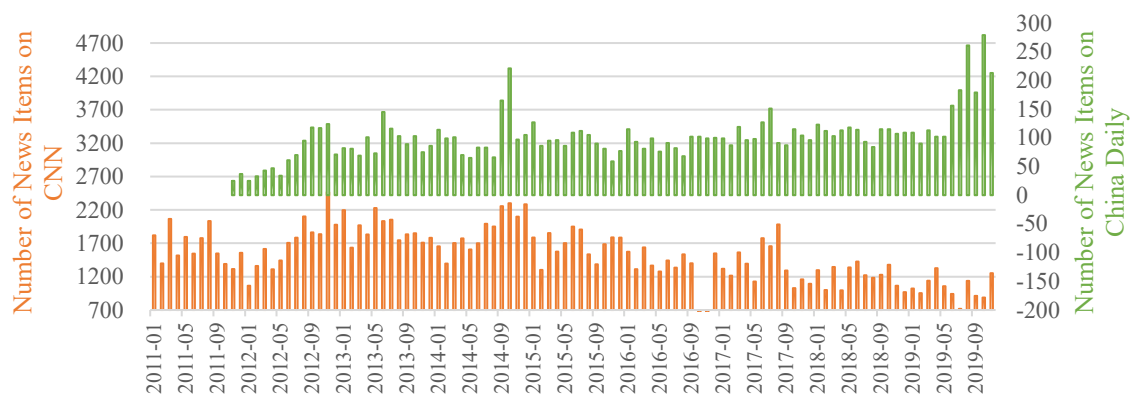


Figure 2. News distribution for China Daily and CNN

Data cleaning is essential before analyzing a corpus of text to improve the text mining results. Before data mining, the study performed a series of text preprocessing steps using the Python Natural Language Tool Kit (NLTK) package, including tokenization, non-alphanumeric

character removal, and lowercase conversion. Part-of-speech tagging was used to select nouns, verbs, adjectives, and adverbs; identify bigram and trigram words; and lemmatize all terms. In addition to NLTK stop words (i.e., frequently appearing but not meaningful), the study included custom stop words (e.g., “also,” “could,” “get”) for each news dataset. Bigram and trigram words (i.e., those with a sequence of two or three tokens) were also used to capture frequently appearing multiword expressions such as “Hong Kong” and “special administrative region.”

3.2 Topic modeling

With the input of preprocessed online news texts, STM automatically extracts latent topics from the text data and set of keywords associated with each topic. This produces two outputs: (1) topic prevalence (θ), which indicates the probability that any document (d) is associated with multiple topics, and (2) topic term proportion (β), which captures the probability that each term from the corpus belongs to a certain topic. Because STM adopts the mixed membership approach, which assumes that a document contains a mixture of multiple topics, the likelihood that each document is associated with multiple topics can be calculated. For single-membership models, a document is assigned solely to the most notable theme. As a news article is likely to address multiple topics (i.e., the impact of “diplomatic issues” on “the tourism industry”), mixed membership models were deemed appropriate for this study’s data.

The generative process for computing the topic models was as follows. First, topic prevalence was inferred from a logistic normal distribution:

$$\theta_d \sim \text{LogisticNormal}_{K-1}(\Gamma'x'_d, \Sigma),$$

where Γ represents a matrix of the coefficients of the topic prevalence covariates and Σ is a covariance matrix. The use of logistic normal distributions makes it possible to estimate topic correlations so that the relationships among topics can be considered to build the models and ultimately improve topic interpretability (Blei & Lafferty, 2007). Based on the topic prevalence (θ_d), a topic (Z_{dn}) was assigned to each term within any document d inferred from a multinomial distribution as follows:

$$Z_{dn} \sim \text{Multinomial}(\theta_d).$$

The probability that a term within the corpus was assigned to each topic was derived from a multinomial logistic regression that included the baseline word’s usage rate across all documents as well as the word usage rate within the particular topic, a document-level covariate, and the interaction between the topic and covariate:

$$\beta_{dkv} \propto \exp(m_v + k_{k,v}^{(\text{topic})} + k_{y_d, v}^{(\text{cov})} + k_{y_d, k, v}^{(\text{int})}).$$

Then, an observed word in a document (W_{dn}) was sampled from the following multinomial distribution:

$$W_{d,n} \sim \text{Multinomial}(\beta_{dk1}, \dots, \beta_{dkV}).$$

Although STM automatically extracts latent topics, researchers must provide the number of topics (K) needed for the final model. To make this “K” decision, this study relied on two metrics: (1) the held-out likelihood that evaluates predictive performance and (2) semantic coherence. After comparing the values of the two metrics over a series of topics with different K, the optimal K for the *China Daily* dataset was determined to be 100 and that for CNN was determined to be 30. The number of topics for both data sources was within the range of topic number recommendations of five to 50 topics for small datasets (those with fewer than 10,000 documents) and 100 topics for large datasets (with over 100,000 documents) (Roberts et al., 2019).

