FORECASTING TOURISM WITH BIG DATA AND AI: A BIBLIOMETRIC REVIEW (2014–2024)

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Abstract

The purpose of the study is to provide a bibliometric overview of forecasting tourist arrivals, documenting the intellectual structures, research volume, emerging trends, and the direction of knowledge development in this domain. The study employed a bibliometric approach, including performance and relational analyses/science mapping. 315 documents were extracted from the Scopus database following the PRISMA framework. Thereafter, various parameters were analyzed, including the most influential authors, journals, and publications, as well as thematic analysis. To address these research objectives, VOSviewer and Biblioshiny software were used for data analysis and visualization. The result revealed that the 2014 tourism forecasting study gained popularity. Tourism Economics journal and Song H are the most influential journal and author, respectively. Moreover, thematic analysis revealed that traditional time series forecasting models rely on generic data, limiting their ability to account for external factors, thereby affecting accuracy and reliability. To address this limitation, recent studies have adopted econometric forecasting models that integrate big data from diverse sources, such as search engines and online review platforms, alongside conventional datasets, thereby enhancing predictive accuracy and helping policymakers and industry stakeholders with data-driven decision-making, resource allocation, revenue management, and optimizing business operations.

Keywords: Bibliometric Analysis; Forecasting; Tourist arrival; Big data; Tourism demand.

PREVISÃO DO TURISMO COM BIG DATA E IA: UMA REVISÃO BIBLIOMÉTRICA (2014–2024)

Resumo

O objetivo do estudo é fornecer uma visão bibliométrica sobre a previsão de chegadas de turistas, documentando as estruturas intelectuais, o volume de pesquisas, as tendências emergentes e a direção do desenvolvimento do conhecimento nessa área. Foi utilizada a abordagem de análise bibliométrica, com análises de desempenho e relacional/mapeamento científico. Um total de 315 documentos foi extraído da base de dados Scopus, seguindo o framework PRISMA. Foram analisados diversos parâmetros, como os autores, periódicos e publicações mais influentes, além de uma análise temática. Para atingir os objetivos da pesquisa, utilizaram-se os softwares VOSViewer e Biblioshiny para a análise e a visualização dos dados. Os resultados revelaram que, a partir de 2014, os estudos sobre previsão do turismo ganharam popularidade. O periódico *Tourism Economics* e o autor Song H destacam-se como os mais influentes. A análise temática indicou que modelos tradicionais de séries temporais utilizam dados genéricos, o que limita sua capacidade de considerar fatores externos e afeta a precisão desses modelos. Para superar isso, estudos recentes vêm adotando modelos econométricos com big data provenientes de diversas fontes, como motores de busca e plataformas de avaliações online, o que melhora a precisão preditiva e auxilia decisões estratégicas no setor.

Palavras-chave: Análise Bibliométrica; Previsão; Chegada de turistas; Big data; Demanda turística.

PRONÓSTICO DEL TURISMO CON BIG DATA E INTELIGENCIA ARTIFICIAL: UNA REVISIÓN BIBLIOMÉTRICA (2014–2024)

Resumen

El propósito del estudio es ofrecer una visión bibliométrica sobre la previsión de llegadas de turistas, con el objetivo de documentar las estructuras intelectuales, el volumen de investigación, las tendencias emergentes y la dirección del desarrollo del conocimiento en este campo. Se utilizó un enfoque de análisis bibliométrico, que incluyó análisis de rendimiento y análisis relacional/mapeo científico. Se extrajeron 315 documentos de la base de datos Scopus siguiendo el marco PRISMA. Posteriormente, se analizaron diversos parámetros, como los autores, las revistas y las publicaciones más influyentes, y se realizó un análisis temático. Para alcanzar los objetivos de investigación, se utilizaron los programas VOSViewer y Biblioshiny para el análisis y la visualización de datos. Los resultados mostraron que, a partir de 2014, los estudios sobre la previsión turística ganaron popularidad. La revista *Tourism Economics* y el autor Song H resultaron ser los más influyentes. Además, el análisis temático reveló que los modelos tradicionales de series temporales se basan en datos genéricos, lo que limita su capacidad para considerar factores externos y afecta su precisión. Para superar esta limitación, estudios recientes han adoptado modelos econométricos que integran big data de diversas fuentes, lo que mejora la precisión y apoya la toma de decisiones basada en datos.

Palabras clave: Análisis bibliométrico; Previsión; Llegada de turistas; Big data; Demanda turística.

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1 INTRODUCTION

Tourism stands as one of the fastest-growing economic sectors globally, playing a pivotal role in the socio-economic development of numerous destinations by creating employment opportunities and generating foreign exchange earnings (Li et al., 2020; Zancan et al., 2023). As global competition in the tourism market intensifies, accurate and reliable tourism demand forecasting has become crucial for policymakers, stakeholders, and researchers (Wu et al., 2023).

Effective forecasting enables strategic planning, resource allocation, and risk management, thereby supporting sustainable tourism development (Chen et al., 2023; Kumar & Sharma, 2016). The growing demand for tourism often leads to overcrowding and overuse of natural resources during peak seasons (Sünnetçioğlu et al., 2021; Yang et al., 2015).

Accurate forecasting of tourist inflows is crucial for effective destination management, optimizing business operations, and resource allocation (Li et al., 2020). For instance, hoteliers can make informed decisions about staffing and pricing by predicting fluctuations in occupancy rates. At the same time, tourism practitioners can develop strategies for both peak and off-season operations (Pan & Yang, 2017; Yang et al., 2015).

The dynamic and multifaceted nature of tourism demand, influenced by economic conditions, political stability, technological advancements, and environmental factors, poses challenges to accurate prediction (Chen et al., 2023). Traditional forecasting approaches, such as econometric models and time series analysis, often struggle to capture the complexity, dynamism, and uncertainty inherent in tourism markets, particularly amid global disruptions including economic crises, pandemics, and climate-related risks (Wu et al., 2023).

This has led to a growing need for more advanced, data-driven approaches that can provide timely, granular, and reliable insights. In this context, integration of big data and artificial intelligence (AI) has emerged as a transformative force in tourism forecasting (Li et al., 2020). The exponential growth of digital technologies, social media platforms, online travel agencies, and sensor-based data sources has generated massive volumes of structured and unstructured data on tourist behaviour, preferences, and mobility patterns (Chen et al., 2023).

Unlike traditional data sources, big data enables real-time tracking of demand signals, offering a multidimensional perspective on tourism flows (Wu et al., 2022). At the same time, AI techniques, including machine learning, natural language processing, and neural networks, enable researchers and practitioners to identify hidden patterns, enhance predictive accuracy, and adapt to rapidly changing market conditions (Yang et al., 2015).

The importance of tourism forecasting has further intensified in the wake of global disruptions such as the COVID-19 pandemic, which has highlighted the tourism industry's vulnerability to unexpected shocks (De Oliveira et al., 2023; Gričar & Bojnec, 2022; Kumar et al., 2022). Understanding and predicting fluctuations in tourism demand is essential for devising resilience strategies and ensuring long-term sustainability of the sector (Dimitrov et al., 2015; Pan and Yang, 2017; Sariişik et al., 2021).

The bibliometric study has been widely conducted in different fields such as Ethics and Entrepreneurship (Vallaster et al., 2019), Innovation and Sustainability (Maier et al., 2020), Strozzi et al. (2017) used bibliometric analysis to explain the notion of "Smart Factory", and Thomas and Gupta (2022) adopted a bibliometric study to evaluate the notion of tacit knowledge in an organization.

