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The impact of public health emergencies on hotel demand -
Estimation from a new foresight perspective on the COVID-19

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Abstract
This paper proposes a new foresight approach to estimate the impact of public health emergencies on hotel demand. The forecasting-based influence evaluation consists of four modules: decomposing hotel demand before an emergency, matching each decomposed component to a forecasting model, combining the predictions as the expected demand after the emergency, and estimating the impact by comparing actual demand against that predicted. The method is applied to analyze the impact of COVID-19 on Macao’s hotel industry. The empirical results show that: 1) the new approach accurately estimates COVID-19’s impact on hotel demand; 2) the seasonal and industry development components contribute significantly to the estimate of expected demand; 3) COVID-19’s impact is heterogeneous across hotel services.

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Introduction

A public health emergency can bring tourism to a standstill. For example, due to the restrictive measures on population mobility after the outbreak of COVID-19, tourism - an industry largely characterized by the congregation of people and essentially only ever an offline form of consumption - has been seriously affected, with a sharp decline in the demand (Sharma, Shin, Santa-María, & Nicolau, 2021). The highly contagious nature of COVID-19 has made tourists more cautious about travel. As a related sector of the tourism industry, hotels also suffer from huge operating losses owing to this pandemic. For example, early in the current pandemic, Macao’s hotel occupancy rate in February 2020 fell to below 15%, and the actual gross domestic product of Macao as a whole plunged about 50% year-on-year in the first quarter of 2020 (Liu, Wang, McCartney, & Wong, 2021). As Jin, Qu, and Bao (2019) pointed out, investigating the effect of crisis events helps to understand the impact and post-event recovery in a mixed political, social, and economic context. Hence, there is an urgent need to be able to produce accurate estimates of the impact of a public health emergency on hotel demand and how quickly it will recover after a pandemic.

Qualitative and quantitative studies have examined the impact of public health emergencies on tourism and hospitality. The qualitative analysis focuses on interviewing individuals, which is suitable for impact analysis from a micro perspective (Bajrami et al., 2021). To evaluate the macro impact of public health emergencies, quantitative analysis is introduced, such as intervention analysis (Crespi-Cladera, Martin-Oliver, & Pascual-Fuster, 2021; Kuo, Chen, Tseng, Ju, & Huang, 2008; Polemis, 2021) and the event...
study approach (Chen, Jang, & Kim, 2007; Sharma & Nicolau, 2020). However, an appropriate control group is difficult to find for intervention analysis. Typically, in the context of public health emergencies, such as SARS and COVID-19, few regions can act as a suitable control group for intervention analysis, e.g., differences-in-differences (Polemis, 2021) and regression discontinuity (Deng, Hu, & Ma, 2019). Similarly, the event study approach is difficult to apply because one of its basic assumptions, regarding the effectiveness of the market (Peterson, 1989), is violated in the context of public health emergencies. Both supply and demand experience a substantial decline in this circumstance, and the cumulative abnormal return in an event study may not truly reflect the impact of the emergency. Thus, a new method particularly suited to estimate the impact of an emergency needs to be investigated, meeting the following characteristics of 1) providing a macro perspective, 2) no need to find a suitable control group, 3) not violating market assumptions, and 4) obtain more accurate estimation results.

To meet the above four conditions, we propose a new forecasting-based influence evaluation method, involving adaptive and hybrid forecasting on the expected hotel demand in a virtual world without public health emergencies (the control group) and comparing expected demand against the real demand. It is necessary to restrain the virtual world without a pandemic from being too complex, and so some factors relevant to hotel demand, such as online search data, weather data, and holiday data, are not considered here. Additionally, as what we predict is the development trend of hotel demand without pandemics, the judgmental inputs are also not included, although they can reflect the levels of severity in terms of a pandemic’s influence (Zhang, Song, Wen, & Liu, 2021). However, factors that can reflect the future economic status are valuable for the forecasting task (Jaipuria, Parida, & Ray, 2021). Therefore, an economic indicator is added into the model. The hotel demand before a public health emergency is decomposed into independent components with specific meanings and different frequencies via complete ensemble empirical mode decomposition (CEEMD). Then, because these components have different degrees of nonlinearity, each is matched with a suitable forecasting model. The model library contains four types of models popular in hotel demand forecasting: a statistical model, called the seasonal autoregressive integrated moving average with exogenous variables (SARIMAX); a deep learning model based on long short-term memory (LSTM); and two machine learning models, namely artificial neural network (ANN) and support vector regression (SVR). The expected hotel demand during an emergency is estimated by combining the predictions of different components. Ultimately, the impact of a public health emergency on hotel demand is evaluated by comparing the difference between actual demand and expected demand.

The new method is applied to analyze the impact of COVID-19 on Macao’s hotel industry to demonstrate its effectiveness. There are five principal empirical findings. 1) The new forecasting-based influence evaluation approach accurately estimates COVID-19’s impact on hotel demand, and the proposed adaptive hybrid forecaster inside it performs better than a series of benchmarks. 2) The seasonal component and development trend make significant contributions to the estimation of hotel demand, respectively contributing more than 10% and 25%. 3) In the absence of COVID-19, the virtual demand for three- and five-star hotels is the most significant, followed by two-star hotels. 5) The recovery speed of the demand for hotels with different star ratings is also heterogeneous: five-star hotels recover the most rapidly, while two- and four-star hotels recover relatively slowly. Five-star hotels provide diverse services, preferred by travelers after the pandemic. Accordingly, hotel managers should increase the diversity of their services to achieve a high standard in order to be more robust during a public health emergency.

The rest of this paper is organised as follows: The next section presents related works on evaluating the impact of public health emergencies on tourism and hospitality and those mainstream forecasting methods. The following section sets out the methodology of the study, and briefly describes the modelling strategies for estimating the impact of a public health emergency with the proposed adaptive hybrid forecaster. Then, the impact of COVID-19 on Macao’s hotel industry is used as a case study to investigate the effectiveness of the new forecasting approach. Finally, the contributions and implications are presented in the conclusion section.