After building the topic models, the researchers reviewed the top terms strongly associated with each topic to ensure the topic quality generated from the algorithm and identify the types of topics frequently covered in the two news datasets. Topic prevalence can reflect the main topics covered in each sampled article. To isolate the news topics reported most frequently each month, the monthly average of document-level topic prevalence was calculated separately for both the *China Daily* and the CNN datasets.

3.3 Forecasting and evaluation models

A framework (see Figure 3) was utilized to forecast tourism demand based on news in the market region. This framework had four aspects: online news sources, topic data mining, estimation and forecasting, and forecast accuracy evaluation. For the first aspect, as reported above, *China Daily* was sampled for news coverage in Mainland China and CNN was sampled for the US. Second, topic modeling was utilized to generate topics from *China Daily* and CNN. The monthly distribution of topics was calculated using topic modeling. Third, both the Boruta algorithm (Kursa & Rudnicki, 2010) and the stepwise algorithm (Venables & Ripley, 2002) were used to select the explanatory variables from the lagged monthly distribution of topics. The selected lagged monthly distribution of topics was used to forecast tourism demand. One time series model with explanatory variables (SARIMAX) was utilized as the forecast model based on the topics from the online news sources. Three pure time series models were taken as the benchmarks (automatically selected ARIMA, automatically selected ETS, and seasonal naïve), which are typically used to test forecasting methods (Hyndman, 2018). Finally, MAE, MAPE, RMSE, and RMSPE were used as the accuracy evaluation models. When comparing two models, an improvement index was used to calculate the relative performance.

