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Tourism Demand Modelling and Forecasting: A Horizon 2050 Paper

Abstract
Purpose – The aim of this paper is to provide a narrative review of previous research on tourism demand modelling and forecasting and potential future developments.
Design/methodology/approach – A narrative approach is taken in this review of the current body of knowledge.
Findings – Significant methodological advancements in tourism demand modelling and forecasting over the past two decades are identified.
Originality – The distinct characteristics of the various methods applied in the field are summarised and a research agenda for future investigations is proposed.

Keywords: Tourism demand; Modelling and forecasting; Methodological advancements; Future trends

Introduction
Tourism has become a pillar industry for numerous countries and regions. Accurate forecasting is therefore essential for tourism businesses and destinations as they work to effectively balance the advantages of tourism demand with their capacities and preserve their local ecological and social roles (Song *et al.*, 2019). Accurate demand forecasts also play a vital role in enabling businesses to establish suitable pricing and operational strategies in the short term and to make informed investment decisions in the medium and long terms.
The literature on tourism demand modelling and forecasting is substantial, with over 600 studies published between 1946 and 2023 (Song *et al.*, 2019; Song *et al.*, 2023). Crouch (1994) and Witt and Witt (1995) first reviewed papers published from the 1960s to the 1990s, followed by Li *et al.* (2005), who examined 420 studies published between 1960 and 2002. Song and Li (2008) later analysed 119 studies published between 2000 and 2007. Goh and Law (2011) conducted a review of the methodological developments emerging from 155 papers published between 1995 and 2009. However, few reviews have focused specifically on hotel modelling and forecasting. Koupriouchina *et al.* (2014) reviewed 26 studies on hotel demand forecasting from 1985 to 2013, and Huang and Zheng (2023) assessed 85 empirical studies focused on data sources and methodological developments in hotel demand forecasting. Additionally, Wu *et al.* (2017) conducted a review of hotel and tourism demand studies from 2007 to 2015, while Song *et al.* (2019) conducted a comprehensive literature review of the methodological developments in this field from the 1960s to 2018.
This study focuses on the tourism demand modelling and forecasting literature from 1946 to 2020 and conducts a narrative review to analyse the methodological advancements made during this period. The findings offer valuable insights into the emerging themes and trends in this field, thus contributing to a deeper understanding of tourism demand modelling and forecasting research.
The subsequent sections of this paper are structured as follows: Section 2 presents an overview of the methodological advancements in tourism demand modelling and forecasting. Section 3 provides a summary of the effects of COVID-19 on tourism modelling and forecasting. Section 4 outlines a future research agenda for this field, and Section 5 concludes the paper.

Past developments, 1946–2020
Methodological advancements
Most studies of tourism demand modelling and forecasting primarily aim to identify the determinants of tourism demand using novel forecasting methods to generate accurate *ex-post* forecasts based on the developed models, which are mainly based on econometric methods. Many studies also aim to provide practical *ex-ante* forecasts. The methods applied to achieve

these objectives can be broadly grouped into two categories: quantitative models (e.g., non-causal time series models, causal econometric models, artificial intelligence [AI]-based models) and qualitative or judgmental methods (e.g., the Delphi technique and scenario analysis; Song and Li, 2008). Hybrid forecasting methods in which multiple approaches are integrated have also been developed and can enhance forecasting performance. Figure 1 summarizes the characteristics of the advancements of these methods from 1946 to 2020.

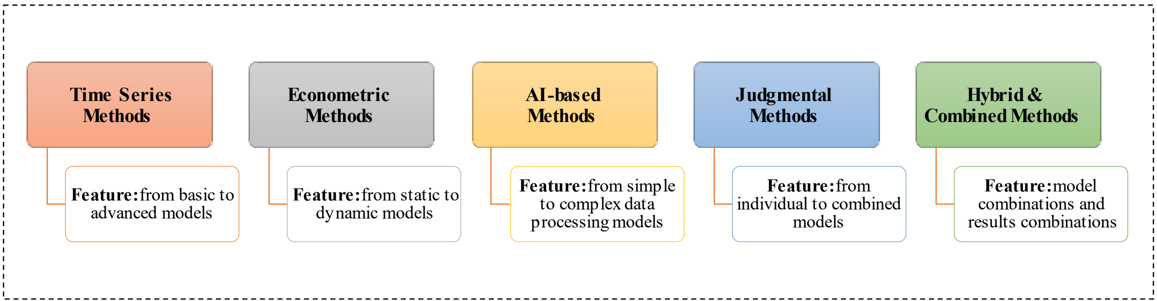

Figure 1 Methodological advancements in tourism demand modelling and forecasting
(Source: Authors' own creation)