**Literature review**

*Impact analysis of crisis events on tourism and hospitality*

Many works have investigated the impact of public health emergencies, especially the current COVID-19, on tourism and hospitality, qualitatively or quantitatively; they have utilized interviews (Chen, Demir, García-Gómez, & Zaremba, 2020; Kaushal & Srivastava, 2021; Shapoval et al., 2021), questionnaires (Bajrami et al., 2021; Chadee, Ren, & Tang, 2021; Foroudi, Tabagdehi, & Marvi, 2021; Kim, Kim, & Lee, 2021; Sobalih, Elshaer, Hasanain, & Abdelaziz, 2021; Tu, Li, & Wang, 2021), and laboratory experiments (Bresciani, Ferraris, Santoro, Premazzi, & Vigila, 2021; Li, Yao, & Chen, 2021). Interviews are particularly useful for the construction and development of relevant theory and are better suited to small samples. However, the findings based on interviews apply only to a particular group, and it is not wise to generalize them. Questionnaires are a conventional and widely used quantitative research method that is better suited to larger samples than interviews. Nevertheless, this method can only measure variables within an established model, and so focus on the impact of relatively few variables, from a particular perspective, such as the employees (Bajrami et al., 2021). As for the laboratory experiment, its great advantage lies in the ability to control the influence of exogenous variables in order to verify causal relationships between variables. However, findings from laboratory experiments also lack generalizability to some extent. As Bresciani et al. (2021) point out, while the results of their study with
laboratory experiment are robust to hotels in different European locations, the circumstance that US hotels are rather different from European hotels might affect tourists’ perceptions.

The generalizability of micro findings produced by using the above methods is limited. Therefore, to explore the macro impact of public health emergencies on tourism and hospitality, some researchers have chosen to use intervention analysis (Crespi-Cladera et al., 2021; Kuo et al., 2008; Polemis, 2021) and the event study approach (Chen et al., 2007; Sharma & Nicolau, 2020). Intervention analysis is regression-based and needs to meet strict assumptions (Box & Tiao, 1975). In such studies, the public health emergency is generally regarded as a dummy variable, which is introduced in a regression model to test whether the emergency causes changes in the development of tourism and hospitality. The impact is measured by the coefficient on the dummy variable (Zhang, Yu, Wang, & Lai, 2009). For example, Crespi-Cladera et al. (2021) used logit regression to identify which hospitality firms in Spain faced financial distress due to the COVID-19 disaster, and found that strong financial ability characterized those that survived. Looking at earlier pandemics and drawing on single-firm as well as panel data, Kuo et al. (2008) adopted the autoregressive moving average model and dynamic panel model to estimate the overall impact of SARS and avian flu on Asian countries. However, many regions will be affected by any given public health emergency, which leaves few comparable regions to act as a suitable control group in the commonly used forms of intervention analysis, such as differences-in-differences (Polemis, 2021) and regression discontinuity (Deng et al., 2019). Thus, the impact of public health emergencies evaluated by them may have systematic errors.

The event study approach is a standard analytical approach in economics and management (Mackinlay, 1997). It can assess the impact of unforeseen events, such as public health emergencies, based on the cumulative abnormal return, which is defined as the sum of differences between the actual return and the estimated return, that is, the measure of abnormality caused by events. For example, Chen et al. (2007) explored the impact of SARS on the stock value of hotels with an event study. The findings indicated that the earnings and share prices of seven listed hotels fell sharply during the SARS outbreak. Sharma and Nicolau (2020) assessed the impact of COVID-19 on the travel industry based on a market-based valuation method and found four sub-industries - hotels, airlines, cruise lines, and car rentals - had experienced a substantial fall in valuation. However, the foundation of event studies - the assumption of the effectiveness of the market - is violated in the context of a public health emergency (Peterson, 1989). The cumulative abnormal return calculated by an event study may not truly reflect the impact of that public health emergency, and the estimation results may be detrimentally affected.

Forecasting methods related to tourism and hospitality

There are also works that analyze the impact of unforeseen events on tourism and hospitality from the perspective of forecasting. For example, Qiu, Wu, Dropsy, Petit, and Ohe (2021) provided an assessment concerning the future development of tourism under the uncertainty surrounding COVID-19 based on a two-stage three scenario forecast framework. Wu, Hu, and Chen (2022) predicted the latest hotel occupancy rates in the context of the COVID-19 pandemic based on the mixed data sampling models (MiDAS). Zhang et al. (2021) combined econometric and judgmental indicators into their model to forecast the possible paths of public health emergencies on tourism and hospitality, some researchers have chosen to use intervention analysis (Crespí-Cladera et al., 2021; Kuo et al., 2008; Polemis, 2021) and the event study approach (Chen et al., 2007; Sharma & Nicolau, 2020). Intervention analysis is regression-based and needs to meet strict assumptions (Box & Tiao, 1975). In such studies, the public health emergency is generally regarded as a dummy variable, which is introduced in a regression model to test whether the emergency causes changes in the development of tourism and hospitality. The impact is measured by the coefficient on the dummy variable (Zhang, Yu, Wang, & Lai, 2009). For example, Crespi-Cladera et al. (2021) used logit regression to identify which hospitality firms in Spain faced financial distress due to the COVID-19 disaster, and found that strong financial ability characterized those that survived. Looking at earlier pandemics and drawing on single-firm as well as panel data, Kuo et al. (2008) adopted the autoregressive moving average model and dynamic panel model to estimate the overall impact of SARS and avian flu on Asian countries. However, many regions will be affected by any given public health emergency, which leaves few comparable regions to act as a suitable control group in the commonly used forms of intervention analysis, such as differences-in-differences (Polemis, 2021) and regression discontinuity (Deng et al., 2019). Thus, the impact of public health emergencies evaluated by them may have systematic errors.

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The ideas and methods of the above-mentioned forecasting works have important guiding values for our research, which convey a basic assumption on reasonable forecasting, i.e., the law of data generation is stable in a virtual world without the interference of emergencies. On the basis of this assumption, a new foresight approach is proposed by using a new adaptive hybrid forecaster to estimate the impact of public health emergencies on hotel demand. We combine statistical regression analysis and mainstream methods in artificial intelligence; then match each of them with the most suitable sequence to increase their adaptability; finally, confirm the practicability of this method by the empirical study on Macao’s hotel demand under the surrounding of COVID-19.

Methodology

In this section, we propose a new forecasting-based influence evaluation method. Fig. 1 is a schematic diagram that briefly describes our methodology. Taking the COVID-19 as an example, we first divide the data before the occurrence of COVID-19 (Time < T2) into three groups: training set (O1|t0), validation set (T0|T1), and test set (T1|T2). We use the training set to train a model; use the validation set to optimize its parameters; and then make predictions on the test set. In the first sub-graph, the purple dotted line
Fig. 1. A schematic diagram for the methodology.
represents the prediction result of the model on the test set, which reflects its performance. If the predicted sequence is very close to the original sequence, the corresponding model will be selected. In the second sub-graph, we use the data corresponding to $T_1T_2$ to update the parameters of the selected model and then predict the future development trend of hotel demand without

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**Fig. 2.** The framework for evaluating the impact of public health emergencies on hotel demand.
COVID-19. Similarly, the dotted line denotes the future development trend of hotel demand without COVID-19, while the blue refers to the real demand after COVID-19.  

