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TOURISM DEMAND INTERVAL FORECASTING WITH AN INTELLIGENCE OPTIMIZATION-BASED INTEGRATION METHOD

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Highlight

1. This study is the first to use multi-source data to forecast tourism demand intervals.
2. This study references probability density methods for tourism demand forecasting.
3. This study pioneers the use of the MTSO algorithm to forecast travel demand intervals.
4. The results show that MTSO-ARIMAX has superior performance compared with benchmarks.

Abstract

Interval forecasting for tourism demand holds significant theoretical and practical insights. However, research on integrating social reviews into multi-source for interval prediction is still developing. To fill this research gap, this study proposes an integrated method for tourism demand interval prediction by combining multi-source data with a modified swarm intelligence optimizer. This method can extract essential intrinsic features from multi-source and select an appropriate probability density function to extend point predictions to initial prediction intervals, then further refine the initial prediction intervals to improve the prediction accuracy. Empirical studies on the tourism demand of Mount Siguniang and Jiuzhaigou validate the superior predictive capabilities of the proposed model. Experimental results demonstrate that (a) incorporating a multi-source dataset with social reviews significantly enhances the accuracy of the proposed model; (b) the modified transit search algorithm effectively balances the coverage and width of prediction intervals, thus improving the generalizability of the model.

Keywords: Tourism demand forecasting; Interval forecasting; Modified transit search optimization algorithm; Multi-source big data

1. Introduction

As the tourist industry expands, forecasting tourism demand has become a pivotal element in societal progress. Accurately predicting tourist demand at various destinations not only provides valuable insights for sectors related to tourism but also offers objective guidance for decision-makers involved in infrastructure development and the planning of accommodation locations (Y. Li et al., 2024; Ma et al., 2024). Consequently, precise and timely tourism demand forecasting has gained significant prominence in recent academic research within the field of tourism (Y. Li et al., 2022).

The construction of effective tourism demand forecasting models has become a focal point for researchers due to its significant theoretical and practical implications (Song, Qiu, et al., 2019). Traditional tourism demand forecasting relies on structured data, which is often delayed and difficult to obtain, thus limiting forecast precision (Andrawis et al., 2011; Gunter & Önder, 2015; H. Liu et al., 2021). With the advent of the Internet, the incorporation of "online" data sources such as search engines now provides timely insights into tourist preferences (Wamba et al., 2015). Recent advancements have shown that leveraging high-frequency Internet data can significantly improve forecasting effectiveness (Law et al., 2019; X. Li et al., 2021; Xie et al., 2021).

Furthermore, the vast amount of textual data available online offers potential insights about destinations (Chen et al., 2024; M. Hu et al., 2022). Notably, the evolution of computer technology has given rise to various social and review platforms, with some studies highlighting the critical role of online reviews in improving the efficiency of tourism forecasting (He et al., 2023; H. Li et al., 2020). However, most research has primarily utilized reviews from dedicated tourism websites, overlooking the impact of more abundant social reviews on forecasting models (Mendieta-Aragón et al., 2024). Therefore, exploring the integration of social reviews to develop an effective multi-source data paradigm remains an important challenge in refining the tourism demand forecasting frameworks.

Another essential attempt to improve tourism demand forecasting is to develop more effective models. However, recent research on tourism demand forecasting, as highlighted by Wu et al. (2017) and G. Li et al. (2019), has mainly focused on point forecasts. Although point forecasting is straightforward and easily interpretable (Wang, Zhou, et al., 2023), its limited information often fails to meet the comprehensive needs of decision-makers. In contrast, uncertainty analysis based on interval prediction provides a valuable alternative by generating different prediction intervals at different confidence levels. This approach not only enriches the granularity of information available to decision-makers, but also enhances strategic flexibility, enabling more robust responses to market dynamics and potential volatilities (Wang, Zhang, et al., 2023; Xie et al., 2023).

Despite the fact that interval forecasting can provide richer forecast information and practical insights, research focusing on tourism demand interval forecasting is still relatively limited compared to point forecasting (G. Li et al., 2019). Early interval forecasting of tourism demand was mainly based on bias-corrected bootstrap methods (Song, Wen, et al., 2019; Xie et al., 2023). In the context of high-frequency fluctuations in tourism demand, such parameter-sensitive and strict data assumption statistical methods may not reflect the true uncertainty. Moreover, integrated interval forecasting methods based on decomposition and artificial intelligence have been gradually proposed in recent studies (Jiang, 2023; Wang, Zhang, et al., 2023; Xie et al., 2023). However, the distribution of forecast sequences and the synergistic constraints between the coverage and the width of forecast intervals are not sufficiently considered when extending the forecast sequences to forecast intervals, which makes most forecasting models unable to adapt to fluctuating demand forecasts, especially large fluctuations in demand caused by extreme situations such as pandemic. Therefore, it is particularly important to construct a stable and effective tourism demand interval forecasting model to provide decision-makers with comprehensive risk decision support.

To address the above problems, we propose a new tourism demand interval prediction model (MTSO-ARIMAX) based on the combination of multi-source data, autoregressive integrated moving average model with exogenous variables (ARIMAX), and modified transit search optimizer (MTSO). The MTSO-ARIMAX model can effectively balance the interval coverage and interval width according to different confidence levels, and then optimize the prediction intervals.

The contribution of this paper is multi-perspective. First, previous studies on tourism demand forecasting have seldom delved deeply into the optimization mechanisms of interval forecasting models. In this paper, a new tourism demand interval model based on the integration strategy is proposed for the first time, and the model is successfully applied to the tourism demand forecasting of several destinations. The MTSO-ARIMAX model integrates multi-source data, the ARIMAX method, the distribution analysis method, and the MTSO algorithm. It overcomes the limitations of traditional interval forecasting methods that do not comprehensively consider interval forecasting metrics. This study provides a clear and feasible exploration for future research on tourism demand interval forecasting. Unlike existing studies, this paper not only explores the potential distribution characteristics of the forecasting sequences, but also utilizes the MTSO algorithm to further optimize the forecasting intervals. This approach takes into account the statistical distribution of the forecast sequences and co-optimization of the interval forecasting metrics to improve the accuracy and practicality of the forecasts.

Second, this study is one of the first to incorporate historical tourist data, search engine data, travel website reviews, and social reviews as predictor variables for tourism demand interval forecasting. This approach integrates and downscales multi-source data by employing principal component analysis (PCA), which is a significant shift from traditional models that predominantly utilize search engine and travel website data. The proposed approach leverages a diverse dataset and analytical techniques to overcome the limitations of previous variable configurations, thus establishing an important data framework for future research in tourism demand interval forecasting.

Third, this study innovatively integrates the ARIMAX model and the maximum likelihood estimation (MLE) method to expand point prediction sequences into prediction intervals. Unlike previous studies, this paper fully considers the distribution of the sequence based on point forecasting and employs the MLE method to effectively fit the probability distribution of the prediction sequence, thus expanding the prediction sequence into prediction intervals. This method strengthens the connection between point forecasting and interval forecasting, and provides a reference for the subsequent study of tourism demand interval forecasting from the perspective of probability density.

2. Literature review

2.1 Current methods of tourist demand forecasting

Two prominent methodologies in tourism demand forecasting include point forecasting and interval forecasting. In point forecasting, commonly used models include time series, econometric, and artificial intelligence (AI) models (A. Liu et al., 2022). Time series models utilize intrinsic patterns in historical data for forecasting (Wu et al., 2024). Common time series models are simple moving average (SMA), exponential smoothing (ES), ARIMA, and Naïve models. While effective in revealing historical patterns, these models have limitations in quantifying the impact of external variables on future demand (Jiao et al., 2021).

Econometric models can explore causal relationships between tourism demand and influencing factors. However, as predictor variables increase, econometric models face limitations such as overfitting and multicollinearity (Huang & Zheng, 2023). To address this, scholars have introduced AI-driven forecasting methods. AI models like support vector regression (SVR), random forest (RF), least absolute shrinkage and selection operator (LASSO), long short-term memory (LSTM), and backpropagation neural network (BPnn) are widely used in tourism demand forecasting (Fan et al., 2023; T. Hu et al., 2023; Zhang et al., 2020). While each model has merits, none has shown unequivocal superiority across all scenarios (H. Li et al., 2020).

Furthermore, interval forecasting focuses on providing a series of forecasts based on different confidence levels. These models can provide destination managers with a richer understanding of demand fluctuations for different decision needs (Wang, Zhang, et al., 2023). Despite the advantages of interval forecasting, the application of interval forecasting to tourism demand has been considered limited (G. Li et al., 2019). Recently, interval forecasting models based on AI methods, quantile regression (QR) approach, and decomposition-ensemble strategy have been applied to tourism demand forecasting (Jiang, 2023; Wang, Zhang, et al., 2023; Xie et al., 2023). However, extensive research on interval forecasting is still lacking in the tourism literature (Jiang, 2023).

2.2 Current status of tourism demand forecasting systems using multi-source data

The application of Internet data has been an important driver in the evolution of tourism demand forecasting methods (Song, Qiu, et al., 2019). With the advent of the Web 2.0 era, the development of Internet technologies has not only drastically changed users' travel decisions but also provided industry practitioners with more data to make decisions (Wu et al., 2024). Consequently, numerous studies in recent years have attempted to combine Internet data for more accurate forecasting (Bi et al., 2022; Han et al., 2024; M. Hu & Song, 2020). M. Hu and Song (2020) validate that BPnn model incorporating search engine data outperform other benchmark models. Bi et al. (2022) combined historical tourist data, search engine data, weather data, and public holiday data into a multi-source dataset to predict daily tourist demand for the Huangshan Mountain area. Han et al. (2024) used the aforementioned multi-source dataset to analyze the daily tourism demand in Jiuzhaigou, demonstrating the effectiveness of multi-source data in enhancing the accuracy of tourism demand forecasting.

Furthermore, unlike search engine data which can reflect tourists' information needs and preferences (M. Hu et al., 2021), unstructured travel website reviews and social reviews can more directly reflect the sentiments of the public. Therefore, existing studies have attempted to incorporate review data to enhance forecasting efficiency (H. Li et al., 2020, 2023; Mendieta-Aragón et al., 2024). H. Li et al. (2020) combined travel website reviews from Ctrip and Qunar with search engine data to construct an effective tourism demand forecasting model. By integrating travel website reviews, search engine data, and official announcements, H. Li et al. (2023) accurately forecasted weekly and monthly tourism demand for the Kulangsu Scenic area. Mendieta-Aragón et al. (2024) verified the positive impact of Twitter data in improving traditional time series models. However, most studies rely primarily on travel website reviews, and the practice of constructing multi-source datasets based on unstructured social reviews for tourism forecasting needs further exploration (Wu et al., 2024).

2.3 Current status of tourism demand interval forecasting

Research on interval forecasting for tourism forecasting is relatively limited, with early studies often relying on bootstrap methods (Kim et al., 2010, 2011). For instance, Kim et al. (2010) used a bias-corrected bootstrap approach to predict visitor arrival intervals in Hong Kong, and found that it to be particularly effective for small sample sizes. However, its effectiveness is highly sample dependent and susceptible to noise and variability.

