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Tourism demand forecasting using tourist-generated online review data

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ABSTRACT

This study aims to forecast international tourist arrivals to Hong Kong from seven English-speaking countries. A new direction in tourism demand modeling and forecasting is presented by incorporating tourist-generated online review data related to tourist attractions, hotels, and shopping markets into the destination forecasting system. The main empirical findings indicate that tourism demand forecasting based on tourists' online review data can substantially improve the forecasting performance of tourism demand models; specifically, mixed data sampling (MIDAS) models outperformed competing models when high-frequency online review data were included in traditional time-series models.

1. Introduction

Accurate and timely tourism demand forecasts are crucial to destination policymaking and planning. These forecasts also play essential roles in staff scheduling, business operations, and revenue management for tourism-related companies (Song & Li, 2008). However, a lag in the publication of tourism demand predictors, such as tourism prices and tourists' income, prevents tourism forecasters from making timely demand predictions (Gunter, Önder, & Gindl, 2019). Internet big data and the development of information technologies provide one possible solution. Wu, Song, and Shen (2017) contended that Internet big data possess advantages over traditional economic data, as the former are available in real time, with high frequency, and free of charge. Internet big data precisely reflect tourists' behavior and are thus sensitive to tourists' behavioral changes. Moreover, the Internet is regarded as an important knowledge source for tourist information searches and as a key driver of tourism demand (Law, Leung, & Buhalis, 2009). Therefore, Internet big data and analytics can reveal tourists' destination choices (Fuchs, Höpken, & Lexhagen, 2014) and predict tourism demand (Colladon, Guardabascio, & Innarella, 2019).

In general, Internet big data in tourism management are drawn from the following three sources: (1) users (e.g., online reviews); (2) devices (e.g., mobile and GPS data); and (3) operations (e.g., website traffic, Google Trends, and online booking data) (Li, Xu, Tang, Wang, & Li, 2018). Scholars have recently begun using Internet big data, such as Google Trends search queries and website traffic, to forecast tourism demand (Gunter et al., 2019). Although search query and website traffic data are important information sources for tourism demand forecasting and can be accessed at low costs, they have drawbacks compared with social media data (Geva, Oestreicher-Singer, Efron, & Shimshoni, 2017). For example, search query and website traffic data are less rich than social media data and are limited in reflecting tourists' preferences/sentiments; that is, these forms of data can only indicate an individual's interest in a specific tourism destination but not whether such an interest is due to positive or negative circumstances.

Compared with search query and website traffic data, social media data are readily accessible, vast, and information-rich (Geva et al., 2017). Social media data can convey individuals' thoughts and feelings at a resolution previously unimaginable (Phillips, Dowling, Shaffer, Hodas, & Volkova, 2017). Social media data, which are generated in real time, have become increasingly important in monitoring events and sentiment (Chen, Chen, Wu, Hu, & Pan, 2017; Yin et al., 2015). Given these advantages, data from social media have been recognized as useful by researchers and practitioners in explaining and forecasting business sales (Geva et al., 2017). The dominant research stream has focused on collecting social media data to measure a product's word-of-mouth

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(WOM), indicating that the number of mentions a product receives and preferences/sentiments expressed in social media data can predict product sales, revenue, and other offline economic activities (Chern, Wei, Shen, & Fan, 2015; Cui, Gallino, Moreno, & Zhang, 2018; Dellarocas, Zhang, & Awad, 2007; Schneider & Gupta, 2016).

In tourism, social media data play a key role in tourists' information search behavior, knowledge exchange, and decision making (Gavilan, Avello, & Martinez-Navarro, 2018). When people plan a trip, they often start with information searches to obtain local destination knowledge. Compared with information from a company's website or advertisements, consumers are becoming more discerning and likely to believe peer consumers' opinions (Colladon et al., 2019). The prevalence of user-generated online reviews has also led to growth in the availability of electronic WOM (Geva et al., 2017). Therefore, online reviews have grown in importance, spurring the popularity of third-party review websites. User-generated online review data shared on social media can reveal tourists' preferences, sentiments, and the popularity of destinations and attractions (Gandomi & Haider, 2015; George, Haas, & Pentland, 2014; Li, Law, Vu, Rong, & Zhao, 2015). Some studies have investigated the effects of online reviews on tourists' destination choices and hotel bookings (e.g., Jacobsen & Munar, 2012; Sparks & Browning, 2011), whereas others have extracted and analyzed social media online review data. However, no prior studies in tourism management have considered online review data to forecast a destination's tourism demand. Accordingly, the present study aims to forecast international tourist arrivals to Hong Kong from seven English-speaking countries by integrating tourist-generated online review data in the destination forecasting system. This study fills a relevant research gap by proposing a systematic approach to leverage online review data for destination tourism forecasting.

2. Literature review

2.1. Tourism demand forecasting based on internet big data

Two types of Internet big data are often used in tourism and hotel demand forecasting, namely search query and website traffic data (Li, Hu, & Li, 2020). A few studies have demonstrated that tourism demand forecasting performance can be enhanced by search engine data. For example, Pan, Wu, and Song (2012) and Rivera (2016) used Google search query data to forecast regional hotel demand. Yang, Pan, Evans, and Lv (2015), Bangwayo-Skeete and Skeete (2015), Li and Law (2020), and Li, Li, Pan, and Law (2020) found that Internet search queries can improve the forecasting accuracy of destination tourist arrivals. Other studies (Huang, Zhang, & Ding, 2017; Volchek, Liu, Song, & Buhalis, 2019) have demonstrated the utility of search query data in boosting forecasting performance for tourist attractions, such as the Forbidden City in China and London museums. However, some studies have encountered a problem wherein excessive search query data series may be highly correlated when introduced into a forecasting model. To overcome this limitation, scholars have adopted dimensional reduction algorithms, including a generalized dynamic factor model (Li, Pan, Law, & Huang, 2017) and principal component analysis (Li, Chen, Wang, & Ming, 2018). Peng, Liu, Wang, and Gu (2017) applied a feature selection method to choose search keywords with the highest predictive power. Results revealed that these proposed methods can improve tourism demand forecasting accuracy. Furthermore, Dergiades, Mavragani, and Pan (2018) observed language and platform biases in search query data and found that correcting these biases enhanced tourism demand forecasting performance. In addition to web search query data, a few researchers have used website traffic data from Google Analytics in tourism/hotel demand forecasting. For instance, Yang, Pan, and Song (2014) and Pan and Yang (2017) found that the number of visitors and number of visits to a destination marketing organization (DMO) website could increase the forecasting accuracy of hotel demand. Similarly, Gunter and Önder (2016) found that 10 DMOs' website traffic data from Google Analytics boosted the forecasting performance of city tourism demand.

2.2. Role of social media and online reviews in tourism demand forecasting

According to previous studies (Cui et al., 2018; Dellarocas et al., 2007; Duan, Gu, & Whinston, 2008), social media information and online reviews can influence consumers' purchase behavior in two ways: the attention effect and endorsement effect. Relevant literature has confirmed these effects (Chen, Wang, & Xie, 2011; Li & Wu, 2018; Xie, Zhang, Zhang, Singh, & Lee, 2016). Specifically, scholars have contended that consumers will not purchase a product without being aware of it, representing a precursor to purchase behavior. Peers' purchases and endorsements ultimately inspire consumers' purchase decisions.

The attention effect refers to customers' product awareness. Researchers have argued that attention can influence individuals' purchase behavior in addition to being used to forecast economic outcomes. For instance, several studies in economics (Cai, Chen, & Fang, 2009; Moretti, 2011) have shown that social media attention can enhance product sales. The attention effect is usually measured by count or popularity data. Dellarocas et al. (2007) addressed that the reason behind using the volume of review lies in that the more customers talk about a product, the higher the possibility that others will see and be aware of it. Duan et al. (2008) further pointed out that review volume indicates the intensity of the underlying electronic WOM, a type of awareness effect, which plays an important role in driving the product sales. The endorsement effect reflects product quality based on peers' online comments. This endorsement differs from the attention effect; it captures a consumer's preference or sentiment orientation, which reflects one's satisfaction and attitude towards a product. Both Dellarocas et al. (2007) and Duan et al. (2008) used review rating (or review valence) to test the product endorsement effect, while others used review sentiment. Sentiment can be classified as negative, neutral, or positive (Liu, 2015). Sentiment has also been described as exhibiting varying intensity or strength (Ye, Zhang, & Law, 2009; Li, Zhang, Meng, & Janakiraman, 2017,b). Individuals can share their sentiments on different social media platforms. Studies have indicated that, compared with count- or volume-based information, sentiment can provide additional information and benefits (Geva et al., 2017; Lau, Zhang, & Wu, 2018). Dellarocas et al. (2007) discussed the reason behind using review valence or consumer sentiment, which lies in that negative reviews will deter consumers from purchasing a product while positive reviews will encourage them to buy. Moreover, several researchers have affirmed the endorsement effect in individuals' purchase behavior. For example, a consumer's sentiment on a product page has been found to affect others' perceptions of product quality and in turn product sales (Schneider & Gupta, 2016; See-To & Ngai, 2018).

2.3. Tourism demand forecasting using social media data

In a review article, Phillips et al. (2017) contended that researchers have devoted substantial effort to adopting social media data for forecasting. The authors divided such research into five topics: (1) stocks and marketing; (2) elections and politics; (3) user characteristics; (4) threat detection; and (5) public health. While encouraging empirical evidence has been identified in these areas, the degree of success depends on other factors (Phillips et al., 2017). Findings may support the use of social media data in improving tourism forecasting accuracy. However, a limited number of studies have examined the effectiveness of using social media data to forecast tourism demand, as summarized below.

Önder, Gunter, and Gindl (2020) used "likes" on DMOs' Facebook webpages to forecast destination tourism demand. They found that one-step-ahead mean forecasts via restricted MIDAS autoregression (R-MIDAS-AR) and autoregressive distributed lag (ADL) models incorporating Facebook likes improved the forecasting performance of benchmark models, such as the NAÏVE-1 model, for arrivals to Vienna and Graz, Austria. The reverse was true for arrivals to Salzburg and Innsbruck, Austria. In another study, Gunter et al. (2019) incorporated Facebook likes and Google Trends data into MIDAS and ADL models to forecast tourism demand. The results were mixed: for Salzburg, the ADL model outperformed benchmark models and the MIDAS model in most cases; for Vienna, the MIDAS model in which Google Trends and Facebook likes were integrated as predictors showed superior performance; and the benchmark models (i.e., NAÏVE, autoregressive moving average, and error-trend-seasonal model) outperformed the MIDAS and ADL models for Innsbruck and Graz.

Colladon et al. (2019) applied social media data from a TripAdvisor travel forum to forecast tourism demand. They used the social network method and semantic analysis to extract variables from user-generated content on a TripAdvisor forum, which were integrated in traditional forecasting models to forecast tourist arrivals to seven European cities. Results from the bridge model and the factor augmented autoregressive model highlighted communication network centralization and language complexity as key predictors. Moreover, these extracted variables were found to improve tourism demand forecasting accuracy compared with a model containing only volume-based web search query data as a predictor in most cases and over most forecasting horizons.

Online news has also been used to forecast destination tourism demand. Önder, Gunter, and Scharl (2019) incorporated the sentiments of online news media coverage into their tourism demand forecasting models. The total web sentiment (i.e., the number of mentions) was classified as either positive, neutral, or negative. The MIDAS model with news sentiment as a predictor outperformed benchmark time-series models in most cases. Specifically, for Paris, France and Berlin, Germany, the results of a MIDAS model including positive sentiment outperformed the competitive and benchmark models. For Brussels, Belgium, the MIDAS model containing negative news sentiment improved forecasting accuracy to the greatest extent. However, forecasting accuracy did not increase noticeably for Vienna when including news sentiment as an explanatory variable. Later, by extracting key topics from news discourse via structural topic modeling, Park, Park, and Hu (2021) used identified topics to forecast tourist arrivals to Hong Kong. Their empirical results confirmed the positive role of news data in improving tourism demand forecasting performance.