Finally, the third sub-graph illustrates how to estimate the impact of COVID-19 on hotel demand, during a period, based on the predictive result. Wherein \( I_{1} \) represents the impact of COVID-19 between \( T_{2} \) and \( T_{3} \); \( I_{1} + I_{2} \) represents the impact between \( T_{2} \) and \( T_{4} \); \( I_{1} + I_{2} + I_{3} \) represents the impact between \( T_{2} \) and \( T_{5} \). Our methodology can also be used to assess the overall impact of COVID-19 if the point when COVID-19 is over comes. In the third sub-graph, the green dotted line indicates the future end of a public health emergency on hotel demand. The framework of the methodology is illustrated in Fig. 2.

### Decomposing hotel demand before a public health emergency

The obvious nonlinear and seasonal characteristics affect the forecasting of hotel demand. Thus, it is helpful to decompose demand data in advance and then construct forecasting models by incorporating the decomposed components. Previous studies have used wavelet analysis to decompose demand data (Balli, Shahzad, & Uddin, 2018). Wavelet analysis lacks adaptability, and its performance relies on the selection of the wavelets. Compared with wavelet analysis, empirical mode decomposition (EMD) has good adaptability and is more suitable for the decomposition of nonlinear, nonstationary, and complex sequences (Xie, Qian, & Wang, 2020; Tuo & Zhang, 2020). However, a drawback named mode mixing exists for EMD: a decomposed component may comprise signals with different frequencies, or signals with the same frequency are in different components. Thus, we choose complementary ensemble empirical mode decomposition (CEEMD), an improved version of EMD, to decompose hotel demand as it can cope with mode mixing by adding white Gaussian noise to hotel demand before decomposing it (Yeh, Shieh, & Huang, 2010). We do not consider the role of factors such as online search data and weather data because these factors need to be forecast in advance. The forecasting errors would inevitably accumulate and eventually lead to a greater evaluation error. But, we introduce an exogenous factor - the month-on-month growth rate of forecasting value on the consumer price index - because it can reflect and judge future economic and hotel development in a virtual world without public health emergencies. According to Wong and Song (2006), the factor is an important macroeconomic variable that describes the hospitality stock indices.

The detailed steps for this stage are as follows:

#### Step 1: Add white noise

Add white noise \( \mathcal{E}(t) \) \((i = 1, 2, ..., m)\) to hotel demand before a public health emergency, denoted \( DB(t) \), to form two sets of sequences:

\[
DB^+_{i}(t) = DB(t) + \mathcal{E}_{i}(t);
\]

\[
DB^-_{i}(t) = DB(t) - \mathcal{E}_{i}(t).
\]

#### Step 2: Decompose

Decompose \( DB^+_{i}(t) \) and \( DB^-_{i}(t) \) into intrinsic mode functions (IMFs) and residues (RES) by using the EMD method. The process is set out in detail by Zhang, Lai, & Wang (2008):

\[
DB^+_{i}(t) = \sum_{j=1}^{n-1} c_{ij}^+(t) + r^+_{ij}(t);
\]

\[
DB^-_{i}(t) = \sum_{j=1}^{n-1} c_{ij}^-(t) + r^-_{ij}(t).
\]

where \( n - 1 \) refers to the number of intrinsic mode functions; \( c_{ij}^+ \) and \( c_{ij}^- \) are the \( j \)-th intrinsic mode function decomposed respectively by \( DB^+_{i}(t) \) and \( DB^-_{i}(t) \); and \( r^+_{ij}(t) \) and \( r^-_{ij}(t) \) are the residues.

#### Step 3: Generate the final intrinsic mode functions

Generate the final intrinsic mode functions based on Eqs. (3) and (4):

\[
c_{ij}(t) = \left( c_{ij}^+(t) + c_{ij}^-(t) \right)/2;
\]
LSTM, ANN, and SVR. The training principles and processes of these four models are set out in detail by, respectively, Wu et al. A single model can deal with all of them effectively. To solve this, we built a library that contains four mainstream models: SARIMAX, LSTM, ANN, and SVR. These four models are different from each other, which helps to improve the stability of the hybrid forecasting of hotel demand. Based on the library, we match each component with the most appropriate model. Specifically, the components of hotel demand and the exogenous factor are divided into three groups: the training set, the validation set, and the test set. Then, samples from the training set are used to train the models and those from the validation set are used to optimize models’ parameters. The steps for Stage 2 are as follows.

Step 1: Divide hotel demand, its decomposed components, and exogenous factor (EF(t)) into training sets, validation sets, and test sets, as described in Table 1.

Step 2: Randomly choose a combination of parameters, denoted as PC1, and train four models based on \{C(T−1)(t),EF(t), ..., C(T−n−1)(t),EF(t)\}, and \{Res(T−1)(t),EF(t)\}.

Step 3: Make predictions on hotel demand components C(T−1)(t), ..., C(T−n−1)(t), and Res(t) by using four trained models. As there are four models and n components, a matrix \(PC_1 \cdot PC_{1m}^{\text{VWS}}\) containing \(4 \times n\) prediction results can be formed:

\[
PC_1 \cdot PC_{1m}^{\text{VWS}} = \begin{bmatrix}
    f_{\text{SARIMAX}}(C_{T-1}(t),EF(t)) & \cdots & f_{\text{SARIMAX}}(C_{T-n-1}(t),EF(t)) & f_{\text{SARIMAX}}(Res_{T-1}(t),EF(t)) \\
    f_{\text{LSTM}}(C_{T}(t),EF(t)) & \cdots & f_{\text{LSTM}}(C_{T-n}(t),EF(t)) & f_{\text{LSTM}}(Res_{T}(t),EF(t)) \\
    f_{\text{ANN}}(C_{T}(t),EF(t)) & \cdots & f_{\text{ANN}}(C_{T-n}(t),EF(t)) & f_{\text{ANN}}(Res_{T}(t),EF(t)) \\
    f_{\text{SVR}}(C_{T}(t),EF(t)) & \cdots & f_{\text{SVR}}(C_{T-n}(t),EF(t)) & f_{\text{SVR}}(Res_{T}(t),EF(t)) \\
\end{bmatrix}
\]

Step 4: Analyze the forecasting performance. The root means square error (Eq. (12)) is used as the performance index, and the performance matrix, \(PC_1 \cdot PC_{1m}^{\text{VWS}}\), is:

\[
C_j(t) = \frac{1}{m} \sum_{i=1}^{m} c_i(t);
\]

\[
Res(t) = DB(t) - \sum_{j=1}^{n-1} C_j(t).
\]
Verifying the performance of models for forecasting hotel demand before an emergency