Recently, interval prediction models based on integration strategies have been widely applied in tourism demand forecasting. G. Li et al. (2019) developed a combination interval prediction (PIC) strategy based on normal distribution to enhance the accuracy of tourism demand forecasting by studying the fluctuations of inbound tourism to Hong Kong. Wang, Zhang, et al. (2023) developed a short-term tourism demand interval prediction model using AI algorithms (MMGTO-ESN) and applied it to analyze the daily visitor arrivals in Jiuzhaigou and Hawaii during the pandemic. Meanwhile, Jiang (2023) successfully predicted future visitor arrivals in Jiuzhaigou using an optimized QR method. Xie et al. (2023) constructed a new tourism demand interval prediction model using AI model and decomposition-ensemble strategy to analyze weekly tourism demand fluctuations in Jiuzhaigou and Hawaii. However, integration models are not always superior, and the complexity of artificial intelligence models may limit their practicality (Jiang, 2023; G. Li et al., 2019). Moreover, most studies do not comprehensively consider the tradeoffs between the coverage and width of the forecast interval. Therefore, the development of new tourism interval forecasting models remains of significant theoretical and practical importance.

2.4 Rationale for the current research

Reviewing the above literature, first, research on multi-source data-driven tourism demand forecasting has mainly relied on search engine data and travel website reviews, with limited exploration of social reviews (Wu et al., 2024). However, structured search engine data typically reflects the public's interest in destination-related information and does not capture subtle emotional shifts (M. Hu et al., 2022). Reviews on travel websites are limited and may hinder the ability of researchers to identify accurate demand trends. In contrast, social media platforms, with their unique "many-to-many" network, facilitate extensive public discussion and rapid dissemination of review information (Yang et al., 2021). Additionally, extracting emotional and thematic information from unstructured online comments is key to advancing the field of demand forecasting (Wu et al., 2024). Based on these considerations, this study integrates historical tourist data, search engine data, travel website reviews, and social reviews, and uses SnowNLP and Latent Dirichlet Allocation (LDA) to extract emotional and thematic information from social reviews, thereby providing an important multi-source data foundation to enhance tourism demand forecasting.

Second, research on interval forecasting for tourism demand is relatively scarce and lacks thorough theoretical and practical exploration. On the one hand, most distribution-based interval forecasting studies for tourism demand assume that prediction sequences follow a normal distribution and do not specifically address the issue of the probability density distribution of prediction sequences, which may reduce the accuracy of prediction intervals (G. Li et al., 2019; Xie et al., 2023). On the other hand, the lack of comprehensive consideration of prediction interval coverage and width leads to poor performance of forecasting models, especially when faced with data fluctuations caused by external interventions such as pandemics (Wang, Zhang, et al., 2023). To address this issue, this paper first uses the ARIMAX model and the MLE method to select the appropriate probability density function based on the fit between the forecast sequence and common distributions, thereby effectively extending point forecasts to forecast intervals. Then, utilizing the advantages of swarm intelligence optimization algorithms in improving the generalization of the model (Wang, Zhou, et al., 2023), this paper investigates and improves a swarm intelligence optimization algorithm and applies it to adjust forecast intervals, thus effectively balancing the coverage and width of forecast intervals.

3. Methodology

3.1 Principal components analysis

The algebraic form of PCA was first proposed by Hotelling (1933), and this technique is mainly employed for dimensionality reduction of data (Sarbu & Pop, 2005).

Suppose the original variable set $\boldsymbol{O}$ is an $m \times n$ matrix, and through PCA technique, $\boldsymbol{O}$ can be transformed into $\boldsymbol{Z}$. The transformation process can be expressed as follows.

$$\begin{aligned} \boldsymbol{Z} &= \boldsymbol{PO} \\ &= \begin{bmatrix} \boldsymbol{P_{11}} \cdot \boldsymbol{O_{11}} & \boldsymbol{P_{12}} \cdot \boldsymbol{O_{12}} & \dots & \boldsymbol{P_{1n}} \cdot \boldsymbol{O_{1n}} \\ \boldsymbol{P_{21}} \cdot \boldsymbol{O_{21}} & \boldsymbol{P_{22}} \cdot \boldsymbol{O_{22}} & \dots & \boldsymbol{P_{2n}} \cdot \boldsymbol{O_{2n}} \\ \dots & \dots & \dots & \dots \\ \boldsymbol{P_{m1}} \cdot \boldsymbol{O_{m1}} & \boldsymbol{P_{m2}} \cdot \boldsymbol{O_{m2}} & \dots & \boldsymbol{P_{mn}} \cdot \boldsymbol{O_{mn}} \end{bmatrix} \end{aligned} \tag{1}$$

In PCA technique, the *ith* principal component $\boldsymbol{Z}_i$ can be calculate as:

$$\boldsymbol{Z_i} = \boldsymbol{P_{i1}} \cdot \boldsymbol{O_{i1}} + \boldsymbol{P_{i2}} \cdot \boldsymbol{O_{i2}} + \dots + \boldsymbol{P_{in}} \cdot \boldsymbol{O_{in}}, \quad i = 1, 2, \dots, m \tag{2}$$

Under the above transformation, the principal components can be selected step by step, until most of the information of the guiding variables is considered.

3.2 ARIMAX model

The ARIMAX model, which is developed based on ARIMA, can include other series as forecast inputs. Assuming that both output ($\boldsymbol{Op}_t$) and input variables ($\boldsymbol{Ip}_t$) are time sequences consisting of random variables, the regression model between output and input can be expressed as follows (Paul, 2015):

$$\left(1 - \sum\nolimits_{\sigma=1}^{\boldsymbol{P}} \boldsymbol{\theta}_\sigma B^\sigma\right) \Delta \boldsymbol{Op}_t = \boldsymbol{\mu} + \sum\nolimits_{\sigma=1}^{\boldsymbol{Q}} \boldsymbol{\vartheta'}_\sigma B^\sigma \boldsymbol{Ip}_t + \left(1 + \sum\nolimits_{\sigma=1}^{\boldsymbol{R}} \boldsymbol{\xi}_\sigma B^\sigma\right) \overline{e}_t \tag{3}$$

where $\boldsymbol{\theta}_\sigma$, $\boldsymbol{\mu}$, $\boldsymbol{\vartheta}_\sigma$ and $\boldsymbol{\xi}_\sigma$ are the unknown parameters, $\boldsymbol{\sigma}$ and $\overline{e}_t$ express the errors. Furthermore, the usual lag operator B and the difference between adjacent output variable $\Delta \boldsymbol{Op}_t$ can be determined by:

$$\begin{cases} B^\sigma \boldsymbol{Op}_t = \boldsymbol{Op}_{t-\sigma} \\ \Delta \boldsymbol{Op}_t = \boldsymbol{Op}_t - \boldsymbol{Op}_{t-1} \end{cases} \tag{4}$$

3.3 Modified transit search optimizer

The transit search optimizer (TSO) is inspired by one of the most successful methods for detecting planets, known as the transit method. This algorithm consists of several main phases, including galaxy, transit, planet, neighbor and exploitation (Mirrashid & Naderpour, 2022).

TSO algorithm first determines the search space L_{RR} by a random selection method.

$$L_{RR,i} = CL_g + D - Noise, \quad i = 1, 2, ..., Ns \times Sn \tag{5}$$

$$D = \begin{cases} c_\alpha \times CL_g - L_r, & \text{if in the negative region} \\ c_\alpha \times CL_g + L_r, & \text{if in the positive region} \end{cases} \tag{6}$$

$$Noise = \left(c_\beta\right)^3 L_r \tag{7}$$

where CL_g is the center position of the galaxy, L_r is the random position in the search space, and $Ns \times Sn$ presents the total number of the initial individual. c_α and c_β are two random coefficients between $[0,1]$.

Then, for each star, its merit is evaluated by calculating the fitness value. For those stars that perform well, we record them planets. The luminosity ψ of the planet (i.e., the fitness value) can be estimated from the distance between the star and the observer (Dd) and from the spectra observed by the observer.

$$\psi_k = \frac{R_{t,k}/Ns}{\left(Dd_k\right)^2}, \quad k = 1, 2, ..., Ns, \quad R_{t,k} \in \{1, 2, ..., Ns\} \tag{8}$$

$$Dd_k = \sqrt{\left(L_p - L_o\right)^2} \tag{9}$$

where L_p and L_o are the position of the star and the observer, respectively.

During the calculation, the algorithm maintains the optimal solution for each star. After each transit, the algorithm updates the position of the star if the new solution proves superior. This process is analogous to planets moving to new position after passing by the sun.

$$L_{p,k}^{new} = L_{p,k} + D_\delta - Noise_\delta \tag{10}$$

$$D_\delta = c_\delta L_{p,k} \tag{11}$$

$$Noise_\delta = (c_\delta)^3 L_p \tag{12}$$

where c_δ is a random vector between $[-1,1]$. Eventually, the algorithm stops searching when it finds the global optimal solution or reaches the maximum number of iterations.

Furthermore, it is important to emphasize that the traditional TSO algorithm tends to converge prematurely to local optima. To address this limitation, this paper introduces a modified version of the TSO algorithm, termed MTSO. By incorporating the tent chaos mapping into the random selection process, MTSO enhances its exploratory capabilities, making it more adept at handling complex optimization problems characterized by nonlinearity, high uncertainty, and multiple peaks. In the MTSO algorithm, a novel formula for selecting the search space L_{RR}^{MTSO} has been defined to optimize the performance of the algorithm.

$$L_{RR,i}^{MTSO} = CL_g + D^{MTSO} - Noise^{MTSO}, \quad i = 1,2,\dots,Ns \times Sn \tag{13}$$

where D^{MTSO} and $Noise^{MTSO}$ can be presented by the tent chaos map random vector Tc:

$$D^{MTSO} = \begin{cases} Tc \times CL_g - Tc \times L_r, & \text{if in the negative region} \\ Tc \times CL_g + Tc \times L_r, & \text{if in the positive region} \end{cases} \tag{14}$$

$$Noise^{MTSO} = (Tc)^3 L_r \tag{15}$$

3.4 Benchmark models

ARIMA model

The ARIMA model is a sophisticated statistical model employed for time series analysis. This model integrates three principal components: autoregression ($\left(1-\sum_{j=1}^{p}\phi_j L^j\right)$), differencing ($(1-L)^d$), and moving average ($\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$), which together facilitate the forecasting of future values in time series data. The general form of this model is presented as follows (H. Li et al., 2020):

$$\left(1-\sum_{j=1}^{p}\phi_j L^j\right)(1-L)^d H_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t \tag{16}$$

where H_t is the time series data.

ES model

The ES model is a sophisticated technique for forecasting time series data. The core principle of this method is to assign exponentially decreasing weights to the observations over time. Consequently, this weighting scheme prioritizes more recent observations, giving them a greater influence on the forecast than their older counterparts.

Naïve/Seasonal Naïve model

The Naïve and SNaïve models assume that future predictions are determined only by historical data (G. Li et al., 2019). For Naïve model, $\hat{H}_t = H_{t-1}$, where $\hat{H}_t$ is the forecast value, H_{t-1} is the current tourism demand. For SNaïve model, $\hat{H}_t = H_{t-s}$, where $s = 4$ in this paper.