Additionally, scholars have started to use online review data to forecast tourism demand for individual tourist attractions or hotels. Li, Hu, and Li (2020) forecasted tourist arrivals to a national park using Internet big data from multiple sources, including search engines and online reviews. Empirical results showed that tourism demand forecasting based on multiple-source big data could enhance tourist attraction forecasting performance compared to single-source big data using either search engines or online reviews. By analyzing online review data from the Chinese websites Ctrip and Qunar, Wu, Zhong, Qiu, and Wu (2021) studied online review sentiment to forecast demand for four luxury hotels in Macau. Results affirmed the positive effect of online review sentiment in hotel demand forecasting; however, the authors took online review count as a proxy for hotel tourism demand in the absence of real hotel demand data. Chang, Chen, Lai, Lin, and Pai (2021) similarly used online review ratings and review sentiment to forecast hotel room occupancy rates in Taiwan. They found that integrating hotel online reviews increased the accuracy of hotel occupancy forecasting.

2.4. Rationale for this study

Although scholars have indicated that Internet social media data have potential to enhance tourism demand forecasting, prior studies have returned controversial and inconsistent results. Given that a uniform best practice is nonexistent and numerous methods have been adopted, research on tourism demand forecasting based on social media data remains in its infancy. A comprehensive literature review revealed several research gaps in social media tourism demand forecasting.

First, most research on big data–based tourism demand forecasting has involved volume-based web search query and website traffic data. Although volume-based data are useful for increasing tourism demand forecasting accuracy, there are considerable limitations to this type of data. Compared with social media data, volume-based Internet big data only reflect tourists' attention to, and awareness of, tourism products and services; they do not indicate tourists' preferences or sentiments. In other words, we do not know whether an increase in tourist awareness is due to positive or negative circumstances. In addition, search query and website traffic data are only available at aggregate levels to researchers. The inability to access individual raw data prevents researchers from identifying, analyzing, and correcting possible bias and limitations in data (Geva et al., 2017). On the contrary, social media data are rich and can overcome the above-mentioned constraints. However, few attempts have been made to apply volume- and valence-based (or sentiment-based) social media data in tourism demand forecasting.

Second, although research on tourism demand forecasting has used social media data such as "likes" posted on DMOs' Facebook pages, sentiments about online news media coverage, and travel forum data, no existing work has applied online review data to forecast destination tourism demand. Due to information overload, social media platforms have become main information sources for tourists (Önder et al., 2020). Individuals are turning from millions of Google search results to tourism-related online review platforms, where they can find more focused and trustworthy travel-related information from experienced travelers.

Third, in tourism demand forecasting, only a few studies have applied mixed-frequency models. Bangwayo-Skeete and Skeete (2015), Önder et al. (2019), and Önder et al. (2020) are the notable exceptions. Wu et al. (2017) pointed out that mixed-frequency models are worth exploring in tourism demand forecasting. Traditionally, to keep all variables at the same frequency when estimating econometric models, researchers tend to aggregate high-frequency data into low-frequency data; however, this process often results in information loss. The MIDAS model, used in this study, can effectively address the information loss problem because variables of different frequencies can be used simultaneously in model estimation. As more information is considered in the MIDAS model, it is plausible to assume that this model could generate more accurate tourism demand forecasts.

Because tourist-generated online reviews provide useful reflections of tourists' attention and preferences (Ye, Law, & Gu, 2009), it is reasonable to apply tourism-related online review data to forecast tourism demand using the MIDAS model. Specifically, review volume data can reflect tourists' attention, whereas review rating data can represent tourists' preferences and sentiments towards a destination (Fang, Ye, Kucukusta, & Law, 2016; Geetha, Singha, & Sinha, 2017; Liu & Park, 2015). Fang et al. (2016) argued that review ratings constitute an overall assessment of consumers' experience quality, and people can identify consumers' sentiments and attitudes through review ratings in a timely manner. Moreover, estimation results from Geetha et al. (2017) revealed consistency between customers' review ratings and their feelings (i.e., review sentiments) for budget and premium hotels. As such, the current study integrates high-frequency volume- and valence-based variables (i.e., review volume and review rating) in a destination tourism demand forecasting system. In addition, a robustness check is conducted through replacing review valence (i.e., review rating) by review sentiment by analyzing the review textual content.

3. Methodology

Hong Kong is known as "Asia's World City" for its unique culture that combines a Western lifestyle with Chinese traditions (Brand Hong Kong, 2018). The objective of this study was to employ user-generated online review data to forecast tourist arrivals in Hong Kong. Review data used in this study were obtained from TripAdvisor. Compared with other

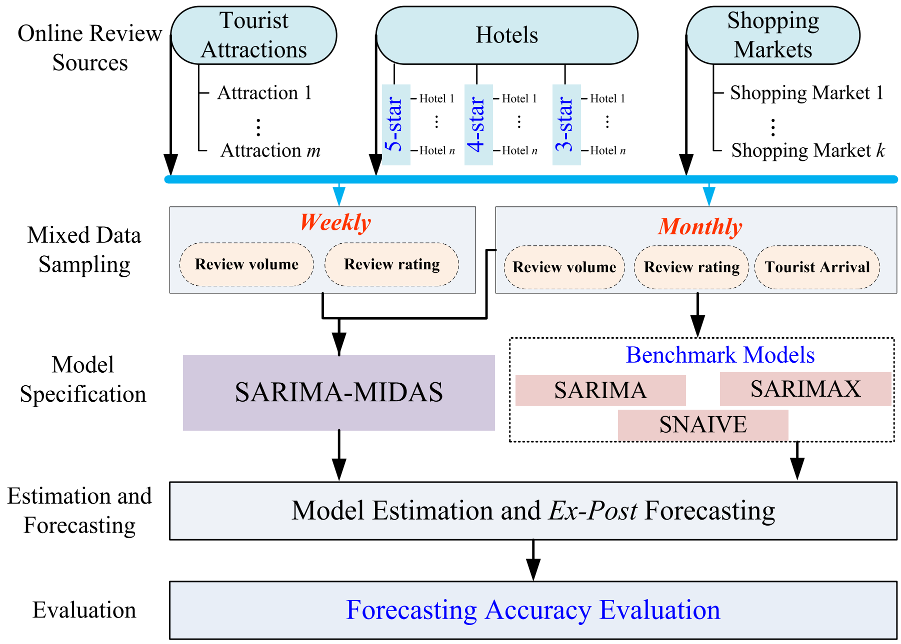

Fig. 1. Online review-based tourism demand forecasting system.

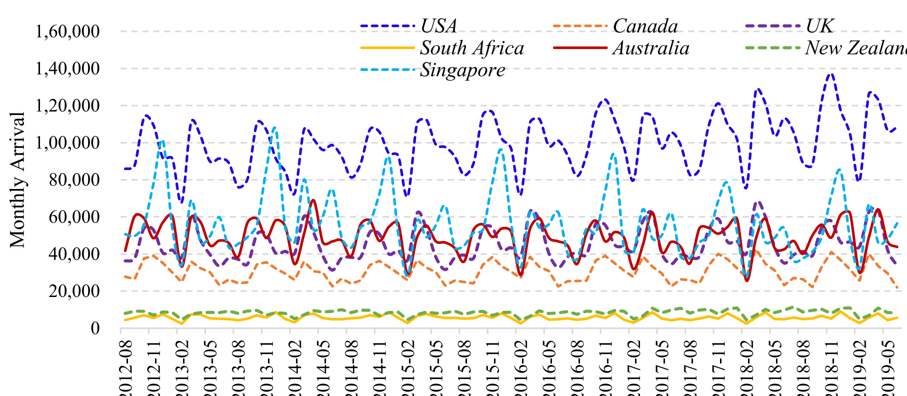

Fig. 2. Monthly tourist arrivals in Hong Kong from seven source countries.

online review websites, TripAdvisor has been recognized as the most popular review platform in the tourism industry (Taecharungroj & Mathayomchan, 2019). More than 70% of reviews on the platform appeared in English; as such, tourist arrivals from seven major English-speaking source markets (the USA, Canada, the UK, South Africa, Australia, New Zealand, and Singapore) were examined to avoid language bias (Dergiades et al., 2018). According to Hong Kong Tourism Board, the respective market share of tourist arrivals from these countries in 2018 was 20.02‰, 5.80‰, 8.79‰, 1.05‰, 8.91‰, 1.68‰, and 9.37‰, respectively.

3.1. Framework and data

A holistic framework (see Fig. 1) is proposed to integrate weekly user-generated online review data with monthly tourist arrival data in the forecasting system. This framework includes five steps: (1) collecting destination online review data, (2) processing data and generating variables to be included in the models, (3) specifying the models, (4) estimating the models and generating forecasts, and (5) evaluating *ex-post* forecasting accuracy.

The first step involved identifying the number of tourist arrivals and gathering online review data. Monthly tourist arrivals from the seven chosen source markets were obtained from the Hong Kong Tourism Board (www.discoverhongkong.com; see Fig. 2). To construct user-generated online review variables for a destination such as Hong Kong, online review data were collected for the following major tourism-related sectors: tourist attractions, hotels, and shopping markets. Specifically, seven well-known tourist attractions in Hong Kong were chosen, each of which was reviewed more than 10,000 times on the platform (i.e., Victoria Peak, Star Ferry, Hong Kong Disneyland, Hong Kong Skyline, Tian Tan Buddha, Hong Kong Tramways, and Ocean Park). For hotels, the top three with the highest number of reviews per level (5, 4, and 3 stars) were selected; online review data for nine hotels were collected in total. Regarding shopping markets, online review data for the three markets with the most reviews (i.e., Stanley Market, Ladies Market, and Temple Street Night Market) were collected. Online reviews were obtained on the selected platform from August 2012 to June 2019, with a total of 157,223 reviews included. The number of reviews for each chosen tourist attraction, hotel, and shopping mall is shown in Table 1A in the Appendix.

The second step entailed data processing and variable generation. Reviews on each tourist attraction, hotel, and shopping mall are recorded daily. As they are not continuous and stable in explaining tourism demand, weekly and monthly online review volume and average review

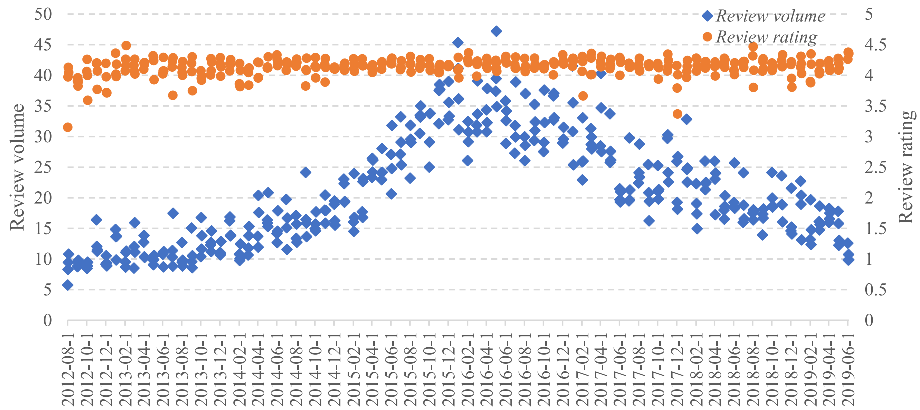

Fig. 3. Weekly online review volume and average review rating.