Moreover, in the field of tourism and hospitality, bibliometric analysis has been widely used. For example, Khanra et al. (2021) utilized a bibliometric study in the context of ecotourism. Khan et al. (2024) used it in the context of Sustainable Practices in the Hotel Industry. Çıkı and Tanriverdi (2024) conducted a bibliometric study on Last Chance Tourism.

Yilmaz (2019) conducted a bibliometric analysis to evaluate tourism-related studies in Turkey's peer-reviewed journals. Furthermore, for forecasting studies, Baker et al. (2021) conducted a bibliometric study for the journal, i.e., only using the database of the Journal "Journal of Forecasting". This journal is widely known for publishing articles on forecasting and related topics, primarily in business, economics, and finance.

However, the bibliometric analysis for forecasting tourist arrivals remains underexplored. Thus, this research on the bibliometric analysis of forecasting tourist arrivals is the first attempt and may provide new insights and a future direction in this domain.

In the past, many scholars have conducted forecasting studies on tourism, and over time, many different forecasting techniques have evolved and been applied in this domain (Li et al., 2017; Li et al., 2020; Pan & Yang, 2017; Rivera, 2016; Yang et al., 2015; Zancan et al., 2023). However, many questions arise regarding forecasting studies in tourism, as highlighted below. Therefore, the bibliometric method is used for this study to address the following questions.

The main purpose of the study is to identify emerging topics in the field of tourism forecasting. In other words, to provide or identify the new directionality in tourism forecasting studies.

In this study, we will be addressing the following research questions:

1. What is the total number of articles with the domain of forecasting and tourist arrival?
2. Who are the most influential authors in the particular field of study?
3. Which are the most influential articles and journals in the particular field?
4. What is the most addressed topic researched in this domain?
5. What is the intellectual structure in the particular domain?
6. To examine the tools and methods applied in the study of tourism forecasting.

Therefore, the objective of the study is to provide a holistic overview of tourism forecasting studies.

2 METHODOLOGY

The methodology employed in this study is a bibliometric analysis, a quantitative approach that provides a thorough overview of the field of tourism forecasting (Donthu et al., 2021; Thomas & Gupta, 2022; Vallaster et al., 2019). There are ample advantages of using Bibliometric analysis; it helps to explore the intellectual structure in a particular domain of the study, further it helps to understand the collaboration patterns, research constituents, journal performance and to cover the emerging trends in a particular domain (Donthu et al., 2021; Maier et al., 2020).

In other words, bibliometric analysis has gained popularity for its ability to summarize the available knowledge on a particular research topic (Baker et al., 2021; Khanra et al., 2021). Bibliometric analysis is divided into two categories, i.e., performance analysis and relational analysis/science mapping (Tanwar et al., 2024).

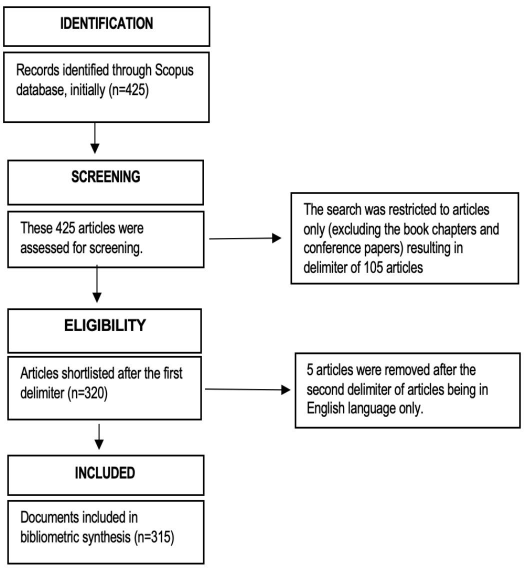
Where leading authors, leading sources, leading institutions, and the publication structure fall under performance analysis, which addresses research questions 1, 2, and 3. Citation analysis, co-citation analysis, collaboration analysis, co-word analysis, bibliographic coupling, and co-authorship analysis are forms of relational bibliometric analysis (Donthu et al., 2021; Khan et al., 2024).

In this study, co-citation and co-word analyses have been conducted to address research questions 4, 5, and 6. To conduct this analysis, two software packages have been used: VOSviewer and the Bibliometrix package in R.

2.1 Database

Scopus database is the most scientific and well-established bibliometric database (Tanwar et al., 2024). Thus, to extract data for the study, the Scopus database was used. For data extraction, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method was adopted (Maier et al., 2020). The search string used was “Forecasting”, “Tourist” and “Arrival”. Initially, 425 articles on the topic were found.

Figure 1. The PRISMA flow diagram was used to identify, screen, and include papers for our bibliometric review. (Summary of the selection process)



Source: own elaboration.

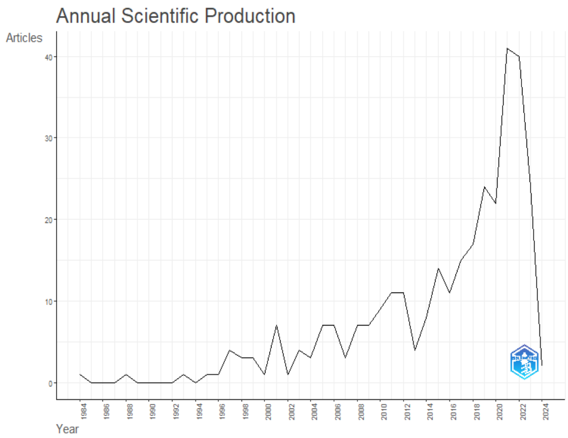
Then, several inclusion and exclusion criteria were adopted to reduce the number of articles (Tanwar et al., 2024). Firstly, the search was limited to journal articles only (excluding research papers published as book chapters and conference papers), resulting in the elimination of 105 articles.

Thus, 320 articles remained, and the search was finally limited to English, resulting in a further 5 articles being excluded. Thus, 315 articles were included and used as a sample for the bibliometric study. The extraction, inclusion and exclusion criteria of articles are shown in Figure 1.

3 ANALYSIS AND DISCUSSION

3.1Evolution of Research on Forecasting Tourist Arrivals

Figure 2. Evolution of Forecasting research on tourism.



Source: Own elaboration based on the Bibliometrix R package. Articles published per year. *As on February 15, 2024 (using Bibliometrix R-Package).

The authors started writing about forecasting tourist arrivals in 1984. However, the volume was very low; in 1984, only one article was published. During the periods 1985-87 and 1989-1992, no articles were published on the topic. Since 2014, tourism forecasting studies have gained popularity, peaking in 2021 and 2022, with 41 and 40 articles, respectively.

However, it slightly decreased in 2023 with 24 articles. Finally, in 2024, there were only 2 articles (this was due to the data being accumulated on February 15, 2024). We can identify from Figure 1 that after 2019, there has been a remarkable hike in the tourism forecasting study.

3.1 Influential Authors and Articles in the Tourism Forecasting Field

Citation analysis was performed to recognize the most prominent articles in the sample database. The fundamental principle of this analysis is that the more citations an article receives, the greater its impact in the research field and the higher its recognition. (Donthu et al., 2021; Maire et al., 2020). In other words, the number of citations is taken as a substitute for the significance of an article or a good quality of paper (Khan et al., 2024). However, the citation analysis considers only the article's popularity, not its importance within a research domain (Khanra et al., 2021).