The forecasting performance needs to be evaluated in advance. Thus, in this stage, we use those models selected in Stage 2 to make predictions on the test sets of all components, and then add them to obtain the prediction on the test set of hotel demand. Here, three indexes are adopted to evaluate the performance of our adaptive hybrid forecaster when forecasting hotel demand before an emergency: the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). We also take the following six models as benchmarks: exponential smoothing (ETS), SARIMA, SARIMAX, LSTM, ANN, and SVR. The information about ETS can refer to Chen, Li, Wu, and Shen (2019). In this stage, the training set and validation set of hotel demand are used to train these benchmarks and adjust their parameters, respectively. Then, the trained benchmarks with the optimal parameters are employed to predict the test set of hotel demand. The steps for Stage 3 are as follows:

Step 1: Train six models based on DB\(^{Va}(t)\), with a randomly given parameter combination, and then make predictions on the validation set DB\(^{Va}(t)\). Here, the matrix \(F_{BM}^{Va}\) contains six prediction results:

\[
F_{BM}^{Va} = \begin{bmatrix}
\hat{f}_{ETS}(DB^{Va}(t), EF(t)) \\
\hat{f}_{SARIMA}(DB^{Va}(t), EF(t)) \\
\hat{f}_{SARIMAX}(DB^{Va}(t), EF(t)) \\
\hat{f}_{LSTM}(DB^{Va}(t), EF(t)) \\
\hat{f}_{ANN}(DB^{Va}(t), EF(t)) \\
\hat{f}_{SVR}(DB^{Va}(t), EF(t))
\end{bmatrix}
\]  

Step 2: Analyze the forecasting performance. The root means square error (Eq. (12)) is used as the performance index and the performance matrix \(P_{BM}^{Va}\) is:

\[
P_{BM}^{Va} = \begin{bmatrix}
RMSE(F_{BM}^{Va}(1, 1), DB^{Va}(t)) \\
\vdots \\
RMSE(F_{BM}^{Va}(6, 1), DB^{Va}(t))
\end{bmatrix}^T
\]  

Step 3: Change a parameter combination for the six models and repeat Steps 1 and 2 until the optimal parameter combination is discovered.

Step 4: Make predictions of on DB\(^{Vi}(t)\) by using the six benchmarks with optimal parameter combination.

Step 5: Make predictions on components C\(^{1}(t)\), C\(^{2}(t)\), C\(^{3}(t)\), C\(^{4}(t)\), and Res\(^{V}(t)\) by using the corresponding models with optimal parameters selected in Stage 2 and add them to obtain the prediction on DB\(^{Vi}(t)\).

Step 6: Verify the performance of all models in forecasting hotel demand. Three performance indexes are used here, which are represented by Eqs. (12–14):

\[
RMSE(x_h, \hat{x}_h) = \sqrt{\frac{1}{H} \sum_{h=1}^{H} (x_h - \hat{x}_h)^2}.
\]
MAE($x_h, \hat{x}_h$) = \frac{1}{H} \sum_{h=1}^{H} |x_h - \hat{x}_h|, \quad (13)

MAPE($x_h, \hat{x}_h$) = \frac{1}{H} \sum_{h=1}^{H} \frac{|x_h - \hat{x}_h|}{|x_h|}, \quad (14)

where $H$ is the number of samples; and $x_h$ and $\hat{x}_h$ denote the $h$-th actual and predicted value respectively.

Analyzing the impact of a public health emergency

This stage investigates the impact of a public health emergency on hotel demand. To achieve a more accurate evaluation, the sequences before a public health emergency are used to train the adaptive hybrid forecaster to update its parameters. Then, the virtual demand for hotel without the public health emergency is predicted. The impact is evaluated by comparing the real demand after the emergency (the observed group) with the expected demand (the control group), and the degree of the impact is evaluated by the average value. Here, Fig. 1 is used again to illustrate how to calculate the impact and its degree. Assume that $T_2$ represents the month when COVID-19 occurred. $T_3$, $T_4$, and $T_5$ represent 1, 2, and 3 months after $T_2$, respectively. $DA(t)$ denotes the purple dotted line, and $DA(t)$ denotes the green solid line. Then, the impacts for 3 months after the occurrence of COVID-19 are $I_1 = DA(T_3) - DA(T_2)$, $I_2 = DA(T_4) - DA(T_2)$, and $I_3 = DA(T_5) - DA(T_2)$. Its degree for 3 months after the occurrence of COVID-19 are $I_1$, $(I_1 + I_2)/2$, and $(I_1 + I_2 + I_3)/3$. The detailed steps for this stage are as follows.

Step 1: Combine the training set and validation set of each component in Stage 2 to retrain the selected model of this component, and then use the test set in Stage 2 to update their optimal parameters.

Step 2: Make a prediction of the virtual hotel demand after an emergency (the control group). The prediction result $DA(t)$ can be regarded as demand without emergencies.

Step 3: Analyze the impact of an emergency. The impact of an emergency, $I(t)$, can be described as the difference between the real demand $DA(t)$ and the forecast demand $DA(t)$. That is:

$$I(t) = DA(t) - DA(t). \quad (15)$$

Step 4: Analyze the degree of the impact, which is considered as the average value of $I(t)$. Then, relevant statistical tests are introduced as an additional description for this step.

Step 5: Analyze the recovery rate after the emergency. The recovery rate, $RE(t)$, is calculated based on the following growth rate:

$$RE(t) = \begin{cases} \frac{DA(t) - DA(t)}{DA(t-s)} & t_{re} < t \leq t_{re} + s; \\ \frac{DA(t) - DA(t)}{DA(t-s)} & t > t_{re} + s. \end{cases} \quad (16)$$

where $s$ takes a value of 1, 4, or 12 for yearly, quarterly, and monthly data, respectively.

Step 6: Analyze the average recovery rate after the emergency. The average recovery rate, $ARE$, is calculated as:

$$ARE = \frac{1}{N} \sum RE(t). \quad (17)$$

where $N$ is the number of recovery rates. Relevant statistical tests are also introduced as an additional description in this step.