Time series methods
Time series models generate forecasts by identifying trends, slopes, and cycles based on patterns observed in historical data (Song *et al.*, 2019). These models are cost-effective in terms of data collection and model estimation as they are solely based on values of consecutive measurements taken at regular intervals, such as monthly, quarterly, or annual intervals. These time series models have gradually evolved (Peng *et al.*, 2014) from basic forms – such as naïve models, single exponential smoothing (ES) models, autoregressive (AR) models, moving average (MA) models, and historical average (HA) models – which have traditionally served as benchmarks, to more advanced models. These advanced models incorporate additional time series features, such as trends and seasonality, by integrating advanced ES methods and Box–Jenkins type methods such as autoregressive integrated moving average (ARIMA) models (Box and Jenkins, 1976).
Models in the autoregressive moving average (ARMA) family are widely applied in time series analyses, and various forms have been developed to adapt to specific situations and improve forecast accuracy. These include the seasonal ARIMA (SARIMA) model, the autoregressive fractional integrated moving average (ARFIMA; Chu, 2009) model, and the SARIMA-In model, which considers interventions from special events (Goh and Law, 2002). The inherent seasonality of tourism activities is often considered in tourism demand forecasting (Song and Li, 2008), and models such as the seasonal-naïve model (Önder and Gunter, 2016), the seasonal-AR model (Gil-Alana, 2010), the SARIMA model, the Holt–Winters ES model, the ARIMA-seasonal decomposition model (Koc and Altinay, 2007), and the seasonal fractional-ARIMA model (Gil-Alana *et al.*, 2004) have been developed to address this factor.
State space models, including structural time series (STS) models and innovation state space (ISS) models, have performed well in tourism forecasting competitions (Athanasopoulos and Hyndman, 2008; Jiao and Chen, 2019). These models use unobserved components and allow for maximum likelihood estimation within the ES framework. In contrast to traditional time series models that predict both signal and noise, singular spectrum analysis (SSA) is a nonparametric forecasting technique that focuses solely on forecasting the signal component. This technique decomposes a time series into independent components (trend cycles, seasonal

cycles, and business cycles) to filter out noise, thus generating less noisy forecasts (Hassani *et al.*, 2015). Nonlinear time series models, such as the self-exciting threshold autoregressive model and the Markov-switching model, have also been applied to tourism and hotel demand forecasting (Chen, 2013; Claveria and Datzira, 2010). Sinewave and cubic form models have also proven useful in generating forecasts for diverse scenarios, as they can decompose trends and fit tourism demand data with trend curves for future analysis (Chan, 1993).

Econometric models

Econometric models are based on economic theory and analyse the causal relationships between various factors and tourism demand through demand elasticity analysis. This type of analysis can inform policy recommendations and evaluations of the effectiveness of established tourism policies. Econometric models can now develop dynamically rather than statically. The single static regression (SR) model previously applied in tourism demand forecasting studies (Martin and Witt, 1987) has its limitations and struggles to capture dynamic relationships. SR models may inaccurately diagnose data properties such as unit roots and cointegration, leading to spurious regressions. The forecasting performance of dynamic econometric models is generally superior, as temporal changes in the causal variables can be incorporated.

Modern econometric approaches, such as the distributed lag (DL) model, the autoregressive distributed lag model (ADLM), and the error correction model (ECM), have been applied in research on intertemporal relationships, including those of the long-term equilibrium and short-term dynamics of tourism demand and its determinants (Kulendran and King, 1997; Smeral, 2010; Song and Witt, 2003). The time-varying parameter model, which allows coefficients to vary over the sample period, has also been used to track the impacts of explanatory variables on tourism demand over time (Li *et al.*, 2006; Page *et al.*, 2012; Song, Witt and Jensen, 2003).

However, single-equation econometric forecasting approaches have various limitations when analysing the interdependence of multiple demand equations or time series and when testing the symmetry and adding-up hypotheses associated with contemporary theories of demand. System equation models such as the almost ideal demand system (AIDS) model were developed to address these limitations (Deaton and Muellbauer, 1980). The vector autoregressive (VAR) model and the vector error correction model (VECM), which capture the interdependency of multiple time series, are other extensions of the single-equation static model. In the VAR framework, all explanatory variables can be treated as endogenous. The classic VAR has been further developed into the Bayesian VAR (BVAR; Wong *et al.*, 2006), global VAR (GVAR; Pesaran *et al.*, 2004), and Bayesian estimation techniques (BGVAR; Assaf *et al.*, 2019).

Other spatial econometrics and mixed-frequency data methods have also been proposed in the literature. Spatial econometrics considers spatial heterogeneity and spillover effects and has been applied to examine the spatial correlations of destinations, origin markets, and neighbouring markets with tourism demand (Deng and Athanasopoulos, 2011; Marrocu and Paci, 2013). Furthermore, the increasing availability of high-frequency big data has led to the emergence of mixed-frequency data methods such as the mixed-data sampling (MIDAS) method, which integrates data with different frequencies. Previous studies have often encountered the issue of frequency mismatch among variables. Three primary methods have been used to address this challenge: interpolating low-frequency data into high-frequency data (Chow and Lin, 1971), substituting a high-frequency variable as a proxy for a low-frequency variable (e.g., using the monthly industrial production index [IP] as a proxy for GDP; Chatziantoniou *et al*., 2016; Liu *et al*., 2021), and transforming high-frequency data into low-frequency data (Li *et al.,* 2019; Wan and Song, 2018). However, these methods may create their own potential issues, such as information loss and publication lags through aggregation as well as the introduction of additional biased information into the original series through interpolation. In response, the MIDAS method has gained research attention as it enables the conversion of data from higher to lower frequencies, ensuring consistency in the frequency of all variables for model estimation (Bangwayo-Skeete and Skeete, 2015; Wu *et al.*, 2017). To overcome these limitations, Wu *et al.* (2023) introduced a novel method based on the reverse MIDAS model, which allows for the direct use of low-frequency explanatory data to forecast a high-frequency dependent variable. This approach enables the generation of tourism demand using multiple mixed-frequency data with the same, higher, and lower frequencies. Wu *et al.* (2023) incorporated multi-source heterogeneous data, including monthly economy-related variables, daily search query indices, and weekly online news data, into the seasonal autoregressive integrated moving average-mixed data sampling (SARIMA-MIDAS) approach to enhance forecasting accuracy.