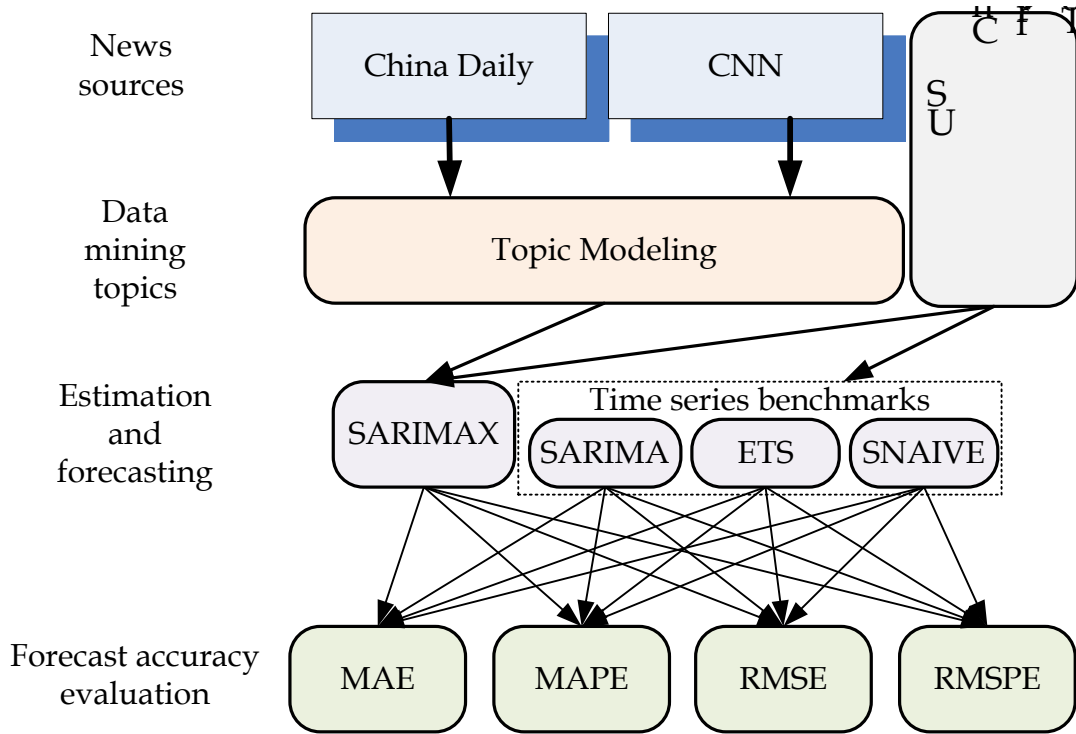


Figure 3. Study framework

3.3.1. SARIMA/SARIMAX.

ARIMA is a classical time series model and frequently utilized to derive benchmarks in tourism demand forecasting because of its strong forecast performance (Song, Qiu, & Park, 2019). It integrates seasonality, autoregressive, and moving average components, allowing it to make otherwise unstable time series more stable. The general model of SARIMA (p, d, q)(P, D, Q) is specified as

$$\Phi(B^m)\phi(B)(1 - B^m)^D(1 - B)^d y_t = \Theta(B^m)\theta(B)\varepsilon_t$$

where y_t is tourism demand at time t (i.e., the number of tourist arrivals in month t).

$\phi(B) = (1 - \sum_{i=1}^p \phi_i B^i)$ is the autoregressive component, $\theta(B) = (1 + \sum_{i=1}^q \theta_i B^i)$ is the moving average component, $(1 - B)^d$ is the d times difference indicator, $(1 - B^m)^D$ is the seasonal D times difference indicator, and $\Phi(B)$ and $\Theta(B)$ represent the seasonal AR(P) and seasonal MA(Q) components, respectively. The “Forecast Package” (Hyndman et al., 2020) in R was used to estimate the SARIMA model and forecast the future value. $d, p, q, P, D,$ and Q are automatically determined using the function `auto.arima()` according to the AICc and return the fitted model. `forecast()` helps generate the future value.

The explanatory variables in SARIMA elevate the model to SARIMAX. When the topic variables generated from online news sources are incorporated into the model, SARIMAX can be specified as

$$\Phi(B^m)\phi(B)(1 - B^m)^D(1 - B)^dTD_t = \mu + \sum_{k=1}^n \beta^k \cdot Topic_t^k + \Theta(B^m)\theta(B)\varepsilon_t$$

where the SARIMA parameter takes the same meaning as described above, $Topic_t^k$ is the selected monthly distribution series of topic k by the Boruta algorithm (Kursa & Rudnicki, 2010) and stepwise algorithm (Venables & Ripley, 2002) to forecast tourism demand, and β^k is the corresponding coefficient.

In the modeling process, the AIC and BIC are generally utilized to determine the explanatory variables and their lags (Önder, Gunter, & Gindl, 2020; Gunter, Önder, & Gindl, 2019). This study involved a large number of topics. Addressing all the study's topic variables would thus have led to overfitting, rendering the AIC and BIC useless. Thus, this study used a combination of the Boruta algorithm (Kursa & Rudnicki, 2010) and stepwise algorithm (Venables & Ripley, 2002) as the feature selection method. The Boruta algorithm was designed to be a wrapper fitting around a random forest classification algorithm. First, it iteratively removes the features proved by a statistical test to be less relevant than random probes. Then, the AIC is used to double check the significance of the variables and remove the less relevant ones. This study used the Boruta and Stats packages in R to conduct the feature selection. The forecast package (Hyndman et al., 2020) in R was used to estimate the SARIMAX model and forecast future values.

3.3.2. ETS model

The ETS method is also automatically selected. This method develops a simple exponential smoothing method by including level, trend, seasonality, and smoothing (Hyndman & Athanasopoulos, 2018). The general ETS model can be written as ETS (e, t, s), where e denotes the error type, t denotes the trend type, and s denotes the seasonality type. `ets()`, as included in the Forecast Package (Hyndman et al., 2020) in R, can be used to select the model automatically according to the AICc among the different error types, trend types, seasonality types, and estimate parameters. `forecast()` can be used to derive future values.

3.3.3. Seasonal naïve

Seasonal naïve is a typical benchmark model for seasonal data. It uses the value of the historical period to forecast future values. To forecast monthly tourism demand, the general model is

$$\hat{y}_t = y_{t-12}$$

where \hat{y}_t denotes the forecast value of tourist arrivals in month t and y_{t-12} is delayed tourist arrivals in month 12.

