African Journal of Hospitality, Tourism and Leisure. ISSN: 2223-814X

August 2021, Vol 10, No 4, pp. 1370-1393

# Tourism Demand Modelling and Forecasting: A Review of Literature

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**How to cite this article**: Abdou, M., Musabanganji, E. & Musahara, H. (2021). **Tourism Demand Modelling and Forecasting: A Review of Literature**. African Journal of Hospitality, Tourism and Leisure, 10(4):1370-1393. DOI: **https://doi.org/10.46222/ajhtl.19770720-168**

## Abstract

This research examines 145 key papers from 1979 to 2020 in order to gain a better sense of how tourism demand forecasting techniques have changed over time. The three types of forecasting models are econometric, time series, and artificial intelligence (AI) models. Econometric and time series models that were already popular in 2005 maintained their popularity, and were increasingly used as benchmark models for forecasting performance assessment and comparison with new models. In the last decade, AI models have advanced at an incredible rate, with hybrid AI models emerging as a new trend. In addition, some new developments in the three categories of models, such as mixed frequency, spatial regression, and combination and hybrid models have been introduced. The main conclusions drawn from historical comparisons forecasting methods are that forecasting models have become more diverse, that these models have been merged, and that forecasting accuracy has improved. Given the complexities of predicting tourism demand, there is no single approach that works well in all circumstances, and forecasting techniques are still evolving.

**Keywords**: Tourism demand; artificial intelligence; time series, econometric model

## Introduction

Tourism is expanding from developed to newly industrialised countries as a result of rapid expansion of international tourism due to social, economic, political, and technical changes. Governments and private companies are increasing showing interest to spend significant funds in tourism-related sectors such as transportation and lodging, in response to the increasing importance of tourism to international economic growth (Li,Chen,Wang&Ming,2018; Song,Qiu & Park, 2019). As more tourist destination countries/regions compete for scarce resources, this growth can result in a combination of costs and benefits (Chan, Lim & McAleer, 2005). As a result, reliable predictions are crucial for destinations attempting to capitalize on tourism industry trends and align their local ecological and social carrying capacities (Peng,Song & Crouch, 2014). Owing to the perishable nature of tourism related goods and services, according to (Xu,Law,Chen &Tang, 2016), both tourism-related enterprises and policymakers need reliable and meaningful forecasts (Li et al., 2018). Companies and

organizations need accurate tourism demand forecasts for planning and decision-making when it comes to staffing, capacity, resource management, as well as pricing strategies. In the meantime, reliable forecasting allows for better and informed government actions, which stimulates tourism and economic growth in the destination (Song et al., 2019).
Owing to the uncertainty of determining variables and external interventions, the tourism sector has seen a series of variations. In order to increase the accuracy of tourism demand forecasting , researchers, professionals, and politicians have paid close attention to tourism growth cycles and demand fluctuations, the general dynamics of origin economies, destinations, and even neighbouring competing destinations that could have an effect on tourist flows in these countries (Qian et al., 2016; Song & Liu, 2017). A series of reports on tourism demand modeling and forecasting have been published in the last few decades, demonstrating the value of reliable predictions in the competitive and diverse tourism industry. The primary emphasis of these studies has been on model design and performance evaluation. However, some of them have suggested innovative hybrid models or used a variety of approaches in combination.

As the importance of tourism forecasting is becoming more widely recognized, several studies have been focusing on improving forecasting techniques to improve predictive performance. A variety of studies have reviewed the methods and models used in tourism demand forecasting. Witt (1995) thoroughly reviewed time series, econometrics, and qualitative models as well as other tourism forecasting strategies developed prior to 1995. Subsequently,Goh & Law (2011) looked at the methodological advancements in tourism demand forecasting between 1995 and 2009. Wu,Song and Shen (2017) recently analyzed forecasting and modeling studies in the tourism and hotel industry from 2007 to 2015 to identifying emerging trends and innovations in line with tourism modeling**.**

The theoretical and methodological development of tourism demand forecasting has been supported by a wealth of scientific data as well as various meta-analyses and review papers. However, there is yet to be a systematic study of the scientific progress and evolution of forecasting approaches that is most recent. Previous reviews have included specific time spans, such as the 1960s to the 1990s (Crouch, 1995; Witt, 1995); 1995–2009 (Goh & Law, 2011); 2000–2007 (Song & Li, 2008), and 2007–2015 (Crouch, 1994), and 2007–2015 (Peng et al., 2014). ( Wu,Song & Shen, 2017). Few specific techniques, such as Delphi (Lin & Song, 2015) and specific econometric models (Li, Song& Witt, 2005), have also been evaluated. From judgmental approaches to various types of predictive techniques, including time series, econometric, and artificial intelligence (AI)-based models, our comprehensive analysis encompasses a broad variety of forecasting methods used from the 1970s to 2020.

The main objectives of this research are to examine the general patterns and evolution of tourism demand forecasting methods over time, as well as to follow the progress of three types of forecasting methods (time series, econometric, AI-based models) from their inception in the tourism sector to their current applications. The current study set out to evaluate how have forecasting approaches for tourism demand have changed over the last four decades (1979–2020), identify the discrepancies between different types of tourism demand forecasting methods, examine the inter-annual patterns in method differentiation or integration, review different forecasting methods and identify which ones worked well, and which combinations of methods increased forecast accuracy.

The remainder of this research is structured as follows. The second section explains how the main studies were chosen. The third section defines and discusses the four types of tourism demand forecasting techniques, as well as the current state of each technique. The fourth section discusses mixture forecasts and hybrid models, as well as general developments in forecasting studies and forecasting results. The findings of the study, as well as suggestions for future studies and an evaluation of the shortcomings of the study, are discussed in the final section.

## Key literature selection criteria

We performed a large scale search of numerous databases, including Google Scholar and Web of Science to identify general patterns and evolution of tourism demand forecasting methods. Citations from published journals and scholarly books were also looked for. We started with 425 relevant publications from 1970s to the first half of 2020. We set out to define a manageable pool of the most relevant studies in order to work with this vast body of evidence in a non-casual manner. Three phases were involved in choosing key articles. To begin, all review papers, as well as non-tourism and non-forecasting research were eliminated. Second, the studies were assessed for their comprehensiveness and significance. For each article, the mean and median annual citation values were determined. We choose papers that obtained more citations than the average for all studies conducted in the same decade to highlight the most representative studies in each decade. We choose a group of the 145 most influential studies based on this criterion. The mean of total publications in each decade revealed that the 2000s (84.7%) had more support for academic advancement of tourism forecasting studies than the 1990s (14.5%). Articles on tourism demand forecasts are published in a variety of discipline-specific journals, with many of these journals serving as key discussion forums in their respective fields. The Most influential Journals include Tourism Management (43 main studies/145 that were used in the current study), Annals of Tourism Research (18/145), Journal of Travel Research (16/145), Tourism Economics (12/145), International Journal of Forecasting (12/145).