Tourism demand is typically measured in econometric models using variables such as tourist arrivals (Smeral, 2010), tourist expenditure, or the number of nights stayed (Athanasopoulos and Hyndman, 2008; Baggio and Sainaghi, 2016; Wu *et al.*, 2017). Studies have also examined disaggregate demand through subcategories such as visit purposes (Cortés-Jiménez and Blake, 2011), expenditure-based categories (Zheng *et al.*, 2013), and transportation modes (Cazanova *et al.*, 2014; Cuhadar *et al.*, 2014; Tsui *et al.*, 2014). Neoclassical economic theory suggests that demand is influenced by prices and income, so variables such as gross domestic product, the consumer price index adjusted by exchange rates, and the weighted average consumer price index of competing destinations are often included in demand models (Li *et al.*, 2005; Song and Li, 2008). Dummy variables are used to account for seasonality and one-off events, including financial crises (Song *et al.*, 2011b), political stability (Saha and Yap, 2014), terrorist attacks (Bonham *et al.*, 2006), and the Olympics (Page *et al.*, 2012). Other factors considered in previous studies include climate-related factors, transportation costs, advertising expenditure, trade volume, population, unemployment rate, various social, cultural, geographic, and political factors, and variables related to online tourist behaviour (Bangwayo-Skeete and Skeete, 2015; Wu *et al.*, 2017; Yang *et al.*, 2015).

Artificial intelligence-based models

As internet technology has rapidly advanced, AI-based models have gained popularity in tourism demand modelling and forecasting due to their ability to predict future demand without prior knowledge of data distribution or input–output relationships. These models have evolved from handling processing-limited and single-source data to managing vast and diverse multi-source data. In the context of tourism demand, AI-based methods include artificial neural networks (ANN; Chen *et al.*, 2012; Claveria *et al.*, 2015a; Claveria *et al.*, 2015b; Pattie and Snyder, 1996), support vector regression (SVR; Chen *et al.*, 2015), fuzzy time series (Wang, 2004), the rough set approach (Goh *et al.*, 2008), grey theory (Sun *et al.*, 2016), and genetic algorithms and Gaussian process regression (GPR; Jiao and Chen, 2019; Wu *et al.*, 2017).

In the context of AI-based methodologies, artificial neural network (ANN) models warrant increased attention due to their superior ability to detect and extract nonlinear patterns in time series data compared with alternative models, as demonstrated in previous research (Liao *et al.*, 2024; Song *et al.*, 2019). ANN modelling is a nonparametric data-driven technique that is widely used in AI-based models for tourism demand forecasting due to its ability to handle imperfect data and distinctive nonlinearity (Song *et al.*, 2019). Various ANN models, including backpropagation NN models (BPN; Chen *et al.*, 2012; Chen *et al.*, 2015), multilayer perception models (MLP; Claveria *et al.*, 2015a), radial basis function models (RBF; Claveria *et al.*, 2015a), generalised regression neural network models (GRNN; Cuhadar *et al.*, 2014), and Elman neutral network models (Elman NN; Claveria *et al.*, 2015b) have been extensively applied in tourism demand forecasting studies (Song *et al.*, 2019; Wu *et al.*, 2017). Kon and