SMA model

The SMA model is a straightforward forecasting technique used in time series analysis to smooth short-term fluctuations and highlight longer-term trends or cycles. The formula for the SMA model is given by $\hat{H}_t = (1/l)\sum_{i=t-l}^{t-1} H_i$, where $l = 4$ in this study.

LASSO model

The LASSO model is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the statistical model it produces (H. Liu et al., 2021). The primary objective of the LASSO model is to minimize the following function:

$$\underset{\beta}{\boldsymbol{arg\,min}}\left\{\frac{1}{2n}\sum_{t=1}^{n}\left(H_t - \boldsymbol{\beta}_o - \sum_{j=1}^{p}\boldsymbol{\beta}_j \overline{Ds_{tj}}\right)^2 + \boldsymbol{\lambda}\sum_{j=1}^{p}\left|\boldsymbol{\beta}_j\right|\right\} \quad (17)$$

where $\overline{Ds_{tj}}$ is the predictors, $\boldsymbol{\beta}_0$ and $\beta_j, j = 1,\ldots,p$ represent the intercept and coefficients, respectively. n and p are the number of observations and predictors, respectively. The λ parameter determines the level of penalty applied to the coefficients. In this paper, the optimal λ is determined by grid search method.

RF model

Random forest is a powerful integrated learning method for classification and regression tasks (H. Li et al., 2020). It builds on the concept of decision trees and combines the prediction of multiple decision trees to improve accuracy and control overfitting. For regression tasks, the prediction of the RF model is the average of the predictions of all individual regression trees:

$$\hat{H}_t = \frac{1}{B}\sum_{b=1}^{B}\hat{H}_t^b \tag{18}$$

where B is the number of trees, and $\hat{H}_t^b$ is the prediction of the *bth* tree. The robust nature of the RF model makes it highly applicable for predicting complex, high-dimensional data. The main parameters of the RF are optimized by grid search in this paper.

LSTM model

In recent years, LSTM networks have become popular in time series analysis, especially in tourism demand forecasting. The LSTM architecture features input, forget, and output gates that manage the flow of data, retaining essential information and discarding the irrelevant, which is crucial for scenarios with long-term dependencies. Figure S1 (a) provides a visual representation of this structure. For detailed framework explanations, refer to Zhang et al. (2020). The main parameters of the LSTM are optimized by grid search in this paper.

SVR model

SVR is a machine learning algorithm widely used in tourism demand forecasting. It maps input variables into a high-dimensional space to linearly regress complex relationships (Fan et al., 2023). The essence of SVR lies in its ability to generate a unique global optimum by solving a quadratic programming problem constrained by linear bounds. This property is beneficial for managing the unpredictable patterns of tourism data. The crucial parameters of

SVR include the regularization parameter c and the kernel coefficient g, which are optimally determined by the grid search method.

BPnn model

BPnn, a multi-layer feedforward neural network, is trained using the error backpropagation algorithm. As depicted in Figure S1 (b), the architecture of BPnn consists of an input layer, several hidden layers, and an output layer, with neurons connected by synapses weighted to minimize prediction error (S. Li et al., 2018). The efficacy of BPnn depends on key parameters such as hidden size and learning rate, which affect its generalization capabilities. This study uses grid search to optimize these parameters.

3.5 Metric Evaluation

In this study, four evaluation metrics, namely root mean square error (RMSE), mean absolute error (MAE), Willmott's index of agreement (IA) and mean absolute percentage error (MAPE), are used to evaluate the forecasting accuracy of the ARIMAX and benchmark models, and these metrics can be calculated as follows.

$$RMSE = \sqrt{\frac{1}{T}\sum\left(H - \hat{H}\right)^2} \tag{19}$$

$$MAE = \frac{1}{T}\sum\left|H - \hat{H}\right| \tag{20}$$

$$IA = 1 - \frac{\sum\left(H - \hat{H}\right)^2}{\sum\left(\left|\hat{H} - \bar{\hat{H}}\right| + \left|H - \bar{H}\right|\right)^2} \tag{21}$$

$$MAPE = \frac{1}{T}\sum\frac{\left|H - \hat{H}\right|}{H} \tag{22}$$

where $\hat{H}$ and H represent the predicted value and the observed value, $\bar{H}$ is the average of the observed sequence, and T is the length of observed sequence. The smaller the value of RMSE, MAE and MAPE, the better the performance of the forecasting model, and the closer the value of IA is to 1, the better the accuracy of the model.

Furthermore, R^2 is used to measure the effect of the fit of the different distributions, and predictive interval coverage probability (PICP), normalized averaged predictive interval width (NMPIW), and coverage width-based criterion (CWC) are selected to evaluate the effectiveness of the MTSO-ARIMAX and benchmark models. The mathematical formulas of these metrics are presented below.

$$R^2 = 1 - \frac{\sum\left(H - \hat{H}\right)^2}{\sum\left(H - \bar{H}\right)^2} \tag{23}$$

$$PICP = \frac{1}{T}\sum Y\_E \tag{24}$$

$$NMPIW = \frac{1}{T}\sum \frac{Up - Low}{\overline{Up} - \underline{Low}} \tag{25}$$

$$CWC = NMPIW\left(1 + \gamma\left(PICP\right)e^{-\beta(PICP-\alpha)}\right) \tag{26}$$

where Up and Low represent the up and low bounds of forecast, $\overline{Up}$ is the maximum of Up and $\underline{Low}$ is the minimum of Low. $\beta = 10$ is the penalty parameter, α is the confidence level. Y_E and $\gamma(\bullet)$ can be calculate by using $Y\_E = \begin{cases} 0, & Y_{act} \notin [Low, Up] \\ 1, & Y_{act} \in [Low, Up] \end{cases}$ and $\gamma = \begin{cases} 0, & PICP \geq \alpha \\ 1, & PICP < \alpha \end{cases}$.

4 Model structure

In this section, we elucidate the comprehensive architecture of our proposed tourism interval prediction system (MTSO-ARIMAX). As depicted in Figure 1, the system's framework is structured into five integral modules: 1) data collection, 2) data preprocessing, 3) ARIMAX model training and forecasting, 4) MTSO interval optimization, and 5) model evaluation. A detailed explanation of the implementation process for each module is provided below.

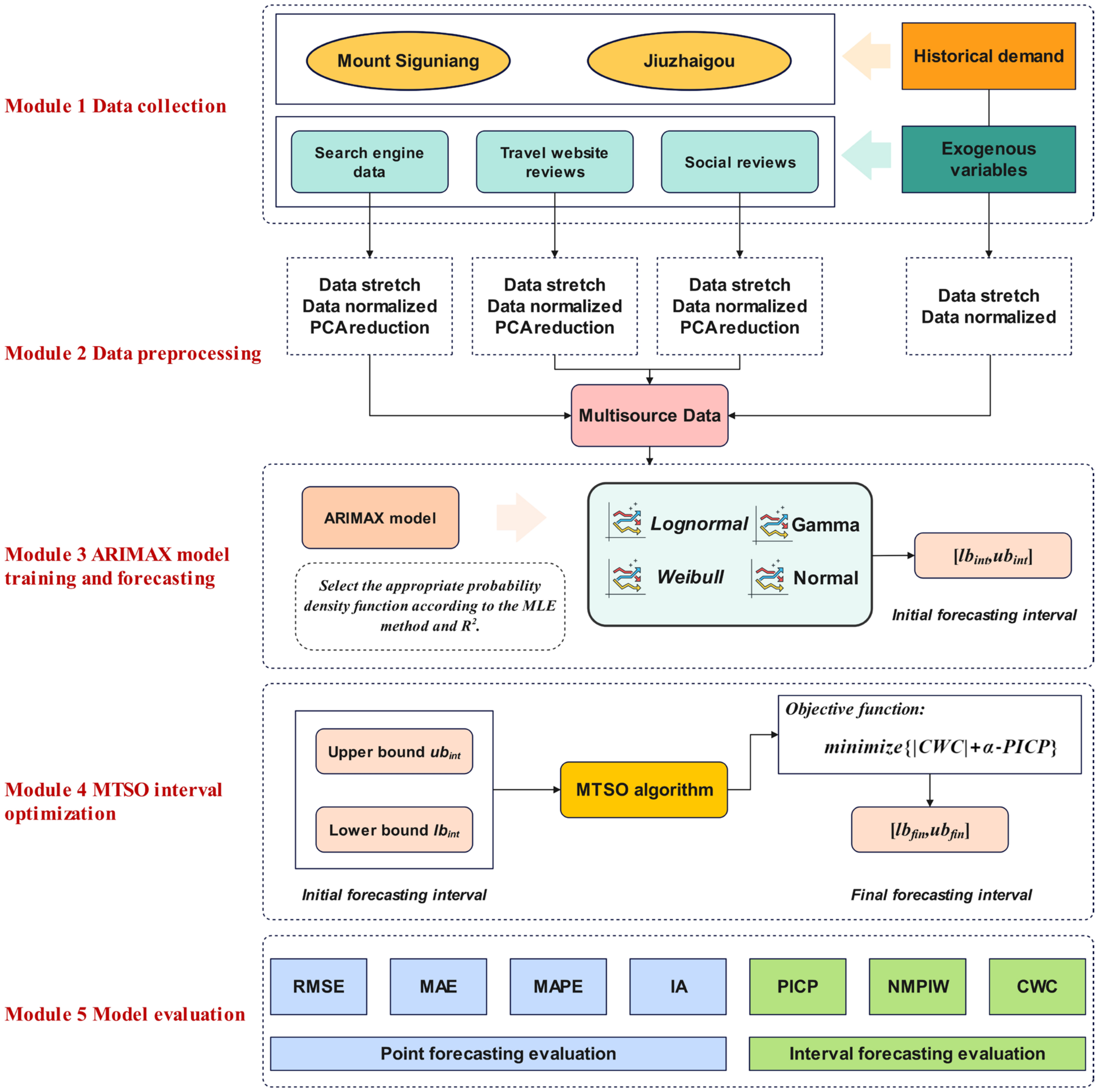

Figure 1 Framework of the designed model.

4.1 Module 1: Data collection

This study investigates the weekly fluctuations in tourist arrivals at Mount Siguniang and Jiuzhaigou, leveraging a multi-source data framework. Table S1 displays the detailed data selection, which encompasses historical tourist data, search engine data, travel website reviews, and social reviews.

First, the historical tourist data are compiled from daily records of visitors entering Mount Siguniang and Jiuzhaigou as officially recorded. These daily records are aggregated into weekly data, denoted as $H = (h_1, h_2, ..., h_N)$ for the purposes of this study.

Second, with the continuous growth of the Internet, the influence of online information on tourist behavior has significantly intensified. Building on the groundwork laid by H. Li et al. (2020), we identify 9 keywords related to the tourism of Mount Siguniang and Jiuzhaigou. The dataset compiled from these keywords is referred to as $Se = \{se^1, se^2, ..., se^{N_1}\}$, where $N_1 = 9$ in this study.