## Discussion of findings and general trends in the literature

### *Categorization of tourism demand forecasting techniques*

There are four major types of methods for tourism forecasting in the traditional typology of forecasting strategies (Doorn, 1984). Investigative methods (such as time series analysis, historical analogy, causal methods, projective scenarios, and morphological analysis), speculative methods (such as Delphi, panel consensus, brainstorming, or individual expert opinion), and socially constructed methods (such as subjective probabilistic forecasting, Bayesian statistics, pattern identification, or prospective scenarios) are among these categories. Witt, (1995) identified three types of forecasting models based on their review of empirical studies: causal models (econometric and spatial models), time series models, and various qualitative approaches. More recently, it has been broadly acknowledged that there are four types of methodological approaches to predicting tourism demand (Song & Li, 2008). The three categories of quantitative methods are time series models, econometric models, and AI-based models (Goh & Law, 2011; Peng et al., 2014). Judgmental approaches, which can be used for both qualitative and quantitative forecasting, fall under the fourth group (Lin & Song, 2015). Regression analysis methods dominated the tourism forecasting and modeling literature prior to the 1990s. In recent years, econometric forecasting models have gained a reputation for higher accuracy since they integrate recent developments in econometric methodologies (Song & Li, 2008). In tourism demand forecasting, other quantitative approaches such as gravity models, artificial neural networks (ANN), and univariate time series models have also played a crucial role. However, there are still disagreements about which models provide the most reliable predictions under various conditions. Each method has its own set of benefits when it comes to solving a specific problem, but none has been shown to be inherently superior.

Quantitative forecasting techniques are divided into three categories: time series models, econometric approaches, and artificial intelligence (AI) models. Time series models, which require no more than one data series, extrapolate from past data in the series to forecast future patterns. Time series forecasting methods are further classified into simple and advanced subcategories based on the complexities of the models. The former includes the Naive, Simple Moving Average (SMA), and Single Exponential Smoothing (SES) models. Double exponential smoothing (DES), exponential smoothing adjusted by trend (ESAT), autoregressive moving average (ARMA), and simple structural time series (BSM) models are some of the more sophisticated methods.

While time series methods are useful tools for predicting tourism demand, one of their major drawbacks is that they are not built on any economic theory that explains how tourists make decisions. As a result, they are incapable of not only analyzing tourist behavior, but also of assisting policymakers in measuring the efficacy of their programs and strategies. Thus, econometric models are superior in this regard (Song,Witt,Wong&Wu, 2009). Econometric methods, rather than focusing on extrapolation, look for dependent interactions between tourism demand and a collection of explanatory variables. Forecasts for tourism will then be made as a result of the future values of these explanatory variables. This method allows for forecasts for a variety of situations (for example, multiple exchange rate outcomes).

***Time series models***

Time series models forecast future patterns based on historical trends by extrapolating from previous time series, and only one data series is needed. These models aim to diagnose time series data patterns, slopes, and cycles. Time series models produce forecasts of future values for the time series after a trend is constructed (Song et al., 2019). Basic and advanced time series methods are two types of time series model (Peng et al., 2014). Time series forecasting approaches can be classified into basic time series and advanced time series methods. Basic time series methods are further subdivided into: Naïve, Simple Moving Average (SMA), and Simple Exponential Smoothing (SES). Advanced time series methods include: Exponential Smoothing adjusted by trend, Double Exponential Smoothing (DES), Basic Structural Time Series Models (BSM) and Autoregressive Moving Average (Peng et al., 2014)

The Naïve, autoregressive (AR), single exponential smoothing (ES), moving average (MA), and historical average (HA) models are the most popular and basic time series models ( Li et al., 2018; Song et al., 2019). The Naïve1, the simplest method, is better suited to make better predictions in case of one-year-ahead forecasts than advanced time series models (Martin & Witt, 1989;Witt,Witt&Wilson,1994). However, Naïve 1 is weak in making long-term forecasting and dealing with times series with linear trends (Chan, Hui &Yuen, 1999;Witt et al., 1994). Naïve 2 model is used when data have constant trend. The Simple Moving Average (SMA) assigns equal weights to the past value to determine the forecast values. However, one of the main weaknesses of this model is that it assigns equal weights to all lagged values yet recent lagged observations are more likely to have more explanatory power on current situation. Therefore, SMA is more likely to produce more meaningful results when time series are stationary (Makridakis, Wheelwright &Hyandman, 1998) and this weakness is overcome by using Double Moving Average (Lim & McAleer, 2002). Moreover, SES model produces more accurate forecasts with de-trended time series (Chen, Liang, Hong&Gu, 2015; Chen et al., 2008).According to (Witt,Newbould &Watkins, 1992) SES are more reliable than Naïve 1 while forecasting tourism demand whose time series are relatively less volatile than international tourism demand.

Time series models have been widely used in tourism demand forecasting studies over the last five decades due to their simplicity and realistic potential to capture historical trends. The basic time series models were used in 43 of the main studies examined for this analysis, for a total 78 models. Of these models, the Naïve 1 and Naïve 2 are by far the most widely used and widely accepted in the tourism forecasting literature. The Naïve model, despite its simplicity, is found to provide relatively accurate predictions, especially for short forecasting horizons (Athanasopoulos, Hyndman &Song , 2011;Wu, Law & Xu, 2012). It is worth noting that, owing to the massive amount of information generated by simple time series forecasting models and their usage in various cross-disciplinary studies over the last five decades, there is a degree of ambiguity in terminology. While the mathematical meaning of a moving average is applied in the computation of HA, the term ‘MA model' (or ‘MA process') has a distinct definition in time series analysis. Nonetheless, the literature keeps showing a mixed usage of MA and HA. As a result, prospective researches should make deliberate vocabulary choices.

Advanced time series models are distinguished from basic time series models by the inclusion of time series features such as trends and seasonality. Seasonality is a term that refers to the fact that Several types of pattern analyses and Box- Jenkins form methods (Box & Jenkins, 1976), such as autoregressive integrated moving average (ARIMA) methods, are often used by the different types of advanced exponential smoothing models, and such methods are receiving increasing interest (Gounopoulos,Petmeraz & Santamaria 2012; Li et al., 2018; Lim & McAleer, 2002) . By incorporating both trend and seasonal terms into the model, advanced ES methods address the shortcomings of basic ES. Brown’s DES model (Brown, 1963) deals with stationary time series. This model is easier to use than Naïve 1 and Box-Jenkins ( Ibrahim, , Nanthakumar & Loganathan, 2010). The model also performs better to predict international tourism expenditure (Sheldon, 2008). However, this model is criticised of not being able to track seasonality and structural breaks (Freditling, 1996). Holt’s DES model offers the flexibility to select smoothing constants (Makridakis, Hibon & Moser,1979). However, Brown’s DES model performs better than the former based on MAPE to forecast tourism arrivals. Holt’s –Winter’s model improves the Holt’s model by capturing both the trend and seasonal patterns (Lim & McAleer, 2001a) . Once a damped trend is added to Holt’s-Winters method, it largely improves long run forecasts compared with Box-Jenkins and BSM (Grubb & Mason, 2001).