3.3.4. Forecast evaluation

To evaluate the forecast accuracy of the above models and show the role of topic variables in tourism demand forecasting, the MAE, RMSE, MAPE, and RMSPE were calculated by the following series:

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

where y_i is the real value of tourist arrivals and \hat{y}_i is the forecast value of tourist arrivals. To compare the two models, the relative improvement of Model 1 was compared with that of Model 2 using the MAPE as follows:

$$RI_{Model_2}^{Model_1} = \frac{MAPE(Model_2) - MAPE(Model_1)}{MAPE(Model_2)}$$

4. RESULTS

4.1 Topic selection and analysis

Employing the data-mining process, 100 topics from *China Daily* and 30 topics from CNN were extracted. The Boruta algorithm (Kursa & Rudnicki, 2010) and stepwise algorithm (Venables & Ripley, 2002) were used to conduct the feature selection and select the most relevant topics related to tourist arrivals from Mainland China and the US. The Boruta algorithm estimated the importance of each independent variable by taking tourist arrivals from Mainland China or the US as a dependent variable and using a lagged series of different topics extracted from *China Daily* or CNN as independent variables. The result was used to identify the most important topics by the AIC based on the results of the Boruta algorithm. The most important topics explaining tourist arrivals are shown in Table 1 for *China Daily* and in Table 2 for CNN.

The 100 topics extracted from *China Daily* highlighted diverse issues, including society, economy, and politics, which were found to be important in explaining Mainland Chinese tourist arrivals. Topic 46, labeled “societal issues,” had a negative association with tourist arrivals from Mainland China. Specifically, the top words (i.e., “child,” “family,” “woman,” “old,” “parent”) of Topic 46 showed that news addressing gender or family issues in Hong Kong had a negative influence on Mainland Chinese tourist arrivals. Turning to sociopolitical

issues, Topic 50 was related to the Hong Kong protest movement. This topic also had a negative association with Chinese tourist arrivals, displaying two topic weight peaks with the Umbrella Movement in 2014 and the Hong Kong protest in 2019–20. Topic 11 was on stock prices and business conditions, while Topic 20 was on capital investments and mergers and acquisitions, which had a negative impact on Mainland Chinese tourist arrivals.

Topic 96 (international events), Topic 93 (Guangzhou), and Topic 65 (China’s economy) were positively associated with Mainland Chinese tourist arrivals. Topic 96 included events such as exhibitions, expos, and conferences. Topic 93 was related to issues in Guangzhou, the capital of Guangdong province, which shares a border with Hong Kong. This topic reflected Guangzhou’s progress in becoming a financial hub and its efforts to develop using transportation infrastructure investments. For Topic 65, events such as economic development in China and the Mainland’s reform efforts were mentioned as well as news on how Chinese economic development has influenced the Hong Kong economy.

Table 1. Selected topics illustrating tourist arrivals from Mainland China

Lag	Topic	Top words	Coefficient	Significance
1	Topic 20: Economy	growth, increase, rise, decline, economy	-11713599	0.0774*
	Topic 39: Industry issues	company, brand, product, market, sale	-22670482	0.0614*
	Topic 46: Societal issues	child, family, woman, old, parent	-62072318	0.00001***
	Topic 50: Protest	police, protest, protester, city, violence	-8900996	0.0000***
	Topic 65: China’s economy	economy, china, market, financial, reform	27509372	0.0008***
	Topic 88: Online market	online, company, alibaba, internet, platform	12135557	0.0911*
	Topic 93: Guangzhou	province, guangzhou, guangdong_province, guangdong, local	32828677	0.0316**
2	Topic 7: Foreign regulation	foreign, regulation, enterprise, authority, policy	17194570	0.1843

	Topic 11: Stock	point, hang_seng, end, wall street, stocks	-29721270	0.0082***
	Topic 21: HK SAR	hong_kong, special_administrative, region, chief_executive, central_government	-6948677	0.1950
	Topic 34: Foreign relations	american, canada, community, canadian, asia	28057262	0.0591*
	Topic 63: Politics	political, election, government, member, vote	5840715	0.1385
3	Topic 9: Figures/Celeb rities	wong, lee, cheung, lam, kwok	-56735768	0.0026***
	Topic 36: Art	art, artist, painting, auction, collector	-9903689	0.0644*
	Topic 96: International event	international, event, forum, exhibition, fair	37500698	0.0002***
	Topic 99: Investment	company, group, investment, acquisition, chairman	-11993099	0.0347**

Note: ***, ** and * denote statistical significance at 1%, 5%, 10% level respectively.