Turner (2005) demonstrated the effectiveness of ANN methods, particularly for short-term forecasting.
The SVR method uses structural risk criteria to minimise the upper bound of generalisation error. This is achieved by nonlinearly mapping the inputs into a high-dimensional space, allowing for the handling of linear regression problems (Cang, 2014; Chen and Wang, 2007). Fuzzy system models, however, have a simple structure and do not require assumptions about data distribution or model formulation. They are particularly suitable for situations involving linguistic terms or datasets with fewer than 50 data points (Chen *et al.*, 2010; Hadavandi *et al.*, 2011; Jiao and Chen, 2019). Additionally, the rough set approach is an informative technique that generates decision rules based on conditions. This approach handles vague data by replacing them with accurate lower and upper approximations and identifying relationships in hybrid data with both quantitative and qualitative components (Goh *et al.*, 2008).
The sparse GPR model is a nonparametric technique used for regressions in high-dimensional space. It provides uncertainty estimations, identifies noise and parameters through training, and offers improvements in terms of generalisability compared with the basic GPR model (Wu *et al.*, 2012). Gandomi *et al.* (2013) and Sun *et al.* (2016) used the cuckoo search (CS) algorithm for tourism demand forecasting due to its robustness, fast convergence, high efficiency, minimal tuning parameters, and ease of implementation (Jiao and Chen, 2019). The k-nearest neighbour (KNN) method, used by Diaz and Mateu-Sbert (2011), predicts future time series by selecting the most similar patterns based on past data.
In recent years, the use of deep learning methods for forecasting has grown. This has led to improvements in various aspects of deep learning forecasting methods. First, there has been an increasing focus on tourism demand forecasting using deep learning, driven by the need for granular sentiment analysis to accurately capture tourists' preferences and attitudes (Li, Gao & Song, 2023). Second, feature selection has been recognised as crucial to identifying relevant input variables related to tourism demand from search engines, thereby enhancing algorithm accuracy (Wang, Hu and Wu., 2023). Third, there has been a lack of research on the impacts of online reviews on hotel demand forecasting, prompting the proposal of an analytic framework based on systematic functional linguistics theory to improve the accuracy of hotel demand forecasts (Zhang and Niu, 2024). Fourth, the impacts of events on tourism demand have been overlooked in existing literature, leading to the development of a Gated Recurrent Unit -based model to forecast tourist arrivals by capturing the concerns of tourists and the loss of potential arrivals that results from these concerns (Zhang *et al.*, 2023). Finally, research on deep learning forecasting that integrates multiple data sources is still in the development phase, with the introduction in 2024 of an initial forecasting method based on bidirectional long short-term memory (LSTM) designed to enhance the extraction of data features from a diverse set of predictor variables (Han *et al*., 2024).
In addition, the use of spatial-temporal information in deep learning models remains limited. Jiao *et al.* (2020) and Yang and Zhang (2019) have developed spatiotemporal autoregressive models that incorporate spatial lag terms with time series and econometric models, yielding accurate forecasting results. However, these models are unable to process nonlinear relationships and prevent error accumulation. To address these limitations, Zheng *et al.* (2021) used an LSTM model to extract temporal dependencies and spatial effects to forecast tourism demand at attractions. Li *et al.* (2022) further proposed a spatial-temporal fused graph convolutional network model for forecasting by extracting spatial effects through graph convolutional networks and extracting temporal dependencies through LSTM. Despite these advancements, limitations remain, including LSTM's inability to capture deep and hidden spatial information and the incomplete reflection of real spatial effects by the spatial Euclidean distance between places. To overcome these limitations, Sun *et al.* (2023) introduced a new convolutional block attention module model for predicting multi-attraction

tourism demand in Beijing and Xiamen based on spatial-temporal grid passenger flow maps. Additionally, Xu *et al.* (2023) proposed a novel deep learning method with an encoder-decoder architecture to exploit the temporal heterogeneity of multiple factors for daily tourism demand forecasting. Finally, considering the increasing accessibility of spatial-temporal data and the limitations of existing models, Zhou *et al.* (2023) proposed a graph-attention based spatial-temporal learning framework, building on the progress of graph neural networks and multi-head attention networks in spatial-temporal forecasting.

Judgmental approaches

In addition to the statistical methods mentioned above, judgmental methods have been applied in tourism demand modelling and forecasting. These methods are particularly useful for *ex-ante* forecasting during major crises. Judgmental forecasting involves incorporating the opinions and insights of experts, stakeholders, and the public to predict future scenarios based on the stakeholders' knowledge and experience (Lin and Song, 2015). The Delphi technique and scenario analysis are also commonly used for tourism demand modelling and forecasting. The Delphi technique is a structured and iterative method that gathers and synthesises expert opinions until a consensus or convergence is reached among a panel of experts (Lin and Song, 2015; Song *et al.*, 2013). It is particularly useful in situations of uncertainty, complexity, or limited data availability. In contrast, scenario analysis considers a range of plausible future outcomes to assess their potential impact on a specific situation. This method can be used to explore uncertainties related to future events or conditions (Yeoman *et al.*, 2007).

However, the subjective biases inherent in collective expert judgment can undermine forecast accuracy (English and Kernan, 1976). To address this limitation, numerous studies have combined judgmental methods with quantitative models to achieve convergent validity (Lin, 2019; Liu *et al.*, 2021; Qiu *et al.*, 2021).

Hybrid and combined methods

Hybrid and combined models have been popular for forecasting since 2008 (Jiao and Chen, 2019). Hybrid models systematically combine various inherent forecasting modelling processes, while combined models integrate the results generated by different models using combination approaches, including simple average, variance–covariance, discounted mean squared forecast error, shrinkage, Granger and Ramanthan regressions, and Time Varying Parameter (TVP) combination methods (Wu *et al.*, 2017). These combined and hybrid approaches have been extensively used to improve forecasting performance, particularly during major crises (Andrawis *et al.*, 2011; Song *et al.*, 2009; Zhang *et al.*, 2021). Hybrid and combined methods can either integrate quantitative models or both quantitative and qualitative models.