Though The Box-Jenkins (ARMA process) is the most basic and frequently used time series method used in forecasting tourism demand, researchers still have mixed views about its performance to forecast tourism demand (Li et al., 2018; Peng et al., 2014). (Makridakis et al., 1979) claimed that The Box-Jenkins improves forecasting accuracy while ( Kim,, Wong, Athanasopoulos & Liu, 2011) argue that Seasonal ARIMA (SARIMA model) overlooks future uncertainties while dealing with interval forecasting. Other studies (Chu, 2008; du Preez & Witt, 2003; Goh & Law, 2002; Gustavsson & Nordströrm, 2001) suggest the use of ARIMA and SARIMA while forecasting tourism demand with time series which do not contain structural breaks. Another advanced time series method that is increasingly attracting the interest of researchers is BSM model. The latter decomposes a time series into trends, season, cyclical and irregular component, and once exogenous variables are included in the model, BSM becomes Structural time series model ( Edgell, Seely & Iglarsh , 1980; González & Moral, 1995). However, there is little evidence on whether the inclusion of explanatory variables in the model improves the forecasting accuracy using BSM model (Kulendran & Witt, 2003; Vu & Turner, 2005). Overall, while time series methods are useful tools for predicting tourism demand, one of their major drawbacks is that they are not built on any economic theory that explains how tourists make decisions. As a result, they are incapable of not only analysing tourist behavior, but also of assisting policymakers in measuring the efficacy of their programs and strategies. Thus, econometric models are superior in this regard Song, Witt, Wong & Wu, 2009).

By incorporating both pattern and seasonal terms into the model, advanced ES approaches address the shortcomings of basic ES. Other techniques are often used to fit tourism demand data with trend curves for further examination, in addition to conducting decompositions of patterns. The sinewave and cubic type methods, in particular, have been shown to make accurate forecasts for a variety of scenarios (Chan, 1999 & Chu, 2004). In time series studies of tourism demand, a number of ARIMA models are commonly used. These ARIMA models are very adaptable in modelling tourism demand because they take into account both current and lagged values (AR components), current and lagged random shocks (MA components), degrees of integration (I components), and often seasonality changes (S components). ARIMA-type models are used 85 times in our pool of key articles. More than 65 of the publications that use time series techniques (94 papers) use ARIMA-type models.

The seasonal ARIMA (SARIMA) model has received a lot of interest and has been shown to provide excellent forecasts (Chu, 2011&Chu, 2014). The ARFIMA (autoregressive fractional integrated moving average) model (Chu, 2009 &Chu,2011), the ARIMA-GARCH (generalized autoregressive conditional heteroskedastic) model (Chan et al., 2005; Li, Chen, Wang,Ming, 2018 & Chu,2011), and the SARIMA-In model (Chan, Lim, & McAleer, 2005; Li et al., 2018) are both dependent on ARIMA-type models (Goh & Law, 2002). Some techniques that were historically used in other fields (such as spectrum analysis or wavelet analysis) have also appeared in the tourism demand literature in the last five decades as a result of increased cross-disciplinary interaction (Athanasopoulos et al., 2011; Balli, F., Shahzad, S. J. H., & Uddin , 2018; Hassani,Webster, Silva & Heravi, 2015; S. Li et al., 2018).

Seasonality has long been recognized as a core feature of tourism demand forecasting due to the essence of tourism activity (Song & Li, 2008). Seasonality is taken into account in all of the models discussed above. Many tourism demand studies use a seasonal- Naïve model based on the principle of the Naïve 1 model (Jackman & Greenidge, 2010; Önder & Gunter, 2016). In the forecasting of tourism demand by Asian tourists in Australia, the Holt-Winters type of ES, which has a seasonal portion, outperforms other types of ES (Lim & McAleer, 2001b). To decompose and analyse the seasonal dynamics of tourism demand, various forms of trend analyses and varieties of the simple structural model (BSM) are used (Vu & Turner, 2005). After its adoption in tourism studies, the SARIMA model has done well and has drawn increasingly growing interest overtime (Li et al., 2018). Over the past three decades, the number of research articles that use SARIMA has increased from three to thirteen to eighteen. In addition to these widely used methods, the tourism demand literature contains several seasonality-sensitive forms of classical time series models. The seasonal-AR, which was used in a study of international arrivals in the Canary Islands (Gil-Alana, 2010), the ARIMA-seasonal decomposition model, which was used to examine Turkish inbound tourism (Koc & Altinay, 2007), and the seasonal fractional-ARIMA, which was used to predict Spanish tourism demand ( Sun, Lin, & Higham, 2020; Gil-Alana, 2004).

***Econometric models***

The renewed interest in econometric forecasting models over the last five decades has greatly helped in the pursuit for cause and effect relationships between economic conditions and tourism demand in a variety of empirical settings. While time series models predict the trends in a historical data series will have the greatest impact on the future, econometric models are more concerned with determining the structure of causality, or how much the different predictor variables influence future demand (Peng et al., 2014)**.** Put differently, Econometric methods, rather than focusing on extrapolation, look for dependent interactions between tourism demand and a collection of explanatory variables. Forecasts for tourism will then be made as a result of the future values of these explanatory variables (Song et al., 2019). This method allows for forecasts for a variety of situations. Econometric models can be classified into basic econometric models or advanced econometric models (Goh & Law, 2011; Hu, Jiang

& Lee, 2019). Basic econometric models are such as regression models, gravity models, Static Almost- Ideal Demand System (AIDS). Dynamic econometric models include Vector Autoregressive (VAR), Time Varying Parameter (TVP), Error Correction Model (ECM), Cointegration and Autoregressive Distributed Lag Model (Goh & Law, 2011; Peng et al., 2014).

***Static econometric models***

Over the last five decades, econometric forecasting models have played a remarkable role in tourism demand forecasting research and practice by executing this purpose. A single static regression is used in the simplest econometric forecasting model (SR). The main purpose of such basic models is to figure out how different variables contribute to the current values. The variables in these regressions are normally expected to be stationary to prevent the spurious regression problem. This group includes much of the early studies on tourism demand (Martin & Witt, 1988). In more recent years, SR has been used as a benchmark for tourism demand forecasting evaluation (Athanasopoulos,Hyndman,Song &Wu, 2011). However, regression models are not suited to non-stationary time series because they generate spurious estimates which make the estimates statistically insignificant. Regression models do not handle the effects of changing behaviour of tourists. In addition, procedures followed while estimating models remain unclear and, as a result, the same data will generate different estimates once the model is estimated by different researchers ( Song, Witt, Wong & Wu, 2009).