Table 1
Descriptive statistics of variables.

Variables	Description	Period	Frequency	Max	Min	Mean	Std. Dev.
TD^1	Tourist arrivals from the USA	August 2012–June 2019	Monthly	137,397	67,851	99,873	14,822
TD^2	Tourist arrivals from Canada	August 2012–June 2019	Monthly	42,708	22,159	30,518	5392
TD^3	Tourist arrivals from the UK	August 2012–June 2019	Monthly	67,731	31,307	45,269	9128
TD^4	Tourist arrivals from South Africa	August 2012–June 2019	Monthly	9009	2445	5705	1507
TD^5	Tourist arrivals from Australia	August 2012–June 2019	Monthly	69,005	25,649	49,083	9011
TD^6	Tourist arrivals from New Zealand	August 2012–June 2019	Monthly	11,521	4395	8432	1588
TD^7	Tourist arrivals from Singapore	August 2012–June 2019	Monthly	107,150	27,431	56,135	16,490
$VOLUME_{MONTHLY}$	Monthly online review volume of the destination	August 2012–June 2019	Monthly	1195.67	266.67	631.42	252.17
$RATING_{MONTHLY}$	Monthly average online review rating of the destination	August 2012–June 2019	Monthly	4.34	3.83	4.13	0.09
$VOLUME_{WEEKLY}$	Weekly online review volume of the destination	August 2012–June 2019	Weekly	47.18	5.75	20.94	8.77
$RATING_{WEEKLY}$	Weekly average online review rating of the destination	August 2012–June 2019	Weekly	4.49	3.15	4.13	0.15
$H-VOLUME_{WEEKLY}$	Hotels' online review volume by week	August 2012–June 2019	Weekly	19.89	3.44	10.39	3.04
$H-RATING_{WEEKLY}$	Hotels' average online review rating by week	August 2012–June 2019	Weekly	4.79	3.32	4.39	0.19
$SM-VOLUME_{WEEKLY}$	Shopping markets' online review volume by week	August 2012–June 2019	Weekly	17.33	1.00	6.29	2.72
$SM-RATING_{WEEKLY}$	Shopping markets' average online review rating by week	August 2012–June 2019	Weekly	4.50	1.11	3.59	0.37
$A-VOLUME_{WEEKLY}$	Tourist attractions' online review volume by week	August 2012–June 2019	Weekly	109.86	11.57	46.16	21.54
$A-RATING_{WEEKLY}$	Tourist attractions' average online review rating by week	August 2012–June 2019	Weekly	4.59	4.12	4.43	0.07

rating ($VOLUME_{WEEKLY}$, $RATING_{WEEKLY}$, $VOLUME_{MONTHLY}$, and $RATING_{MONTHLY}$) were generated based on the data collected in Step 1. Weekly variables were computed following Qin and Liu (2019). Specifically, the first, second, and third seven days of a month were considered as the first, second, and third weeks of that month, and the remaining days encompassed the fourth week. Initially, all reviews for a given tourist attraction, hotel, or shopping market were listed by their time stamps. Online review ratings in the corresponding week or month (identified by time stamps) were next averaged to generate the weekly or monthly rating variable for a certain tourist attraction, hotel, or shopping mall. Then, the online review volume in the corresponding week or month (again identified by time stamps) was summed to generate the weekly or monthly volume variable for a specific tourist attraction, hotel, or shopping mall. The values for the first three weeks for the weekly online review variable can be simply calculated as the rule. The value of the fourth week of a month for the weekly online review volume can be calculated as seven times the average online review volume on the remaining days. Descriptive statistics for the online review variable for our chosen attractions, hotels, and shopping malls are presented in Table 1A in the Appendix. Weekly online review volume and review ratings appear in Fig. 3; here, the weekly online review volume and rating were calculated using the mean of all tourist attractions, hotels, and shopping malls. Descriptive statistics for all key variables in this study are listed in Table 1.

The third step was model specification. Several models containing user-generated online reviews were included to evaluate forecasting performance: (a) the SARIMA-MIDAS model, which incorporated weekly online review volume, rating, and monthly tourist arrival data; and (b) benchmarks. Benchmark models included a seasonal autoregressive integrated moving average (SARIMAX) model with monthly online review volume and rating data as explanatory variables; a seasonal autoregressive integrated moving average (SARIMA) model, which corresponded to the SARIMA-MIDAS model; and a seasonal NAÏVE (SNAÏVE) model.

In the fourth and fifth steps, models were estimated and *ex-post* forecasts were generated and compared. For each source country, the SARIMA-MIDAS and benchmark models were estimated based on training data (August 2012–June 2016), and 36 one-step-ahead forecasts were generated recursively with an extending window. The forecasting performances of the SARIMA-MIDAS and benchmark models were examined based on the mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), root mean square percentage error (RMSPE), and mean absolute scaled error (MASE). Relative comparisons of forecasting models were conducted using the Diebold-Mariano test (Harvey, Leybourne, & Newbold, 1997) and relative improvement, which was calculated based on pairwise comparisons of MAE, MAPE, RMSE, RMSPE, and MASE.

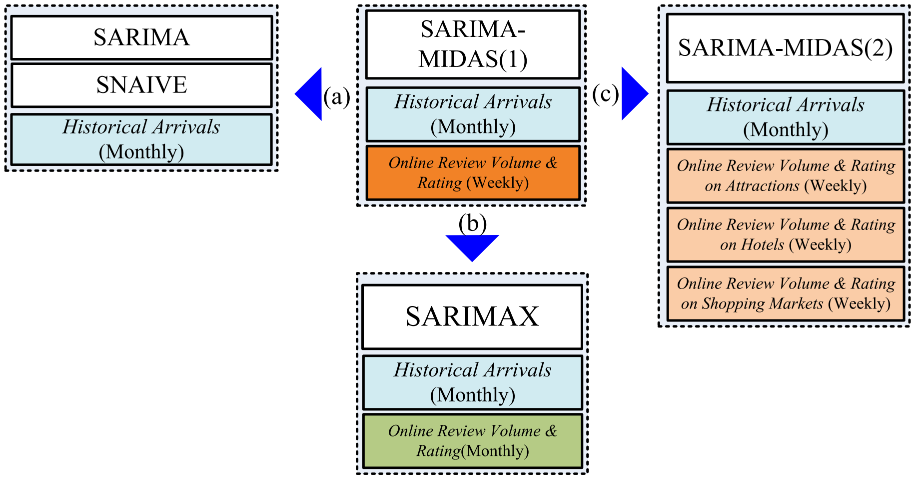

Fig. 4. Empirical framework.

3.2. The models

3.2.1. Seasonal autoregressive integrated moving Average–Mixed data sampling (SARIMA-MIDAS) model

When high- and low-frequency variables exist simultaneously, the traditional approach involves conducting estimation by aggregating all high-frequency variables to low-frequency variables using an equal weight strategy for high-frequency variables. Aggregated low-frequency variables may lose some features in high-frequency data, leading to inefficient and biased model estimation (Armesto, Engemann, & Owyang, 2010). The MIDAS regression model, proposed by Ghysels, Santa-Clara, and Valkanov (2006) and Andreou, Ghysels, and Kourtellos (2011), can incorporate high-frequency variables into a low-frequency process with a parsimonious weighting scheme. Few tourism studies have applied the MIDAS model, with the following exceptions: Bangwayo-Skeete and Skeete (2015), Gunter et al. (2019), Volchek et al. (2019), Önder et al. (2020), and Wen, Liu, Song, and Liu (2021). Following the mixed-frequency forecasting model used by Wen et al. (2021), a SARIMA-MIDAS model was employed in this research. Consider the following SARIMA-MIDAS model with weekly online review volume and average review rating ($VOLUME_{WEEKLY}$ and $RATING_{WEEKLY}$):

$$TD_t = \mu + \lambda_1 \cdot \sum_{k=1}^{m} \omega(k,\Theta) L_{HF}^{k} VOLUME_{WEEKLY\,t-h} + \lambda_2 \cdot \sum_{k=1}^{m} \omega(k,\Theta) L_{HF}^{k} RATING_{WEEKLY\,t-h} + \eta_t$$

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

where TD_t denotes current tourism demand; μ is a constant; η_t is the error from the MIDAS regression model; B is the backshift operator; $\varphi(x)$ and $\theta(x)$ represent the nonseasonal AR(p) and MA(q) components, respectively; m represents the data frequency; $\Phi(x)$ and $\Theta(x)$ represent the seasonal AR(P) and seasonal MA(Q) components, respectively; $\lambda_1 \cdot \sum_{k=1}^{m} \omega(k,\Theta) L_{HF}^{k} VOLUME_{WEEKLY\,t-h}$ and $\lambda_2 \cdot \sum_{k=1}^{m} \omega(k,\Theta) L_{HF}^{k} RATING_{WEEKLY\,t-h}$ constitute the MIDAS component; λ_1 and λ_2 are the coefficients of the high-frequency explanatory variables $VOLUME_{WEEKLY}$ and $RATING_{WEEKLY}$, respectively; h is the forecasting horizon; and $\omega(k,\Theta)$ denotes polynomials that determine the weights for high-frequency variable aggregation. The Akaike information criterion (AIC) was used in the model selection process.

When integrating the weekly online review volume and average review rating for a tourist attraction, hotel, or shopping mall (i.e., $VOLUME_{WEEKLY}^{Tourst\ Attraction}$, $VOLUME_{WEEKLY}^{Hotel}$, $VOLUME_{WEEKLY}^{Shopping\ mall}$, $RATING_{WEEKLY}^{Tourst\ Attraction}$, $RATING_{WEEKLY}^{Hotel}$, and $RATING_{WEEKLY}^{Shopping\ mall}$), a SARIMA-MIDAS model with six weekly variables can be specified as follows:

$$TD_t = \mu + \lambda_1 \cdot \sum_{k=1}^{m} \omega_1(k,\Theta) L_{HF}^{k} VOLUME_{WEEKLY}^{Tourst\ Attraction} t-h$$

$$+ \ldots + \lambda_6 \cdot \sum_{k=1}^{m} \omega_6(k,\Theta) L_{HF}^{k} RATING_{WEEKLY}^{Shopping\ mall} t-h + \eta_t$$

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

The most popular specifications for $\omega(k,\Theta)$ are the Almon lag polynomial model, exponential Almon lag polynomial model, and beta model (Bangwayo-Skeete & Skeete, 2015; Gunter et al., 2019; Volchek et al., 2019; Önder et al., 2020; Wen et al., 2021). Bangwayo-Skeete and Skeete (2015) and Wen et al. (2021) both indicated that different weighting schemes make little difference when estimating the MIDAS model. Wen et al. (2021) suggested that the exponential Almon lag polynomial (Almon, 1965) performs optimally in forecasting and nowcasting. The forecasting comparison in Table 3A and the MCS test (Hansen, Lunde, & Nason, 2011), shown in Table 4A of the Appendix, confirmed that the SARIMA-MIDAS(1) model with an exponential Almon lag polynomial weight scheme performed best. We therefore used this same weight scheme:

3.2.2. Seasonal autoregressive integrated moving average (SARIMA) model

ARIMA is a classical time-series model that integrates autoregressive and moving average processes and the differences of variables into model specification. It belongs to the family of autoregressive and moving average (ARMA) models. ARMA family models are commonly used as benchmarks in tourism demand forecasting (Hu & Song, 2020; Li, Hu, & Li, 2020; Li, Pan, Law, & Huang, 2017; Pan & Yang, 2017;