Topics 2 and 7 were found to be positively associated with tourist arrivals from the US. Topic 2 consisted of news related to massive Chinese tech companies such as Alibaba and Huawei as well as the Asian market overall. The rapid development of companies such as Alibaba and Huawei has led to fierce competition for market share, leading to issues such as the US–China trade war. Topic 7 comprised attributes that describe Hong Kong as a tourism destination. Both its natural attractiveness (e.g., island, beach) and tourism infrastructure (e.g., hotel, bar, pool) were mentioned in relation to Topic 7. Similar to the *China Daily* results, CNN’s coverage of the Hong Kong protests proved to have a negative association with tourist arrivals from the US.

Table 2. Selected topics illustrating tourist arrivals from the US

Lag	Topic	Meaning	Coefficient	Significance
2	Topic 2: Chinese tech	company, apple, alibaba, huawei, market	101006	0.0263**
3	Topic 7: HK destination	hotel, bar, room, city, island	252327	0.0019***

2	Topic 9: Protest	police, protester, protest, hong_kong, government	-111403	0.0060***
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Note: ***, ** and * denote statistical significance at 1%, 5%, 10% level respectively.

4.2 Cointegration test

The study conducted a cointegration test using the Engle–Granger two-step method to confirm the long-term equilibrium relationship between tourist arrivals and the selected topics from the targeted online news sources (Huang, Zhang, & Ding, 2017). The augmented Dickey–Fuller (ADF) unit root test results in Table 3 show that all the variables except Topic 36 in Mainland China and Topic 7 in the US were first-order integrated. These first-order integrated variables were used to conduct a cointegration test. The ADF value of the residuals of the fitting variables relating to Mainland China was -6.78 ($P = 8.49 \times 10^{-10}$) and the value relating to the US was -8.81 ($P = 8.72 \times 10^{-14}$). This means that tourist arrivals from Mainland China and the US showed a long-term equilibrium relationship with the topics selected from both *China Daily* (as shown in Table 1) and CNN (as shown in Table 2).

The Granger causality test was used to confirm the causal relationship between tourist arrivals and each selected topic. The results in Table 4 show that the Granger causality relationships of most of our selected topics from *China Daily* and all the topics selected from CNN were confirmed. This finding indicates that the selected topics from *China Daily* and CNN led to enhanced tourist arrivals from Mainland China and the US. They can thus be used to forecast tourist arrivals.

In addition, the Granger causality test result of Topic 36 from *China Daily* was not significant, while that of Topic 7 from the CNN was significant. This indicates that the Granger causality relationship between Topic 36 from *China Daily* and tourism demand from Mainland China was not confirmed, while the relation between Topic 7 from CNN and tourism demand from the US was confirmed. Therefore, we removed Topic 36 of *China Daily* from the exogenous variable datasets to forecast tourism demand from Mainland China. Topic 7 of CNN was used as an exogenous variable to forecast tourism demand from the US.

Table 3 ADF unit root test results

Variable	ADF	Prob.	Conclusion	Variable	ADF	Prob.	Conclusion
Mainland China							
y_t	-0.55	0.58	Non-	Topic 46	-1.11	0.27	Non-
Δy_t	-10.73	0.00	Stationary	Δ Topic 46	-12.70	0.00	Stationary
Topic 7	-1.01	0.314	Non-	Topic 50	0.77	0.44	Non-
Δ Topic 7	-10.58	0.00	Stationary	Δ Topic 50	-7.65	0.00	Stationary
Topic 9	-1.13	0.26	Non-	Topic 63	-0.696	0.49	Non-
Δ Topic 9	-9.91	0.00	Stationary	Δ Topic 63	-8.18	0.00	Stationary
Topic 11	-1.66	0.10	Non-	Topic 65	0.93	0.35	Non-
Δ Topic 11	-13.47	0.00	Stationary	Δ Topic 65	-10.72	0.00	Stationary