Gravity model is another example of static econometric model. This model looks at how factors such as distance and population size affect tourism demand. Some authors (Kharadoo and Seetanah, 2008) have used gravity models to investigate the effects of transport infrastructure on tourism demand. However, due to the lack of powerful theoretical underpinning, the gravity model's estimates are questionable, resulting in an adhoc selection of independent variables ( Chen & Wang, 2007; Wang & Hsu, 2008).

Almost Ideal Demand System (AIDS) is another line of thought that goes beyond the static single equation model to account for the interrelatedness of multiple demand equations or time series. AIDS has had a solid economic theory underpinning since its inception in the 1980s (De Mello & Fortuna, 2005). Instead of using a single equation to predict demand, the model uses several equations to estimate and forecast tourism demand. The static Linear AIDS as developed by Deaton and Muellbauer in 1980 (De Mello & Fortuna, 2005), which is now one of the most widely used system of equation methods for evaluating the market share of tourism demand, and it offers a collection of information about the responsiveness of demand with respect to price and expenditure variations (De Mello & Fortuna, 2005; Durbarry & Sinclair, 2003; Syriopoulos & Sinclair, 1993).This method has also shown the ability to capture demand for specific products and services as determined by market share within an economic system. Various versions of AIDS are used to predict the market shares of US outbound visitors traveling to Europe in tourism demand modelling and forecasting (O'Hagan & Harrison, 1984).

While static econometric models are powerful in analysing and interpreting elasticities, they are ineffective at forecasting tourism demand as their estimations undermines long-run relationship as well as short-run variability (Smeral, Witt, & Witt, 1992). The poor performance of static econometric models can be attributed to the fact that they ignore factors like "word-of-mouth", shifting travel habits and the maturation of tourists' tastes and preferences, all of which mean that demand elasticities vary rather than stay stable over comparatively long period of time. Moreover, since static models are non-stationary, spurious regression is a very rare possibility (Li, 2009).

### *Dynamic econometric models*

Over the years, advanced econometric techniques that have increasingly attracted the interest of different scholars include techniques such as Vector Autoregressive (Gunter & Önder, 2015; Önder & Gunter, 2016), Time Varying Parameter (Gunter & Önder, 2016; Song, Li, Witt & Athanasopoulos, 2011), Error Correction Model (Gunter & Önder, 2015; Lee, 2011; Vanegas, 2013) and Autoregressive Distributed Lagged Model (Ayeh & Lin, 2011; Gunter & Önder, 2015; Tukamushaba,Lin, & Bwire, 2013; Zhang, Huang, Li & Law, 2017) and TVP structural time series model (Gunter & Önder, 2016; Song et al., 2011). The introduction of causality relationship increases the predictive power of these predictive models, enabling them to capture sequential changes in customer tastes and preferences (Peng et al., 2014). These models have also been adopted into this field to account for the intertemporal relationships among tourism demands and their numerous influencing factors. The Distributed Lag models, in particular, take into account not only current values, but also previous values of the factors that influence current tourism demand (Guizzardi & Stacchini, 2015; Wan & Song, 2018).

**The Autoregressive Distributed Lag Models** (ADLMs) include the effects of lagged demand variables in addition to measuring the influence of lagged influencing factors. The models, in particular, take into account not only current values, but also previous values of the factors that influence current tourism demand. The Autoregressive Distributed Lag Model has proven to be at predicting turning points ( Nadal, Font & Rosselló, 2004).One of potential with these models is that the construction of the final model overly on the data used, despite the fact that the economic theory is an instrumental factor in the general model specification ( Song, Wong & Chon,2003 & Witt, Song, & Louvieris, 2003) . In addition, due to competition from their more general and specialized equivalent, ADLMs, the use of DL models in tourism demand forecasting is minimal. In forecasting evaluation and comparisons, the DL models are often used as a benchmark (Guizzardi & Stacchini, 2015; Wan & Song, 2018).

**The Error Correction Models (ECM**), which builds on the ADLM's foundation, takes into account the long-run relationship between tourism demand and its driving factors as well as the short-run error correction process when assessing tourism demand (Song et al., 2019). When both the long-run and short-run disequilibrium interactions are of concern, The Error Correction Model (ECM) and Cointegration (CI) models are powerful (Dritsakis, 2004; Halicioglu, 2010) . Error Correction Model addresses the problems of growth of rate model, which uses only differenced data, by overcoming the problem of spurious regression. It alleviates the issue of data mining during the estimation process (Chan et al., 2010). Ouerfelli, (2008); Veloce, (2004) demonstrated that ECM produces more accurate forecasts than time series when a differenced demand component is included. While forecasting tourism demand for the UK, Germany, Greece, Netherlands, Portugal , Spain and the United States, (Kulendran & Witt, 2001) show that the Error Correction models are more reliable than tradition econometric models.

**Vector Autoregressive Regression** (VAR) model: Another kind of extension of the single static equation model is the vector autoregressive (VAR) model. The interconnectedness of several time series can be captured using this extension model. Many of the explanatory variables are treated as endogenous in a VAR context, with the assumption that they all influence each other intertemporarlly. The VAR model has been used in tourism demand forecasting since the late 1990s ( Kim & Uysal, 1998). VAR models have been shown to provide reliable mid-to long-term tourism predictions (Song & Witt, 2006) than single equation owing to one of the following reasons: To begin with, the VAR models, do not need underpinning implicit theoretical framework to be able to build and estimate them. Second, predictions of independent variables do not need to be produced first before forecasts of the explained variable can be produced. Despite the fact that the VAR technique has been extensively and consistently used in macroeconomics, there have been no several attempts to apply it to tourism forecasting till now. ( Wong, Song and Chon (2006) developed the Bayesian VAR (BVAR) model to improve the effectiveness of the classical VAR model by imposing informative constraints (Bayesian priors) onto the model estimation. They realize that the BVAR outperforms its non-Bayesian equivalent when it comes to forecasting. Pesaran, Schuermann, (Li et al., 2018) also develop a global VAR (GVAR) structure based on the classical VAR model. ( Assaf, Li, Song, & Tsionas, 2019) expand this method by introducing Bayesian estimation techniques (BGVAR) for modelling and predicting international travel demand in Southeast Asia.

ARIMAX Model is a model that extends ARMA models by using explanatory variables as predictors. Explanatory variables are being used to supplement time series models of tourism demand forecasting. Big data–based variables are the most common augmented variables (Pan & Yang, 2017; Park, Lee & Song, 2017).While the ADLM and ECM introduce time dynamics to a static single equation model, the already dynamic time series models described in the previous subsection can be given similar extensions by adding exogenous variables. The ARIMAX model, in which X represents the exogenous variables, is one of these models. The ADLM and the ECM also place a strong emphasis on determining the cause and effect relationships between contributing factors and tourism demand. The ARIMAX models, on the other hand, place a strong emphasis on determining the dynamics of tourism demand (Song et al., 2019). To investigate the impact of relative climate variability on tourism demand, Li, Goh, Hung, and Chen (2018) use an ARX model.