The most prominent document was generated from a total of 315 articles (see Figure 1 for n=315). Putting a restriction of a minimum of 183 occurrences of the articles, i.e., the particular document has been cited at least 183 times, and finally, 10 documents meet the threshold.

Table 1. Top 10 cited papers (using VOSviewer)

R	Article Title	Authors	Years	TC
1	Critical references on the economic impact assessment of a mega-event: the case of 2002 FIFA world cup.	Lee, Choong-Ki; Taylor, Tracy.	2005	316
2	Support vector regression with genetic algorithms in forecasting tourism demand.	Chen, Kuan-Yu; Wang, Cheng-Hua.	2007	293
3	A neural network model to forecast Japanese demand for travel to Hong Kong.	Law, Rob; Au, Norman.	1999	254
4	Tourism demand forecasting: a deep learning approach.	Law, Rob: Gang: Fong, Davis Ka Choi; Han, Xin.	2019	238
5	Forecasting tourist arrivals with machine learning and internet search index.	Sun, Shaolong; Wei, Yunjie, Tsui, Kwok-Leung; Tusi, Kwok-Leung; Wang, Shouyang.	2019	235
6	Can google data improve the forecasting performance of tourist arrivals? Mixed data sampling approach.	Bangwayo-Sheete, Prosper f; Skeete, Ryan W.	2015	235
7	A comparison of three different approaches to tourist arrival forecasting.	Cho, Vincent.	2003	221
8	Time series forecasting of international travel demand for Australia.	Lim, Christine; Mcaleer, Michael.	2002	216
9	Tourism demand modelling and forecasting: how should demand be measured?	Song, Haiyan; Gang; Witt, Stephen f; Fei, Baogang.	2010	197
10	Predicting tourism demand using fuzzy time series and hybrid grey theory.	Wang, Chao-Hung.	2004	183

Source: Compiled by the authors using VOSviewer.
Abbreviations: R= Rank; TC= Total Citations.

From Table 1, we can see that the paper “Critical references on the economic impact assessment of a mega-event: the case of 2002 FIFA World Cup,” published in the journal Tourism Management and written by Lee and Taylor (2005), is the most-cited article in the field of tourism forecasting. Lee and Taylor (2005) critically highlighted the forecasting of foreign tourist arrivals during the 2002 FIFA World Cup in South Korea, noting that the Korean World Cup Organizing Committee predicted 640,000 international visitors.

However, only 403,466 foreign tourists (excluding World Cup visitors) arrived during the 2002 World Cup. Actual tourist arrivals were 37% lower than predicted. Further, the cited author argues that there is a methodological pitfall in forecasting, as the data were based solely on generic tourist data, which does not capture exogenous effects or the effects of different events. The cited author further highlighted various reasons for these low arrivals during the FIFA World Cup in South Korea.

The 2nd most-cited paper is “Support vector regression with genetic algorithms in forecasting tourism demand,” published in the Journal of Tourism Management by Chen & Wang (2007). Chen and Wang (2007) forecast tourist arrivals in China using a dataset from 1985–2001 and various forecasting methodologies, including Backpropagation Neural Networks (BPNN), the Autoregressive Integrated Moving Average (ARIMA) model, and Genetic Algorithm (GA)-Support Vector Regression (SVR).

Using two measures to check for the best forecasting method, i.e., Normalized Mean Square Error (NMSE) and Mean Absolute Percentage Error (MAPE). The results indicate that SVR outperforms the BPNN and ARIMA models.

3.2 Journal Analysis of Tourism Forecasting Articles

Citation analysis was performed to recognize the most prominent journals from our sample database. From the analysis, it was found that a total samples or articles (315) was published in 152 different sources or journals. Further, with a minimum of 5 documents per source and 16 citations, 10 Journals meet the threshold (see Table 2).

Table 2 reveals that Tourism Economics is the journal with the highest number of publications (27) and the highest total citations (888). Tourism Management is the second-highest-impact journal in this domain, with 25 articles and the most citations among all journals, i.e., 3239.

Table 2: Top 10 journals with the most published article on forecasting of tourist arrivals. (using VOSviewer).

Rank	Journal Name	No of Articles	Citations	Total Link Strength
1	TOURISM ECONOMICS	27	888	113
2	TOURISM MANAGEMENT	25	3239	161
3	ANNALS OF TOURISM RESEARCH	23	1295	108
4	JOURNAL OF TRAVEL RESEARCH	15	750	76
5	EXPERT SYSTEMS WITH APPLICATIONS	8	197	54
6	TOURISM ANALYSIS	8	86	9
7	CURRENT ISSUES IN TOURISM	6	123	19
8	SUSTAINABILITY (SWITZERLAND)	6	47	19
9	INTERNATIONAL JOURNAL OF TOURISM RESEARCH	5	44	27
10	AFRICAN JOURNAL OF HOSPITALITY, TOURISM AND LEISURE	5	16	2

Source: Compiled by the authors using VOSviewer.

3.3 Most Relevant Authors on Tourism Forecasting Research

Table 3. Most relevant or renowned authors on the forecasting of tourist arrivals. (using Bibliometrix R-Package)

Rank	Authors Name	No of Articles
1	SONG H	16
2	SUN S	11
3	WANG S	11
4	LAW R	10
5	LI G	9
6	LI X	9
7	CHIKOBVU D	6
8	CHU F-L	6
9	ZHANG C	6
10	LI H	5

Source: Compiled by the authors using Bibliometrix R-Package.

In Table 3, there are the top ten authors who have contributed the maximum volume of articles in the field of tourism forecasting. The author Song H has the most articles (16), and his paper is on the list of the top 10 most-cited papers, ranked 9. The authors Sun S and Wang S have contributed 11 articles each. Where Sun S's article is the most cited paper with rank 5, and Wang S also has a few papers in the top cited paper list with the ranks of 2,5,10 (refer to Table 1).

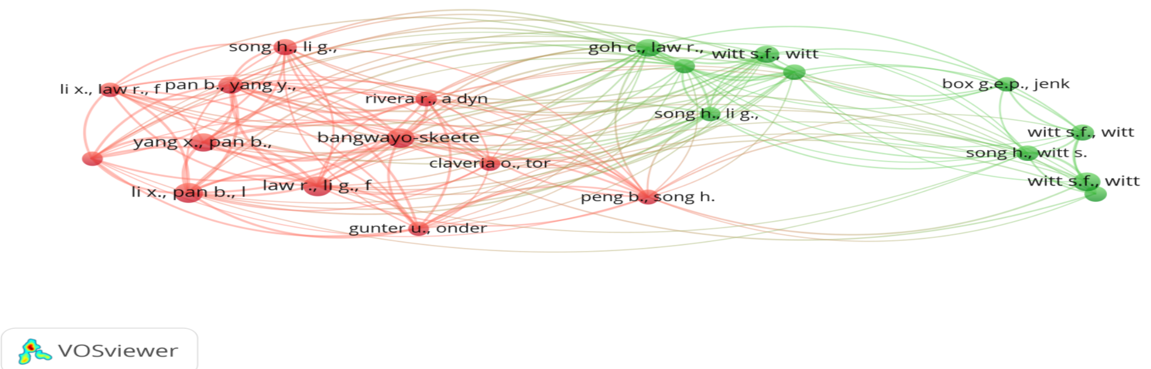
3.4 More Relevant Affiliations on Tourism Forecasting Research

Table 4. More relevant affiliations on forecasting of tourist arrivals (using the Bibliometrix R-Package).