Topic 20	-1.36	0.18	Non-	Topic 88	-1.47	0.15	Non-
Δ Topic 20	-12.85	0.00	Stationary	Δ Topic 88	-11.89	0.00	Stationary
Topic 21	-1.47	0.15	Non-	Topic 93	-0.90	0.37	Non-
Δ Topic 21	-11.37	0.00	Stationary	Δ Topic 93	-11.34	0.00	Stationary
Topic 34	-1.324	0.18	Non-	Topic 96	-1.29	0.20	Non-
Δ Topic 34	-12.32	0.00	Stationary	Δ Topic 96	-10.00	0.00	Stationary
Topic 36	-2.55	0.01	Stationary	Topic 99	-1.45	0.15	Non-
Δ Topic 36	\	\	\	Δ Topic 99	-11.84	0.00	Stationary
Topic 39	-1.51	0.14	Non-				
Δ Topic 39	-12.39	0.00	Stationary				
US							
y_t	-0.91	0.37	Non-	Topic 7	-2.157	0.03	Stationary
Δy_t	-10.90	0.00	Stationary	Δ Topic 7	\	\	\
Topic 2	-1.17	0.24	Non-	Topic 9	-1.07	0.29	Non-
Δ Topic 2	-10.39	0.00	Stationary	Δ Topic 9	-7.07	0.00	Stationary

Note: 1% critical value is -2.58, 5% critical value is -1.95, and 10% critical value is -1.62 for the variables relating to Mainland China; 1% critical value is -2.6, 5% critical value is -1.95, and 10% critical value is -1.61 for the variables relating to the US; Δy_t indicates that y_t is integrated of order 1.

Table 4 Granger causality test results

Null hypothesis	F-	Prob.	Null hypothesis	F-	Prob.
Mainland China					
Topic 7 does not Granger cause tourist arrivals	3.6768	0.0580 *	Topic 46 does not Granger cause y_t	9.4499	0.0027 ***
y_t does not Granger cause Topic 7	2.7071	0.1030	y_t does not Granger cause Topic 46	0.8466	0.3597
Topic 9 does not Granger cause y_t	3.0372	0.0845 *	Topic 50 does not Granger cause y_t	2.5269	0.1151
y_t does not Granger cause Topic 9	2.9795	0.0874 *	y_t does not Granger cause Topic 50	2.5916	0.1106
Topic 11 does not Granger cause y_t	3.7293	0.0563 *	Topic 63 does not Granger cause y_t	0.0714	0.7898
y_t does not Granger cause Topic 11	7.1521	0.0087 ***	y_t does not Granger cause Topic 63	0.2816	0.5969
Topic 20 does not Granger cause y_t	26.7170	0.0000 ***	Topic 65 does not Granger cause y_t	1.9687	0.1637
y_t does not Granger cause Topic 20	5.7816	0.0180 **	y_t does not Granger cause Topic 65	0.0016	0.9686
Topic 21 does not Granger cause y_t	0.0609	0.8056	Topic 88 does not Granger cause y_t	3.3622	0.0697 *
y_t does not Granger cause Topic 21	0.0711	0.7902	y_t does not Granger cause Topic 88	12.3153	0.0007 ***
Topic 34 does not Granger cause y_t	3.3124	0.0718 *	Topic 93 does not Granger cause y_t	2.2028	0.1409
y_t does not Granger cause Topic 34	3.8338	0.0530 *	y_t does not Granger cause Topic 93	6.8966	0.0100 **
Topic 36 does not Granger cause y_t	1.2978	0.2573	Topic 96 does not Granger cause y_t	6.5964	0.0117 **
y_t does not Granger cause Topic 36	1.6094	0.2075	y_t does not Granger cause Topic 96	1.8364	0.1784
Topic 39 does not Granger cause y_t	10.8786	0.0013 ***	Topic 99 does not Granger cause y_t	0.2007	0.6551
y_t does not Granger cause Topic 39	4.6038	0.0343 **	y_t does not Granger cause Topic 99	0.0439	0.8345
US					
Topic 2 does not Granger cause tourist arrivals	5.8826	0.0173 **	Topic 9 does not Granger cause y_t	8.826	0.0038 ***
y_t does not Granger cause Topic 2	1.8485	0.1774	y_t does not Granger cause Topic 9	0.6297	0.4295
Topic 7 does not Granger cause y_t	12.433	0.0007 ***			
y_t does not Granger cause Topic 7	1.913	0.1701			

Note: ***, ** and * denote statistical significance at 1%, 5%, 10% level respectively.