Experimental study

The COVID-19 pandemic has led to operating losses for hotels. As a city known for its tourism and service industries, Macao has been badly affected by this public health emergency. In this section, the new method is applied in the analysis of the impact of the current pandemic on hotel demand in Macao.
Data on Macao’s hotel demand

The information on demand for Macao’s hotels with ratings from two to five stars can be retrieved from the official website of Macao tourism department. As for the exogenous factor, we use the month-on-month growth rate of forecasting value on the consumer price index (CPI). The index, according to Wong and Song (2006), is an important macroeconomic variable that describes the hospitality stock indices, so its forecasting value reflects the future economic development in a virtual world without public health emergencies. The data on the index can be found in the iFinD database (http://www.51ifind.cn/). The sample set of this work comprises the monthly data from June 2012 to March 2021 (106 monthly values in total) and the hotel demand in Macao are divided according to its star ratings (two to five stars), resulting in 424 monthly values. Fig. 3 depicts the exogenous

![Fig. 3. The exogenous factors (forecasting value on the consumer price index) from June 2012 to March 2021.](image)

![Fig. 4. The monthly demand for hotels with different star ratings, June 2012 to March 2021.](image)
factors across the study period, and Fig. 4 plots the hotel demand separately for the four sets of star ratings. After the outbreak of COVID-19, demand dropped sharply in 2020. To find the most accurate estimation function for expected demand without the pandemic, for the separate samples of hotels with each star rating, samples before 2020 (i.e., from 1 to 91) are used as the training set, validation set, and test set. The lengths of the validation and test sets are both set to 12 months. Specifically, samples before 2018 are used as the training set (i.e., from 1 to 67); samples from January 2018 to December 2018 (i.e., from 68 to 79) are the validation set; and samples from January 2019 to December 2019 (i.e., from 80 to 91) are the test set.

Processes of decomposition of hotel demand before the emergency

Fig. 5 demonstrates the components derived by CEEMD from the demand separately for hotels with different star ratings. The parameters for CEEMD are set in a basic way: the number of repetitions is set to 100, and the standard deviation of white noise in

| two-star hotels | Three-star hotels |
|-----------------|-------------------|
| Mean period (month) | Pearson correlation | Std | Std as % of (ΣIMFs + RES) | Mean period (month) | Pearson correlation | Std | Std as % of (ΣIMFs + RES) |
| IMF1 | 3.68 | 0.51 | 2020.90 | 28.31% | 2.56 | 0.17 | 4610.98 | 11.59% |
| IMF2 | 8.36 | 0.43 | 1524.60 | 21.51% | 5.75 | 0.16 | 2588.88 | 6.51% |
| IMF3 | 15.33 | 0.63 | 1552.38 | 21.75% | 13.14 | 0.02 | 2359.88 | 5.93% |
| RES | – | 0.66 | 2022.45 | 28.33% | – | 0.97 | 30,214.97 | 75.97% |
| Sum | – | – | – | 100.00% | – | – | – | 100.00% |

| Four-star hotels | Five-star hotels |
|-----------------|-----------------|
| Mean period (month) | Pearson correlation | Std | Std as % of (ΣIMFs + RES) | Mean period (month) | Pearson correlation | Std | Std as % of (ΣIMFs + RES) |
| IMF1 | 3.17 | 0.31 | 9958.48 | 19.91% | 2.88 | 0.22 | 14,518.81 | 15.59% |
| IMF2 | 5.75 | 0.16 | 3768.82 | 7.53% | 7.08 | 0.23 | 8315.62 | 8.93% |
| IMF3 | 18.40 | 0.30 | 6921.85 | 13.84% | 15.33 | 0.17 | 7033.15 | 7.55% |
| RES | – | 0.92 | 2937.64 | 58.72% | – | 0.95 | 63,232.32 | 67.92% |
| Sum | – | – | – | 100.00% | – | – | – | 100.00% |

Note: the mean period of RES is not provided as it reflects the long-term development trend of hotel demand.
each repetition is set to 0.2. As depicted in Fig. 5, IMFs indicate the different frequency components in hotel demand, and the RES is the component that slowly varies around the long-term average, which is essentially the average trend (Zhang et al., 2009). To analyze the characteristics and meanings of these components, we adopted the following measures: 1) the average period of each component of hotel demand is calculated, which is defined as the value derived by dividing the total number of points by the number of peaks for each component (Zhang, Lai, & Wang, 2008); 2) the correlation between each component of hotel demand and the original demand data was measured using the Pearson correlation coefficient (Xu, Tang, He, & Man, 2016); 3) the contribution of each component to general hotel demand is further analyzed. Considering that the components of hotel demand in a category are independent of each other (Zhang et al., 2008), we use the percentage of variance to explain the contribution. Table 2 shows the results and we can draw the following findings.

The mean periodicity of components
For all hotels with a given star rating, the average period from IMF1 to IMF3 gradually increases. IMF1 and IMF2 are close to 3-month and 6-month periods, respectively. Thus, they can be regarded as seasonal and semi-annual periodic components, respectively. The average period of IMF3 is more than one year and can be regarded as the yearly pattern. According to Rosselló and Sansó (2017) and Li, Ge, Liu, and Zheng (2020), the longest seasonal periodic in tourism demand seems to be the annual, so here we get three IMFs. As for RES, it is the demand component that slowly varies around the long-term average and can be considered as reflecting the development trend more generally. In the short term, the hotel demand has obvious seasonality. In the long run, the hotel industry is affected by the economic situation and the changing preferences of tourists. As RES indicates, the demand for three-star and five-star hotels has increased continuously over recent years, whereas demand for four-star hotels fell after an initial rise and the demand for two-star hotels experienced an overall decline.

The contributions of the different components of hotel demand
The RES component has a high contribution to hotel demand (reaching more than 25%), which means that the development trend plays a key role in hotel demand. For all hotels with a given star rating, the component IMF1 is found to make a higher contribution than the corresponding low-frequency components, i.e., IMF2 and IMF3, whose contribution to the original hotel demand reaches more than 10%. This finding is different from the findings for other industries, where the low-frequency component generally contains more information than the high-frequency component (Zhang et al., 2008). Here, IMF1 (the seasonal periodic component) contains more information than IMF2 (the semi-annual periodic component) and IMF3 (the yearly periodic component). In summary, the components of seasonal periodicity and the general development trend mainly determine demand within the hotel industry.

Matching each component of hotel demand with a forecasting model
Since the various components of hotel demand have varying degrees of nonlinearity, it is wise to select the most suitable forecasting model for each component from a model library. The library contains SARIMAX, ANN, SVR, and LSTM. Before selecting models, the parameters need to be set. For these four models, the key parameters (those with the greatest impact on their performance) are mainly considered, while the remaining parameters are set in a default manner.