Rank	Affiliations	No of Articles
1	THE HONG KONG POLYTECHNIC UNIVERSITY	40
2	XI'AN JIAOTONG UNIVERSITY	20
3	UNIVERSITY OF SURREY	14
4	SICHUAN UNIVERSITY	13
5	UNIVERSITY PUTRA MALAYSIA	13
6	ANADOLU UNIVERSITY	11
7	HONG KONG POLYTECHNIC UNIVERSITY	11
8	UNIVERSITY OF THE FREE STATE	11
9	ACADEMY OF MATHEMATICS AND SYSTEMS SCIENCE	8
10	BOURNEMOUTH UNIVERSITY	8

Source: Compiled by the authors using Bibliometrix R-Package.

Figure 3: Co-citation of cited reference.



Source: Compiled by the authors using VOSviewer.

Table 4 reveals the affiliations that have supported and published articles in this domain. The Hong Kong Polytechnic University ranks first with 40 documents, followed by XI'AN Jiaotong University with 20 articles.

3.5 Thematic analysis

3.5.1 Co-Citation analysis

Maier et al. (2020) defined co-citation as "the frequency with which two units (journals, authors, and papers) are cited together". In other words, co-citation of two articles occurs when a third article cites both (Tanwar et al., 2024). Further, the co-citation network is based on clustering techniques, in which research papers within the same cluster exhibit similar characteristics, and each distinct cluster indicates a different direction of study in the particular domain (Tanwar et al., 2024).

In the author co-citation analysis, a total of 10603 cited references were found. After setting a restriction on citations to a cited reference to 15, 22 documents meet the threshold. Therefore, the analysis was carried out using 22 units; see Figure 3.

Thus, the VOSviewer analysis yields two clusters: cluster one (red) and cluster two (green). As mentioned above, the articles grouped in each cluster are written in a similar direction. Thus, thematic analysis was performed to determine the directionality of the cluster documents.

The articles in Cluster 1 can be given a theme as "Forecasting Tourism Demand with Big Data": In recent year the forecasting method have shifted from traditional method of forecasting using the actual volume of tourist arrival with monthly or yearly data by using different time series models i.e., autoregressive–moving-average (ARMA) models, naïve model, exponential smoothing model, and structural time series model to the more sophisticated and more robust forecasting techniques or models such as econometric models and artificial intelligence (AI) models.

Cluster 1: Theme: Econometric models and forecasting tourism demand using big data from different sources or search engines: Li et al. (2017) used search query volume data from a search engine Baidu which is most popular search engine in China to predict tourism demand for a tourist destination Beijing, using Generalized Dynamic Factor Model (GDFM), there results indicated that the composite search index used along with GDFM provides more accurate forecast than the traditional methods.

Yang et al. (2015) also applied search query data from different search engines, i.e., Google and Baidu, to forecast tourist volume to Hainan Province of China. Their results indicated that Baidu's forecast outperformed Google's, given Baidu's large market share in China.

Furthermore, the prediction using Baidu data was more appropriate than that of the traditional benchmark model, ARIMA. Pan and Yang (2017) predicted weekly hotel occupancy for the destination Charleston, South Carolina (United States) using time series models Autoregressive Integrated Moving Average with External Variables (ARMAX) and a Markov Switching Dynamic Regression model (MSDR) along with big data, which they retrieved from search engine queries, website traffic and weekly weather information of the destination.

Pan and Yang's (2017) results indicated that ARMAX models, used along with big data, predict more efficiently than the MSDR model. Rivera's (2016) results indicated that the Dynamic Linear Model, when applied to big data, provides better forecasts than other traditional methods. Li et al. (2020) found that, across all forecasting methods, using multisource big data from a search engine and online review platforms yields significantly better forecasts.

Cluster 2: Theme: Tourism demand forecasting techniques and their accuracy: Various forecasting techniques have evolved to date, and many have been applied to predict tourism demand, but which model achieves the highest accuracy remains a concern (Song and Li, 2008). Law (2020) predicted tourism demand using various forecasting models, including time-series models, regression models, and neural networks such as backpropagation neural networks.

Law (2020) results indicated that the back-propagation neural network outperforms any other traditional time series models. Goh and Law (2002) applied different forecasting models (Naïve model, Exponential smoothing, moving average, ARIMA, Multivariate ARIMA, or MARIMA) to forecast tourism demand from 10 different sources to Hong Kong.

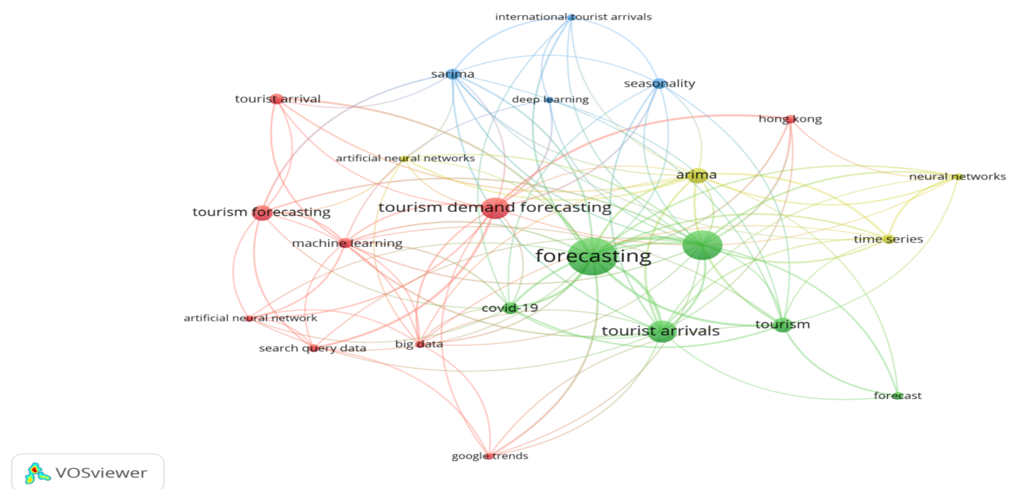
(Goh & Law, 2002) The results indicated that, for all counties, tourist forecasts to Hong Kong, SARIMA and MARIMA models outperformed the other models. Moreover, no single forecasting model consistently outperforms other models across all situations (Song & Li, 2008; Witt & Witt, 1995).

3.5.2 Co-word analysis

In this co-word analysis, “words” are used as a unit of analysis, and it is a technique that examines the real content/provides a snapshot of the publication itself (Donthu et al., 2021; Khanra et al., 2021). Co-word analysis is based on the assumption that words frequently appearing together share a thematic connection (Donthu et al., 2021).

It explores patterns and trends in a particular domain (Strozzi et al., 2017; Tanwar et al., 2024). Furthermore, a co-word analysis can be used to forecast future trends by leveraging information available within a specific discipline (Donthu et al., 2021; Strozzi et al., 2017; Vallaster et al., 2019).

Figure 4. Network visualization of co-word (keyword co-occurrence) using VOS viewer.



Source: Compiled by the authors using VOSviewer.