It is worth noting that the ARX model is often referred to as a partial adjustment model because it has the same functional form as a reduced ADLM (Veloce, 2004); Chevillon & Hendry, 2005). When it comes to predicting hotel occupancy, the ARMAX model outperforms the ARMA model (Pan & Yang, 2017). Tsui, Balli, Gilbey, and Gow (2014) found that the ARIMAX model produces superior long-run predictions than the SARIMA model when predicting airport passenger numbers in Hong Kong. The SARIMAX model also produces stronger predictions of Japanese tourist demand for Korean destinations than regular time series models like the SARIMA or the Holt-Winters ES ((Park et al., 2017). The ARIMAX-type models, including the ADLM and the ECM, perform well for modelling and predicting tourism demand when paired with static varying parameters (VP) and MIDAS features (Bangwayo-Skeete & Skeete, 2015; Pan & Yang, 2017).

The Time Varying Parameter (TVP): The TVP models account for the like likelihood of parameter adjustments overtime, which eliminates the structural instability issue induced by external shocks. It can model various types of external shocks to the tourism demand processes such policy and regime changes, economic reforms, and political uncertainties (Song & Li, 2008). In addition, the TVP model performs better in capturing external shocks that are incremental such as shifts in customer preferences and other social and psychological patterns (Song, Wong & Chon, 2003). According to Song,Witt, & Li, (2003), the TVP model generated the most reliable short-run forecasts while estimating tourism arrivals, which is consistent with previous studies (Song et al., 2003; Song, Romilly& Liu,2000). Introduced by Song et al., (2011), The TVP structural time series model (TVP STSM) improved the explanatory power of the STSM by adding exogenous variables modelled by TVP for the first time. The advantages of TVP and STSM have been blended is that simple STSM captures seasonality, patterns, and cycles, whereas TVP is used to estimate cause and effect variable coefficients. In addition, Bayesian estimation was introduced into VAR models in the analysis by (Gunter & Önder, 2016) to eliminate overparameterization caused by the use of Google big data as explanatory variables.

General to Specific Method (GETS)**:** Excessive data mining is a common criticism of the specific-to-general approach. The general-to-specific (GETS) method, on the other hand, begins with a general model that includes as many variables as possible, including their lags, as economic theory suggests. Via repetitive estimations, the general model is reduced to a specific form by removing irrelevant or incorrectly signed variables. In tourism demand studies, the GETS method is a relatively recent approach. The ADLM is often used in conjunction with the GETS method (Önder & Gunter, 2016; Song,2003; Witt et al., 2003; Song & Li, 2008). The specification begins with a general ADLM to sequentially eliminate unnecessary variables. The GETS method then addresses both the data mining and the spurious regression issues (Song; 2003;Witt et al., 2003). One issue with the GETS method is that the inconsistent decision rule used to exclude irrelevant variables for model reduction might not be 'optimal' in terms of model estimation and forecasting. Athanasopoulos et al.,( 2018) show that bootstrap aggregation GETS models can provide optimal model reduction and produce more accurate forecasts than simple GETS models to solve this potential challenge.

**Explanatory variables**: Recently, there has been growing literature about the determinants of both inbound and international tourism demand. Economic variables related to both origin and destination appeared to be commonly used as predictors of tourism demand. The most important determinants of tourism demand that have been frequently used as explanatory variables in tourism demand modeling are tourists' income levels, exchange rates, the prices of tourism products in destinations relative to those in origins (i.e., relative price), and the prices of tourism products in competing destinations Lin, Liu & Song, 2015; Song et al., 2013; Song & Li, 2008; Vanegas, 2013). Other factors that affect tourism demand include climate change (Moore, 2010), political stability (Saha & Yap, 2014), one-off- events (Lin et al., 2015), terrorist attacks ( Bonham, Edmonds & Mak, 2006), and financial crises (Song, Lin, Witt, & Zhang, 2011). The coefficient of travel costs is insignificant in most of tourism demand models, according to Song et al., (2013), and data is difficult to get data about transport costs. As a result, travel costs are rarely used in tourism demand forecasting. While these data have no clear causal relationships with the demand variables, search engine data from sites such as the Google and Baidu indices have proven to be good estimates of tourism demand fluctuations ( Dergiades, Mavragani & Pan , 2018; Yang, Pan, Evans & Lv, 2015)

Panel data regression: Another method of study often used in tourism demand studies is panel data regression (PDR). Unlike the other models discussed so far, which focus on functional form and parameterisation, the PDR emphasizes the characteristics of the data used to evaluate demand models. This regression takes into account both the data's intertemporal and cross-sectional heterogeneity. Many of the aforesaid models will use panel data analysis, with PDR features incorporated (see, for example, ( Dogru, Sirakaya-Turk & Crouch , 2017; Naudé & Saayman, 2005). With the exception of Wen, Liu and Song (2019), the use of the PDR in tourism demand forecasting has been comparatively uncommon.

The main tools used in social sciences, such as tourism demand modeling and forecasting studies, are time series and econometric models. The above-mentioned methodological advances and models are in turn intertwined, with later models addressing issues raised by earlier models. The ARX model, for example, is used to account for the influence of exogenous variables in the AR process. Many of the models mentioned in this section are summarized in Fig. 1, which also indicates the interactions between them. Under of model's name, the year it first appeared in the pool of key studies, the total number of applications, and the number of "highest performing cases" are all mentioned. On the top right of each model, additional model features such as time-varying parameters (T), state-varying parameters (V), mixed-data sampling (M), and Bayesian inference (B) are indicated.

### *AI- based models*

In recent years, researchers have increasingly shown interest in the use of Artificial Intelligence (AI- based models) in the context of tourism demand forecasting. AI forecasting techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), rough sets, Fussy time series, grey theory, genetic algorithms, and expert systems have been proven to be more effective than traditional forecasting methods (Hong, Dong, Chen, &Wei, 2011; Li et al., 2018; Pai, Hung & Lin, 2014; Wang, 2004). Goh & Law, (2011) further categorized AI-based tourism demand forecasting models into two groups: AI-based time series methods and AI-based casual methods. Despite their theoretical and methodological flaws, AI-based approaches have been commonly used to forecast a broad range of phenomena in a variety of scientific disciplines (Díaz & Mateu-sbert, 2011). The effectiveness of these methods capture nonlinear relationships and trends within time series and exogenous variables, as well as AI's capacity to improve forecasting efficiency to has prompted tourism researchers to apply them to demand forecasting (Li et al., 2018). As a result, over the last 20 years, AI methods have been extensively used for tourism forecasting. Support vector regression (R. Chen et al., 2015; Hong et al., 2011), fuzzy time series (Tsaur & Kuo, 2011; Wang, 2004), rough sets approach (Goh et al., 2008), and grey theory are some of the AI approaches used to forecast tourism demand (Wang et al., 2015). The studies of grey theory based fuzzy time series forecasting performed by Wang (Wang, 2004) and (Yu & Schwartz, 2006) are examples of the first type of these approaches being used. (Uysal & El Roubi, 1999) contrast the forecasting performance of an ANN model to that of a multiple regression model with partial adjustment, which is similar to the previous studies (e.g., with inclusion of a lagged dependent variable).