In this experiment, there are six parameters for SARIMAX: the order for differences (d), the order for auto-regressive process (p), the order for moving average process (q), the order for seasonal differences (D), the order for seasonal auto-regressive process (P), and the order for seasonal moving average process (Q). There are two parameters for ANN: size of input layers and size of hidden layers. Finally, there are two parameters for SVR: kernel types and number of features. To obtain suitable parameters, the training set is used to train the forecasting models, and the validation set is used to select the optimal parameter combinations. In other words, models with different parameter combinations are used to predict samples in the validation set, and then the parameter combination corresponding to the minimum RMSE is selected as the optimal parameter. As for the optimization method, the parameters of SARIMAX are determined by statistical testing, while the parameters of the other three models are determined by the exhaustive grid-search technique (Cho, 2003). The ranges of the corresponding parameters of the four models are shown in Table 3. Considering that the training processes for LSTM and ANN involve a certain degree of randomness, different prediction results may be obtained for LSTM and ANN with the same parameters. Therefore, we run the LSTM and ANN five times for each parameter and take the average of the five RMSEs as the evaluation index.
Here, RES for two-star hotels is taken as an example to illustrate the procedure for parameter selection. Fig. 6 presents the performance of LSTM with different parameter combinations on RES for two-star hotels. In Fig. 6, each small square corresponds to a combination of parameters, and the number in the square represents the average value of five RMSEs. For the RES of two-star hotels, LSTM can obtain higher prediction accuracy when the time step is 1 and 2, which means that the development trend for two-star hotels is more short-term dependence. When the number of units and time steps are respectively 40 and 2, LSTM achieves the best performance on the validation set (the average of five RMSEs is only 249.2). Using the same method, we obtained the optimal parameter combinations of the four models corresponding to all components of demand for hotels with different stars. Given that RES needs to be differentiated multiple times to be stable, we take the natural logarithm of RES when training the SARIMAX model and then restore the prediction results to reduce data loss. The results are presented in Table 4.

As shown in Table 4, no model is suitable for predicting all components of hotel demand. These four models have different performances on the 16 components (the bold means the best performance of all models for each component). LSTM performs best overall and is selected five times. ANN and SVR rank second overall and are selected four times respectively. SARIMAX have average performance, only being selected three times. LSTM, especially the one with many layers, has good fitting capabilities. However, because the structure of Macao’s monthly hotel demand is not overly intricate, a shallow LSTM (here, the number of layers is 1) can also achieve better performance on the training set. Furthermore, the complex generation process of demand data can also be simplified by decomposition, which also reduces the sample volume requirement of LSTM. Machine learning models, represented by ANN and SVR, are sensitive to sample size and can also adapt to nonlinear data. Thus, their performance is not as good as that of LSTM. SARIMAX has a low requirement on sample size, but it cannot fit nonlinear data well. The adaptive hybrid forecaster is expected to provide more accurate predictions than single models as it can take full advantage of each of them.

| Time step | Number of units | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 |
|-----------|----------------|---|----|----|----|----|----|----|----|----|----|
| 1         | 1336           | 1956 | 1479 | 761.9 | 669.4 | 637 | 284.3 | 280.9 | 372.4 | 469.7 |
| 2         | 2484           | 1072 | 1458 | 1302 | 867.6 | 314.3 | 538 | 249.2 | 587.4 | 348.5 |
| 3         | 2641           | 2133 | 1530 | 1290 | 561.6 | 568.2 | 649.6 | 358.7 | 521.7 | 693.8 |
| 4         | 2741           | 2055 | 2040 | 1298 | 1091 | 740.8 | 373.3 | 679.7 | 1226 | 525 |
| 5         | 2625           | 2325 | 1946 | 1581 | 1014 | 684.8 | 1148 | 676.3 | 944.7 | 717.3 |
| 6         | 2832           | 2296 | 2049 | 2048 | 1714 | 1977 | 1351 | 1487 | 855.4 | 1125 |
| 7         | 2923           | 2355 | 2189 | 2188 | 1782 | 1781 | 2030 | 1564 | 2019 | 1868 |
| 8         | 2714           | 2697 | 2391 | 2207 | 2330 | 2385 | 2180 | 2068 | 2027 | 2019 |
| 9         | 2841           | 2708 | 2640 | 2469 | 2266 | 2496 | 249 | 2432 | 2394 | 2190 |
| 10        | 2633           | 2537 | 2524 | 2674 | 2611 | 2604 | 2470 | 2450 | 2260 | 2543 |

Fig. 6. The performance of LSTM on the RES of two-star hotels under different parameter combinations.
This section presents the performance of the adaptive hybrid forecaster in forecasting hotel demand before COVID-19. In Table 4, each component of hotel demand selects the most suitable forecasting model from the model library with the optimal parameter combination. To explore the performance of the adaptive hybrid forecaster, we make predictions on the test set of the 16 components using the models and parameter combinations given in Table 4, and then integrate the results to obtain the final forecasts of demand for hotels with different star ratings. We also make predictions by using the same samples with the six benchmark models. The advantages of the adaptive hybrid forecaster are illustrated by comparing its forecasting results with those of benchmarks. Their optimal parameters are also determined with the exhaustive grid-search technique.

Fig. 7 depicts the performance of all models on the test set of demand for hotels with different star ratings before COVID-19. Compared with the benchmarks, the adaptive hybrid forecaster more accurately follows the trend and makes better predictions. 

Table 4

| Star rating | SARIMAX | LSTM | ANN | SVR | Selected model |
|-------------|---------|------|-----|-----|---------------|
| Two-star hotels | IMF1 (2,0,1)(0,0,0) | 2641.80 (1,20) | 2303.05 (2,6) | 2292.26 | ANN |
|             | IMF3 (4,0,1)(0,0,0) | 443.17 (8,5) | 1511.45 (7,2) | 1487.15 | SARIMAX |
|             | RES (0,2,0)(0,0,0) | 57.68 (2,40) | 174.73 (4,4) | 736.56 | SARIMAX |
| Three-star hotels | IMF1 (0,5)(0,0,0) | 5313.05 (5,35) | 4215.18 (3,2) | 3586.26 | SVR |
|              | IMF2 (2,0,2)(0,0,0) | 1649.16 (3,20) | 2523.85 (9,14) | 1274.82 | SVR |
|              | IMF3 (4,0,1)(0,0,0) | 1464.84 (4,45) | 442.40 (4,4) | 515.87 | LSTM |
| Four-star hotels | IMF1 (5,0,0)(0,0,0) | 11,690.59 (3,35) | 10,202.66 (1,4) | 3520.99 | LSTM |
|                | IMF2 (4,0,1)(0,0,0) | 4787.16 (10,5) | 4112.00 (9,6) | 10,172.70 | ANN |
|                | IMF3 (4,0,1)(0,0,0) | 1813.10 (9,30) | 1433.95 (1,10) | 4084.35 | ANN |
| Five-star hotels | IMF1 (3,0,1)(0,0,0) | 16,861.49 (2,40) | 15,939.98 (2,4) | 15,844.90 | SVR |
|                | IMF2 (4,0,1)(0,0,0) | 8017.17 (2,10) | 5994.77 (3,2) | 6664.49 | LSTM |
|                | IMF3 (5,0,0)(0,0,0) | 7202.25 (5,5) | 6343.40 (4,8) | 5849.88 | ANN |
|                | RES (0,2,0)(0,0,0) | 847.53 (1,45) | 5420.72 (1,2) | 9551.09 | SARIMAX |