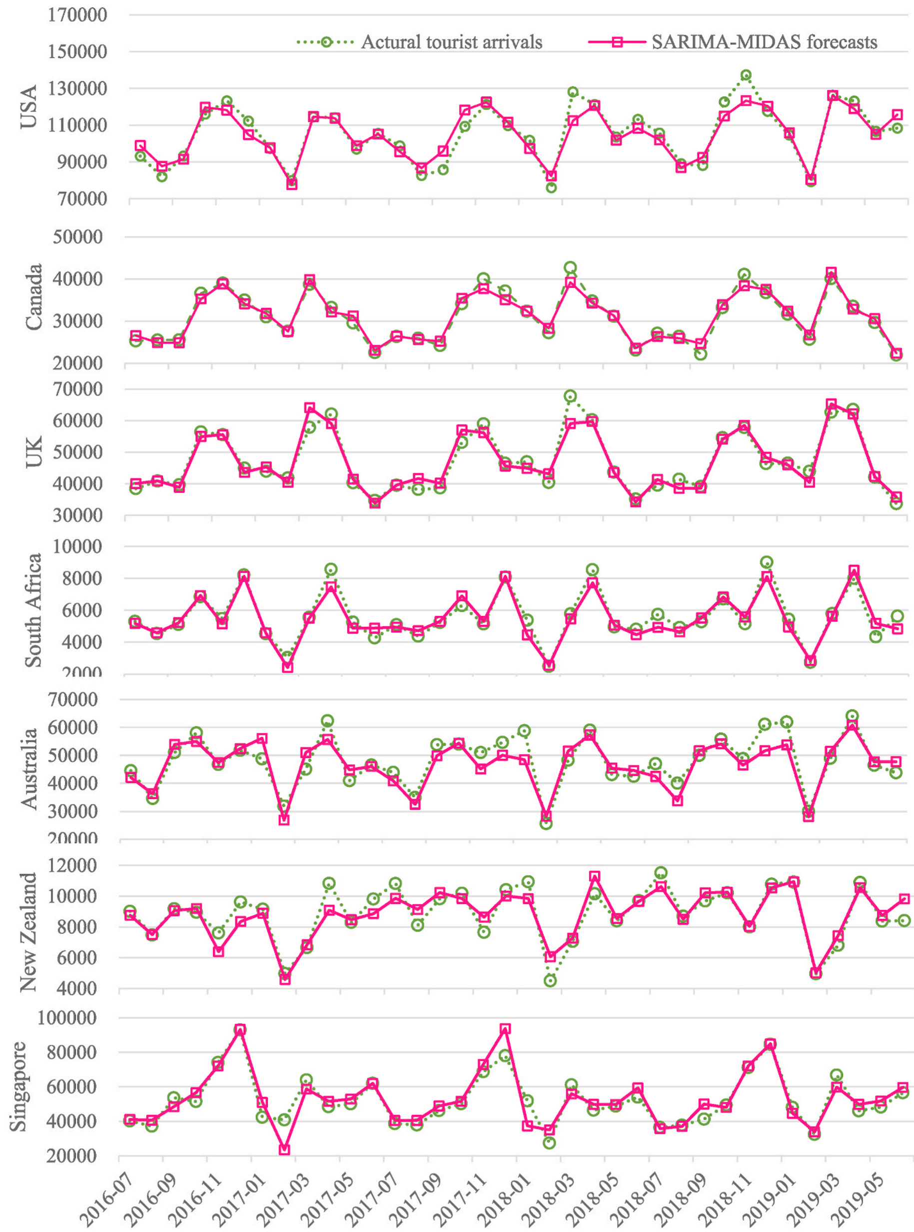

Fig. 5. One-step-ahead out-of-sample forecasting values of SARIMA-MIDAS(1).

Park, Lee, & Song, 2017; Wang, Luo, Tang, & Ge, 2018; Zhang, Li, Muskat, Law, & Yang, 2020). The ARIMA(p,d,q) model is written as

When considering the seasonality of tourism demand, seasonal ARIMA (SARIMA) can be used. The SARIMA (p, d, q)(P, D, Q) model in this study is written as

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

where TD_t denotes tourism demand at time t; $\varphi(B) = (1 - \sum_{i=1}^{p} \varphi_i B^i)$ is the AR component; $\theta(B) = (1 + \sum_{i=1}^{q} \theta_i B^i)\varepsilon_t$ is the MA component; $(1-B)^d$ is the d times difference indicator; $\Phi(B)$ and $\Theta(B)$ are the components of seasonal AR(P) and MA(Q), respectively.

3.2.3. Seasonal autoregressive integrated moving average model with exogenous variable (SARIMAX)

SARIMAX integrates the explanatory variables in the SARIMA model. In this case, the lagged monthly online review volume and average review rating variables ($VOLUME_{MONTHLY}$ and $RATING_{MONTHLY}$) were included as the exogenous variable. The SARIMAX model is specified as

$$\Phi(B^m)\varphi(B)(1-B^m)^D(1-B)^d TD_t = \mu + \sum_{j=1}^{m} \beta_j \cdot VOLUME_{MONTHLY\,t-j} + \sum_{j=1}^{m} \gamma_j \cdot RATING_{MONTHLY\,t-j} + \Theta(B^m)\theta(B)\varepsilon_t$$

Table 2
One-step-ahead out-of-sample forecasting accuracy measures.

	SARIMA-MIDAS(1)	Benchmark models		Improvement (SARIMA-MIDAS[1] vs.)	
		SARIMA	SNAÏVE	SARIMA	SNAÏVE
MAE					
USA	4109.79	4380.80	5043.86	**6.19%**	**18.52%**
Canada	1007.95	1038.85	1173.86	**2.97%**	**14.13%**
UK	1822.61	1903.97	2220.97	**4.27%**	**17.94%**
South Africa	365.93	382.90	417.67	**4.43%**	**12.39%**
Australia	3615.57	3221.81	3372.00	−12.22%	−7.22%
New Zealand	554.62	562.75	585.75	**1.45%**	**5.32%**
Singapore	4295.47	4440.41	4491.97	**3.26%**	**4.37%**
MAPE					
USA	0.0392	0.0416	0.0469	**5.83%**	**16.47%**
Canada	0.0319	0.0335	0.0374	**4.88%**	**14.80%**
UK	0.0377	0.0388	0.0447	**2.94%**	**15.75%**
South Africa	0.0666	0.0707	0.0811	**5.80%**	**17.88%**
Australia	0.0755	0.0660	0.0734	−14.45%	−2.91%
New Zealand	0.0663	0.0669	0.0656	**0.93%**	**−1.03%**
Singapore	0.0888	0.0903	0.0946	**1.68%**	**6.15%**
RMSE					
USA	5527.31	5387.06	6323.05	−2.60%	**12.58%**
Canada	1273.33	1383.69	1436.86	**7.98%**	**11.38%**
UK	2526.74	2619.13	2892.47	**3.53%**	**12.64%**
South Africa	476.98	499.86	508.93	**4.58%**	**6.28%**
Australia	4375.58	4231.33	4031.80	−3.41%	−8.53%
New Zealand	741.30	752.12	769.70	**1.44%**	**3.69%**
Singapore	5992.51	6060.24	5916.23	**1.12%**	−1.29%
RMSPE					
USA	0.0510	0.0499	0.0568	−2.18%	**10.23%**
Canada	0.0392	0.0450	0.0442	**12.90%**	**11.32%**
UK	0.0485	0.0492	0.0540	**1.43%**	**10.19%**
South Africa	0.0864	0.0917	0.0998	**5.78%**	**13.43%**
Australia	0.0886	0.0827	0.0913	−7.08%	**3.01%**
New Zealand	0.0956	0.0960	0.0823	**0.39%**	−16.19%
Singapore	0.1268	0.1274	0.1366	**0.46%**	**7.17%**
MASE					
USA	0.9913	1.0568	1.2062	**6.19%**	**17.81%**
Canada	0.9460	0.9795	1.1005	**3.42%**	**14.04%**
UK	1.0304	1.0713	1.2566	**3.81%**	**18.00%**
South Africa	0.8441	0.8849	0.9645	**4.61%**	**12.48%**
Australia	1.2273	1.0909	1.1434	−12.51%	−7.34%
New Zealand	1.1285	1.1434	1.1975	**1.30%**	**5.76%**
Singapore	0.7181	0.7354	0.7520	**2.35%**	**4.50%**

Note: Forecasting accuracies of SARIMA-MIDAS(1) with different weight functions for the high-frequency component are presented in Table 3A in the Appendix.

where $VOLUME_{MONTHLY\,t-j}$ is the j^{th} month delayed online review volume; $RATING_{MONTHLY\,t-j}$ is the j^{th} month delayed average online review rating; and β_j and γ_j are the coefficients for $VOLUME_{MONTHLY\,t-j}$ and $RATING_{MONTHLY\,t-j}$, respectively.

3.2.4. Seasonal NAÏVE (SNAÏVE) model

Seasonal NAÏVE (SNAÏVE) is an important benchmark for monthly or quarterly tourism demand forecasting; therefore, we used SNAÏVE as one of our benchmark models. SNAÏVE returns forecasts from an ARIMA (0,0,0)(0,1,0)*m* model:

$$\widehat{TD}_t = TD_{t-m}$$

where m is the seasonal period; $\widehat{TD}_t$ is the forecasted tourism demand for time t; and TD_{t-m} is the historical tourism demand for time *t-m*.

3.3. Forecasting accuracy evaluation

MAE, *MAPE*, *RMSE*, *RMSPE*, and *MASE* were used to determine forecasting errors. A smaller value of these indices reflects better performance, calculated as follows:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \widehat{y}_i|}{n} \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{y}_i|}{y_i} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \tag{3}$$

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \widehat{y}_i}{y_i}\right)^2} \tag{4}$$

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \widehat{y}_i|}{\frac{1}{T_i - m}\sum_{j=1}^{T_i - m}|y_{j+m} - y_j|} \tag{5}$$

where y_i is the actual number of tourist arrivals; $\widehat{y}_i$ is the forecasted number of tourist arrivals; n is the number of testing samples; m is the frequency of tourist arrivals; and T_i is the number of model estimation samples when forecasting $\widehat{y}_i$.

4. Results

In our study, one time-series model (i.e., SARIMA) and one simple and effective model suitable for highly seasonal data (i.e., SNAÏVE) were used as benchmarks. SARIMAX with monthly online review ratings and volume as explanatory variables was used as another benchmark model to evaluate the forecasting performance of the SARIMA-MIDAS(1) model, in which weekly tourism-related online review volume and rating were integrated as explanatory variables. We also compared the SARIMA-MIDAS(1) and SARIMA-MIDAS(2) models; in the latter, decomposed weekly tourism-related online review variables reflecting destination dimensions (e.g., tourist attractions, hotels, and shopping malls) were taken as explanatory variables.

In general, there were three comparison groups (see Fig. 4): (a) comparing SARIMA-MIDAS(1) with time-series models, including the SARIMA and SNAÏVE; (b) comparing SARIMA-MIDAS(1) with the constant frequency SARIMAX model, where the aggregated monthly online review volume and rating were incorporated as an explanatory variable; and (c) comparing SARIMA-MIDAS(1) with the online review volume and rating to the SARIMA-MIDAS(2) model with decomposed weekly online review variables.