4.3 Forecast performance

By incorporating the topic variables generated from *China Daily* and CNN, as shown in the proposed framework in Figure 3, SARIMAX was used to forecast tourism arrivals from Mainland China and the US. SARIMA, ETS, and seasonal naïve were used as the benchmark models. The full dataset used to forecast tourism demand from Mainland China spanned 107 months, from January 2011 to November 2019, while the dataset used to forecast tourism demand from the US started in November 2011. The most recent 12 months were used to test the forecast accuracy of the models.

The average forecast errors of the 12-month one-step-ahead rolling forecast are listed in Table 5. The results indicate three critical points. First, comparing SARIMAX with SARIMA shows that the topics from *China Daily* and CNN both play positive roles in improving forecasting accuracy when estimating tourist arrivals from Mainland China and the US. This result indicates that news reported in a source market affects the image of a destination and plays a role in determining tourism demand. Additionally, comparing *China Daily* with CNN shows that Chinese news coverage played a greater role in determining tourism demand than did US coverage. There are two possible explanations for these findings. First, Hong Kong is a special administrative region in China. *China Daily*, as a mainstream online news source and the first national daily English-language newspaper in China, necessarily pays more attention to Hong Kong than CNN can pay to any particular tourist destination. Second, short-haul tourists from Mainland China to Hong Kong tend to be more malleable to news coverage than are long-haul US tourists. Short-haul tourists thus have a greater capacity to change their travel plans based on recent news reporting, while long-haul travel plans may be “locked in” and unaffected by such an influence. Finally, comparing the forecasting performance of SARIMAX with that of the time series benchmarks shows that SARIMAX with topic variables drawn from source market news sources consistently proved to be the best model.

Table 5 Forecast performance

	Model	MAE	RMSE	MAPE	RMSPE
Mainland China					
Forecast error	SARIMAX	555651	655897	0.1623	0.2076
	SARIMA	611167	816256	0.1961	0.2862
	ETS	741649	878114	0.2327	0.3083
	SNAIVE	1099889	1363247	0.3802	0.5550
	SARIMA	9.08%	19.65%	17.24%	27.44%
	ETS	25.08%	25.31%	30.26%	32.66%

Improvement of <i>SARIMAX</i> compared with	SNAIVE	49.48%	51.89%	57.32%	62.59%
US					
	SARIMAX	7754	11121	0.1030	0.1539
Forecast error	SARIMA	8656	12015	0.1157	0.1710
	ETS	18112	23048	0.2309	0.3234
	SNAIVE	15274	24378	0.2023	0.3291
Improvement of <i>SARIMAX</i> compared with	SARIMA	10.42%	7.45%	10.97%	10.03%
	ETS	57.19%	51.75%	55.39%	52.42%
	SNAIVE	49.24%	54.38%	49.07%	53.24%

Given the recent social unrest in Hong Kong and its severe impact on tourism, the study investigated the role of news coverage in improving forecasting accuracy, especially during turbulent times at the destination level. To this end, the study extracted the forecast performance of each model between August and November in 2019. These data are shown in Table 6. Two findings are notable. First, SARIMAX with news source topics again consistently outperformed the benchmark models during Hong Kong's social unrest. This indicates that such topics remained relevant and improved forecasting accuracy. Second, the performance of the model with topics from *China Daily* during the social unrest improved significantly over the one-year test results, while that of the model using CNN topics remained almost unchanged. There are two possible reasons for this difference. First, news coverage of the social unrest on *China Daily* might have attracted more attention in China. This could cause destination image (re)formation and ultimately influence travel intentions. Second, as mentioned, short-haul tourists from Mainland China have the flexibility required to change their travel itineraries in response to news reports on social unrest.