The performance of the adaptive hybrid forecaster in estimating demand before the emergency

This section presents the performance of the adaptive hybrid forecaster in forecasting hotel demand before COVID-19. In Table 4, each component of hotel demand selects the most suitable forecasting model from the model library with the optimal parameter combination. To explore the performance of the adaptive hybrid forecaster, we make predictions on the test set of the 16 components using the models and parameter combinations given in Table 4, and then integrate the results to obtain the final forecasts of demand for hotels with different star ratings. We also make predictions by using the same samples with the six benchmark models. The advantages of the adaptive hybrid forecaster are illustrated by comparing its forecasting results with those of benchmarks. Their optimal parameters are also determined with the exhaustive grid-search technique.

Fig. 7 depicts the performance of all models on the test set of demand for hotels with different star ratings before COVID-19. Compared with the benchmarks, the adaptive hybrid forecaster more accurately follows the trend and makes better predictions.
Taking two-star hotels as an example, the adaptive hybrid forecaster not only tracks the development trend in the demand data but also captures the irregular fluctuations, at least to a certain extent. In contrast, the benchmarks cannot follow well the general demand trends and overestimate demand for two-star hotels. Furthermore, the adaptive hybrid forecaster seems to find a balance between volatility and trend. Owing to the sharp fluctuations in the hotel demand data, the adaptive hybrid forecaster places more emphasis on following trends to reduce the error of evaluation as much as possible, which is an advantage. To further compare the performance of the models, three indicators based on Eqs. (12)–(14) are calculated and presented in Table 5 (the bold means the best performance and the underlined represents the second-best). The adaptive hybrid forecaster performs better than the benchmarks. For two-, three-, four-, and five-star hotels, the MAPE values of the adaptive hybrid forecaster are lower than those of the best benchmark model, with gaps of 7.03%, 0.74%, 0.19%, and 1.15%, respectively. Therefore, according to the results presented in Table 5, it can be considered that the adaptive hybrid forecaster proposed in this paper accurately evaluates demand before the emergency for hotels with different star ratings.

Table 5

The performance of all models on the test set of hotel demand with different star ratings before the emergency.

| Models | The demand for two-star hotels | The demand for three-star hotels |
|--------|--------------------------------|---------------------------------|
|        | MAE       | RMSE     | MAPE (%) | MAE       | RMSE     | MAPE (%) |
| ETS    | 3839.09   | 5012.77  | 21.84    | 7514.29   | 8688.63  | 5.65     |
| SARIMA | 5226.25   | 6071.21  | 29.71    | 8530.12   | 9507.09  | 6.38     |
| SARIMAX| 4622.41   | 5344.73  | 26.06    | 8736.02   | 9688.27  | 6.53     |
| SVR    | 4707.14   | 6321.21  | 27.38    | 8438.84   | 9293.34  | 6.27     |
| ANN    | 4385.18   | 5765.56  | 25.11    | 18,304.60 | 23,752.26| 12.91    |
| LSTM   | 5218.48   | 6187.18  | 29.31    | 12,235.43 | 14,943.72| 9.33     |
| AHF    | **2830.77**| **3355.92**| **14.81**| **6725.56**| **7702.35**| **4.91**|

| Models | The demand for four-star hotels | The demand for five-star hotels |
|--------|--------------------------------|--------------------------------|
|        | MAE       | RMSE     | MAPE (%) | MAE       | RMSE     | MAPE (%) |
| ETS    | 28,785.08 | 34,650.01 | 14.28    | 40,126.04 | 45,080.94| 9.50     |
| SARIMA | 26,680.30 | 31,959.57 | 13.38    | 30,218.38 | 33,901.42| 7.09     |
| SARIMAX| **14,435.65**| **18,493.77**| **7.29**| 29,337.73 | 32,996.93| 6.89     |
| SVR    | 18,908.77 | 23,756.77 | 9.56     | 34,485.69 | 38,431.43| 8.09     |
| ANN    | 18,235.92 | 21,193.89 | 8.93     | 29,988.08 | 35,330.33| 6.98     |
| LSTM   | 15,398.44 | 20,273.77 | 7.67     | 28,840.78 | 32,643.22| 6.78     |
| AHF    | **14,108.49**| **17,891.01**| **7.10**| **24,820.78**| **28,606.31**| **5.63**|

Fig. 8. Hotel demand and the expected demand without COVID-19 from using the foresight method.
Fig. 9. The impact of the COVID-19 pandemic on hotel demand.
The recovery rate of hotel demand after the COVID-19 pandemic.
The impact of COVID-19 on hotel demand, differentiated by star ratings

In this section, the adaptive hybrid forecaster is used to evaluate the impact of COVID-19 on the demand for hotels with different star ratings. To explore the impact of the current pandemic, we use the hotel demand before the public health emergency to train and adjust the parameters used in the adaptive hybrid forecaster, and then forecast the expected hotel demand for the virtual case where COVID-19 did not emerge. Accordingly, we have also updated the parameter combinations of the models selected in Table 5 to obtain more accurate predictions. Specifically, we use the samples from months 1 to 79 to retrain the selected models, and use the samples from months 80 to 91 to update their parameters. The impact of the pandemic is then taken to be the difference between the actual demand and that forecast for the same period but without the emergence of COVID-19.

Fig. 8 describes the actual and expected demand for hotels with different star ratings. Fig. 9 depicts the impact of the pandemic on the four categories of hotels. Firstly, without the pandemic, the trend in future demand for two- and four-star hotels declines, while the demand for three- and five-star hotels increases. Secondly, the impact of COVID-19 is heterogeneous for hotels with different star ratings: its impact on two-star hotels is relatively low, while that on five-star hotels is the most serious, followed by four-star hotels and three-star hotels. In other words, the impact of the current public health emergency accords with the following sequence: five-star hotels > four-star hotels > three-star hotels > two-star hotels. We also confirm the robustness of the finding based on statistical tests. Considering that the impacts of COVID-19 on hotels with different star ratings may be relevant, we choose Friedman’s test to verify this finding. Friedman’s test can make full use of the information contained in relevant samples (Pahnehkolaei, Alfi, & Machado, 2021). Fig. 11 presents the results of Friedman’s test, in which rank represents the degree of impact. It can be seen that the results obtained by Friedman’s test confirm the findings.