One type of forecasting model for time series data involves combinations of different single models (Shen *et al.*, 2011; Song *et al.*, 2009). Previous studies have proposed models such as Autoregressive model with exogenous variables and Autoregressive Moving Average model with exogenous variables, which incorporate exogenous variables such as climate variability (Li *et al.*, 2018) and Google trend variables (Pan and Yang, 2017) to generate forecasts. The combination of Autoregressive Integrated Moving Average model with exogenous variables-type models with static varying parameters and MIDAS has also been shown to perform well (Bangwayo-Skeete and Skeete, 2015; Pan and Yang, 2017; Song *et al.*, 2019). Additionally, the ISS model, which incorporates exogenous variables, has been used to capture time series dynamics and run regression models (Athanasopoulos and Hyndman, 2008). Song *et al.* (2011a) demonstrated that combining STS with the TVP model leads to accurate quarterly forecasts for tourist arrivals. Guizzardi and Stacchini (2015) also discovered that incorporating business sentiment indicators in naïve and STS models can improve forecasting performance.

ADLMs and ECMs are often combined with other models such as the TVP to enhance their flexibility and capture gradual structural changes (Li *et al.*, 2006). Bangwayo-Skeete and Skeete (2015) proposed an AR-MIDAS model that combines a reduced form of the ADLM with MIDAS to estimate tourist arrivals in the Caribbean. Previous studies have also integrated dynamic and systematic econometric models. For example, Li *et al.* (2004, 2006) incorporated the dynamic ECM into the static AIDS model, resulting in more accurate predictions of tourist arrivals to the United Kingdom (UK) from various European destinations. Li *et al.* (2006) further combined the TVP with the ECM-AIDS model to improve forecast accuracy. Wu *et al.* (2012) extended this model by proposing a TVP-ECM-AIDS model.

Various AI-based models have been systematically combined to enhance forecast accuracy. Examples include the combination of support vector machines (SVM) with adaptive genetic algorithms (AGA); the combination of seasonal SVR with the fly optimisation algorithm (FOA); the modular genetic-fuzzy forecasting system (MGFFS) model, which integrates genetic fuzzy expert systems and data pre-processing; and the combination of linear autoregression structures (e.g., ES, naïve, and ARIMA) with nonlinear AI components (e.g., NN and SVR) (Chen, 2011). Genetic algorithms (GA) have been applied in various AI-based models, including the fuzzy system model (Hadavandi *et al.*, 2011) and the SVR model (Chen and Wang, 2007). Additionally, Pai *et al.* (2014) combined the fuzzy system, the SVR technique, and GA and demonstrated the superior forecasting performance of this combined model. Furthermore, ANN models have been combined with time series approaches such as the Box–Jenkins method (Nor *et al.*, 2018).

Hybrid models that combine quantitative and qualitative approaches have been used to overcome the limitations of statistical forecasting, particularly when forecasting *ex-ante* tourism demand during crises. Traditional statistical models are unable to account for structural breaks in data patterns or to incorporate relevant information such as policy implementation. To address these issues, qualitative methods like Delphi surveys and scenario analysis have been used to adjust baseline forecasts and improve accuracy. Edgell *et al.* (1980), Lin *et al.* (2014), and Song *et al.* (2013) have demonstrated the effectiveness of these combined models.

COVID-19 and its impacts on tourism modelling and forecasting

The COVID-19 pandemic has had a significant disruptive effect on tourism demand patterns, and traditional statistical models have become ineffective in quantifying the impact of crisis-related factors on tourism demand. In response to this challenge, researchers have proposed innovative approaches to tourism demand forecasting. These include the use of judgmental forecasting methods such as the Delphi survey and scenario analysis, which have been demonstrated to be effective in improving forecasting performance during crises (Kourentzes *et al.*, 2021; Qiu *et al.*, 2021; Zhang *et al.*, 2021). COVID-19-related indices have also been developed to incorporate variables such as confirmed cases, travel restrictions, vaccine distribution, and policy interventions. These indices have been used to classify travel markets for scenario-based forecasting (Liu *et al.*, 2021; Zhang and Lu, 2022). Additionally, historical recovery rates from previous crises have been used to train deep learning algorithms within AI-based models and to predict tourism demand recovery patterns resulting from the COVID-19 pandemic (Fotiadis *et al.*, 2021; Polyzos *et al.*, 2021). Furthermore, conventional tourism demand forecasting models may face challenges in this context when incorporating multiple search intensity indices as indicators of tourism demand. In response, Bufalo and Orlando (2024) proposed the CIR# model, a nonlinear, single factor, stochastic model designed to address the disrupted pattern in the time series caused by the COVID-19 pandemic, thereby improving both the accuracy of forecasting and the simplicity of the model.