One-step-ahead out-of-sample forecasts were generated to test the forecasting performance of the SARIMA-MIDAS model with the weekly online review variables (i.e., SARIMA-MIDAS[1]). Following Bangwayo-Skeete and Skeete (2015), we chose 36 months as the out-of-sample forecasting period. For all models, our initial in-sample estimations were conducted based on data from August 2012 to June 2016. Then, the estimations were continuously calculated by

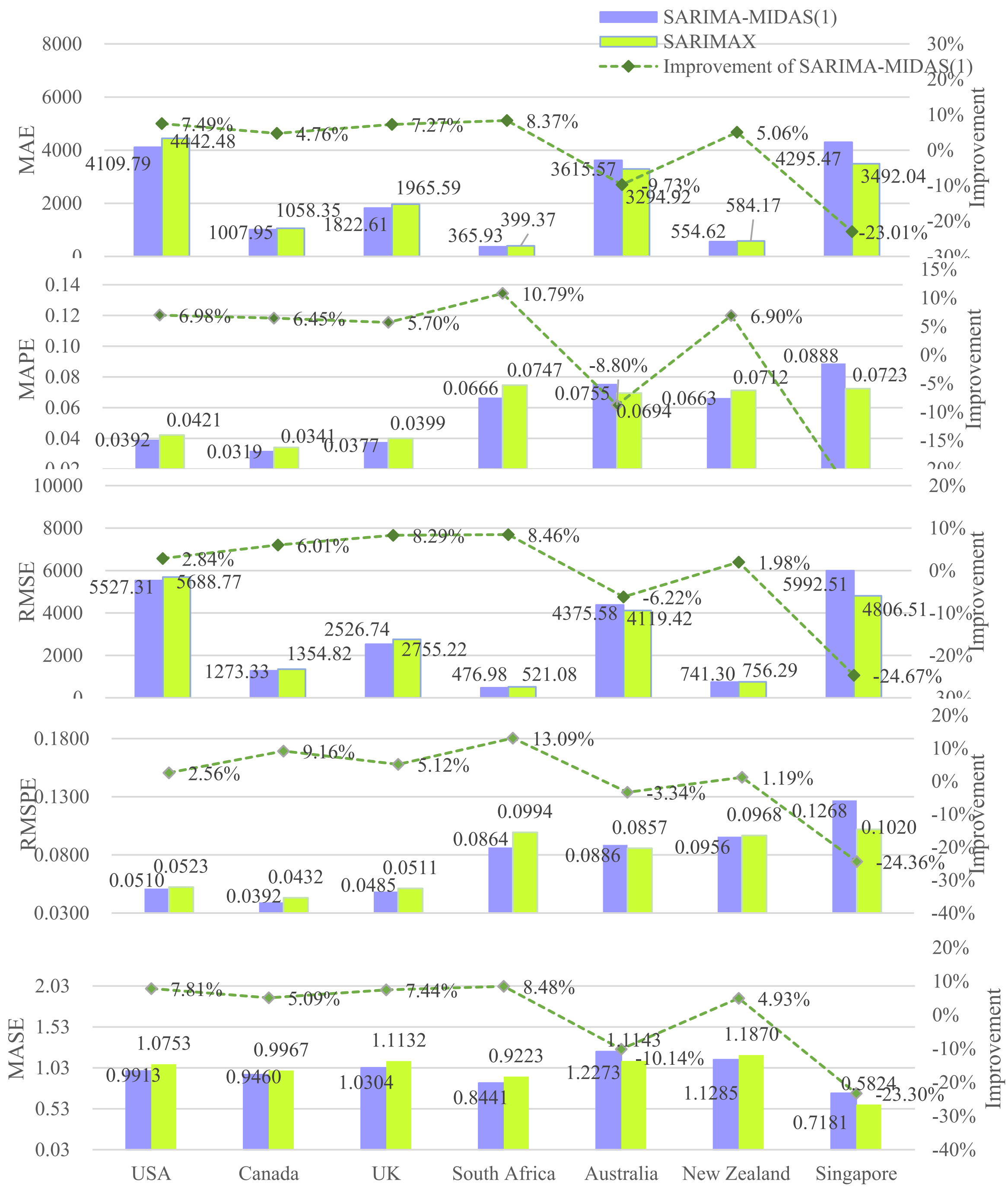

Fig. 6. Forecasting accuracy of SARIMA-MIDAS(1) and SARIMAX models.

Table 3
Forecasting accuracy comparisons across source markets.

	MAE			MAPE			MASE		
Source Countries	SARIMA-MIDAS(1)	SARIMA-MIDAS(2)	Improvement	SARIMA-MIDAS(1)	SARIMA-MIDAS(2)	Improvement	SARIMA-MIDAS(1)	SARIMA-MIDAS(2)	Improvement
USA	4109.79	4454.88	**7.75%**	0.0392	0.0415	**5.71%**	0.9913	1.0742	**7.71%**
Canada	1007.95	1100.64	**8.42%**	0.0319	0.0348	**8.32%**	0.9460	1.0351	**8.60%**
UK	1822.61	1837.67	**0.82%**	0.0377	0.0377	**0.11%**	1.0304	1.0368	**0.61%**
South Africa	365.93	380.93	**3.94%**	0.0666	0.0694	**4.04%**	0.8441	0.8783	**3.90%**
Australia	3615.57	3412.45	−5.95%	0.0755	0.0729	−3.68%	1.2273	1.1465	−7.05%
New Zealand	554.62	568.47	**2.44%**	0.0663	0.0687	**3.58%**	1.1285	1.1580	**2.55%**
Singapore	4295.47	5133.75	**16.33%**	0.0888	0.1032	**14.00%**	0.7181	0.8539	**15.90%**
	RMSE			**RMSPE**					
Source Countries	SARIMA-MIDAS(1)	SARIMA-MIDAS(2)	Improvement	SARIMA-MIDAS(1)	SARIMA-MIDAS(2)	Improvement			
USA	5527.31	5881.86	**6.03%**	0.0510	0.0526	**3.09%**			
Canada	1273.33	1450.07	**12.19%**	0.0392	0.0436	**10.12%**			
UK	2526.74	2622.16	**3.64%**	0.0485	0.0495	**1.95%**			
South Africa	476.98	512.32	**6.90%**	0.0864	0.0878	**1.65%**			
Australia	4375.58	4393.18	**0.40%**	0.0886	0.0925	**4.31%**			
New Zealand	741.30	738.66	−0.36%	0.0956	0.0971	**1.49%**			
Singapore	5992.51	6898.04	**13.13%**	0.1268	0.1429	**11.28%**			

Note: **SARIMA-MIDAS(1):** SARIMA-MIDAS with online review volume and rating. **SARIMA-MIDAS(2):** SARIMA-MIDAS with decomposed online review variables, reflecting different tourism destination dimensions (i.e., tourist attractions, hotels, and shopping markets). The performance of SARIMA-MIDAS with decomposed online review variables is shown in Table 4A in the Appendix.

Table 4
Diebold-Mariano (DM) test statistics.

	DM test statistics (SARIMA-MIDAS[1] vs.)			
	SARIMA	SNAÏVE	SARIMAX	SARIMA-MIDAS (2)
USA	**−1.9242****	**−5.6829*****	**−1.9963 ****	**−4.2167 *****
Canada	**−1.1503**	**−4.1682*****	**−2.2148 ****	**−8.0505 *****
UK	**−1.9024****	**−6.2647*****	**−2.4672 *****	**−1.5525 ***
South Africa	**−1.5606***	**−3.2984*****	**−2.8616 *****	**−1.3078 ***
Australia	7.84	2.08	5.07	0.78
New Zealand	**−1.5850***	**−1.3536***	**−2.9271 *****	**−1.2001**
Singapore	**−1.3754***	**−1.1212**	6.95	**−2.8163 *****

Note: *, **, and *** indicates the significance levels at 1%, 5%, and 10%, respectively. A negative significant value indicates that the forecasting performance using SARIMA-MIDAS is significantly better than the benchmark models, including SARIMA and SNAÏVE.

incorporating one observation at a time until May 2019. SARIMA-MIDAS(1) estimation results for all selected source markets are presented in Table 2A in Appendix. A one-step-ahead out-of-sample forecast was generated after each estimation. Therefore, 36 one-step-ahead forecasts were generated in total, corresponding to July 2016–June 2019. Forecasts from the SARIMA-MIDAS(1) model for all source markets appear in Fig. 5.

Forecasting performance measures (MAE, MAPE, RMSE, RMSPE, and MASE) were calculated for each model, as these accuracy measures are often used in tourism demand forecasting (Wen et al., 2021; Önder et al., 2020). Furthermore, the forecasting performance measures were compared between SARIMA-MIDAS(1) and other benchmark models.

First, the forecasting performance of SARIMA-MIDAS(1) was compared with time-series models. Forecasting accuracy and enhancements are presented in Table 2. Relative comparisons were based on the Diebold-Mariano test and the improvement in Model A compared to Model B, which was measured as follows, taking MAE as an example:

$$\text{Improvement} = \frac{MAE(B) - MAE(A)}{MAE(B)} \times 100\%.$$

According to Table 2, compared with benchmark models (i.e., SARIMA and SNAÏVE), the SARIMA-MIDAS(1) model with high-frequency online review volume and rating as leading indicators improved the forecasting accuracy for most source countries under consideration. In particular, when comparing the forecasting performance of the SARIMA-MIDAS(1) model with that of the SARIMA and SNAÏVE models, the former demonstrated better forecasting accuracy in most source markets except Australia. These results verified the positive roles of online review volume and review ratings in tourism demand forecasting. Online review volume represents the number of tourists discussing a destination on the platform, which reflects tourists' awareness of the destination's tourism products. Online review ratings mirror previous tourists' endorsement of these products, thereby capturing tourists' preferences or sentiment orientation (Dellarocas et al., 2007; Duan et al., 2008). Both concepts can theoretically inform tourists' destination choices. Our empirical results showed that the SARIMA-MIDAS(1) model, with high-frequency online review volume and ratings as leading indicators, could significantly improve tourism demand forecasting accuracy.

Second, when comparing the forecasting performance of the SARIMA-MIDAS(1) model with that of the SARIMAX model when including monthly online review variables as explanatory variables, the results indicated enhanced forecasting accuracy for the SARIMA-MIDAS (1) model versus the SARIMAX model (see Fig. 6). MAE, MAPE, RMSE, RMSPE, and MASE measures for the two models revealed that the SARIMA-MIDAS(1) model consistently outperformed the SARIMAX model for most source markets except Australia and Singapore. For instance, forecasting performance improved from 4.76% to 8.37% in terms of MAE, from 5.7% to 10.79% in terms of MAPE, from 1.98% to 8.46% in terms of RMSE, from 1.19% to 13.09% in terms of RMSPE, and from 4.93% to 8.48% in terms of MASE. These results suggest the superiority of the SARIMA-MIDAS(1) model in extracting high-frequency

Table 5
2- and 3-steps-ahead forecasting accuracy.