**The artificial neural network (ANN) model**, as the most widely used AI-based technique, has been shown to have high feasibility and versatility for processing imperfect data or managing almost any type of nonlinearity. These capabilities illustrate why artificial neural networks (ANNs) have become common in forecasting (Chen, Lai& Yeh, 2012; Claveria, Monte,Torra , 2015a; Claveria et al, 2015b; Law, 2000; Law & Au, 1999;Pai, 2005; Pattie & Snyder, 1996; Teixeira & Fernandes, 2012; Uysal & El Roubi, 1999; Wong et al., 2006). The ANN model outperforms the partial adjustment regression model (Law, 2000), and as a result, (Law, 2000) proposes a neural network model that integrates the back-propagation learning method to predict nonlinearly separable tourist arrivals based on the determinants of tourism demand. The ANN outperforms the multiple regression models Goh, Law, & Mok, 2008). The ANN overcomes the limitations of the multiple regression analysis and allows the estimation of non-linear functions while forecasting tourism demand. Owing to the repetitions of predicted related seasonal trends, ANN models can be easily adjusted overtime and performs relatively better than in one-year-ahead forecast ( Burger, Dohnal, Kathrada & Law , 2001)

In different empirical studies on tourism demand forecasting, ANN models such as the multilayer perceptron (MLP), the radial basis function (RBF), and the Elman network have been used. Where the accuracy of the time series data is uncertain, the empirical findings show that ANN models perform well. With significant success, (Pattie & Snyder, 1996) use the neural network approach to predict tourism demand. Other studies comparing the forecasting performance of neural networks and traditional forecasting methods began to emerge in the late 1990s as a result of their studies. In these studies, the performance of ANNs was compared to that of multivariate regression and time series models (Law & Au, 1999; Uysal & El Roubi, 1999). The neural network methods can perform well for short-term forecasting, according to (Kon & Turner, 2005), and this result has functional implications for new destinations with shorter records of tourism demand and volatile tourism conditions.

Though non- linear methods such as ANN have been gaining popularity in recent years, researchers have challenged the explanatory power of nonlinear methods (Law & Au, 1999;

Pai, 2005; Uysal & El Roubi, 1999). Researchers often criticize ANNs for missing a theoretical basis and for containing a "black box" with hidden layers between the input and output variables, according to Zhang, Patuwo,& Hu,1998). He hidden layer learning method necessitates a huge volume of data, and the model is unable to predict the effect of independent variables on tourism demand (Chenguang,Haiyan, & Shen,2010). Inside the network, it's hard to separate the input variables from the outputs, and the transparency of the optimisation mechanism (for changing weights) is often disregarded. The fundamental problem with AI-based models' "black box" nature is that "a small volume of liquid" can be mathematically portrayed, but "an ocean" is difficult to reflect ( Xu, Law, Chen, & Tang, 2016). Moreover, Traditional time series models may outperform ANNs in dealing with pre-processed data (in which outliers are removed and the original series is smoothed), according to recent research (Claveria & Torra, 2014). Studies mixing ANN models with traditional time series methods have become a common focus of study in tourism demand forecasting. For example, Nor, Nurul, and Rusiman (2018) propose combining the Box-Jenkins and ANN models, and ( Chen, 2011). Chen (2011) evaluates the models' turning points in forecasting performance by combining linear models (such as the Nave, ES, or ARIMA models) with nonlinear AI models (such as back-propagation neural networks or SVRs).

**Support Vector Regressions (SVRs):** SVRs have also been used in a number of studies on tourism demand forecasts (Chen et al., 2015; Hong, Dong, Chen, & Wei , 2011; Lin, 2019; Pai et al., 2014). Unlike ANN, which uses empirical risk minimization to reduce training error, SVR uses systemic risk minimization to reduce the generalization error's upper limit. In this way, a global optimum is obtained rather than a local optimum as in ANN (Hong et al., 2011). SVR methods have been introduced for use with genetic algorithms (GA) to select parameters in SVMs (support vector machines), resulting in the GA-SVR hybrid solution. Pai, Hong, Chang, and (Chen & Wang, 2007) who suggested this approach for tourism demand modeling and forecasting. The genetic fuzzy system (GFS), as suggested Hadavandi, Ghanbari, Shahanaghi, & Abbasian-Naghneh (2011) , is a hybrid AI model of fuzzy rule-based systems that uses GAs for the learning rule base and the tuning database of a fuzzy system. Using a descriptive rule induction technique, the GFS extracts valuable trends of tourist arrivals data. The proposed GFS model has been used to predict tourist arrivals in Taiwan from a variety of source markets, including Hong Kong, the United States, and Germany. By adding a loss function, the support vector regression (SVR) method is an alternative approach to for addressing the classification, estimation of non-linear regression and forecasting challenges. (Chen & Wang, 2007) compared the forecasting performance of different methods including GA-SVR, back propagation and neural network and ARIMA models by incorporating genetic algorithm (GA) technique into SVR to form GA-SVR model to predict tourism arrivals. According to the findings, GA-SVR produces more accurate forecasts than the other two approaches.

**Fuzzy Time series**: Fuzzy time series is another type of AI that has been increasingly gaining popularity in the context of tourism demand forecasting ( Chen et al., 2010; Hadavandi et al., 2011; Shahrabi, Hadavandi, & Asadi, 2013). To generate tourism demand predictions, Fuzzy time series method make use of linguistic variables. It centers on the premise that the deviations from one year to the next would suit the recent patterns. As a result, if observed volatility differs significantly, from recent patterns, the forecasting error is more likely to be significant (Yu & Schwartz, 2006). Though Wang (2004) confirmed that Fuzzy time series method was proven to be effective in forecasting tourism demand in short-run, one of its biggest flaws is that it cannot adjust to the shocks of unforeseen events ( Wang & Hsu, 2008)

**Search engine and big data**: The use of online big data is a recent development for predicting tourism demand using explanatory variables. Individuals are increasingly relying on the Internet in decision-making in different ways, such as stock market, trade, and buying, due to the exponential growth of the Internet (Jiao & Chen, 2019). The Internet is transforming how people obtain information and how they behave on that information, and it is providing more convenient and diverse resources (Barber and Odean, 2001). Meanwhile, due to the difficulty of the decision-making process, the Internet, especially online search engines, is commonly used by potential tourists and has a significant impact on tourism decisions. For example, a number of factors affect tourists' destination preferences, such as the average cost of travel, the quality of lodging, food, and attractions, and so on. Individuals prefer to use internet search engines for up-to-date information and online reviews to get an overall impression of a possible destination (Jiao & Chen, 2019). Major search engines, such as Google and the Baidu Index ( Li et al., 2018) make search patterns on individual keywords easily accessible to the public. As a result, the majority of research papers in this field depend on search data from Google or Baidu, a prominent Chinese search engine. In addition, web traffic data from destination marketing organisations are used as an indicator of visitor online behavior (Gunter & Önder, 2016).