Figure 4 provides an overview of the co-word analysis. Each node in a network represents a keyword (Tanwar et al., 2024). Where, (1) the node size indicates the frequency of occurrence of the keyword (Khan et al., 2024), (2) the link between the nodes represents the co-occurrence between keywords i.e., keywords that co-occur or occur together (Khanra et al., 2021), (3) thickness of the link indicated the occurrence of co-occurrences between keywords (i.e., the number of times that the keywords co-occur or occur together (Tanwar et al., 2024), and (4) thicker the link between nodes, the greater the occurrence of the co-occurrences between keywords (Tanwar et al., 2024). Each colour represents a thematic cluster, i.e., each colour points research to a similar direction (Donthu et al., 2021).

The keyword co-occurrence map was created from the 878 keywords found across the 315 articles (see Figure 1 for n=315). We set a minimum of 7 occurrences for keywords; i.e., the particular keywords have been used in 7 articles. Finally, 23 keywords meet the threshold. In a bibliographic study, the keywords provided by the authors indicate the article's theme and content (Khan et al., 2024).

VOS viewer provides four clusters, which have been discussed below:

Cluster 1: With red colour, there are 9 items or keywords, i.e., Artificial Neural Network, Big Data, Google Trends, Hong Kong, Machine Learning, Search Query Data, Tourism Demand Forecasting, Tourism Forecasting, Tourist Arrival. (Theme: Emerging tools and Artificial Intelligence-based methods in forecasting tourist arrivals). In this cluster, Artificial Neural Network, Big Data, Google Trends, Machine Learning, and Search Query Data are the research tools of artificial intelligence (Yang et al., 2015), except Hong Kong, Tourism Demand Forecasting, Tourism Forecasting, Tourism Forecasting and Tourist Arrival, which indicates that in Hong Kong, more AI methods of forecasting are used to forecast the tourist arrivals.

Cluster 2, in green, contains 6 items or keywords: COVID-19, Forecast, Forecasting, Tourism, Tourism demand, Tourist arrivals. (Theme: Relevance of tourism forecasting in the post-COVID dynamics)After manually analyzing the sample data, it was found that only 10 documents exclusively address COVID-19 and forecasting. This can also be analyzed in Figure 5, as the term frequency for COVID-19 is less than 20. The authors have used various new models and techniques in this regard, particularly AI-based forecasting models.

Kumar et al. (2022) predicted foreign exchange earnings and international tourist arrivals to India using an AI model based on parameters such as COVID-19, vaccinations, and the stringency index. Chen et al. (2023) applied different AI models (BPNN: backpropagation neural network; BL: broad Learning; FEWT-BL: fuzzy entropy empirical wavelet transform-based broad learning) to forecast tourist arrivals to Hainan Island in China. Gričar and Bojnec (2022) used an ARIMA model to identify the decline in tourist arrivals before COVID-19 and to forecast them after the pandemic.

Wu et al. (2023) used multisource data comprising search query data, economy-related variables and online news data to forecast tourist arrivals from China to Hong Kong. Jaipuria et al. (2021) used artificial neural networks (ANN) to forecast international tourist arrivals to India and foreign exchange earnings. Sariişik et al. (2021) predicted global tourist arrivals and total income after the COVID-19 shock.

Cluster 3, in blue, contains 4 items or keywords: international tourist arrivals, SARIMA, Seasonality, and deep learning. (Theme: Forecasting international tourist arrivals and capturing seasonality using the SARIMA model). The keywords international tourist arrivals, SARIMAform, and Seasonality together make the theme "Forecasting international tourist arrivals and capturing seasonality using SARIMA model". However, aside from the keyword "deep learning," it is an AI-based forecasting tool.

In the presence of seasonality, the Box-Jenkins (SARIMA) method provides accurate forecasts, as seasonality is a basic component of tourism. Many studies have used monthly tourist arrival data to capture the seasonality (Hossen et al., 2021; Tushara et al., 2019). Makoni et al. (2023) forecast international tourist arrivals to Zimbabwe using monthly foreign tourist arrival data for the period January 2000 to December 2018 with a SARIMA model.

Tsui and Balli (2017) predicted Australia's international passenger arrivals at the airport using monthly international guest arrivals for the period January 2006 to September 2012, applying various time series models such as SARIMA, SARIMAX, and EGARCH/SARIMAX. Tushara et al. (2019) applied the SARIMA model to predict foreign tourist arrivals to Sri Lanka from different sources, using monthly foreign tourist arrival data from January 1984 to December 2017.

Hossen et al. (2021) predicted international tourist arrivals in Bangladesh using the SARIMA model, using data from January 2015 to July 2019. Kumar and Sharma (2016) forecasted and captured the seasonality of foreign arrivals to Singapore using the SARIMA model.

Cluster 4: With colour yellow, there are 4 items or keywords, i.e., ARIMA, Artificial Neural Networks, Neural Networks, and Time Series. (Theme: Different tools for forecasting time series data). Cluster 4 deals with the different forecasting tools applied in tourism forecasting. ARIMA is a time-series benchmark model, also known as the Box-Jenkins methodology. Artificial Neural Networks, or Neural Networks, are forecasting models within econometric modelling. Time series forecasting studies are conducted on time series data, and traditional time series models include ARIMA, SARIMA, Naïve, etc.

Other than this, various forecasting models are applied in tourism forecasting studies. Some common approaches or models of tourism forecasting can be classified into five categories: Time series model, Econometric Model, Artificial Intelligence Model, Judgmental Forecasting Methods, and Combined and Hybrid Methods (Chen et al., 2023; Yang et al., 2015).

Time series models include Naïve 1, Naïve 2, Simple moving average, double moving average, Single Exponential Smoothing, Double Exponential Smoothing, ARIMA, SARIMA, and Basic Structural Time Series (Hossen et al., 2021; Tushara et al., 2019; Yang et al., 2015). An econometric model consists of various forecasting models, such as Vector Autoregression, Time-Varying Parameter, Autoregressive Distributed Lagged Model, Dynamic Almost Ideal Demand System, Error Correction Models, Traditional Regression Approach, Gravity Model, and Static Almost Ideal Demand System. Artificial Intelligence-based models include Artificial Neural Networks, Rough Set Approach, Support Vector Regression, Fuzzy Time Series Method, Grey Theory, Monte Carlo simulation, expert systems, and genetic algorithms (Wang, 2004; Yang et al., 2015).

Judgmental Forecasting Methods include models like the Delphi Technique and Scenario-Building (Yang et al., 2015). Finally, Combined and Hybrid Methods consist of

Average-based methods, Forecast Error-based Weightings and Regression-based Integration (Yang et al., 2015).

The thematic analysis suggests that various forecasting methods and models have evolved to predict tourism demand. Initially, ARIMA was a time-series benchmark model, followed by various time-series models, econometric models, AI models, and combined and hybrid methods, including Google Trends. It is evident that modern forecasting techniques, such as econometric models, AI models, and hybrid methods that incorporate Google Trends, are more efficient than traditional time-series forecasting models.

The results of this thematic analysis are aligned with theoretical support. Tourism demand forecasting has long been rooted in classical forecasting theory, which emphasizes accuracy, reliability, and methodological rigour (Makridakis et al., 2018). However, the increase in the adoption of artificial intelligence (AI) and Big Data represents not only a methodological shift but also theoretical progress, in line with broader frameworks of technology adoption and organizational learning.