	2-steps-ahead forecasting			3-steps-ahead forecasting		
	SARIMA-MIDAS(1)	SARIMA	SNAÏVE	SARIMA-MIDAS(1)	SARIMA	SNAÏVE
MAE						
USA	***4361.93***	5047.22	5043.86	***3904.66***	5010.86	5043.86
Canada	***997.91***	1258.95	1173.86	***933.49***	1249.91	1173.86
UK	***1728.84***	1861.75	2220.97	***1790.20***	1978.83	2220.97
South Africa	***385.55***	388.41	417.67	391.13	***363.39***	417.67
Australia	3344.90	***3295.14***	3372.00	***3284.82***	3299.85	3372.00
New Zealand	***577.09***	592.28	585.75	***569.64***	611.08	585.75
Singapore	4592.98	***3702.41***	4491.97	4709.81	***3718.63***	4491.97
MAPE						
USA	***0.0414***	0.0477	0.0469	***0.0373***	0.0469	0.0469
Canada	***0.0317***	0.0413	0.0374	***0.0303***	0.0412	0.0374
UK	***0.0349***	0.0377	0.0447	***0.0369***	0.0405	0.0447
South Africa	0.0717	***0.0704***	0.0811	0.0738	***0.0658***	0.0811
Australia	0.0701	***0.0675***	0.0734	0.0684	***0.0677***	0.0734
New Zealand	***0.0684***	0.0688	0.0656	***0.0678***	0.0708	0.0656
Singapore	0.0930	***0.0751***	0.0946	0.0997	***0.0759***	0.0946
RMSE						
USA	***5510.07***	6040.00	6323.05	***5329.45***	6170.79	6323.05
Canada	***1307.11***	1594.73	1436.86	***1248.62***	1578.84	1436.86
UK	***2489.06***	2574.62	2892.47	***2568.34***	2671.54	2892.47
South Africa	545.71	***495.31***	508.93	481.95	***475.60***	508.93
Australia	***4209.64***	4351.65	4031.80	***4156.09***	4292.26	4031.80
New Zealand	783.00	***767.94***	769.70	***740.05***	797.73	769.70
Singapore	6168.01	***5009.28***	5916.23	6427.42	***5029.00***	5916.23
RMSPE						
USA	***0.0501***	0.0557	0.0568	***0.0494***	0.0565	0.0568
Canada	***0.0402***	0.0525	0.0442	***0.0397***	0.0528	0.0442
UK	***0.0462***	0.0483	0.0540	***0.0487***	0.0506	0.0540
South Africa	0.1008	***0.0886***	0.0998	0.0934	***0.0854***	0.0998
Australia	0.0863	***0.0845***	0.0913	***0.0828***	0.0835	0.0913
New Zealand	0.0972	***0.0908***	0.0823	0.0956	***0.0926***	0.0823
Singapore	0.1308	***0.1011***	0.1366	0.1444	***0.1019***	0.1366
MASE						
USA	***1.0501***	1.2111	1.2062	***0.9478***	1.1998	1.2062
Canada	***0.9391***	1.1860	1.1005	***0.8796***	1.1729	1.1005
UK	***0.9766***	1.0468	1.2566	***1.0129***	1.1122	1.2566
South Africa	***0.8926***	0.8966	0.9645	0.9039	***0.8410***	0.9645
Australia	1.1327	***1.1126***	1.1434	1.1144	***1.1114***	1.1434
New Zealand	***1.1779***	1.2032	1.1975	***1.1538***	1.2507	1.1975
Singapore	0.7639	***0.6167***	0.7520	0.7853	***0.6205***	0.7520

Note: Bold and Italic values indicate the best forecasting performance among different models.

information from tourism-related online review data (Armesto et al., 2010). The recency effect elucidates this outcome. That is, consumers pay greater attention to recent and real-time reviews than to distant reviews before making purchase decisions (Sahin & Robinson, 2002; Zhang, Liang, Li, & Zhang, 2019). In other words, the most recent online reviews (e.g., those posted within the last week) may heavily influence tourists' travel decisions compared with reviews posted last month. Filieri and McLeay (2014) contended that information timeliness can strongly predict whether consumers put stock in hotel online reviews. These considerations could explain why high-frequency online review variables used in the mixed frequency model were more powerful in destination tourism demand forecasting.

Third, the forecasting performance of the SARIMA-MIDAS(1) model with the online review volume and rating was compared to the SARIMA-MIDAS(2) model including multidimensional online review variables reflecting numerous tourism destination dimensions (e.g., tourist attractions, hotels, and shopping markets). The results in Table 3 indicate that the SARIMA-MIDAS(1) model with the weekly online review volume and rating outperformed that with multidimensional weekly online review volume and rating in all source countries except Australia according to MAE, MAPE, RMSE, RMSPE, and MASE. One reason for this pattern might be that multicollinearity could arise when multidimensional weekly online review variables were incorporated into the SARIMA-MIDAS model. Another possible reason is that the value and variance of tourist attractions' online reviews were much higher than those of hotels and shopping markets. Outliers may affect model performance as well. A forecasting performance comparison between SARIMA-MIDAS(2) with multidimensional/decomposed online review variables and benchmark models appears in Table 5A in the Appendix.

Fourth, we conducted the Diebold-Mariano test between SARIMA-MIDAS(1) and other benchmark models to test the significance of improvement and to check the robustness of our findings. The results in Table 4 demonstrate that the improvement of SARIMA-MIDAS(1) with the online review volume and rating was significant in 71.43% of cases among all benchmarks and source markets.

Furthermore, we tested the 2- and 3-steps-ahead forecasting accuracy of SARIMA-MIDAS(1) and compared it with the time-series benchmark models (i.e., SARIMA and SNAÏVE). Table 5 shows that

Table 6
Forecasting results with extended online reviews.

	SARIMA-MIDAS(1)	Benchmark models		Improvement (SARIMA-MIDAS[1] vs.)	
		SARIMA	SNAÏVE	SARIMA	SNAÏVE
MAE					
USA	3843.46	4380.8	5043.86	**12.27%**	**23.80%**
Canada	977.81	1038.85	1173.86	**5.88%**	**16.70%**
UK	1710.16	1903.97	2220.97	**10.18%**	**23.00%**
South Africa	363.01	382.9	417.67	**5.20%**	**13.09%**
Australia	3144.15	3221.81	3372	**2.41%**	**6.76%**
New Zealand	544.52	562.75	585.75	**3.24%**	**7.04%**
Singapore	4670.16	4440.41	4491.97	−5.17%	−3.97%
MAPE					
USA	0.0365	0.0416	0.0469	**12.22%**	**22.14%**
Canada	0.0313	0.0335	0.0374	**6.44%**	**16.20%**
UK	0.0345	0.0388	0.0447	**11.02%**	**22.77%**
South Africa	0.0680	0.0707	0.0811	**3.84%**	**16.17%**
Australia	0.0660	0.066	0.0734	**0.02%**	**10.10%**
New Zealand	0.0650	0.0669	0.0656	**2.88%**	**0.96%**
Singapore	0.0957	0.0903	0.0946	−6.02%	−1.20%
RMSE					
USA	5123.95	5387.06	6323.05	**4.88%**	**18.96%**
Canada	1267.96	1383.69	1436.86	**8.36%**	**11.76%**
UK	2586.86	2619.13	2892.47	**1.23%**	**10.57%**
South Africa	466.28	499.86	508.93	**6.72%**	**8.38%**
Australia	3962.70	4231.33	4031.8	**6.35%**	**1.71%**
New Zealand	720.47	752.12	769.7	**4.21%**	**6.40%**
Singapore	6339.69	6060.24	5916.23	−4.61%	−7.16%
RMSPE					
USA	0.0469	0.0499	0.0568	**5.97%**	**17.39%**
Canada	0.0403	0.045	0.0442	**10.40%**	**8.78%**
UK	0.0472	0.0492	0.054	**4.08%**	**12.61%**
South Africa	0.0924	0.0917	0.0998	−0.77%	**7.41%**
Australia	0.0807	0.0827	0.0913	**2.40%**	**11.59%**
New Zealand	0.0939	0.096	0.0823	**2.16%**	−14.12%
Singapore	0.1322	0.1274	0.1366	−3.79%	**3.20%**
MASE					
USA	0.9346	1.0568	1.2062	**11.57%**	**22.52%**
Canada	0.9215	0.9795	1.1005	**5.93%**	**16.27%**
UK	0.9650	1.0713	1.2566	**9.92%**	**23.21%**
South Africa	0.8398	0.8849	0.9645	**5.10%**	**12.93%**
Australia	1.0628	1.0909	1.1434	**2.57%**	**7.05%**
New Zealand	1.1044	1.1434	1.1975	**3.41%**	**7.78%**
Singapore	0.7807	0.7354	0.752	−6.15%	−3.81%

Table 7
Forecasting results using review sentiment.

	SARIMA-MIDAS(1)	Benchmark models		Improvement (SARIMA-MIDAS[1] vs.)	
		SARIMA	SNAÏVE	SARIMA	SNAÏVE
MAE					
USA	3662.56	4380.8	5043.86	**16.40%**	**27.39%**
Canada	1005.91	1038.85	1173.86	**3.17%**	**14.31%**
UK	1738.08	1903.97	2220.97	**8.71%**	**21.74%**
South Africa	417.95	382.9	417.67	−9.15%	−0.07%
Australia	3168.15	3221.81	3372	**1.67%**	**6.05%**
New Zealand	541.46	562.75	585.75	**3.78%**	**7.56%**
Singapore	4885.40	4440.41	4491.97	−10.02%	−8.76%
MAPE					
USA	0.0346	0.0416	0.0469	**16.87%**	**26.26%**
Canada	0.0319	0.0335	0.0374	**4.77%**	**14.70%**
UK	0.0348	0.0388	0.0447	**10.32%**	**22.16%**
South Africa	0.0794	0.0707	0.0811	−12.33%	**2.08%**
Australia	0.0666	0.066	0.0734	−0.98%	**9.20%**
New Zealand	0.0643	0.0669	0.0656	**3.87%**	**1.97%**
Singapore	0.1004	0.0903	0.0946	−11.17%	−6.12%
RMSE					
USA	4912.31	5387.06	6323.05	**8.81%**	**22.31%**
Canada	1382.86	1383.69	1436.86	**0.06%**	**3.76%**
UK	2600.75	2619.13	2892.47	**0.70%**	**10.09%**
South Africa	510.39	499.86	508.93	−2.11%	−0.29%
Australia	3869.27	4231.33	4031.8	**8.56%**	**4.03%**
New Zealand	710.29	752.12	769.7	**5.56%**	**7.72%**
Singapore	6457.16	6060.24	5916.23	−6.55%	−9.14%
RMSPE					
USA	0.0446	0.0499	0.0568	**10.67%**	**21.52%**
Canada	0.0421	0.045	0.0442	**6.49%**	**4.80%**
UK	0.0475	0.0492	0.054	**3.45%**	**12.04%**
South Africa	0.0969	0.0917	0.0998	−5.71%	**2.87%**
Australia	0.0792	0.0827	0.0913	**4.19%**	**13.21%**
New Zealand	0.0920	0.096	0.0823	**4.15%**	−11.80%
Singapore	0.1340	0.1274	0.1366	−5.18%	**1.90%**
MASE					
USA	0.8906	1.0568	1.2062	**15.73%**	**26.16%**
Canada	0.9485	0.9795	1.1005	**3.17%**	**13.82%**
UK	0.9816	1.0713	1.2566	**8.37%**	**21.88%**
South Africa	0.9662	0.8849	0.9645	−9.19%	−0.18%
Australia	1.0707	1.0909	1.1434	**1.85%**	**6.36%**
New Zealand	1.0947	1.1434	1.1975	**4.26%**	**8.58%**
Singapore	0.8209	0.7354	0.752	−11.63%	−9.16%

SARIMA-MIDAS(1) with weekly review volume and rating outperformed both of these benchmarks for 60.00% of markets and measurements in 2-steps-ahead forecasting and for 62.86% of markets and measurements in 3-steps-ahead forecasting. In summary, Tables 2 and 5 demonstrate that SARIMA-MIDAS(1) with high-frequency review variables performed significantly better on 1-step-ahead short-term forecasting.