To produce online big data metrics, various studies used various approaches. Some studies, such as Bangwayo-Skeete & Skeete, (2015), used normalized search volume data as big data variables since Google Trends reports normalized and scaled search volume data. (X. Li et al., 2017) run correlation tests and search queries that were heavily correlated with visitor volume were chosen, many relevant keywords were also extracted from pre-set basic keywords and five classification areas were selected based on frequency of mentions and connections. In contrast, Rivera (2016) took a new approach, selecting keywords based on input from experts .To eliminate instable parameter estimation, Yang et al. (2015) and (Rivera, (2016) combined the patterns data into a search index composite. Using the generalized dynamic factor model, (X. Li et al., 2017) created a composite search index that embodied both the search series data and the series' lead and lag information (GDFM). The dynamic features of big data have been mitigated by these approaches, and the integration of big data into models has been simpler. The models used in the field of big data, on the other hand, vary from study to study. To integrate big data–based explanatory variables into econometric models, ADLM (Li, Pan, Law & Huang, 2017; Rivera, 2016;Yang et al., 2015) and Bayesian VAR have been used (Gunter & Önder, 2015). However, when such data-driven methods are used in our knowledge domain, concerns about the inputs and interpretation of the empirical findings remain (Song & Liu, 2017). Many technological problems exist, which must be solved in the pursuit of improved data shrinkage methodologies. These methodologies should be considered in order to improve the forecasting accuracy of tourism demand models (Park et al., 2017) and avoid over-parameterization of big data models (Önder & Gunter, 2016).

Despite their theoretical and methodological flaws, AI-based approaches have been commonly used to forecast a broad range of phenomena in a variety of scientific disciplines (Díaz & Mateu-sbert, 2011). The effectiveness of these methods has prompted tourism researchers to apply them to demand forecasting. As a result, over the last 20 years, AI methods have been extensively used for tourism forecasting. Support vector regression (SVR) (Hong et al., 2011), fuzzy time series (Tsaur & Kuo, 2011;Wang, 2004), rough sets approach (Goh et al., 2008), and grey theory are some of the AI approaches used to forecast tourism demand (Wang, Zhang & Guo,2015). ANNs, on the other hand, have been the most widely used AI-based models (Claveria et al., 2015a, Claveria et al., 2015b; Law, 2000; Pattie & Snyder, 1996; Teixeira & Fernandes, 2012).

### *General trends in the tourism demand forecasting literature*

Our analyses of methodological advances in tourism demand forecasting studies over the last four decades reveal two general patterns. To begin, forecasting methods can be classified into two different categories: qualitative and quantitative approaches. Although the Delphi technique has actually contributed in this field, quantitative methods have been the primary methodological advances in tourism demand forecasting. Non-causal time series models, causal econometric models, and AI-based models are the three types of quantitative methods currently available. Combined and hybrid models have appeared more recently, and since 2000s, a growing number of articles on these models have been published. The combined forecasting method is described in our analysis as an approach that produces a series of forecasts for the same demand variable using various methods, and then combines these forecasts into a single final, summarized forecast. A hybrid forecasting model combines the characteristics of two or more models into a single model. During that period (decade), some researchers continued to use SR models in their research, and they focused on improving time series models (e.g., Naive, AR, ES, and pattern analysis). In the 1990s, time series models rose in popularity, but models focused on dynamic regressions (such as the Box-Jenkins method with exogenous variables and the ADLM) grew in popularity as well. New AI-based or systems-based econometric models (e.g., STSM, VAR, and AIDS) have also appeared. This trend continued in the 2000s, with the growth of econometric models, AI-based models, and mixed or hybrid methods flourishing.

Researchers proposed various methods of tourism demand forecasting during the two decades between 1990s and 2000s. In the literature on tourism demand forecasting since 2010, sophisticated time series and econometric models have emerged. In terms of methodological advancement, however, combined models and AI-based models have made significant progress. AI-based techniques have been widely used, and the accuracy of predictions has increased as a result of mixed or hybrid approaches that integrate AI with other quantitative models. In tourism demand research and forecasting, recently evolved econometric methods such as the MIDAS method.  Ghysels, Sinko & Valkanov (2007) suggested the mixed-data sampling (MIDAS) method, which uses a parsimonious weighting system to change the forecasting of low-frequency variables at a higher frequency. However, despite its widespread use in general forecasting fields, especially economic forecasting, MIDAS application in tourism demand forecasting is still uncommon (Li et al., 2018).

Another motivating factor in the advancement of forecasting models is the use of Internet data in tourism forecasting. The Internet offers a wealth of information for tourism demand analysis, prompting researchers to explore new data sources like Google Trends or Baidu Index for tourism demand modeling and forecasting. Methods for data collection and shrinkage are also being created. The least absolute shrinkage and selection operator (LASSO) and factor model are two of the best examples of such developments in tourism demand forecasting (Song & Liu, 2017). In published studies of tourism forecasting, various time series models have emerged, complemented by Google data or other Internet data as exogenous variables. Diverse optimisation systems have been suggested and combined with neural network models for using multifaceted tourism information data ( Li et al., 2018).

In their analysis, (Song & Li, 2008) stated that no single model can consistently outperform all others in terms of forecasting precision. (Athanasopoulos et al., 2011; Gunter & Önder, 2016) all come to the same inconclusive results .As a result, attempts have been made to use further models in the comparison of tourism demand forecasts over time. According to a survey of tourism forecasting research, each report has considered an average of 2.5 models since 1990, while the figures were just 1.9 before the 1990s and 1.1 before the 1980s. Nonetheless, it should be noted that most forecasting method comparisons do use a few subjectively chosen models. As a result, as point out, the results taken from such comparisons are subject to very particular circumstances. (Song & Li, 2008)

### *Combination and hybrid methods*

Despite the continuous prevalence of single forecasting methods, Li,Song and Witt, (2005) observed that no single forecasting system outperforms other methods in all circumstances. Fritz,Brandon and Xander (1984) emphasize that 'the combination of many competing forecasts will minimize errors and achieve progress in overall accuracy' in their pioneering analysis of forecast combination in the tourism sector. Combination forecasts have been a recent theme, and a growing amount of study on combination forecasts in tourism forecasting has been generated. Combination forecasts, unlike hybrid models, combine the forecasting results produced by single forecasting methods, with the justification that synthesizing and integrating information from several different models will avoid risks and complexity in model selection, and thus result in greater precision (Shen, Li, & Song, 2011). Bates and Granger (1969) were the first to mention combination forecasts in the general field of forecasting. Combination forecasts have also been used in tourism (Fritz et al., 1984; Song et al., 2009; Wong, Song &Witt, 2007), with the findings demonstrating the promise of combination forecasts in tourism. According to Shen et al (2008), forecasting combination has been common in business and economics for the past four decades, and most studies have shown that combination forecasts are more accurate than single forecasting approaches. With the exception of four studies (Chu, 1998; Fritz et al., 1984; Oh & Morzuch, 2005; Wong et al.,2007), application of combination forecasts in tourism was uncommon in the field of tourism forecasting before 2008. We anticipate that mixed and hybrid forecasting models will continue to evolve and play a vital role in tourism demand forecasting in the future.