Future research agenda

Theoretical foundations of factors influencing tourism demand

Supplementary variables, including climate-related factors and transportation costs, have been previously integrated into various models to enhance their explanatory power (Bangwayo-Skeete and Skeete, 2015). However, it is important to note that, while these additional variables help to explain variations in tourism demand, according to economic theory, they do not have a direct influence on this demand (Wu *et al.*, 2017). Thus, future research should establish a comprehensive theoretical framework that encompasses insights from disciplines such as economics, geography, and sociology to further explore how related factors influence tourism demand. In addition, the theoretical basis for supporting big data remains largely unexplored despite its strong predictive capabilities. Criticisms of research on tourism demand forecasting using big data have centred on the absence of theoretical foundations. The rationale for utilising big data is still unclear, and it might be helpful to consider theories across various disciplines and fields, such as psychology, communication, and information processing, to illustrate the theoretical underpinnings for forecasting. Examples of relevant theories concerning web-based volume data and social media data include signalling theory, social learning theory, and information search behaviour theory. Emotional contagion theory and media richness theory could be used to explore online textual data. All of these theories support online photo and video data. Future studies should therefore explore and integrate pertinent theories from disciplines such as psychology, communication, and information processing to establish a comprehensive theoretical framework to explain how related factors influence tourism demand (Wu et al., 2024), as a more nuanced understanding of the intricate dynamics underlying tourism demand could be obtained by integrating knowledge from these diverse fields.

Enhancing the interpretability of AI-based models to elucidate the 'black box'

Although data-driven AI-based models generate relatively accurate forecasts, the lack of a strong theoretical foundation for their estimation processes is a major shortcoming. These models contain a 'black box' of hidden layers between the input and output variables, resulting in unknown underlying relationships between the variables. Consequently, the variables fail to sufficiently explain the impact of economic factors on tourism demand. Integrating AI-based techniques into econometric models offers a promising approach to addressing this limitation. This integration could allow for the specification of theories in model estimations, leveraging both behavioural insights and big data to enhance forecast accuracy and to gain further insights into the mechanisms driving tourism demand. Future research could reveal further nonlinear relationships by applying consumer behaviour theories to clarify the forecasting process, thereby capitalising on tourism big data rather than solely focusing on data mining (Yang *et al.*, 2014). By combining the strengths of AI and econometric modelling, researchers could obtain new perspectives and methodologies to advance the understanding and prediction of tourism demand dynamics. Moreover, exploring the temporal persistence patterns of input data in forecasting tourism demand represents an innovative approach to reveal the 'black box' of deep learning methods and enhance their interpretability. The novel deep learning framework proposed by Xu *et al.* (2023) enhances the interpretability of deep learning models through the incorporation of a variable selection network and attention mechanism, which consider both factors and timeline perspectives. The attention mechanism contributes to the interpretability of deep learning models by identifying the contribution of each element to the forecasting results through the measurement of learned attention scores (Law *et al.*, 2019; Zhang *et al.*, 2020).

Generating high-frequency forecasts by detecting subtle changes in seasonality

Previous studies have primarily concentrated on long- and medium-term forecasts, with limited attention paid to short-term high-frequency forecasts such as hourly demand, which can provide detailed, high-temporal-resolution information using 5G networks and various tourism apps (Huang *et al*., 2022; Lu and Xie, 2023; Wu *et al*., 2024), with exceptions noted in the work of Wang, Hu and Wu (2023) and Hu *et al.* (2021). As low-frequency seasonality, such as annual and monthly patterns, may not capture subtle changes in tourism demand, Wang, Hu and Wu (2023) analysed tourism seasonality at a fine-grained level, identifying intra-day patterns and inter-day similarities to measure high-frequency seasonality. This approach is valuable for detecting special tourism periods and subtle changes in seasonality, including staggered peak travel phenomena. Additionally, Hu *et al.* (2021) proposed a hierarchical prediction method that considers the seasonality of daily data for floating holidays. Consequently, future research could leverage diverse data types and models to enhance the forecasting performance of short-term forecasts, particularly at hourly or minute frequency levels (Ramos et al., 2021).

Improving the performance of AI-based models by addressing potential limitations

AI-based models have been widely adopted in tourism demand forecasting due to their strong performance. However, there are several potential shortcomings of this model type that require attention. First, there is a lack of definitive criteria for selecting hyper-parameters when using AI-based models. Therefore, future research should focus on addressing issues of randomness and uncertainty in the process of parameter adjustment for AI-based models (Wu *et al.*, 2024). Second, previous studies have demonstrated the effectiveness of decomposition methods in improving forecasting accuracy, but they have also encountered unresolved limitations. For example, these methods may struggle to effectively handle seasonal changes, may provide insufficient treatment of abrupt changes in trends and random components, and may be incompatible with data exhibiting long seasonal cycles. Certain methods such as the A Robust Seasonal-Trend Decomposition Algorithm for Long Time Series proposed by Wen *et al.* (2019) have shown promise in addressing such challenges. Li *et al.* (2024) proposed a novel decomposition and ensemble forecasting model based on a decomposition algorithm to partition the original data into interpretable constituents. Differing from the denoising and divide-and-conquer strategies of decomposition techniques, Yang *et al.* (2023) developed a multivariate decomposition deep learning model to extract the multi-scale relationships among regional tourism flows and to produce tourism demand forecasts. Future research should explore additional approaches to overcome these limitations, aiming to demonstrate robust decomposition features to combat noise and outliers, favourable interpretability, low complexity, and adaptability to complex time series.