Lastly, we conducted two groups forecasting to check the robustness of the above results and findings. First, we examined the forecasting performance of SARIMA-MIDAS(1) with the extended review variable incorporating reviews on all hotels in Hong Kong. In addition to the selected reviews from tourist attractions, shopping malls, and nine hotels, online reviews of 1291 other hotels in Hong Kong (379,455 online reviews in total) were incorporated to generate the weekly review volume and rating. Forecasting results are shown in Table 6 and appear similar to Table 2; that is, the SARIMA-MIDAS(1) model with high-frequency online review volume and rating as the leading indicator improved the forecasting accuracy for most source countries. Second, we investigated the forecasting performance of SARIMA-MIDAS(1) using review sentiment as a replacement for review rating. Due to technical complexity and because we aimed to forecast tourism demand from English-speaking countries to Hong Kong, only the 134,262 English-language online reviews were extracted and analyzed from the selected tourist attractions, shopping malls, and hotels. The review sentiment score, ranging from 0 to 1, was calculated using the Valence Aware Dictionary for sEntiment Reasoner model (Elbagir & Yang, 2019; Hutto & Gilbert, 2014); a larger sentiment score indicates a more positive experience. Review sentiment scores for a corresponding week were averaged to generate the weekly review sentiment for each attraction, hotel, and shopping mall. The average for the weekly review sentiment for all attractions, hotels, and shopping malls, along with the weekly review volume in Table 1, served as high-frequency explanatory variables in SARIMA-MIDAS(1). The 1-step-ahead forecasting results are shown in Table 7, demonstrating that the SARIMA-MIDAS(1) model with the newly generated review variable can also outperform SARIMA and SNAÏVE in the majority of source markets and measurements. However, its forecasting ability is a bit weaker than that using review rating in Table 6. A possible reason is that review sentiment was generated based on only English-language reviews whereas review rating was calculated based on all reviews regardless of language. The 2- and 3-steps-ahead forecasting results using review sentiment are shown in Table 6A in the Appendix. The findings in Tables 7 and 6A are similar to those in Tables 2 and 5 when using review rating: the SARIMA-MIDAS (1) model with high-frequency review volume and sentiment performed significantly better in 1-step-ahead short-term forecasting.

5. Discussion and implications

By integrating tourist-generated online review data into a destination tourism demand forecasting system, this study forecasted international tourist arrivals to Hong Kong from seven major English-speaking countries. Online review data used in this work included reviews of major tourist attractions, different accommodation tiers, and major tourism shopping markets in Hong Kong. The volume and valence of online review data were also included in the forecasting models. In addition, we calculated the review sentiment and investigated the forecasting performance of SARIMA-MIDAS using review sentiment by replacing the review valence/rating. Findings indicate that (a) tourism demand forecasting based on online review data can significantly improve forecasting performance; and (b) MIDAS models outperformed alternative models in tourism demand forecasting when high-frequency online review data were incorporated into the forecasting exercise.

5.1. Theoretical contributions

5.1.1. The contributions of this research are multifold

First, our study is one of the first to use both tourists' attention and preferences/sentiments to predict tourism demand. Most other research has only considered attention-based data, such as search queries or website traffic, when forecasting tourism demand at the destination level. A demand forecasting model based solely on attention-based or Internet traffic data (i.e., search query and web traffic data) will not work well when a tourism destination is experiencing negative circumstances but tourist attention is still increasing. Therefore, imperfect data must be enriched with meaningful information to improve forecasting accuracy.

Second, this study makes an initial and meaningful attempt to incorporate online review data into destination-based tourism demand forecasting, although a few scholars have used other types of social media data for tourism forecasting. As an important source of electronic WOM, previous studies have documented the effects of online reviews on tourists' destination choices and hotel bookings (e.g., Jacobsen & Munar, 2012; Sparks & Browning, 2011). However, no prior studies have used online review data to forecast a destination's tourism demand. A major difficulty for researchers lies in the lack of an online review website where tourists can evaluate their overall travel experiences in a destination. A tourist destination experience is highly complex and can be influenced by numerous destination aspects/components, such as experiences involving tourist attractions, accommodation, and shopping. Innovatively, this study considered online reviews of major tourist attractions, accommodations, and shopping markets in Hong Kong, which enhances the literature on social media–based tourism demand forecasting.

Third, this study is one of the first few to adopt mixed-frequency modeling in tourism demand forecasting. The mixed-frequency technique is an effective way to avoid information loss from higher-frequency data (Wu et al., 2017). The empirical results of this study indicate that the MIDAS model (including high-frequency online review data) generated more accurate forecasts compared with competing models containing aggregated online review data as explanatory variables and benchmark time-series models. Therefore, this work contributes to model development in tourism demand forecasting.

5.2. Practical implications

This study also unveils important managerial implications for destination managers. First, given that social media data are sensitive to the real world and play a critical role in tourism demand forecasting, DMOs should monitor destination-related social media—including online reviews. Tourists' reviews posted one week and four weeks earlier appeared to most strongly influence current demand in this study. DMOs should thus pay particular attention to these time frames to assess potential tourism demand in a timely manner. Social media monitoring for marketing purposes is less expensive than traditional marketing approaches, such as questionnaires, interviews, or focus groups (Geva et al., 2017). Therefore, DMOs should allocate a portion of their marketing budget to social media marketing and tourism-related online review data tracking, including monitoring major tourism attractions, hotels, and shopping markets. Second, the indicators extracted from online review platforms reflect tourists' attention, awareness, preferences, and sentiments about various aspects of destinations. The rich information generated from online review data enables more accurate and timely tourism demand forecasting. Therefore, DMOs should incorporate online review data reflecting different tourism industry dimensions into tourism demand forecasting. Third, policymakers in destinations such as Hong Kong should take advantage of accurate, timely forecasting results for planning purposes. Last but not least, policymakers can easily identify possible reasons behind fluctuations in predicted tourist arrivals based on this new method. In other words, decision makers can determine which sectors contribute most to fluctuating destination demand based on tourists' attention and sentiments.

5.3. Limitations and future research

This study has a few limitations to be addressed in future work. Online review manipulation is becoming increasingly common in tourism and hospitality (Dellarocas, 2006; Mayzlin, Dover, & Chevalier, 2014). To promote review valence, many companies have posted fraudulent positive reviews for their own companies and fraudulent negative reviews for their competitors. Roughly 16% of reviews online are suspected to be fake (Luca & Zervas, 2016). The likelihood and degree of manipulation depend on several factors, such as the level of competition and businesses' initial reputation (Luca & Zervas, 2016). Therefore, incorporating potentially fake reviews into tourism demand forecasting would bias forecasts. Subsequent studies should filter out these fake reviews during model estimation and forecasting. In addition, social media data may not be fully representative (Ruths & Pfeffer, 2014): although social media data can convey aspects of the real world, it is challenging to represent the total population (Phillips et al., 2017). According to prior studies (Kalampokis, Tambouris, & Tarabanis, 2013;

Schoen et al., 2013; Weller, 2015), research using social media data may encounter generalizability problems; that is, predictions based on one type of social media data from a destination may not apply to diverse datasets and circumstances, such as when forecasting tourism demand from different source countries. To overcome this problem, future studies should include multi-source and varied social media data in tourism demand forecasting for destinations from different source markets. Moreover, scholars should consider combining social media data with other Internet big data and traditional economic data to improve models' forecasting accuracy. Lastly, we only studied the sentiment of English-language online reviews to forecast destination tourism demand. Future work could reinforce these findings by using the sentiment of online reviews written in different languages to predict tourism demand.

Impact statement

This study forecasts monthly international tourist arrivals to Hong Kong by using tourist-generated online review data, including reviews on tourist attractions, hotels, and shopping markets. Findings will inform decision makers in tourism destinations of the importance of social media data (particularly online reviews) in improving tourism forecasting accuracy. The impacts of this study are as follows:

- This study is the first to design a novel online review data analytics framework to forecast destination tourism demand and to monitor tourists' interests and preferences regarding various aspects of a tourism destination.
- Governments, destination management organizations, and tourism stakeholders can use the proposed destination forecasting system to generate accurate and timely monthly tourist forecasts and for crowd management.
- This tourism demand forecasting system can inform policymaking and increase destination competitiveness in the long term.

Author contribution statements

Mingming Hu, Hengyun Li and Xin Li conceived of the presented idea and derived the models. Mingming Hu conducted the modeling and data analysis, and discussed with Hengyun Li during the process. Mingming Hu and Hengyun Li wrote the manuscript, and Haiyan Song and Rob Law provided suggestions for improvement. Haiyan Song made a major revision on the manuscript, and Rob Law and Xin Li reviewed the manuscript and made minor revisions.

Declaration of competing interest

None.

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Rob Law participated in the early stages of this project when he was at the Hong Kong Polytechnic University.

Appendix

Table 1A
Online Review Variables description

No.	Names	*Weekly Online Review Volume*				Weekly Online Review Rating				*Number Of Reviews*
		Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	
Hotels										
3-Star-1	Butterfly on Morrison	18	0	4.49	2.86	5.00	2.00	4.25	0.43	1616
3-Star-2	Butterfly on Prat	32	0	8.14	4.56	5.00	2.00	4.31	0.39	2946
3-Star-3	Ibis Hong Kong Central & Sheung Wan	32	0	11.25	4.68	5.00	3.00	4.10	0.28	4061
4-Star-1	Dorsett Mongkok Hong Kong	26	2	11.99	4.51	4.86	3.44	4.24	0.26	4327
4-Star-2	Novotel Hong Kong Nathan Road Kowloon	33	1	12.38	4.75	4.83	3.33	4.17	0.25	4462
4-Star-3	Royal Plaza Hotel	42	0	11.76	6.64	5.00	2.50	4.45	0.33	4243
5-Star-1	InterContinental Hong Kong	35	1	10.64	4.75	5.00	3.00	4.66	0.25	3836
5-Star-2	The Ritz-Carlton, Hong Kong	30	1	11.51	5.51	5.00	4.00	4.85	0.17	4155
5-Star-3	W Hong Kong	36	0	11.35	5.27	5.00	2.50	4.75	0.26	4086
Shopping Markets										
1	Stanley Market	22	0	7.67	4.02	5.00	1.00	3.54	0.44	2775
2	Ladies Market	14	0	4.78	2.59	5.00	1.00	3.82	0.54	1724
3	Temple Street Night Market	34	0	6.41	3.91	5.00	1.50	3.51	0.50	2320
Attractions										
1	Hong Kong Disneyland	102	8	40.82	18.55	4.62	3.22	4.22	0.19	14,734
2	Hong Kong Skyline	107	5	39.26	19.17	5.00	4.16	4.62	0.13	14,183
3	Hong Kong Tramways	75	4	28.06	14.32	4.86	4.13	4.52	0.14	10,109
4	Ocean Park	56	6	24.77	9.62	4.82	3.13	4.24	0.25	8960
5	Star Ferry	167	2	61.20	44.28	5.00	3.67	4.55	0.17	22,097
6	Tian Tan Buddha	87	6	38.62	17.24	4.76	4.06	4.48	0.14	13,957
7	Victoria Peak	228	22	90.38	40.94	4.65	4.04	4.38	0.10	32,632

Table 2A

SARIMA-MIDAS(1) model estimation

USA		Canada		UK		South Africa		Australia		New Zealand		Singapore	
Seasonal Difference	Yes	Seasonal Difference	Yes	Seasonal Difference	Yes	Seasonal Difference	Yes	Seasonal Difference	Yes	Seasonal Difference	Yes	Seasonal Difference	Yes
β_1	69.21	β_1	86.2306**	β_1	64.1486	β_1	−22.5225	β_1	−11.1550	β_1	−0.0708	β_1	−152.1076
θ_{11}	4.28	θ_{11}	−2.7033	θ_{11}	8.9786	θ_{11}	0.6252	θ_{11}	−8.3032	θ_{11}	−4.6630	θ_{11}	2.5204
θ_{12}	6.46	θ_{12}	3.040535	θ_{12}	7.4393	θ_{12}	6.0709	θ_{12}	5.1883	θ_{12}	1.8082	θ_{12}	4.4108
β_2	10816.96	β_2	789.3128	β_2	3964.7202	β_2	456.5120	β_2	−3566.5022	β_2	−557.3112	β_2	5179.251
θ_{21}	−2.31	θ_{21}	−3.5864	θ_{21}	−1.8843	θ_{21}	3.7244	θ_{21}	9.2057	θ_{21}	−1.2174	θ_{21}	−0.1659
θ_{22}	3.33	θ_{22}	5.8256	θ_{22}	−8.9218	θ_{22}	8.2689	θ_{22}	6.1220	θ_{22}	5.8220	θ_{22}	7.2549
AR(1)	0.3817***	AR(1)	0.3494***	AR(1)	−0.2662**	SMA(1)	−0.5989***	AR(1)	−0.2650	MA(1)	−0.6890***	AR(1)	1.3667***
SAR(1)	−0.3275***	SMA(1)	−0.3154**	SAR(1)	−0.3854***			AR(2)	−0.0767	SMA(1)	−0.2169*	AR(2)	−0.6549***
								AR(3)	−0.2675*			MA(1)	−1.3326***
								MA(1)	−0.6643***			MA(2)	0.8512***
								SAM(1)	−0.6705***			SAR(1)	−0.2168
												SMA(1)	−0.4135
AIC	1382.35	AIC	1190.27	AIC	1270.2	AIC	1054.78	AIC	1334.52	AIC	1071.38	AIC	1405.18
BIC	1389.1	BIC	1197.02	BIC	1276.94	BIC	1059.28	BIC	1347.92	BIC	1078.08	BIC	1420.92

Note: ***, ** and * indicate that the estimates are significant at the 1%, 5%, and 10% levels, respectively.