### Data, parameter and estimation

While earlier trends focused on improvements in the functional forms of tourism demand forecasting, more recent developments have largely focused on data utilisation, parameterization, and estimation. Forecasting using mixed-frequency data is possible with MIDAS, and this technique has been shown to increase forecasting accuracy (Bangwayo-Skeete & Skeete, 2015). TVPs can capture structural variations in time dimensions, and they have been shown to perform well with models like AIDS ( Li, Song & Witt, 2006), STSM (Song et al., 2011)and SR (Song & Witt, 2006). Other forms of varying parameters, such as the sign-dependent varying parameter (Smeral & Song, 2015) and the state-varying parameter (Pan & Yang, 2017), can also be useful in modeling regime changes. (Assaf et al., 2019; Wong et al.,2006) discovered that Bayesian estimations had the potential to improve forecasting accuracy by incorporating insightful precedents into tourism demand forecasting models.

## Conclusion

Over the last five decades, techniques for predicting tourism demand have evolved. Researchers have held forecasting competitions, checked combined forecasts provided by various models, and introduced new forecasting/estimation methods in order to improve forecasting accuracy. This study set out to summarize the general patterns of development among four types of forecasting methods after evaluating core studies on tourism demand modeling and forecasting. Forecasting methods have exponentially advanced in recent years as tourist demand forecasting has continued to draw researchers' interest. Time series, econometric, AI, and hybrid models continued to dominate in tourism demand forecasting, though some new trends emerged. Hybrid models appeared to often outperform individual standard models in forecasting performance benchmarking. However, no single model outperforms the others in any case, which is consistent with (Li et al., 2005; Li et al., 2018; Peng et al., 2014). As a result, combination forecasts are increasingly becoming more prevalent, and numerous studies indicate that they improve forecasting accuracy. Nonlinear combination for single component forecasting models is a new and superior approach to traditional linear combination methods in terms of combination techniques.

This study focuses on the links between the two most often used model types, non-causal time series models and causal econometric models. Due to the volatility of forecasting results and the weak explanatory power of non-causal time series models, tourism forecasting researchers are gradually turning to modifications of time series models that have exogenous variables and multivariate dimensions. Advanced time-varying parameter techniques have become increasingly common, as they reflect the probability of structural changes over time. (Calantone & Bojanic, 1988) demonstrated that combined forecasts cannot be less reliable than any of their component forecasts due to the increasing superior performance of combined and hybrid models (Li et al., 2018; Shen, Li & Song, 2008; Shen et al., 2011) .

Though judgmental approaches are being used more and more to improve the accuracy of quantitative forecasting models, more advances and scientific applications of combined and hybrid models are anticipated in response to their increasing significance. Despite the theoretical and technical shortcomings of these methods, the development of AI-based models is noteworthy in recent tourism demand forecasting studies. Several empirical results suggest that AI-based techniques outperform their big data analytics-based time series and econometric counterparts. The use of a mixture of neural network and counterpart models has been shown to be more efficient. Future studies should extensively investigate and analyze combination techniques, especially those that require the collection of forecasting combination weighting schemes.

Tourism forecasting researchers have made significant efforts to generalize their econometric models in order to promote a greater understanding of the determinants of current and potential tourism demand by using aggregate data (at the destination and source market levels). Empirical evidence suggests, however, that forecasting accuracies differ between destination and source market pairs. People flows across borders, cross-border jobs, cultural differences, globalisation or disglobalisation trends, and changes in environmental sustainability have all complicated tourism decision-making, especially for international travel. As a result, methods for predicting international tourism demand need more meticulous attention to discerning tourism demand indicators through the use of disaggregated or micro-data, as well as detailed assessments of a wide range of geographical, socioeconomic, political, and environmental variables.

The use of big data and AI models is another important development. While the use of big data in tourism forecasting is still in its infancy, big data has enormous potential for improving forecasting precision. However, some of the difficulties still exist: first, developing new modeling and forecasting techniques and estimation methods for simultaneously handling traditional time series and high frequency big data; second, addressing forecasting research questions with existing and new consumer behavior theories in order to further capitalize on tourism big data rather than focusing solely on data mining; and third, drawing a correlation between the two.

Mixed-frequency data can be considered a possible development in future tourism demand forecasting study directions. While only a few studies have used mixed-frequency data to predict tourism demand, further studies using this new method are anticipated. Incorporation of big data and mixed-data approaches in tourism demand forecasting may be a potential research path as well, given that big data–based variables are also available in high volumes.

Though spatial regression-based forecasting are still rarely applied, spatial regression models can be considered an innovative approach to tourism demand forecasting because they take into account geographical information. According to Wu et al. (2017), spatial regressive models have also been used in hotel and tourism demand analysis. In tourism economics, there are several applications. Lazzeretti and Capone (2009) and Capone and Boix (2008), for example, looked at the spatial impact on regional tourism development, while Drakos and Kutan ,2003;Yang & Wong, 2012; Blake et al., 2006) looked at the spatial spill over effects on local tourist flow.

As the number of innovative models used in tourism demand forecasting grows, hybrid models incorporating new forecasting models will become a standard in the future to increase forecasting accuracy. This comprehensive analysis of forecasting method advancements over the last five decades has the essential goal of pointing researchers in the right direction for future study. The subjectivity involved in choosing our pool of 145 primary studies, on the other hand, may be seen as a study's weakness. The primary goal of this study is to examine the evolution of forecasting processes. Due to space constraints, the tasks of determining the determinants of tourism demand, isolating the variables impacting demand elasticity, and estimating the impact of intervening events on various scenarios have long been overlooked.

**Acknowledgements**
My special thanks go to the African Centre of Excellence in Data Science-ACEDS, University of Rwanda for having offered financial support. I also extend my sincere appreciation to my PhD Supervisors, Prof. Herman Musahara and Dr. Edouard Musabanganji for their continuous support throughout my research journey.

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