Enhancing forecasting processes for models integrating multiple big data sources

The incorporation of big data in tourism and hospitality demand forecasting is still in its early stages (Wu *et al.*, 2024). As big data has become increasingly prevalent in this domain, several pertinent issues have emerged. First, researchers have utilised multisource big data, including user-generated textual data (Zhang and Niu, 2024) and user-generated visual content (Ma *et al*., 2023), to enhance tourism demand forecasting. However, while structured big data has been extensively examined, unstructured data, such as text, photos, and videos, require further attention. Machine learning techniques, including density clustering, hierarchical clustering (Mou *et al*., 2020), and machine learning-based image recognition, are valuable for identifying patterns and trends in visual data from images and videos, thereby converting unstructured data into numerical variables. Second, existing studies utilising big data have not accounted for the temporal dynamic changes in tourists' sentiment, as the studies have not segmented and extracted information from different time periods of textual data (Wu et al., 2024; Wu *et al*., 2023). Advanced natural language processing techniques, such as latent Dirichlet allocation, dynamic topic modelling (Blei & Lafferty, 2006), and dynamic important-performance analysis (Bi et al., 2019), may be suitable choices for capturing time-dependent changes in tourists' preferences and interests and transforming unstructured data into structured data. Third, there exists a trade-off between the complexity and accuracy of forecasting models. Increasingly sophisticated models may be vulnerable to model risk, including issues such as incorrect specification, improper implementation, insufficient data, and calibration errors (Bufalo and Orlando, 2024). Therefore, future research should explore methods to enhance forecasting accuracy using diverse model forms and data sources while adhering to the parsimonious and transparent criteria of model estimations. Fourth, due to data availability, the majority of tourism demand forecasting studies have used data from Jiuzhai Valley or Gulangsu. Future studies should extend forecasts to involve additional tourism destinations to validate the models' accuracy in tourism demand forecasting (Han et al., 2024). Additionally, because search engine and social media data are useful for improving forecasting accuracy, sentiment analysis has become prevalent in tourism demand forecasting. However, general ratings and generic review sentiments cannot evaluate tourists' preferences for destination attributes. Therefore, an increasing number of studies have explored fine-grained sentiment analysis to provide detailed and aspect-based attitude profiles of tourists. Finally, the proliferation of fake reviews on the internet is a growing concern. Future research employing big data should incorporate new methods to filter fake reviews and generate increasingly accurate forecasts (Li et al., 2023).

Applying generative AI to tourism demand forecasting

Large language models such as ChatGPT have become increasingly influential in the tourism industry (Carvalho and Ivanov, 2024; Gursoy *et al.*, 2023). However, the application of generative AI to forecasting methods is still in its early stages and has not yet been extensively explored in the literature. Generative AI, however, has the potential to be applied to the forecasting process. First, unstructured data sources, such as online reviews and videos, could be efficiently and rapidly analysed and interpreted using generative AI, providing forecasters with insights into tourists' sentiments, preferences, and behaviours (Gursoy *et al.*, 2023). Second, generative AI could be used to create effective forecasts by aggregating large amounts of information, thereby improving performance. Techniques such as forecast combinations or competitions could be used to assess whether generative AI can generate more accurate forecasts than other forecasting methods. Ensuring that generative AI fully understands the context is also necessary to avoid bias in the training data. Additionally, integrating generative AI with other forecasting methods, including other AI-based models, could further enhance forecast accuracy. Furthermore, a number of self-adaptive automatic forecasting systems have been developed (Wu et al., 2024). These systems leverage cloud computing and autonomously select the model that will produce the most accurate forecast in a given situation. Future research should focus on enhancing these systems by integrating advanced models and linking them with generative AI. Both cloud computing and generative AI are valuable for real-time analysis of large volumes of data. For example, a system could monitor and analyse tourists' real-time online reviews, search engine data, and social media data to automatically adjust future tourism demand forecasts in both the short and long term, enabling rapid responses to tourists' feedback. A dynamic keyword selection technique could be used to capture ongoing changes in tourists' needs and preferences.

Is panel data analysis a solution?

Among the current advanced models, panel data analysis warrants increased attention in future research. By incorporating both intertemporal movements and the cross-sectional heterogeneity of tourism demand data, panel data regression (PDR), and, in particular, dynamic panel data regression (DPDR), offers a much more reliable framework to account for multidimensional data (Wen *et al.*, 2018). PDR/DPDR allows for greater model estimation flexibility and addresses the issue of multicollinearity (Serra *et al.*, 2014). However, the use of PDR in tourism demand modelling and forecasting remains limited, with the study by Wen *et al.* (2018) as an exception. Panel data models could therefore be used to further enhance forecast accuracy by exploring unique preferences and behaviours among tourists, capturing temporal variations in tourism demand.