Table 3A
The forecasting accuracy of SARIMA-MIDAS(1) with different weight functions

	Exponential Almon lag polynomial	Almon lag polynomial	Beta	Log-Cauchy	Nakagami
MAE					
USA	**4109.79**	4569.74	4241.34	4223.85	4262.31
Canada	**1007.95**	1166.30	1026.61	1061.11	990.33
UK	1822.61	1977.20	**1743.80**	1872.78	1841.57
South Africa	**365.93**	417.07	**365.93**	392.30	383.61
Australia	3615.57	3816.29	3447.04	**3297.36**	3515.02
New Zealand	554.62	568.76	569.10	573.97	**549.97**
Singapore	4295.47	4949.31	4493.07	**4056.24**	4381.30
MAPE					
USA	**0.0392**	0.0428	0.0408	0.0403	0.0410
Canada	**0.0319**	0.0373	0.0325	0.0342	0.0319
UK	0.0377	0.0408	**0.0355**	0.0381	0.0380
South Africa	**0.0666**	0.0818	**0.0666**	0.0713	0.0704
Australia	0.0755	0.0846	0.0716	**0.0689**	0.0723
New Zealand	0.0663	0.0669	0.0674	0.0679	**0.0660**
Singapore	0.0888	0.0988	0.0915	**0.0823**	0.0890
RMSE					
USA	**5527.31**	5792.51	5395.93	5297.93	5618.24
Canada	**1273.33**	1466.23	1287.89	1365.40	1330.43
UK	2526.74	2814.48	**2512.93**	2592.89	2520.21
South Africa	**476.98**	520.36	**476.98**	496.53	477.02
Australia	4375.58	4930.73	4132.18	**3975.64**	4339.64
New Zealand	**741.30**	751.09	745.77	757.18	745.12
Singapore	5992.51	6313.17	6134.76	**5478.92**	5890.58
RMSPE					
USA	0.0510	0.0526	0.0500	**0.0489**	0.0525
Canada	**0.0392**	0.0463	0.0395	0.0448	0.0430
UK	0.0485	0.0531	**0.0463**	0.0486	0.0485
South Africa	**0.0864**	0.1106	**0.0864**	0.0904	0.0876
Australia	0.0886	0.1202	0.0843	**0.0813**	0.0865
New Zealand	0.0956	**0.0927**	0.0952	0.0961	0.0958
Singapore	0.1268	0.1311	0.1282	**0.1142**	0.1225
MASE					
USA	**0.9913**	1.1075	1.0248	1.0208	1.0270
Canada	0.9460	1.0982	0.9650	1.0021	**0.9327**
UK	1.0304	1.1158	**0.9890**	1.0543	1.0415
South Africa	**0.8441**	0.9606	**0.8441**	0.9067	0.8869
Australia	1.2273	1.2968	1.1691	**1.1178**	1.1945
New Zealand	1.1285	1.1613	1.1530	1.1653	**1.1198**
Singapore	0.7181	0.8253	0.7528	**0.6732**	0.7342

Table 4A
Ranks of different weighting scheme generated by MCS test

	USA	Canada	UK	South Africa	Australia	New Zealand	Singapore
Exponential Almon lag polynomial	1	2	2	1	5	2	2
Almon lag polynomial	5	5	5	5	4	3	5
Beta	3	3	1	2	2	4	4
Log-Cauchy	2	4	4	4	1	5	1
Nakagami	4	1	3	3	3	1	3

Table 5A
Forecasting performance of SARIMA-MIDAS(2) with decomposed online review variables

	SARIMA-MIDAS(2)	Benchmark models		Improvements of SARIMA-MIDAS(2) compared to	
		SARIMA	SNAÏVE	SARIMA	SNAÏVE
MAE					
USA	4454.88	4380.80	5043.86	−1.69%	11.68%
Canada	1100.64	1038.85	1173.86	−5.95%	6.24%
UK	1837.67	1903.97	2220.97	3.48%	17.26%
South Africa	380.93	382.90	417.67	0.51%	8.80%
Australia	3412.45	3221.81	3372.00	−5.92%	−1.20%
New Zealand	568.47	562.75	585.75	−1.02%	2.95%
Singapore	5133.75	4440.41	4491.97	−15.61%	−14.29%
MAPE					
USA	0.0415	0.0416	0.0469	0.12%	11.41%
Canada	0.0348	0.0335	0.0374	−3.75%	7.07%

(continued on next page)

Table 5A (*continued*)

	SARIMA-MIDAS(2)	Benchmark models		Improvements of SARIMA-MIDAS(2) compared to	
		SARIMA	SNAÏVE	SARIMA	SNAÏVE
UK	0.0377	0.0388	0.0447	2.83%	15.66%
South Africa	0.0694	0.0707	0.0811	1.83%	14.42%
Australia	0.0729	0.0660	0.0734	−10.39%	0.74%
New Zealand	0.0687	0.0669	0.0656	−2.74%	−4.78%
Singapore	0.1032	0.0903	0.0946	−14.33%	−9.14%
RMSE					
USA	5881.86	5387.06	6323.05	−9.18%	6.98%
Canada	1450.07	1383.69	1436.86	−4.80%	−0.92%
UK	2622.16	2619.13	2892.47	−0.12%	9.35%
South Africa	512.32	499.86	508.93	−2.49%	−0.67%
Australia	4393.18	4231.33	4031.80	−3.83%	−8.96%
New Zealand	738.66	752.12	769.70	1.79%	4.03%
Singapore	6898.04	6060.24	5916.23	−13.82%	−16.60%
RMSPE					
USA	0.0526	0.0499	0.0568	−5.43%	7.37%
Canada	0.0436	0.0450	0.0442	3.09%	1.34%
UK	0.0495	0.0492	0.0540	−0.53%	8.41%
South Africa	0.0878	0.0917	0.0998	4.20%	11.98%
Australia	0.0925	0.0827	0.0913	−11.89%	−1.35%
New Zealand	0.0971	0.0960	0.0823	−1.11%	−17.94%
Singapore	0.1429	0.1274	0.1366	−12.19%	−4.63%
MASE					
USA	1.0742	1.0568	1.2062	−1.64%	10.95%
Canada	1.0351	0.9795	1.1005	−5.67%	5.95%
UK	1.0368	1.0713	1.2566	3.22%	17.49%
South Africa	0.8783	0.8849	0.9645	0.74%	8.94%
Australia	1.1465	1.0909	1.1434	−5.09%	−0.27%
New Zealand	1.1580	1.1434	1.1975	−1.28%	3.30%
Singapore	0.8539	0.7354	0.7520	−16.11%	−13.55%

Table 6A
2- and 3- steps ahead forecasting results with sentiment variable

	2-steps ahead forecasting			3-steps ahead forecasting		
	SARIMA-MIDAS(1)	SARIMA	SNAIVE	SARIMA-MIDAS(1)	SARIMA	SNAIVE
MAE						
USA	***3970.92***	5047.22	5043.86	***4224.97***	5010.86	5043.86
Canada	***883.59***	1258.95	1173.86	***951.80***	1249.91	1173.86
UK	***1776.61***	1861.75	2220.97	***1781.92***	1978.83	2220.97
South Africa	***382.82***	388.41	417.67	429.20	***363.39***	417.67
Australia	3574.27	***3295.14***	3372	3525.09	***3299.85***	3372
New Zealand	***583.45***	592.28	585.75	***563.43***	611.08	585.75
Singapore	4500.12	***3702.41***	4491.97	4879.04	***3718.63***	4491.97
MAPE						
USA	***0.0375***	0.0477	0.0469	***0.0405***	0.0469	0.0469
Canada	***0.0279***	0.0413	0.0374	***0.0304***	0.0412	0.0374
UK	***0.0360***	0.0377	0.0447	***0.0363***	0.0405	0.0447
South Africa	0.0719	***0.0704***	0.0811	0.0789	***0.0658***	0.0811
Australia	0.0744	***0.0675***	0.0734	0.0752	***0.0677***	0.0734
New Zealand	0.0697	***0.0688***	0.0656	***0.0671***	0.0708	0.0656
Singapore	0.0925	***0.0751***	0.0946	0.1033	***0.0759***	0.0946
RMSE						
USA	***5310.62***	6040	6323.05	***5310.01***	6170.79	6323.05
Canada	***1234.92***	1594.73	1436.86	***1255.10***	1578.84	1436.86
UK	2638.31	***2574.62***	2892.47	***2568.93***	2671.54	2892.47
South Africa	***467.89***	495.31	508.93	592.63	***475.6***	508.93
Australia	4432.83	4351.65	***4031.8***	4219.16	4292.26	***4031.8***
New Zealand	776.30	***767.94***	769.7	778.13	797.73	***769.7***
Singapore	6088.93	***5009.28***	5916.23	6689.94	***5029***	5916.23
RMSPE						
USA	***0.0487***	0.0557	0.0568	***0.0501***	0.0565	0.0568
Canada	***0.0371***	0.0525	0.0442	***0.0402***	0.0528	0.0442
UK	0.0495	***0.0483***	0.054	***0.0484***	0.0506	0.054
South Africa	***0.0868***	0.0886	0.0998	0.1053	***0.0854***	0.0998
Australia	0.0886	***0.0845***	0.0913	0.0896	***0.0835***	0.0913
New Zealand	0.0999	***0.0908***	0.0823	0.0982	***0.0926***	0.0823
Singapore	0.1293	***0.1011***	0.1366	0.1571	***0.1019***	0.1366
MASE						
USA	***0.9646***	1.2111	1.2062	***1.0242***	1.1998	1.2062
Canada	***0.8344***	1.186	1.1005	***0.8997***	1.1729	1.1005

(*continued on next page*)

Table 6A (*continued*)

	2-steps ahead forecasting			3-steps ahead forecasting		
	SARIMA-MIDAS(1)	SARIMA	SNAIVE	SARIMA-MIDAS(1)	SARIMA	SNAIVE
UK	***1.0050***	1.0468	1.2566	***1.0106***	1.1122	1.2566
South Africa	***0.8840***	0.8966	0.9645	0.9903	***0.841***	0.9645
Australia	1.2107	***1.1126***	1.1434	1.1953	***1.1114***	1.1434
New Zealand	***1.1879***	1.2032	1.1975	***1.1475***	1.2507	1.1975
Singapore	0.7482	***0.6167***	0.752	0.8181	***0.6205***	0.752

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