Third, reviews on travel websites are an important channel to understand the features and related services of the destination. Therefore, this study utilizes data mining techniques to collect tourist reviews, the number of reviews, and ratings from two major travel websites, Ctrip and Qunar. The data is denoted by $T = \{t^1, t^2, ..., t^{N_2}\}$, where $N_2 = 3$.

Finally, the unique “many-to-many” network structure of social platforms allows for diversification of information interactions, and tourists are no longer limited to travel websites for information. This study collects reviews, retweets, and likes related to Mount Siguniang and Jiuzhaigou from Weibo. Furthermore, we apply SnowNLP and LDA method to deeply explore the sentiment and topic information contained in the unstructured text data. The final integrated data is represented by $Sr = \{sr^1, sr^2, ..., sr^{N_3}\}$.

4.2 Module 2: Data preprocessing

After the data collection phase, we obtain the following dataset.

$$D_{N\times(N_1+N_2+N_3+1)}=\begin{bmatrix} Se \\ T \\ Sr \\ H \end{bmatrix}^T=\begin{bmatrix} se_1^1 & \dots & se_1^{N_1} & t_1^1 & \dots & t_1^{N_2} & sr_1^1 & \dots & sr_1^{N_3} & h_1 \\ se_2^1 & \dots & se_2^{N_1} & t_2^1 & \dots & t_2^{N_2} & sr_2^1 & \dots & sr_2^{N_3} & h_2 \\ se_3^1 & \dots & se_3^{N_1} & t_3^1 & \dots & t_3^{N_2} & sr_3^1 & \dots & sr_3^{N_3} & h_3 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ se_{N-1}^1 & \dots & se_{N-1}^{N_1} & t_{N-1}^1 & \dots & t_{N-1}^{N_2} & sr_{N-1}^1 & \dots & sr_{N-1}^{N_3} & h_{N-1} \\ se_N^1 & \dots & se_N^{N_1} & t_N^1 & \dots & t_N^{N_2} & sr_N^1 & \dots & sr_N^{N_3} & h_N \end{bmatrix} \tag{27}$$

Consider that the changes in tourism demand are not only influenced by historical tourist arrivals and exogenous variables from the previous period, but may also be influenced by earlier data. Through experiments, this study first adopts data stretching to reconstruct the original data to help the model better understand the inherent trend of data fluctuations. Taking the historical tourist data H as an example, the stretched historical data Hs is shown below.

$$Hs=\begin{bmatrix} h_1 & h_2 & \dots & h_l & h_{l+1} \\ h_2 & h_3 & \dots & h_{l+1} & h_{l+2} \\ \dots & \dots & \dots & \dots & \dots \\ h_{N-l-1} & h_{N-l} & \dots & h_{N-2} & h_{N-1} \\ h_{N-l} & h_{N-l+1} & \dots & h_{N-1} & h_N \end{bmatrix}_{(N-h)\times(l+1)} \tag{28}$$

Then, to ensure that the ARIMAX model and other benchmarks have a full view of the role of features, this study normalize the stretched data. The normalized stretched data is shown below.

$$\overline{Ds}_{(N-h)\times(N_1+N_2+N_3+1+4l)}=\begin{bmatrix} \overline{Ses} & \overline{Ts} & \overline{Srs} & \overline{Hs} \end{bmatrix} \tag{29}$$

where $\overline{Ses}$, $\overline{Ts}$, $\overline{Srs}$ and $\overline{Hs}$ denote the normalized stretched Se, T, Sr and H respectively.

Although the incorporation of multi-source data is an effective way to improve the predictive accuracy, the increased dimensionality of the input data also introduces greater complexity. To address this, the study employs PCA for dimensionality reduction, and the downscaled data $\overline{Dsp}$ is:

$$\overline{Dsp} = \left[\overline{Sesp} \quad \overline{Tsp} \quad \overline{Srsp} \quad \overline{Hs} \right] \tag{30}$$

where $\overline{Sesp}$, $\overline{Tsp}$, and $\overline{Srsp}$ denote the downscaled $\overline{Ses}$, $\overline{Ts}$, and $\overline{Srs}$ respectively.

4.3 Module 3: ARIMAX model training and forecasting

The ARIMAX model training and forecasting module aims to identify the optimal combination of multi-source data and hyperparameters, thereby enhancing the predictive accuracy of the ARIMAX model and subsequently improving the interval forecasting performance of the MTSO-ARIMAX framework. In this study, the Akaike information criterion (AIC) is employed to optimize the hyperparameters of the ARIMAX model.

In this research, the data after preprocessing is divided into a training set (4th-151th) and a test set (152th-213th). The test set is used to compare the predictive performance across different models. Furthermore, a rolling forecast method is introduced to further improve the predictive capabilities of the ARIMAX model. Specifically, when the forecast step is 1, for the forecast period n, data from periods 1 to (n-1) are used to train the model and optimize its hyperparameters to obtain the forecast for period n. Subsequently, for the forecast period (n+1), data from periods 1 to n are used for training and hyperparameter optimization, and so on. The rolling forecast method makes the ARIMAX model more sensitive to short-term fluctuations in the data and enables more accurate forecast values to be obtained, thus providing an effective database for generating forecast intervals.

4.4 Module 4: MTSO interval optimization

After the processing in Module 3, this study obtains the initial prediction sequence. To extend this sequence to the prediction interval, we incorporate the MLE theory and apply four common probability density functions to fit the prediction sequence. The optimal probability density function is selected based on the R^2 value, which is then used to construct the initial prediction interval $[lb_{int}, ub_{int}]$:

$$\begin{cases} lb_{int} = \hat{H} - \dfrac{Dis_{\alpha/2} \times \sigma_{Dis}}{\sqrt{n}} \\ ub_{int} = \hat{H} + \dfrac{Dis_{1-\alpha/2} \times \sigma_{Dis}}{\sqrt{n}} \end{cases} \tag{31}$$

where $Dis_{\alpha/2}$ is the critical value of distribution function at significance level α. Furthermore, to improve the quality of the prediction intervals, we introduce reduction coefficients ($\vartheta_I, \vartheta_{II} \in [-50000, 50000]$) optimized by the MTSO algorithm to further balance the coverage and the width of the prediction interval. Therefore, the fitness function of the MTSO algorithm is defined as follows:

$$Objective\ Function = \boldsymbol{minimize}\left\{\left|\mathbf{CWC}\right| + \alpha - \mathbf{PICP}\right\} \tag{32}$$

where the formulas and definitions for PICP, CWC and α are detailed in Section 3.5. Through continuous iterative optimization by the MTSO algorithm, the final global optimum is the optimal reduction coefficients ($\vartheta_I^*, \vartheta_{II}^*$) at a specific confidence level α. The final prediction intervals obtained based on these reduction coefficients are:

$$\begin{cases} lb_{fin} = lb_{int} + \vartheta_I^* \\ ub_{fin} = ub_{int} + \vartheta_{II}^* \end{cases} \tag{33}$$

4.5 Module 5: Model evaluation

To evaluate the predictive performance of the MTSO-ARIMAX model based on multi-source data, this study conducts three sets of comparative experiments involving 20 different models. First, to identify the optimal combination of multi-source data, we compare the predictive performance of the ARIMAX model across different data combinations (ARIMAX_s^I, ARIMAX_t^{II}, ARIMAX_s^{III}, ARIMAX_{s+s}^{IV}, ARIMAX_{t+s}^{V}, ARIMAX_{s+t}^{VI}, and $\text{ARIMAX}_{s+t+s}^{VII}$) using RMSE, MAE, IA, and MAPE as metrics. The formulas for these metrics are consistent with Eqs. (19) to (22). Subsequently, we introduce 10 common univariate and multivariate tourism demand forecasting models to validate the appropriateness of selecting ARIMAX as the basic model for interval prediction. The univariate benchmark models consist of SMA, Naïve, SNaïve, ARIMA, and ES models. The multivariate benchmark models encompass the LASSO, RF, SVR, BPnn, and LSTM models. The input selections for these models are detailed in Table S2. Moreover, the selection of hyperparameters for the above benchmark model is mainly obtained through grid search, and the selection range of these parameters is shown in Table S3.

Finally, to further validate the interval prediction performance of the MTSO-ARIMAX model, three commonly used interval prediction models are selected as benchmark models. These include the traditional QR method, the PIC method, and the MMGTO-ESN method. Specifically, under different confidence levels ($\alpha = 0.05$, $\alpha = 0.10$ and $\alpha = 0.15$), this study compares the prediction results of the proposed model with the benchmark models under different risk scenarios. The predictive performance of these models is quantified using the PICP, NMPIW, and CWC metrics, with the corresponding formulas provided in Eqs. (24) to (26).

5. Experiment results and analysis

5.1 Data description

This study focuses on the weekly interval prediction of tourism demand for Mount Siguniang and Jiuzhaigou, aiming to enhance the efficiency of these predictions. Building on the research by H. Li et al. (2020), this study incorporates social reviews and explores the optimal combination of multi-source data. Table S1 details the data collected under each category, and the following sections provide a comprehensive elaboration of each category.

First, we systematically collect daily tourist arrival data from March 30, 2020 to April 28, 2024, from the official websites of Mount Siguniang (https://www.sgns.cn/) and Jiuzhaigou (https://www.jiuzhai.com/). These daily records are aggregated into weekly datasets, each consisting of 213 observations. The analysis of the tourism sequence, as illustrated in Figure S2, reveals significant weekly fluctuations at both destinations, highlighting the importance and practical relevance of developing robust data-driven forecasting models.

Second, given the significant market share of Baidu search engine in China, this study has targeted tourist destinations as themes to collect data via Baidu Index (https://index.baidu.com/). We collect nine key search terms related to each destination, covering aspects such as weather, accommodation options, travel guides, geographical locations, and pandemic information.

Third, the travel website utilized in this study is sourced from Ctrip (https://www.ctrip.com/) and Qunar (https://www.qunar.com/). The variables collected include review texts, number of reviews, and means of star rating. For the review texts, this study employs the SnowNLP algorithm to perform sentiment analysis on each review.

Finally, this study utilizes data mining technique to extract a substantial volume of social reviews from Weibo (https://weibo.com/) using “Mount Siguniang” and “Jiuzhaigou” as keywords. After eliminating duplicates, the research compiles 92021 reviews related to Mount Siguniang and 170241 reviews related to Jiuzhaigou. Additionally, structured data related to social reviews are also collected, including weekly number of reviews, means of retweets, comments, and likes.

To transform the unstructured social reviews into structured sequences for subsequent predictive analysis, sentiment analysis is performed using the SnowNLP algorithm. Moreover, the LDA method is employed to explore the thematic distribution of social reviews. The optimal number of topics for the LDA method is determined based on coherence scores, ensuring a robust analysis of the underlying themes in the data.