According to the Diffusion of Innovation theory, AI-based forecasting methods were initially adopted by innovators and early adopters in tourism research. and are increasingly being adopted for wider scholarly and practical use (Sahin, 2006). Similarly, according to the Technology Acceptance Model (TAM), practitioners are increasingly favouring AI-driven approaches because adoption decisions are influenced by perceived utility (e.g., higher accuracy) and perceived ease of use (e.g., automation and scalability) (Davis, 1989). At the organizational level, the integration of Big Data and AI into forecasting reflects the Resource-Based View (RBV) and the Knowledge-Based Theory of the Firm, in which data analytics capabilities are considered strategic resources that generate competitive advantage (Grant, 1996).

3.6 Trend Topics in Tourism Forecasting Research Over the Years

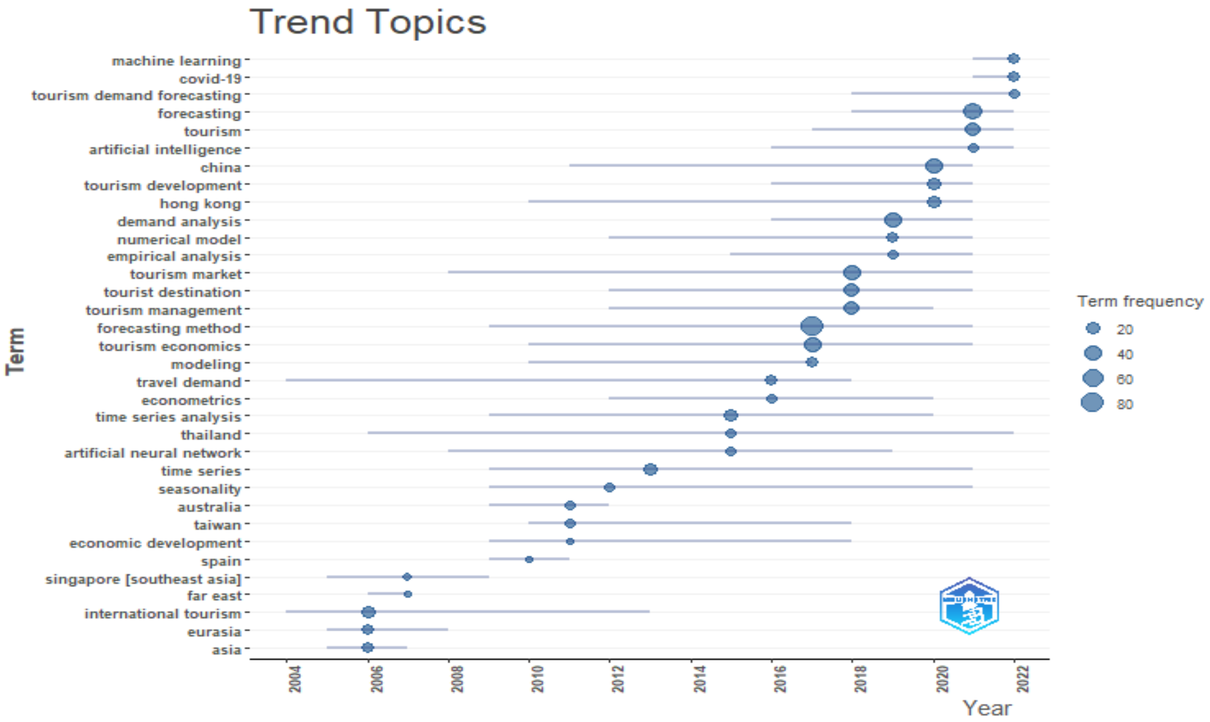
Figure 5 provides the trend topics of study in forecasting tourist arrivals over the years. Yildirim et al. (2022) create trend topics based on the most frequent keywords in the literature, a method similar to co-word analysis (keyword co-occurrence); see Figure 4. However, trend topics highlight the most frequent words and their temporal occurrence (Yildirim et al., 2022).

The vertical line demonstrates the word, the horizontal axis demonstrates the time frame of the frequency of occurrences of a word, and finally, the size of the dots represents the frequency of the word. In the figure above, there are four nodes with values of 20, 40, 60, and 80.

Where 20 is the smallest node, it represents that the word has occurred at least 20 times; the node with 40 represents that the word has occurred 40 times. Similarly, the larger sizes of nodes 60 and 80 represent words that have occurred at least 60 and 80 times, respectively. For example, authors started writing about different methods of forecasting since 2008-2001with a node size of 80.

We can see from Figure 5 that during 2004-2012, simple time-series forecasting that captures seasonality became popular. However, authors began shifting from traditional forecasting methods to artificial neural networks starting in 2008. The paradigm shift from traditional forecasting methods didn't stop here; many new methods evolved, including numerical modelling, deep analysis, machine learning, and artificial intelligence (see figure 5).

Figure 5. Trend topics in forecasting tourist arrivals over the years. (using Bibliometrix R-Package)



Source: Compiled by the authors using Bibliometrix R-Package.

4 Discussion and Conclusions

This paper identifies the research gap, provides an overview of tourism forecastingoutlin, and provides a future direction for this topic using a bibliometric study. The paper empirically documented the intellectual structures, the volume of documents, emerging trends, and directions in knowledge development. The results of this study provide valuable insights. Since 2014, tourism forecasting studies have gained popularity.

Citation analysis reveals that Tourism Economics is the most prominent journal in this domain, with the highest number of publications (27) and total citations (888). Moreover, the paper titled "Critical references on the economic impact assessment of a mega-event: the case of 2002 FIFA World Cup" was the most influential in this domain. The Hong Kong Polytechnic University is the most prominent affiliation that has supported and published articles in this domain, with 40 documents.

The citation and thematic analyses indicated that benchmark models, or traditional time series forecasting models, use generic data and thus cannot capture the effects of other factors or variables, resulting in low accuracy and reliability. To resolve this issue, scholars have adopted econometric forecasting models that use big data from various sources, including search engines and online review platforms, along with generic data.

(Li et al., 2017; Li et al., 2020; Pan and Yang, 2017; Rivera, 2016; Yang et al., 2015) In their study, they applied different econometric models and used big data to forecast tourist arrivals, finding that these models outperformed other traditional time series models. Furthermore, to validate the results of this study, a few recent case studies after the COVID-19 pandemic were evaluated, which also indicated the same result.

Chen et al. (2023) predicted tourist arrivals to Kulangsu, China, during the COVID-19 recovery phase using big data along with generic data, applying a Radial Basis Function Neural Network (RBF) model, and compared the results with conventional time series models such as ARIMA, Exponential Smoothing, and Naïve. Chen et al. (2023) found that using big data alongside generic data yields better, more accurate, and more reliable forecasts; i.e., the RBM model outperformed other traditional forecasting models. Moreover, Wu et al. (2022) predicted tourist arrivals in Paris, Amsterdam, and Lisbon during the COVID-19 recovery phase using Google Trends data and tourist arrival data, employing a deep learning method, i.e., the Adaptive Differential Evolution Algorithm-Temporal Fusion Transformer (ADE-TFT). Wu et al.'s (2022) results also indicated that the (ADE-TFT) method using big data was superior to that of the other traditional methods, ARIMAX, SARIMAX, and BPPN.

Co-word analysis revealed future trends in this domain. As mentioned above, forecasting accuracy and reliability have been concerns, leading to the development of new forecasting methods. Initially, traditional time series models were extensively applied in forecasting studies. Many new forecasting tools came into play, such as econometric models, artificial intelligence-based models, judgmental forecasting methods, and finally, combined and hybrid methods (different components of these methods are discussed in cluster 4 of co-word analysis).