Table 6 Forecast performance during the protest (August to November 2019)

	Model	MAE	RMSE	MAPE	RMSPE
Mainland China					
	SARIMAX	658021	793554	0.2693	0.3135
Forecast error	SARIMA	1043809	1257605	0.4141	0.4737
	ETS	1143979	1254478	0.4682	0.5037
	SNAIVE	2045633	2105590	0.8809	0.9374

Improvement of <i>SARIMAX</i> compared with	SARIMA	36.96%	36.90%	34.95%	33.83%
	ETS	42.48%	36.74%	42.47%	37.77%
	SNAIVE	67.83%	62.31%	69.42%	66.56%
US					
Forecast error	SARIMAX	18431	18756	0.2612	0.2628
	SARIMA	20012	20142	0.2882	0.2913
	ETS	32952	34157	0.4874	0.5191
Improvement of <i>SARIMAX</i> compared with	SNAIVE	39141	41870	0.5444	0.5677
	SARIMA	7.90%	6.88%	9.38%	9.79%
	ETS	44.07%	45.09%	46.42%	49.37%
	SNAIVE	52.91%	55.20%	52.03%	53.71%

5. CONCLUSION AND IMPLICATIONS

Tourist arrivals are highly dependent on the external environment of the destination, including newsworthy phenomena such as social changes and political events. However, most studies have built their forecasting models on quantitative historical data that may ignore the influence of unforeseen but significant social occurrences. H. Li et al. (2020) suggested the need for a tourism demand forecasting model that reflects real-time changes using Internet big data. Accordingly, this study presented a tourism demand forecasting model for Hong Kong that combines news topics from two online news sources derived from probabilistic topic modeling.

The STM results revealed the key news topics that are most frequently and prominently exposed by two major online news sources. For instance, the topic weights related to the Hong Kong protests surged twice, in 2014 and 2019, when mass protests escalated there. These sudden increases during social unrest were found to be significantly associated with tourist arrivals in Hong Kong. This study discovered that the inclusion of a monthly timeframe of topic weights can improve the performance of forecasting models and reduce forecasting errors. Specifically, this study identified the lag effects (i.e., one-, two-, and three-month lags) that show when news topics display the best predictive performance. These findings indicate that some news topics may have immediate or short-term impacts on tourism demand, while others may have long-term effects.

By comparing the number of online news articles and topic structures regarding Hong Kong published in *China Daily* and CNN, the study found that the extent and diversity of social discourses about a tourism destination differed between tourism markets. Moreover, including online news as exogenous variables was found to be more effective if the geographical distance between the tourism market and tourism distance was short and bilateral relations were established in various areas. The impact of online social discourses on tourist behavior is largely dependent on geographical proximity and international

relationships. Therefore, tourism stakeholders such as the Hong Kong Tourism Board should consider including news sources to improve tourism demand forecasting, especially for tourism markets that are close and feature high interaction levels.

This finding makes an important contribution to the literature. Although text-based sets of big data contain rich information corresponding to major events and market trends, they have rarely been utilized to formulate tourism demand forecasting models. Moreover, online news releases are underexplored as a means of forecasting tourist arrivals relative to other types of big data sources such as search query data, online reviews, and website traffic data (H. Li et al., 2020; Li, Li, Pan, & Law, 2020; Pan, Wu, & Song, 2012; Sun, Wei, Tsui, & Wang, 2019). Online news sources not only convey the latest information at a faster pace but are also accessible immediately and readily from anywhere. Therefore, this study proposes that online news is a novel source of volume data that can serve as an indicator of significant social changes.

This study has several limitations that suggest potential avenues for future studies. First, this study has demonstrated the potential value of including key news topics based on STM for tourism demand forecasting. As different news channels may have different perspectives of the same event, the latent sentiment or tone with which news is delivered may vary. Hence, future studies should combine sentiment analysis with topic modeling to assess the association between latent sentiment toward a particular news topic and potential tourist behaviors. Second, while online news is clearly a key medium for information dissemination, this study included only a single type of online data source. Future studies may consider including other types of unstructured texts from additional information sources such as articles from blogs, Internet forums, and user-generated content (Chen & Chen, 2019). Third, this study demonstrated that the forecasting model with news topics outperformed the others not only in the normal period but also at a time of social unrest in the destination at the local level. As impacts of crisis can be determined by geographical scale (Ritchie & Jiang, 2019) and the devastating global impact of the COVID-19 pandemic now confronting the world, tourism demand forecasting studies should endeavor to conduct innovative and robust forecasts (Qiu, Wu, Dropsy, Petit, Pratt, & Ohe, 2021). Future studies on tourism demand forecasting with discourse analysis at the global level are encouraged when tourism relaunches and tourism statistics recover after the pandemic. Fourth, this study evaluated model performance based on 12-month one-step-ahead forecasting for a limited sample size. Future research should test the model's forecasting performance over two- or three-month forecast horizons by incorporating more samples.

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