Harnessing the potential of forecast combinations

Previous research has proposed various hybrid and combined models for tourism demand forecasting, but the selection criteria for individual models and the optimal combination of models remain unclear. Future studies should therefore focus on systematically developing these hybrid and combined methods. Additionally, many studies have demonstrated the effectiveness of hybrid models through judgmental adjustments to quantitative forecasts, particularly during major crises. Integrating statistical and judgmental forecasts is another potential approach. Combining data from multiple sources, such as search engines, web traffic, social media, online reviews, and videos, with large language models like ChatGPT could provide valuable insights into tourists' behaviours and preferences, especially with the increasing availability of big data (Li *et al.*, 2021).

Understanding the heterogeneity of demand through disaggregation

Analysing tourism demand at a disaggregated level is essential for obtaining comprehensive and diverse information on disaggregated market demands, particularly when examining niche tourism products (e.g., wine, film, or golf tourism; Avraham, 2021) and market segments (e.g., volunteers, backpackers, gap-year students; Wu *et al.*, 2017). By investigating the specific components and segments of tourism demand, researchers could gain further insights into the unique characteristics, preferences, and behaviours of different tourist groups. This could enable a more nuanced understanding of the dynamics and drivers of tourism demand in specialised market segments (Wang et al., 2023b). Tourism demand analyses at the disaggregated level could be extremely valuable for decision-makers when considering factors such as purpose of travel and country of origin, as considering these analyses could provide more detailed and diverse information than solely considering total tourism demand.

Mitigating model instability due to major crises

As the tourism industry is extremely vulnerable to crises and important one-off events, identifying reliable and robust modelling techniques that can effectively address the inherent instability caused by associated risks is essential. A proposed model must account for irregular data resulting from unforeseen events or crises (Bufalo and Orlando, 2024). Future research should focus on developing models that can accurately capture and predict the effects of these disruptions on tourism demand and the resulting dynamic environments. Although several studies have proposed different approaches to predicting crises like the COVID-19 pandemic (Kourentzes *et al.*, 2021; Liu *et al.*, 2021; Qiu *et al.*, 2021; Zhang *et al.*, 2021), such as combining econometric methods with scenario analysis based on severity, probability, event type, and certainty level, other effective approaches that can handle structural breaks in the data should be identified to effectively respond to potential future crises.

Accounting for uncertainties through interval forecasts

Point estimation and forecasting have been the primary focuses of the recent literature on tourism and hotel demand. However, few studies have considered the development of interval forecasts in tourism demand modelling and forecasting, despite these forecasts' ability to provide a range of potential outcomes based on future uncertainties (Kim *et al.*, 2011; Song *et al.*, 2010). Fluctuating market conditions and unforeseen external factors such as the COVID-19 pandemic have presented significant challenges to accurate tourism demand forecasting. To address this, Wang *et al.* (2023a) proposed the use of interval forecasting to capture uncertain, nonlinear, and unstable characteristics in tourism demand time series. Interval forecasts could offer valuable information to business practitioners and policymakers, enabling them to establish strategies and to formulate policies with greater confidence. Additionally, forecast combinations that involve interval forecasting remain unexplored. For example, interval forecasting may encounter constraints such as the trade-off between interval coverage rate and width. To address these limitations, Wang *et al.* (2023a) proposed an interval reduction coefficient optimised through modified multi-objective optimisation to balance coverage rate and width, thereby improving forecasting accuracy. Furthermore, the potential integration of big data into interval forecasting is a prospective area for exploration. Wang *et al.* (2023a) developed a novel hybrid interval forecasting system by incorporating feature selection to facilitate lower and upper bound estimation of daily tourism demand interval forecasting, integrating multiple exogenous explanatory variables such as search engine data and COVID-19 information. Further interval forecasting methods should therefore be developed in future research.

Concluding remarks

Tourism demand forecasting is increasingly important for both business practitioners and policymakers, leading forecasters to seek innovative methods to enhance forecasting performance. This has resulted in the development of non-causal time series models, which range from basic to advanced models. Causal econometric models have evolved from static forms to dynamic and systematic approaches. AI-based methods have progressed from handling limited and simple data to effectively managing large amounts of multi-source data. Judgmental methods have emerged as critical tools for *ex-ante* forecasts during unprecedented crises, with efforts made to minimise human-related bias through increasingly strict and professional procedures. The integration of combined and hybrid models has also proven valuable in leveraging the strengths of various forecasting approaches.

Despite the numerous methods proposed, no single model consistently outperforms others in all situations. This study suggests several avenues for future research. First, establishing a robust theoretical foundation that draws on multiple disciplines to fully encompass the relationships among tourism demand and its various determinants. Second, integrating AI techniques and other approaches such as econometric methods into demand forecasting models could capture tourist behaviours in the decision-making process and establish necessary theoretical foundations in this field. Third, the application of generative AI such as ChatGPT has gained the attention of forecasters. Fourth, PDR/DPDR, which contains more information than alternative methods, should be extensively applied. Further development of forecast combinations that integrate models or data at different frequencies is also encouraged, as more comprehensive profiles of destinations and diversified markets could then be obtained. In addition, as the tourism industry is continually changing and is vulnerable to crises, forecasters should seek reliable methods that address potential model instability due to risks. Finally, greater attention should be paid to interval forecasting methods as their benefits for tourism demand forecasting under major crises have not been fully explored.

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