Thus, this research also highlights various forecasting tools and models used in tourism forecasting. A similar result can be seen from the graph of trend topics in tourism forecasting research over the years. Figure 5 indicates a paradigm shift in tourism forecasting methods, with scholars previously primarily using traditional time series models. Still, over the years, many new methods have evolved, and numerical modelling, deep analysis, artificial intelligence, and machine learning are the top-trending models.

Thematic analysis of co-word analysis revealed that, to capture seasonality, the SARIMA model using monthly data is the more efficient model (Hossen et al., 2021; Kumar & Sharma, 2016; Makoni et al., 2023; Tsui & Balli, 2017; Tushara et al., 2019).

This research has successfully addressed all the research questions and has provided an overview of this field. This study can help other researchers gain a solid foundation of knowledge in this domain and identify the key issues, directionality, and trends.

This study contributes to existing theories by showing that the adoption of AI and Big Data in tourism forecasting reflects the diffusion of innovations and is facilitated by perceived usefulness and ease of use, as suggested by the Technology Acceptance Model.

This also aligns with resource-based theory and the dynamic capabilities perspective on organizational competitiveness. Moreover, this study extends forecasting theory by highlighting AI-driven approaches not only as methodological advancements but also as part of a broader theoretical shift in how technology adoption and knowledge creation shape tourism research and practice.

This research has several important practical implications for policymakers, tourism authorities, and industry stakeholders. For policymakers, integrating big data sources such as social media posts, Google search trends, and flight booking data provides valuable tools for identifying emerging travel patterns, seasonality, and shifts in tourist preferences (Chen et al., 2023; Wu et al., 2022).

Such real-time insights enable governments and tourism boards to respond quickly to fluctuations in demand, ensure the optimal use of public funds and allocate resources more efficiently. In turn, this promotes sustainable tourism practices that generate significant benefits for the local economy (Dimitrov et al., 2015; Wu et al., 2022).

For industry stakeholders, including hotels, airlines, and tour operators, big data and AI-driven forecasting models enhance decision-making in operational and strategic planning. By analyzing online reviews, weather patterns, and booking trends, businesses can more accurately predict peak and off-peak demand, thereby adjusting room pricing, staffing levels, and resource allocation accordingly (Li et al., 2020; Makoni et al., 2023; Sünnetçioğlu et al., 2021).

Accurate demand forecasting also supports better revenue management, reduces operational inefficiencies, and facilitates the provision of customized services that enhance customer satisfaction (Chen et al., 2023; Li et al., 2020; Makoni et al., 2023; Zancan et al., 2023).

In addition, destination management organizations can utilize short-term forecasting to design more effective crowd management strategies. Predictive insights into tourist flows can help mitigate congestion at popular sites, promote lesser-known attractions and support balanced regional development. Such approaches not only improve visitor experiences but also enhance the competitiveness and sustainability of destinations in the long run (Li et al., 2020).

Finally, the study underscores the importance of developing data-driven capabilities across the tourism sector. Training practitioners in big data analytics and AI applications is essential to realize the potential of these technologies fully. Moreover, collaboration between governments, academia, and industry is necessary to address issues such as data privacy, ethical use of customer data, and platform interoperability. By embracing these practices, tourism stakeholders can build greater resilience, adaptability and long-term sustainability in an increasingly uncertain global environment.

5 LIMITATIONS AND FUTURE RESEARCH SCOPES

Bibliometric studies can only provide a short-term forecast in a particular domain (Donthu et al., 2021). Moreover, Vallaster et al. (2019) argue that citation habits among scholars can change over time. Thus, after a decade, one can conduct research on the same topic to compare the paradigm shift in the research domain. In this study, data were extracted from the Scopus database; however, for further research, scholars can include data from other databases, which may provide more valuable insights in this field. Furthermore, researchers can conduct a systematic literature review in this domain, which may give more in-depth knowledge.

COVID-19 has adversely impacted the tourism industry; as a result, global domestic and foreign tourists have been affected. In this study, after manually evaluating 315 documents, only 10 studies were exclusively dealing with "forecasting and COVID=19". Furthermore, based on the trend topic graph, the number of studies on COVID-19 was fewer than 20.

Therefore, further tourism forecasting studies on COVID-19 are needed so that local agencies/ Government and local entrepreneurs can be prepared in advance and adopt the necessary strategy accordingly. Moreover, using big data and AI, sentiment analysis of tourists can be conducted, further helping to analyze their perceptions of the destination (De Oliveira et al., 2023).

REFERENCES

Baker, H. K., Kumar, S., & Pattnaik, D. (2021). Research constituents, intellectual structure, and collaboration pattern in the Journal of Forecasting: A bibliometric analysis. *Journal of Forecasting,* 40(4), 577–602. https://doi.org/10.1002/for.2731

Bangwayo-Skeete, P. F., & Skeete, R. W. (2015). Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. *Tourism Management,* 46, 454–464. https://doi.org/10.1016/j.tourman.2014.07.014

Chen, D., Sun, F., & Liao, Z. (2024). Forecasting tourism demand for tourist attractions during the COVID-19 pandemic. *Current Issues in Tourism*, *27*(3), 445-463. https://doi.org/10.1080/13683500.2023.2165482

Chen, J., Yang, J., Huang, S., Li, X., & Liu, G. (2023). Forecasting tourist arrivals for Hainan Island in China with decomposed broad learning before the COVID-19 pandemic. *Entropy,* 25(2), 338. https://doi.org/10.3390/e25020338

Chen, K. Y., & Wang, C. H. (2007). Support vector regression with genetic algorithms in forecasting tourism demand. *Tourism Management,* 28(1), 215–226. https://doi.org/10.1016/j.tourman.2005.12.018

Cho, V. (2003). A comparison of three different approaches to tourist arrival forecasting. *Tourism Management,* 24(3), 323–330. https://doi.org/10.1016/S0261-5177(02)00068-7

Çıkı, K. D., & Tanriverdi, H. (2024). Mapping the past to guide the future: bibliometric insights into last-chance tourism. *Anais Brasileiros de Estudos Turísticos*. Retrieved from https://periodicos.ufjf.br/index.php/abet/article/view/41418

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

De Oliveira, P. S. G., Wada, E. K., Lopes, A. S., & da Silva, L. F. (2023). Machine learning and sentiment analysis to assess the evolution of the COVID-19 pandemic and its impacts on tourism. *Anais Brasileiros de Estudos Turísticos: ABET*, *13*(1), 11. Retrieved from https://dialnet.unirioja.es/servlet/articulo?codigo=9878705

Dimitrov, P., Kalinova, M., Gantchev, G., & Nikolov, C. (2015). Exponential forecasting of the monthly volume of the tourism receipts in Bulgaria. *Tourism & Management Studies*, *11*(1), 104-110. Retrieved from http://agora.edu.es/servlet/articulo?codigo=5014746

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research,* 133, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal,* *17*(S2), 109–122. https://doi.org/10.1002/smj.4250171110

Gričar, S., & Bojnec, Š. (2022). Did human microbes affect tourist arrivals before the COVID-19 shock? Pre-effect forecasting model for Slovenia. *International Journal of Environmental Research and Public Health,* 19(20), 13482. https://doi.org/10.3390/ijerph192013482

Hossen, S. M., Ismail, M. T., Tabash, M. I., & Abousamak, A. (2021). Accrued forecasting on tourist's arrival in Bangladesh for sustainable development. *GeoJournal of Tourism and Geosites,* 36(SPL19), 701–711. https://doi.org/10.30892/GTG.362SPL19-701