5.2 Experimental Results

To comprehensively evaluate the interval prediction performance of the MTSO-ARIMAX model, this study designs three sets of comparative experiments. Initially, by evaluating ARIMAX models based on different multi-source data combinations, this paper investigates the rationale behind supplementing travel website reviews with social reviews. Subsequently, the multi-source data-driven ARIMAX model is contrasted with conventional univariate and multivariate tourism demand forecasting models to validate the efficiency of the ARIMAX model as a foundational tool for interval prediction. Lastly, the study compares prevalent tourism demand interval forecasting models to thoroughly analyze the overall predictive capability of the MTSO-ARIMAX model. Additionally, experiments conducted at different confidence levels further explore the adaptability and practicality of the MTSO-ARIMAX model. The subsequent sections provide a detailed analysis of the experimental results.

Verify the appropriateness of combining social reviews with other Internet data

The forecasting results of the ARIMAX models based on different combinations of multi-source data are presented in Table 1. Notably, the $\mathrm{ARIMAX}_{s+t+s}^{VII}$ model outperforms others in most prediction scenarios in terms of RMSE, MAE, IA, and MAPE. This is mainly due to the fact that Internet big data, such as social reviews, can provide a large amount of user behavioral information and emotional reflections, increasing the model's ability to capture features and structural adjustments, which in turn makes it possible to improve the demand prediction performance. Furthermore, limited and somewhat noisy travel website reviews do not significantly improve the prediction accuracy. Therefore, it is necessary to incorporate a wider range of social reviews and search engine data to enable the model to capture more accurate patterns of tourism demand fluctuations from a combination of multi-source data with complementary information to achieve a steady improvement in forecasting efficiency. The above comparisons not only confirm the positive impact of social reviews on improving prediction accuracy but also identify the optimal data inputs for interval prediction models.

Verify the effectiveness of using the ARIMAX model

To validate the efficiency of the ARIMAX model in forecasting tourism demand, this study selects 10 different forecasting models as benchmarks. The results, as presented in Table 2, demonstrate that the $\mathrm{ARIMAX}_{s+t+s}^{VII}$ model based on the optimal combination of multi-source data significantly outperforms the benchmark models in terms of RMSE, MAE, IA, and MAPE. This difference in performance is mainly due to the fact that the $\mathrm{ARIMAX}_{s+t+s}^{VII}$ model is not only able to better capture those tourism demand trends that are driven by external variables through additional sources of information, but is also able to deal with non-stationary time series data and exogenous variables at the same time, resulting in greater flexibility in practical applications. Additionally, the DM test results shown in Table S4 reveal significant differences between most of the benchmark models and the $\mathrm{ARIMAX}_{s+t+s}^{VII}$ model at $\alpha = 0.10$, which further justifies the selection of the ARIMAX model as the foundation for the subsequent interval prediction.

Table 1 Results based on ARIMAX models.

Horizon	Model	Mount Siguniang				Jiuzhaigou			
		RMSE	MAE	IA	MAPE	RMSE	MAE	IA	MAPE
One-step	ARIMAX$_{s}^{I}$	16353.57	12573.21	0.9401	0.3282	30657.78	20491.73	0.9131	0.2889
	ARIMAX$_{t}^{II}$	19185.88	13544.17	0.9175	0.3270	38477.81	21415.64	0.8632	0.3244
	ARIMAX$_{s}^{III}$	19098.78	13488.64	0.9183	0.3343	31427.55	19859.96	0.9087	0.2778
	ARIMAX$_{s+s}^{IV}$	16859.99	12938.82	0.9363	0.3456	30398.20	20306.98	0.9133	0.2887
	ARIMAX$_{t+s}^{V}$	19300.11	13716.06	0.9166	0.3392	38583.61	21220.10	0.8624	0.3235
	ARIMAX$_{s+t}^{VI}$	16734.63	12921.40	0.9373	0.3308	37192.87	22417.59	0.8722	0.3322
	ARIMAX$_{s+t+s}^{VII}$	**15775.49**	**11392.83**	**0.9442**	**0.2778**	**30385.92**	**19316.48**	**0.9147**	**0.2614**
Two-step	ARIMAX$_{s}^{I}$	**17826.08**	12729.73	**0.9288**	0.3100	31912.54	20216.04	0.9059	0.2824
	ARIMAX$_{t}^{II}$	18839.34	13056.63	0.9205	0.3052	33388.03	20728.78	0.8970	0.3090
	ARIMAX$_{s}^{III}$	18817.21	13208.18	0.9207	0.3179	31642.25	19985.55	0.9075	0.2745
	ARIMAX$_{s+s}^{IV}$	18449.33	13691.92	0.9237	0.3586	31863.98	20559.21	0.9062	0.2851
	ARIMAX$_{t+s}^{V}$	18739.77	13545.57	0.9213	0.3389	33643.78	21050.59	0.8954	0.3220
	ARIMAX$_{s+t}^{VI}$	18211.72	13304.14	0.9257	0.3215	33581.23	21251.45	0.8958	0.3199
	ARIMAX$_{s+t+s}^{VII}$	18497.42	**12670.30**	0.9233	**0.2951**	**31399.42**	**19687.66**	**0.9089**	**0.2693**
Three-step	ARIMAX$_{s}^{I}$	18270.04	13402.80	0.9252	0.3257	31813.92	20244.03	0.9065	0.2851
	ARIMAX$_{t}^{II}$	19136.33	13747.02	0.9180	0.3319	32760.73	21451.79	0.9008	0.3218
	ARIMAX$_{s}^{III}$	19747.81	13802.77	0.9126	0.3427	31714.02	19913.03	0.9070	0.2747
	ARIMAX$_{s+s}^{IV}$	18637.00	13566.86	0.9222	0.3284	31380.80	20132.51	0.9090	0.2874
	ARIMAX$_{t+s}^{V}$	19088.83	13725.35	0.9184	0.3436	32130.23	20811.45	0.9046	0.3086
	ARIMAX$_{s+t}^{VI}$	17385.37	12623.67	0.9323	**0.3120**	33583.83	21737.48	0.8958	0.3313
	ARIMAX$_{s+t+s}^{VII}$	**16578.57**	**12546.21**	**0.9384**	0.3341	**31408.46**	**19711.19**	**0.9088**	**0.2708**

Table 2 Results based on different models in Mount Siguniang and Jiuzhaigou.

Horizon	Model	Mount Siguniang				Jiuzhaigou			
		RMSE	MAE	IA	MAPE	RMSE	MAE	IA	MAPE

One-step	$\mathrm{ARIMAX}_{s+t+s}^{VII}$	**15775.49**	**11392.83**	**0.9442**	**0.2778**	**30385.92**	**19316.48**	**0.9147**	**0.2614**
	ARIMA	18930.10	13008.70	0.9197	0.3141	31538.57	19931.01	0.9081	0.2807
	ES	21534.90	15975.42	0.8961	0.3914	38322.06	27867.70	0.8643	0.4294
	SNaïve	32464.63	24357.45	0.7639	0.6434	57318.78	43024.79	0.6964	0.6328
	Naïve	17924.35	11737.02	0.9280	0.2887	30719.73	20906.35	0.9128	0.2985
	SMA	22499.43	16423.13	0.8866	0.4229	40266.51	29750.85	0.8502	0.4422
	LASSO	20239.28	14488.31	0.9082	0.3631	35296.71	25414.12	0.8849	0.3776
	RF	24310.84	18351.56	0.8676	0.4652	35240.36	26206.26	0.8852	0.4170
	LSTM	45129.36	31489.45	0.5437	0.5710	69917.22	52284.30	0.5482	0.5900
	SVR	24456.60	18036.24	0.8660	0.4672	35825.16	27220.29	0.8814	0.4464
	BPnn	50471.90	38283.30	0.4293	0.7666	78541.90	60816.69	0.4299	0.6967
Two-step	$\mathrm{ARIMAX}_{s+t+s}^{VII}$	**18497.42**	**12670.30**	**0.9233**	**0.2951**	**31399.42**	**19687.66**	**0.9089**	**0.2693**
	ARIMA	25622.83	18890.40	0.8529	0.4780	44148.64	31687.16	0.8199	0.4687
	ES	25770.64	18972.32	0.8512	0.4678	46197.04	34347.69	0.8028	0.5335
	SNaïve	38543.61	29525.10	0.6672	0.6798	68583.88	54129.61	0.5653	0.8772
	Naïve	23876.23	16508.85	0.8723	0.4346	43946.51	31047.81	0.8215	0.4765
	SMA	27098.88	19808.88	0.8355	0.5068	48366.39	35960.60	0.7838	0.5303
	LASSO	31520.40	23109.43	0.7774	0.5592	44908.24	32365.91	0.8136	0.5181
	RF	28731.28	21857.22	0.8151	0.5664	41118.65	32780.16	0.8437	0.6132
	LSTM	45376.36	32715.60	0.5387	0.6040	74181.56	53499.24	0.4914	0.5528
	SVR	40850.05	27307.15	0.6262	0.6071	43033.65	33044.37	0.8289	0.4938
	BPnn	50395.81	38593.21	0.4310	0.7516	74988.43	56757.46	0.4803	0.6305
Three-step	$\mathrm{ARIMAX}_{s+t+s}^{VII}$	**16578.57**	**12546.21**	**0.9384**	**0.3341**	**31408.46**	**19711.19**	**0.9088**	**0.2708**
	ARIMA	31611.28	23461.58	0.7761	0.5712	52877.60	39398.68	0.7416	0.5370
	ES	29050.68	21508.65	0.8109	0.5289	51538.24	38545.42	0.7545	0.5937
	SNaïve	43155.73	33741.42	0.5828	0.7749	69950.50	57268.11	0.5478	1.0618
	Naïve	28456.49	20073.79	0.8186	0.5239	51745.98	37036.56	0.7525	0.5363
	SMA	30298.60	22211.06	0.7943	0.5625	54146.42	40297.04	0.7290	0.5845
	LASSO	45220.91	33524.53	0.5419	0.6913	48195.58	36887.91	0.7853	0.5303
	RF	33831.33	25732.73	0.7436	0.6541	45985.53	35466.22	0.8046	0.7039
	LSTM	45804.29	31998.57	0.5300	0.5771	71170.55	53621.05	0.5319	0.6117
	SVR	46389.68	34898.02	0.5179	0.7394	48623.68	36456.18	0.7815	0.5249
	BPnn	48580.06	35423.54	0.4713	0.6676	73499.88	56161.26	0.5007	0.6365

Verify the comprehensive performance of the MTSO-ARIMAX model

To further improve the research framework of tourism demand forecasting, we first employ the MLE method to realize the extension of forecast sequences to forecast intervals based on the forecasts of the $\text{ARIMAX}_{s+t+s}^{VII}$ model. In this process, we use MLE to fit the probability density function of the forecast sequences generated by the $\text{ARIMAX}_{s+t+s}^{VII}$ model and evaluate the goodness of fit of four common probability distributions by R^2. The initial forecast intervals are then generated based on the optimal distribution function and $\text{ARIMAX}_{s+t+s}^{VII}$ forecast sequences. According to the results in Table S5, compared with other distributions, the R^2 value of the lognormal distribution is closest to 1, indicating a high degree of fitness for the prediction sequence. These findings not only demonstrate the superiority of the lognormal distribution in fitting the prediction sequence, but also highlight its stability in multi-step prediction. This supports our decision to use the lognormal distribution to extend the prediction sequence of the ARIMAX model into prediction intervals. Therefore, the initial interval generation for the subsequent MTSO-ARIMAX model is realized based on the lognormal distribution.