We also analyze the speed of recovery in hotel demand after the emergency. In Fig. 10, the solid line reflects the rate recovery of hotel demand and the dotted line shows its average value. Since there was a gap between the emergence of COVID-19 and its impact on the hotel industry, the recovery rate corresponding to January 2020 in Fig. 10 is regarded as noise and hence is discarded. As depicted in Fig. 10, the recovery in hotel demand after the pandemic has obvious volatility. This is caused by the seasonal characteristics of the hotel industry, as the components with seasonal periodicity are important for hotel demand, as shown in Table 2. The speed of recovery in the demand for hotels with different star ratings is distinct: five- and three-star hotels have the fastest recovery, while two- and four-star hotels recover relatively slowly. Again, this finding is confirmed by Friedman’s test (Fig. 12).

Conclusions

To evaluate the macro impact of a public health emergency on hotel demand with an effective control group and without violating the assumption of market effectiveness, we propose a new forecasting-based influence evaluation method, and apply it in the analysis of the impact of COVID-19 on Macao’s hotel industry. The main findings are as follows. 1) We find that the new approach performs well in evaluating the impact of the public health emergency on hotel demand, and the new adaptive hybrid forecaster inside it outperforms a series of benchmark models in estimating hotel demand. Either the most affected hotel category

![Graph showing the impact of COVID-19 on hotel demand differentiated by star ratings](image)

*Fig. 11. Friedman’s test for the impact of the outbreak of COVID-19 on hotel demand.*
The recovery rate of two-star hotels

The recovery rate of three-star hotels

The recovery rate of four-star hotels

The recovery rate of five-star hotels

Fig. 12. Friedman’s test for the recovery rate of hotel demand after the outbreak of COVID-19.

The hotel star in the present study or that recovering the most rapidly can be identified with the proposed new method. 2) Before the onset of the public health emergency, Macao’s hotel industry was mostly influenced by the general development trend and the seasonal periodicity characteristics of hotel demand; these respectively contributed more than 25% and 10% to overall hotel demand. 3) In the virtual world without the pandemic, the expected demand for three- and five-star hotels grows rapidly, while that for two- and four-star hotels declines. 4) In the real word, the impact of a pandemic on hotel industry exhibits heterogeneity across the four sets of hotels with different star ratings. The impact on five-star hotels is the most significant, followed by that on four-star hotels, while that on two-star hotels was the least. The speed of recovery in hotel demand also shows heterogeneity across the services. Five-star hotels recover the most rapidly, while two- and four-star hotels recover relatively slowly. Since the outbreak of COVID-19, travelers have preferred hotels with diverse high-quality services.

Our work makes three key contributions. First, it supplements the current research on the macro impact of a public health emergency on tourism and hospitality by providing a new foresight perspective. The new approach not only overcomes the lack of generalizability of micro qualitative analysis but also lessens the constraints which conventional quantitative analysis requires, such as the need for the similarity between experimental group and control group. When estimating the expected demand in the virtual world without the public health emergency, the new adaptive hybrid forecaster proposed is good at estimating the general development trend component and the seasonal periodicity component in hotel demand before the public health emergency. Thus, a virtual control group can be generated, which also requires no violation of the assumption of market effectiveness. In order to find which category of hotels is most affected by the pandemic and which one will recover the most rapidly after the pandemic, a multiple impact analysis is used to compare the difference between the real hotel demand and the expected demand. The second contribution is that the new approach provided a real-time monitor or evaluation for the impact of a public health emergency on hotel demand. The method can dynamically analyze the impact of a public health emergency in real-time, thereby helping the government implement new policies or adjust the previous ones. Hotel managers can also look for ways to survive or improve hotel performance in view of this dynamic impact. The third contribution is that the new approach is validated in analyzing the impact of the COVID-19 pandemic on hotel demand in Macao. We find the two significant factors of general development trend and seasonal periodicity impact hotel demand before the pandemic. These two factors are processed well by the adaptive hybrid forecaster to generate a good estimation of expected hotel demand in the virtual world without the public health emergency.

The management implications are as follows. 1) For tourism and hospitality, managers and regulators can refer to the new method to identify the most affected product, such as different hotel star categories, and find the most rapidly recovered one. None of the existing methods is as effective in this. 2) Identification of the fastest-growing product before the public health emergency is a reference to estimate the most rapidly recovered product after the event. In Macao’s hotel industry, five-star hotels would be an important product to promote tourism and hospitality development after an emergency. 3) To survive better during and after a public health emergency, hotels should establish diverse services with an effective mechanism of health protection. Diverse service promotion with health safety as a focus will attract tourists because travelers visiting Macao mainly prefer the diverse services of five-star hotels.
There are also some limitations in this research. First of all, we focus on the impact of a public health emergency on overall hotel demand, and ignore the impact on each component of demand. Subsequent work could analyze the impact of emergencies on each component of hotel demand before the emergency. Then, specialized studies focusing on error analysis with other methods would be useful to verify the superiority of the proposed adaptive hybrid forecaster. Finally, our method currently can only evaluate the impact of an emergency on hotel demand from its appearance to the present as the actual demand is a parameter for assessment. On the one hand, the virus can mutate. Once a new virus is discovered, the effects of COVID-19 may continue. On the other hand, new infections are still being discovered and appear in somewhat random places. As a result, forecasting when COVID-19 will end, or the point at which hotel demand fully recovers, relies on identification of these key factors. In future work, we will consider how to effectively predict the time when hotel demand totally recovers and forecast the overall impact of an emergency on hotel demand before the end of the emergency.

CRediT authorship contribution statement

Ling-Yang He contributed via conceptualization of the original idea, theoretical development; experimental design, algorithm design and coding, data collection, results analysis, and finished the original draft. Hui Li conceptualized the original idea, applied for research funding, and completed the following tasks: results analysis, discussion of implications and study significance, and improvement of the original draft. Jian-Wu Bi contributed by discussing the design and the conceptualization, and improving the analysis and presentation. Jing-Jing Yang contributed on data collection, and improving the theoretical discussion and presentation. Qing Zhou applied for research funding and improved the presentation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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