Jaipuria, S., Parida, R., & Ray, P. (2021). The impact of COVID-19 on tourism sector in India. *Tourism Recreation Research,* 46(2), 245–260. https://doi.org/10.1080/02508281.2020.1846971

Khan, I. S., Najar, A. H., Shafi, I., & Singh, R. (2024). Bibliometric analysis of sustainable practices in the hotel industry: Current trends and future research directions. *Atna Journal of Tourism Studies,* 19(1), 113–132. https://doi.org/10.12727/ajts.31.5

Khanra, S., Dhir, A., Kaur, P., & Mäntymäki, M. (2021). Bibliometric analysis and literature review of ecotourism: Toward sustainable development. *Tourism Management Perspectives,* 37, 100777. https://doi.org/10.1016/j.tmp.2020.100777

Kumar, A., Misra, S. C., & Chan, F. T. (2022). Leveraging AI for advanced analytics to forecast altered tourism industry parameters: A COVID-19 motivated study. *Expert Systems with Applications,* 210, 118628. https://doi.org/10.1016/j.eswa.2022.118628

Kumar, M., & Sharma, S. (2016). Forecasting tourist in-flow in South East Asia: A case of Singapore. *Tourism & Management Studies*, *12*(1), 107-119. https://doi.org/10.18089/tms.2016.12111

Law, R. (2000). Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting. *Tourism Management,* 21(4), 331–340. https://doi.org/10.1016/S0261-5177(99)00067-9

Law, R. (2002). Modeling and forecasting tourism demand for arrivals with stochastic nonstationary seasonality and intervention. *Tourism Management,* 23(5), 499–510. https://doi.org/10.1016/S0261-5177(02)00009-2

Lee, C. K., & Taylor, T. (2005). Critical reflections on the economic impact assessment of a mega-event: The case of 2002 FIFA World Cup. *Tourism Management,* 26(4), 595–603. https://doi.org/10.1016/j.tourman.2004.03.002

Li, H., Hu, M., & Li, G. (2020). Forecasting tourism demand with multisource big data. *Annals of Tourism Research,* 83, 102912. https://doi.org/10.1016/j.annals.2020.102912

Li, X., Pan, B., Law, R., & Huang, X. (2017). Forecasting tourism demand with composite search index. *Tourism Management,* 59, 57–66. https://doi.org/10.1016/j.tourman.2016.07.005

Lim, C., & McAleer, M. (2002). Time series forecasts of international travel demand for Australia. *Tourism Management,* 23(4), 389–396. https://doi.org/10.1016/S0261-5177(01)00098-X

Maier, D., Maier, A., Aşchilean, I., Anastasiu, L., & Gavriș, O. (2020). The relationship between innovation and sustainability: A bibliometric review of the literature. *Sustainability,* 12(10), 4083. https://doi.org/10.3390/su12104083

Makoni, T., Mazuruse, G., & Nyagadza, B. (2023). International tourist arrivals modelling and forecasting: A case of Zimbabwe. *Sustainable Technology and Entrepreneurship,* 2(1), 100027. https://doi.org/10.1016/j.stae.2022.100027

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and machine learning forecasting methods: Concerns and ways forward. *PLOS ONE,* *13*(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

Pan, B., & Yang, Y. (2017). Forecasting destination weekly hotel occupancy with big data. *Journal of Travel Research,* 56(7), 957–970. https://doi.org/10.1177/0047287516669050

Rivera, R. (2016). A dynamic linear model to forecast hotel registrations in Puerto Rico using Google Trends data. *Tourism Management,* 57, 12–20. https://doi.org/10.1016/j.tourman.2016.04.008

Sahin, I. (2006). Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory. *Turkish Online Journal of Educational Technology-TOJET*, *5*(2), 14-23. Retrieved from https://files.eric.ed.gov/fulltext/EJ1102473.pdf

Sariişik, M., Türkay, O., Şengül, S., Bicil, İ. M., & Boğan, E. (2021). Covid-19 shock to Tourism Industry: Possible scenarios for predicted losses between 2020-2024. *Anais Brasileiros de Estudos Turísticos: ABET*, *11*(1), 14. Retrieved from https://dialnet.unirioja.es/servlet/articulo?codigo=9878660

Song, H., & Li, G. (2008). Tourism demand modelling and forecasting—A review of recent research. *Tourism Management,* 29(2), 203–220. https://doi.org/10.1016/j.tourman.2007.07.016

Song, H., Li, G., Witt, S. F., & Fei, B. (2010). Tourism demand modelling and forecasting: How should demand be measured? *Tourism Economics,* 16(1), 63–81. https://doi.org/10.5367/000000010790872213

Sünnetçioğlu, S., Mercan, Ş. O., Özkök, F., & Sünnetçioğlu, A. (2021). Overtourism perception in the islands: The case of Bozcaada and Gökceada. *Anais Brasileiros de Estudos Turísticos*. Retrieved from https://periodicos.ufjf.br/index.php/abet/article/view/32304

Wu, B., Wang, L., & Zeng, Y. R. (2023). Interpretable tourism demand forecasting with temporal fusion transformers amid COVID-19. *Applied Intelligence*, *53*(11), 14493-14514. https://doi.org/10.1007/s10489-022-04254-0

Yang, X., Pan, B., Evans, J. A., & Lv, B. (2015). Forecasting Chinese tourist volume with search engine data. *Tourism management*, *46*, 386-397. https://doi.org/10.1016/j.tourman.2014.07.019

Yilmaz, I. (2019). Bibliometric analysis of bibliometric studies on tourism published in Turkey. *Anais Brasileiros de Estudos Turísticos*, *9*(1, 2 e 3). Retrieved from https://periodicos.ufjf.br/index.php/abet/article/view/27111

Zancan, C., Passador, J. L., & Passador, C. S. (2023). Integrating Python-Based Artificial Intelligence for Enhanced Management of Inter-municipal Tourism Consortia: A Technological Approach. *Caderno Virtual de Turismo*, *23*(3), 25-47. DOI: http://dx.doi.org/10.18472/cvt.23n3.2023.2103

CRediT author statement

Term	Definition	Author 1	A2
Conceptualization	Ideas; formulation or evolution of overarching research goals and aims		X
Methodology	Development or design of methodology; creation of models	x	
Software	Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code components	x	
Validation	Verification, whether as a part of the activity or separate, of the overall replication/ reproducibility of results/experiments and other research outputs	x	x
Formal analysis	Application of statistical, mathematical, computational, or other formal techniques to analyze or synthesize study data	x	
Investigation	Conducting a research and investigation process, specifically performing the experiments, or data/evidence collection	x	x
Resources	Provision of study materials, reagents, materials, patients, laboratory samples, animals, instrumentation, computing resources, or other analysis tools	x	x
Data Curation	Management activities to annotate (produce metadata), scrub data and maintain research data (including software code, where it is necessary for interpreting the data itself) for initial use and later reuse	x	
Writing - Original Draft	Preparation, creation and/or presentation of the published work, specifically writing the initial draft (including substantive translation)	x	
Writing - Review & Editing	Preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision – including pre-or post-publication stages	x	x
Visualization	Preparation, creation and/or presentation of the published work, specifically visualization/ data presentation	x	x
Supervision	Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team	x	x
Project administration	Management and coordination responsibility for the research activity planning and execution	x	x
Funding acquisition	Acquisition of the financial support for the project leading to this publication	x	x

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