After generating the initial prediction intervals, this study proposes a modified optimization algorithm to achieve a reasonable balance between interval coverage and interval width, and then generates higher-quality prediction intervals. To validate the interval prediction performance of the MTSO-ARIMAX model, this study further employs three commonly used tourism demand interval prediction models as benchmarks. The analysis results in Table 3 and Figure S3 show that the interval prediction model based on MTSO-ARIMAX is the most prominent in the comparison of the various models in predicting the tourism demand of Mount Siguniang, with a stable PICP value of 0.9516 ($\alpha = 0.05$). This is because the MTSO algorithm, as a novel optimization algorithm, extends the individual search domain through chaos mapping, which can deeply balance the antagonistic relationship between the coverage and width of the predictions, and thus maximize the accuracy and decision significance of the prediction intervals. In contrast, the sparse internal connectivity that ESN models usually have prevents them from fully utilizing all the potential associations in the input data, thus affecting the learning effect of the model. As a result, the MMGTO-ESN model tends to generate wider prediction intervals, although it can also achieve the expected interval coverage. Additionally, the prediction intervals generated by the PIC method are typically too narrow and often fail to meet the decision-maker's prediction accuracy requirements. The comparison with the above benchmark models not only demonstrates the importance of considering the distribution of the prediction sequences, but also validates the scientific and effectiveness of using the MTSO algorithm for forecast interval adjustment.

As shown in Table 4 and Figure S4, comparing the interval prediction performance of the benchmark model for Jiuzhaigou tourism fluctuations, the MTSO-ARIMAX model has obvious advantages in both single-step and multi-step prediction. This stable performance improvement is mainly due to the integration advantage of the hybrid model, and further adjustment of the prediction intervals is beneficial for the model to overcome the time lag limitation caused by increasing the prediction step size. Specifically, compared with the benchmark QR method, the CWC values of our proposed MTSO-ARIMAX method decrease by 0.9956, 1.7236, and 1.7799, respectively. Furthermore, the prediction intervals of the MTSO-ARIMAX model all satisfy the preset confidence level, which is $PICP > \alpha$, and the width of the prediction intervals of the MTSO-ARIMAX model is relatively narrower when the coverage of the intervals is the same as that of the MMGTO-ESN model. The above results show that the MTSO-ARIMAX method based on the combination of multi-source data can achieve more effective prediction interval adjustment than the benchmark method, which can better meet the needs of decision-making. Based on these results and analysis, we confirm the accuracy and effectiveness of the designed interval forecasting method.

Table 3 Comparison of interval forecasts in Mount Siguniang.

Horizon	Significant level	Model	PICP	NMPIW	CWC
One-step	Alpha=0.05	MTSO-ARIMAX	**0.9516**	0.4059	**0.4059**
		MMGTO-ESN	0.8548	0.4665	1.6746
		QR	0.8871	0.5028	1.4458
		PIC	0.5645	**0.1436**	6.9243
	Alpha=0.10	MTSO-ARIMAX	**0.9032**	0.3533	**0.3533**
		MMGTO-ESN	**0.9032**	0.6887	0.6887
		QR	0.8226	0.3729	1.1818
		PIC	0.5000	**0.1205**	6.7001
	Alpha=0.15	MTSO-ARIMAX	**0.8548**	0.2965	**0.2965**
		MMGTO-ESN	0.8065	0.4636	1.1802
		QR	0.7903	0.3206	0.9028
		PIC	0.4516	**0.105**5	5.7716
Two-step	Alpha=0.05	MTSO-ARIMAX	**0.9516**	0.4749	**0.4749**
		MMGTO-ESN	0.8387	0.5180	2.0942
		QR	0.9032	0.6350	1.6487
		PIC	0.5968	**0.1460**	5.1409
	Alpha=0.10	MTSO-ARIMAX	**0.9032**	0.4120	**0.4120**
		MMGTO-ESN	**0.9032**	0.6699	0.6699
		QR	0.8548	0.5086	1.3076
		PIC	0.5645	**0.1226**	3.6329
	Alpha=0.15	MTSO-ARIMAX	**0.8548**	0.3371	**0.3371**
		MMGTO-ESN	**0.8548**	0.3845	0.3845
		QR	0.8387	0.4363	0.9247
		PIC	0.5161	**0.1073**	3.1303
Three-step	Alpha=0.05	MTSO-ARIMAX	**0.9516**	0.4245	**0.4245**
		MMGTO-ESN	0.9032	1.1096	2.8809
		QR	0.9355	0.6909	1.4898
		PIC	0.5968	**0.1457**	5.1276
	Alpha=0.10	MTSO-ARIMAX	**0.9032**	0.3722	**0.3722**
		MMGTO-ESN	0.8710	0.5686	1.3287
		QR	**0.9032**	0.6094	0.6094
		PIC	0.5323	**0.1222**	4.9564

Alpha=0.15	MTSO-ARIMAX	**0.8548**	0.3250	**0.3250**
	MMGTO-ESN	**0.8548**	0.7806	0.7806
	QR	**0.8548**	0.5237	0.5237
	PIC	0.4839	**0.1070**	4.2700

Table 4 Comparison of interval forecasts in Jiuzhaigou.

Horizon	Significant level	Model	PICP	NMPIW	CWC
One-step	Alpha=0.05	MTSO-ARIMAX	**0.9516**	0.3569	**0.3569**
		MMGTO-ESN	0.9032	0.7620	1.9784
		QR	0.8871	0.4703	1.3525
		PIC	0.6129	**0.1578**	4.7499
	Alpha=0.10	MTSO-ARIMAX	**0.9032**	0.3042	**0.3042**
		MMGTO-ESN	**0.9032**	0.7143	0.7143
		QR	0.8226	0.3678	1.1655
		PIC	0.5323	**0.1324**	5.3682
	Alpha=0.15	MTSO-ARIMAX	**0.8548**	0.2646	**0.2646**
		MMGTO-ESN	**0.8548**	0.6180	0.6180
		QR	0.6774	0.2724	1.8023
		PIC	0.5161	**0.1159**	3.3816
Two-step	Alpha=0.05	MTSO-ARIMAX	**0.9516**	0.4116	**0.4116**
		MMGTO-ESN	0.8226	0.5787	2.6480
		QR	0.8548	0.5948	2.1352
		PIC	0.5968	**0.1568**	5.5182
	Alpha=0.10	MTSO-ARIMAX	**0.9032**	0.3122	**0.3122**
		MMGTO-ESN	**0.9032**	0.7989	0.7989
		QR	0.7581	0.5080	2.6083
		PIC	0.5323	**0.1316**	5.3340
	Alpha=0.15	MTSO-ARIMAX	**0.8548**	0.2627	**0.2627**
		MMGTO-ESN	**0.8548**	0.5531	0.5531
		QR	0.7097	0.3954	2.0040
		PIC	0.5161	**0.1151**	3.3600
Three-step	Alpha=0.05	MTSO-ARIMAX	**0.9516**	0.3977	**0.3977**
		MMGTO-ESN	0.8387	0.5597	2.2630
		QR	0.8710	0.6796	2.1776
		PIC	0.5968	**0.1563**	5.5013
	Alpha=0.10	MTSO-ARIMAX	**0.9032**	0.3129	**0.3129**
		MMGTO-ESN	**0.9032**	0.6637	0.6637
		QR	0.7419	0.5839	3.4203
		PIC	0.5484	**0.1312**	4.5451

Alpha=0.15	MTSO-ARIMAX	**0.8548**	0.2581	**0.2581**
	MMGTO-ESN	**0.8548**	0.5444	0.5444
	QR	0.6935	0.4686	2.7086
	PIC	0.5000	**0.1148**	3.9159

6. Conclusions and implications

Achieving accurate and stable high-frequency travel demand interval prediction from the perspective of multi-source data is an important and challenging task, but little research has been done on this issue. Therefore, in this study, we propose an integrated prediction method based on the MTSO algorithm, PCA technique, MLE method, and ARIMAX model for weekly tourism demand interval prediction. By integrating search engine data, travel website reviews and social reviews into the destination tourism demand forecasting system to predict the tourism demand of the famous Chinese tourist attractions, Mount Siguniang and Jiuzhaigou, this study verifies the effectiveness and stability of the MTSO-ARIMAX model. The experimental results show that (a) the combination of multi-source data based on social reviews can effectively improve the forecasting accuracy of the forecasting model, thus providing an effective data basis for the interval forecasting of the MTSO-ARIMAX model; (b) when introducing complex multi-source data into the forecasting work, the ARIMAX model can effectively exploit the intrinsic patterns of historical tourism demand fluctuations using exogenous variables, which can be used as the basic model for tourism demand interval forecasting; (c) after obtaining the initial forecast intervals by using the ARIMAX forecasting sequence and the MLE method, the introduction of the MTSO algorithm to optimize the reduction coefficients can effectively balance the coverage and width of the forecast intervals, thus generating forecast intervals with high interval coverage and compactness.

6.1 Theorical implications

The findings of this research contribute to the existing literature in several ways. First, this study is among the first to employ historical tourist data, search engine data, travel website reviews, and social reviews as predictor variables to predict tourism demand intervals. This approach is different from the previous consideration of only search engine data and travel website reviews as a combination of multi-source data. Since the correlation between different keywords and destination demand varies, and travel website reviews may be biased toward destinations, models based on search engine and travel website reviews alone may not be sufficient to accurately predict tourism demand. Therefore, incorporating social reviews and analyzing destination aspects with corresponding in-depth topics is essential to improve model prediction accuracy. The methodology proposed in this study enriches the dataset by diversifying the data and analysis to address the limitations of existing variable combinations, and provides an important data framework for future research in tourism demand interval forecasting.

Second, this study innovatively combines the PCA technique, the MLE method, and ARIMAX to achieve the extension of point prediction sequences to prediction intervals. Traditional studies often assume that the probability density function of the prediction sequence is normally distributed, which oversimplifies the distribution in interval prediction and may reduce the prediction accuracy. Therefore, we propose an integrated method based on MLE that effectively fits the probability distributions of the prediction sequence and generates prediction intervals by selecting appropriate distribution functions based on the R^2. This method improves the generalizability of interval prediction and provides a reference for the subsequent study of tourism demand interval prediction from the perspective of probability density.

Third, this study pioneers the application of the MTSO algorithm to the prediction of destination tourism demand intervals. Although some scholars believe that interval prediction is an important complement to tourism demand point prediction, previous studies rarely consider the interaction between interval coverage and interval width, resulting in the generation of intervals that are too wide or too narrow and not highly generalizable. Therefore, this study proposes a modified swarm intelligence optimizer to achieve effective adjustment of the prediction interval through iterative optimization and parallel search with the goal of synergistic optimization of interval coverage and interval width. The method improves the universality and stability of prediction intervals, and provides a certain reference for the subsequent prediction of tourism demand intervals using artificial intelligence algorithms.

6.2 Practical implications

Overall, this study has two practical implications. First, the social reviews used in this study can provide real-time visitor feedback and sentiment analysis. The integration of this immediate, high-frequency data with other sources can significantly improve the accuracy of tourism demand forecasting models, thereby helping tourism decision-makers to make timely adjustments to marketing strategies and service delivery. Second, the MTSO-ARIMAX model can generate precise and stable forecast intervals across different confidence levels, providing policy makers and industry practitioners with a tool to gain a deeper understanding of trends and potential fluctuations in tourism demand. These prediction intervals not only help to identify and manage risks, but also guide the tourism industry to make more strategic and anticipatory decisions in the face of uncertainty. For instance, during peak or downturn periods, policy makers can use these intervals to optimize resource allocation and risk management, thereby increasing the resilience and market adaptability of the tourism industry.

6.3 Limitations and future research

Despite the importance of the above contributions, this study has its limitations. First, there are sample specificities. The empirical study area where the two destinations are located is in China, so the data collection is based on commonly used search engine websites, travel websites and social media in China. If the same methodology is implemented in other countries/regions, Google Trends data could be substituted for Baidu Index data. However, due to the specificities of the country/region and the technical ability of the personnel, there are difficulties in identifying valid travel websites and social networking websites and in obtaining accurate data. Therefore, we encourage future research to use data from other regions to validate the interval forecasting model proposed in this paper and to explore other issues in depth.

Second, the research objective of this paper is to construct a weekly interval forecasting model for tourism demand. Since daily or higher frequency forecasts tend to contain more data, deep learning algorithms could potentially be more suitable as the basic model for such interval forecasting. Therefore, future research could enrich this research framework by investigating optimal models for different frequency forecasts.

Furthermore, due to data availability, we are unable to use more social media data to explore more accurate interval prediction models. However, with the rapid development of the Internet, social reviews are no longer limited to simple textual descriptions, and we encourage future research to use more social media data to improve the accuracy and stability of tourism demand interval prediction, such as secondary comments on original social reviews, image reviews, and video reviews.

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TOURISM DEMAND INTERVAL FORECASTING WITH AN INTELLIGENCE OPTIMIZATION-BASED INTEGRATION METHOD

Appendix.

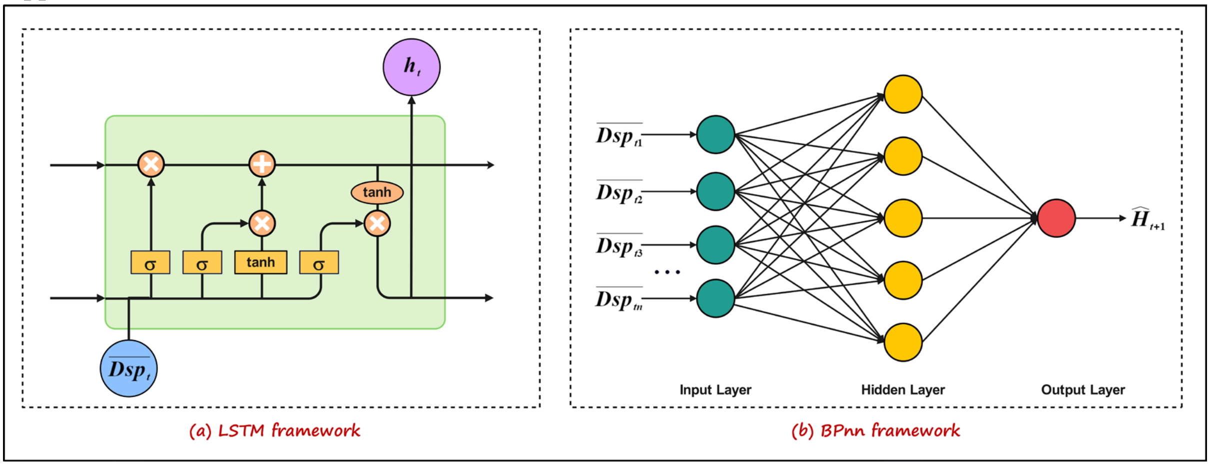

Figure S1 Framework of benchmark models: (a) LSTM, and (b) BPnn.

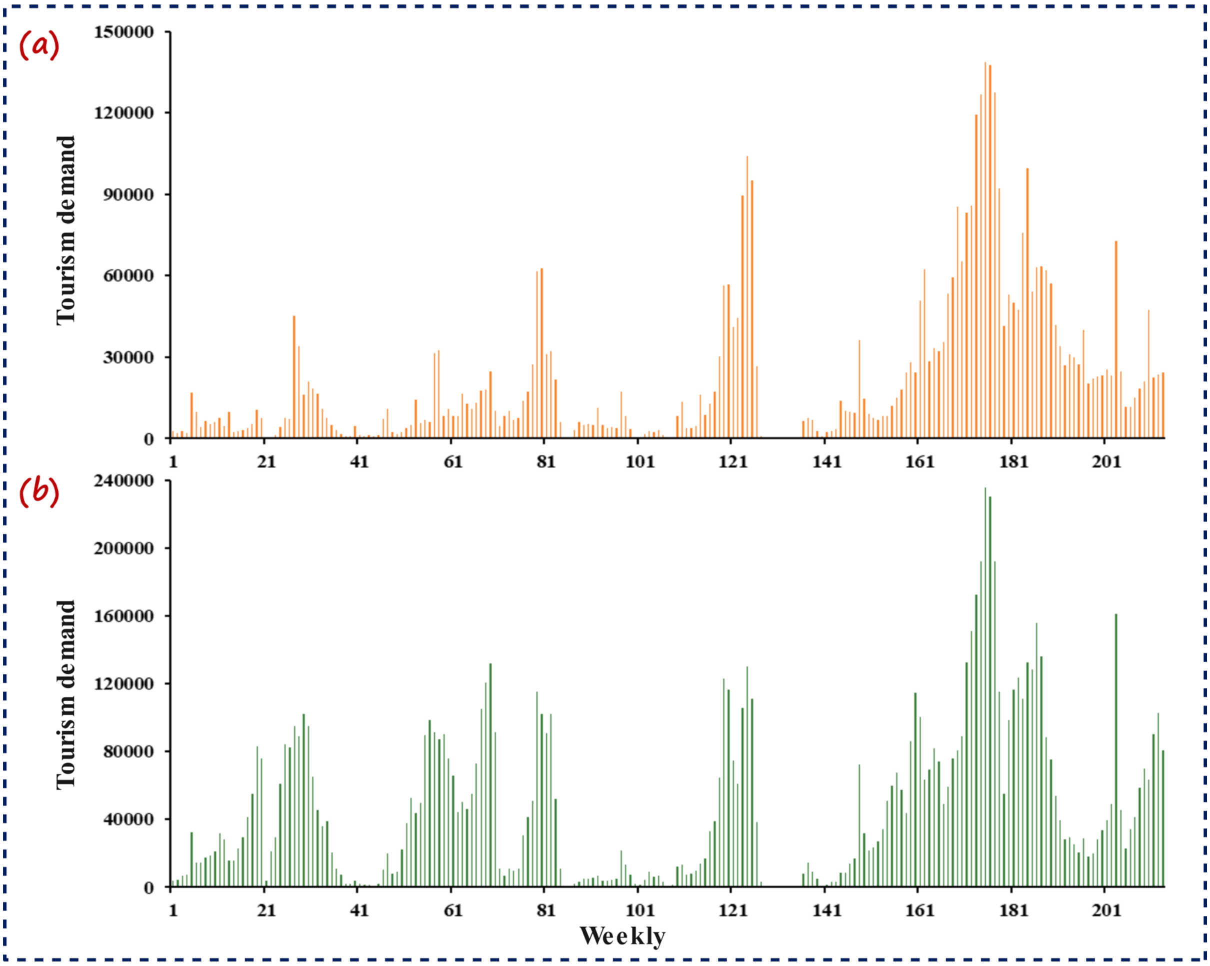

Figure S2 Weekly tourist fluctuations: (a) Mount Siguniang, and (b) Jiuzhaigou.

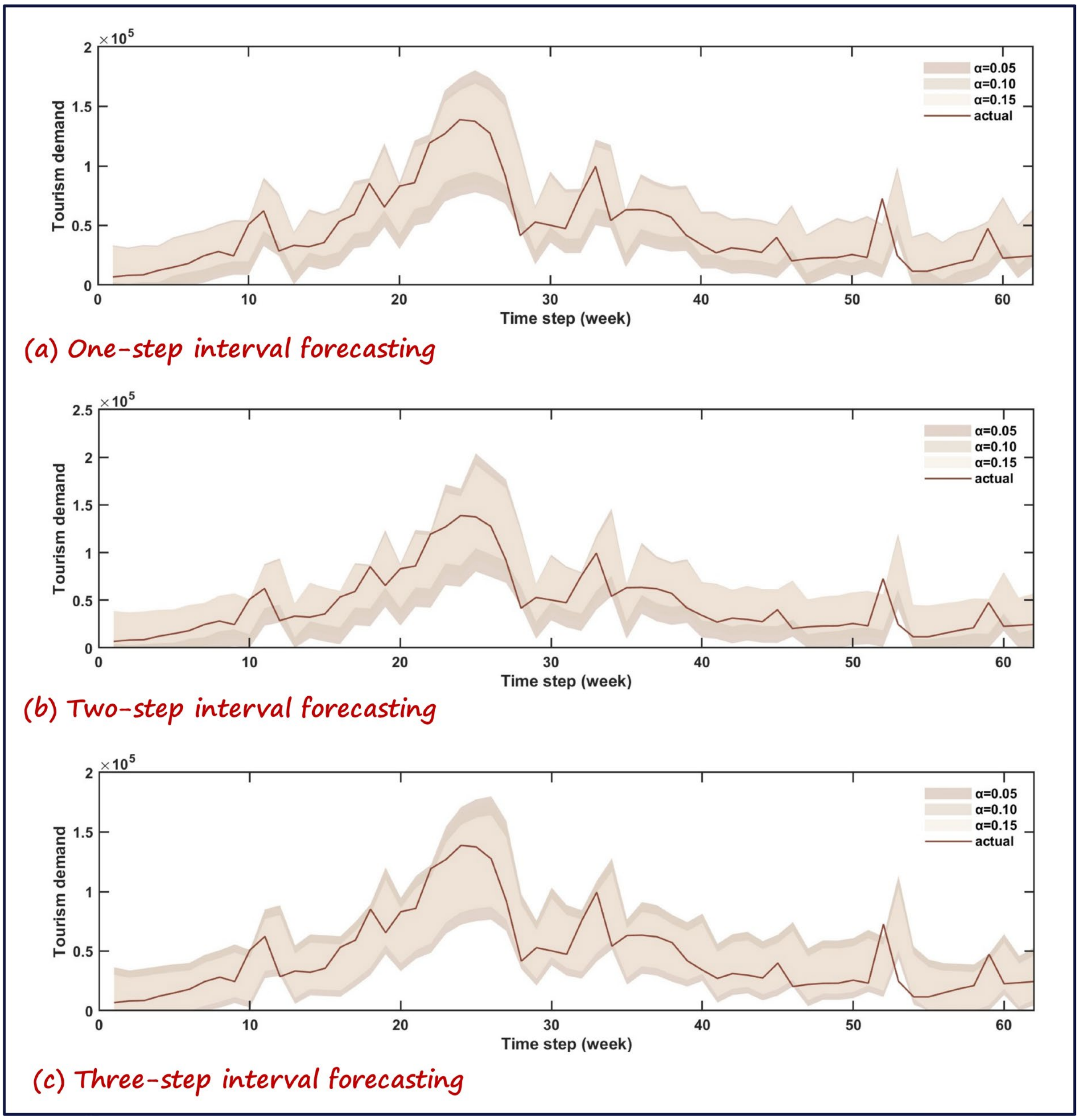

Figure S3 Mount Siguniang's tourism demand forecasting based on MTSO-ARIMAX model: (a) One-step forecasting, (b) Two-step forecasting, and (c) Three-step forecasting.

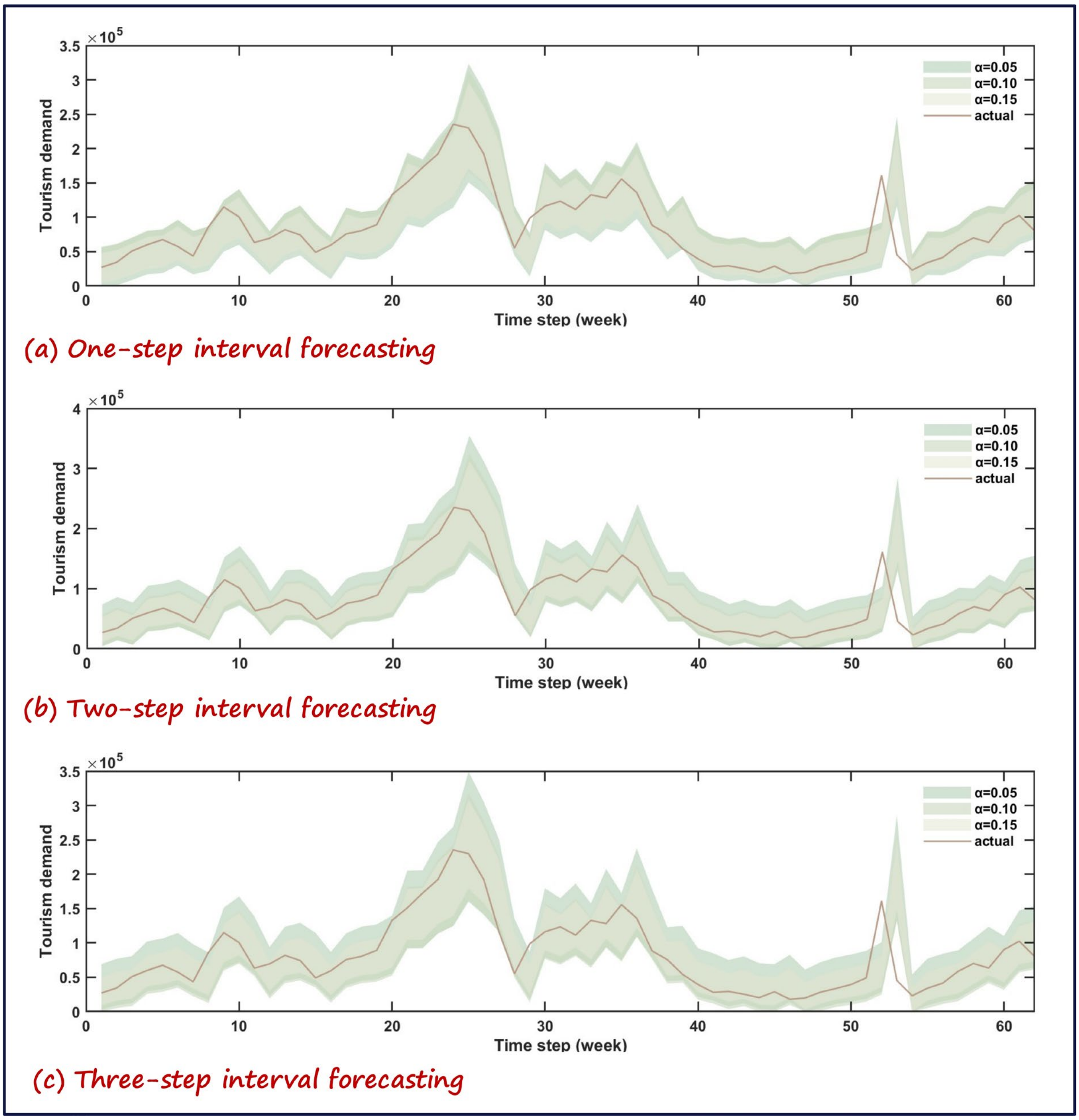

Figure S4 Jiuzhaigou's tourism demand forecasting based on MTSO-ARIMAX model: (a) One-step forecasting, (b) Two-step forecasting, and (c) Three-step forecasting.

Table S1 Four categories of candidate variables.

Category	Mount Siguniang	Jiuzhaigou
Historical Tourist Data	Historical tourists of Mount Siguniang	Historical tourists of Jiuzhaigou
Search Engine	Mount Siguniang's tips, Mount Siguniang's weather, Where is Mount Siguniang, Mount Siguniang scene area, Tickets of Mount Siguniang, Accommodation in Mount Siguniang, Travel at Mount Siguniang, Altitude of Mount Siguniang, epidemic in Sichuan	Jiuzhaigou's tips, Jiuzhaigou's weather, Where is Jiuzhaigou, Tickets of Jiuzhaigou, Accommodation in Jiuzhaigou, Jiuzhaigou airport, Jiuzhaigou hotel, Jiuzhiagou scenery, epidemic in Sichuan
Travel Website Reviews	Sentiment score, Number of reviews, Means of star rating	Sentiment score, Number of reviews, Means of star rating
Social Reviews	Number of reviews, Means of retweets, Means of comments, Means of likes, Sentiment score, Probability of Topic 1, Probability of Topic 2, Probability of Topic 3	Number of reviews, Means of retweets, Means of comments, Means of likes, Sentiment score, Probability of Topic 1, Probability of Topic 2, Probability of Topic 3, Probability of Topic 4, Probability of Topic 5, Probability of Topic 6, Probability of Topic 7

Table S2 Variable selection for ARIMAX models.

Category	Model	Historical demand	Search engine	Travel website review	Social review
Time series model	$ARIMAX_s^I$	✓	✓		
	$ARIMAX_t^{II}$	✓		✓	
	$ARIMAX_s^{III}$	✓			✓
	$ARIMAX_{s+s}^{IV}$	✓	✓		✓
	$ARIMAX_{t+s}^{V}$	✓		✓	✓
	$ARIMAX_{s+t}^{VI}$	✓	✓	✓	
	$ARIMAX_{s+t+s}^{VII}$	✓	✓	✓	✓
	SMA	✓			
	ES	✓			
	Naïve	✓			
	SNaïve	✓			
	ARIMA	✓			
AI model	BPnn	✓	✓	✓	✓
	LASSO	✓	✓	✓	✓
	RF	✓	✓	✓	✓
	SVR	✓	✓	✓	✓
	LSTM	✓	✓	✓	✓

Table S3 Parameter setting of all models.

Model	Parameter	Value range
ES	Smoothing parameter	0.3
LASSO	Alpha parameter	[0.0001,1]
RF	Minimum Samples Split	[2,100]
	Maximum Depth of the Tree	[3,9]
	Minimum Samples Leaf	[1,100]
SVR	Penalty Parameter	[0.1,100]
	Kernel Coefficient	[0.01,1]
	Kernel Type	'RBF'
BPnn	Epochs	500
	Learning rate	[0.0001,0.01]
	Hidden size	[10,100]
	Batch size	4
LSTM	Epochs	500
	Learning rate	[0.0001,0.01]
	Hidden size	[10,50]
	Batch size	4
	Drop rate	0.2
ESN	Reservoir scale	[1,100]
	Reservoir connection rate	[0.01,0.99]
	Reservoir spectral radius	[0.01,0.99]
MMGTO	Population size	100
	Maximum iterations	200
	Archive size	200
MTSO	Population size	100
	Maximum iterations	200

Table S4 The results of DM test.

Data	One-step			Two-step			Three-step		
	Control	Model	DM value	Control	Model	DM value	Control	Model	DM value
Mount Siguniang	$\text{ARIMAX}_{s+t+s}^{VII}$	ARIMA	2.7334***	$\text{ARIMAX}_{s+t+s}^{VII}$	ARIMA	3.0682***	$\text{ARIMAX}_{s+t+s}^{VII}$	ARIMA	4.4698***
		ES	2.6128***		ES	2.9384***		ES	3.7395***
		SNaïve	3.7629***		SNaïve	5.8491***		SNaïve	6.0829***
		Naïve	1.7122**		Naïve	1.9406**		Naïve	3.0142***
		SMA	2.3775***		SMA	3.1605***		SMA	3.7693***
		LASSO	2.6446***		LASSO	4.3962***		LASSO	5.8467***
		RF	3.6659***		RF	4.0315***		RF	4.9103***
		LSTM	3.8408***		LSTM	5.3553***		LSTM	4.9883***
		SVR	2.7049***		SVR	3.8214***		SVR	6.1486***
		BPnn	4.3575***		BPnn	6.7186***		BPnn	5.7721***
Jiuzhaigou	$\text{ARIMAX}_{s+t+s}^{VII}$	ARIMA	0.6220	$\text{ARIMAX}_{s+t+s}^{VII}$	ARIMA	2.8561***	$\text{ARIMAX}_{s+t+s}^{VII}$	ARIMA	4.2259***
		ES	2.8172***		ES	3.6722***		ES	4.2207***
		SNaïve	5.0794***		SNaïve	6.0730***		SNaïve	6.3972***
		Naïve	0.8914		Naïve	2.6788***		Naïve	3.7314***
		SMA	3.2553***		SMA	3.9906***		SMA	4.4929***
		LASSO	3.1688***		LASSO	3.0930***		LASSO	4.1078***
		RF	2.8486***		RF	3.7769***		RF	3.5865***
		LSTM	5.8800***		LSTM	5.2390***		LSTM	5.6643***
		SVR	3.5455***		SVR	3.5715***		SVR	3.7942***
		BPnn	6.7405***		BPnn	6.0544***		BPnn	6.0090***

Note: In this table, "*", "**" and "***" denote rejection of the null hypothesis at $\alpha = 0.2$, $\alpha = 0.1$, and $\alpha = 0.05$.

Table S5 R^2 values of different distribution.

Dataset	**Horizon**	R^2			
		Lognormal	**Normal**	**Gamma**	**Weibull**
Mount Siguniang	One-step	**0.9937**	0.9313	0.9882	0.9801
	Two-step	**0.9935**	0.9177	0.9822	0.9754
	Three-step	0.9917	0.9526	**0.9949**	0.9889
Jiuzhaigou	One-step	**0.9926**	0.9393	0.9878	0.9814
	Two-step	**0.9952**	0.9395	0.9929	0.9864
	Three-step	**0.9949**	0.9381	0.9909	0.9847