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Forecasting Models Used in the Tourism Sector: A Systematic Review of Literature

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Abstract

The tourism forecasting industry is facing challenges in improving its performance. However, this presents an opportunity for research and development, especially for developing countries looking to improve their tourism sector. The objective of a systematic review was identifying the newest and most used models for forecasting tourism demand. Using the PRISMA method and analyzing 40 articles, we concluded that hybrid models are the most effective for tourism demand forecasting. Combining a statistical model with a machine learning-based model is particularly efficient.

Keywords
Forecasting models, tourism, demand.

1. Introduction
According to The World Tourism Organization (UNWTO), tourists' arrival worldwide could come near the 80% to 95% of what it was before the global pandemic for the year 2023 (Massoi, 2023). This being made top priority for many countries that depend on tourism. The United Nations (UN) defines tourism, in exception to business trips, as a seasonal activity where visitors could take advantage of the recipient's climate and perform activities that otherwise could not be done where they are from (Italian Government et al., 2003). Said activities make big financial contributions to the country, getting the attention from investors, generating jobs and affecting other industries such as transportation, communication, financial services, etc. (Italian Government et al., 2003). It is important to know how to forecast demand because of the help it brings with predictions on performance as well as positioning of resources and pricing of the market (Feng et al., 2019a). For this to be achievable, the correct methods of forecasting must be identified and utilized, then a proper forecast of demand could be made. The concept of forecasting demand implies prediction of future demand from consumers during an established period. Without a deep knowledge of demand, businesses could find it harder to make the correct decisions. A forecast of demand is utilized to make annual budgets, as well as the planification and programing of production (Diezhandino, 2022). It is a tool that brings you the possibility of knowing how much to produce and happens to be vital when planning annual sales on any company (ForePlanner, n.d.). During the year 2022 it came to more than 900 million tourists, wouldn't hit 65% of the numbers before the year 2020 (Massoi, 2023), said data recognizes the importance of the following research. Inside Peru during the months of January to June of 2022 the numbers of international tourists reached more than 720 000, that being translated to a sum close of $1.2 billion dollars in foreign exchange for inbound tourism; said numbers used to be for

a single quarter in pre-pandemic times (ComexPerú, 2022). Nevertheless, other regions such us the Middle East were hoping for numbers closer to 80% all the way up to 95% when it comes to tourists' arrivals being compared to pre-pandemic levels (UNWTO, 2023). These are recurring problems the sector faces, starting with climate change. Such as the little amount of information when it comes to natural disasters that is accessible to the public, and the negative perception that it creates for tourists in Quinling Mountain, China (Hao et al., 2022). The flight patterns fluctuation changing the arrival times for tourists as in the Leh district, India (Pelliciardi, 2021). The emission of greenhouse gases being originated from tourism transport, particularly when it comes to air travel (Rodríguez & Domínguez, 2011). The negative impact on the environment and how the natural resources are being affected, as well as landscape contamination, all coming from the elevation of tourism infrastructure (Rubio Hernández, 2020). Another problem being faced on the regular in social conflict. The geopolitical uncertainty as well as social agitation, especially after a series of protests, may generate terror among tourists as it was the case for Hong Kong (Poon & Koay, 2021). Terrorists acts also contribute in big to the instability that negatively impacts tourism as did the Arab Spring in Tunisia (Bauzà Rosselló, 2021). The lack of confidence from the public to politicians, especially when a case of corruption gets revealed, leads to the common people on finding a solution themselves, leading to social conflicts (Welp, 2022). When media tries to cover information from the people, this also brings a sense of treason upon the audience, leading to protest (Alcántar Jaime, 2020). Now for the problems we face when dealing with prediction of future values on a regression series, where only few data is obtained on future values; is that it is required for series data to be known on its entirety so the solution can be purely mathematical, as well as not changing drastically in time (Abril, 2011).

1.1 Objectives

The main objective of this review is to identify the newest and most frequently used models when forecasting tourism demand across published literature. What comes next is the following: the methodology applied to the revision, the results obtained from the investigation as well as the corresponding discussion, and a set of conclusions to finish the review.

2. Literature Review

Previously, revisions on the matter have been made, such as the critical revision on forecasting methods by Fernández, Vilalta & Quintero (Fernández et al., 2019). Inside the article, there is only mention of seasonal series such as Autoregressive Integrated Moving Average (ARIMA) and the Seasonal Autoregressive Integrated Moving Average (SARIMA). Making omission to casual forecasting methods, such as regression analysis; and qualitative methods, making this article not enough for recent times.

Another study to make mention of is Deterministic weather forecasting models based on intelligent predictors: A survey, by Jaseena & Kovoor (2022). Said study covers that weather forecasting is now in need of more intelligent ways to make predictions on weather as traditional computational intelligence models are not adequate anymore when it comes to accurate predictions. This research makes use of parameters within machine learning models, deep learning models and hybrid models; making this research extremely useful and relevant for the sector it tries to engage with.

3. Methods

The present systematic review uses the Prism tool to obtain the information from other review-based studies (Urrútia & Bonfill, 2010). Scopus and Web of Science were chosen as databases for the search of scientific articles using the following set: ((tourism AND forecast) OR (tourism AND demand)). Then we begin with the exclusion criteria; first we limit the publication date to no older than 2019, but also not newer than June of 2023, as well as being in the English or Spanish language. Next exclusion criteria is to limit ourselves only to sources in the article format, that means no book chapters or conference. We are going through with the sources that have gold access and follow the thematic axis of the systematic review, that happens to be a focus on decision science, tourism, business and social science. Second to last step is the deletion of duplicates as well as the selection through the following keywords: "tourism and demand", "tourism and forecast", "forecast". We finish with the exclusion through the revision of the title and abstract of the article.

4. Data Collection

The following Prism diagram presents the methods used above and the selection process detail.

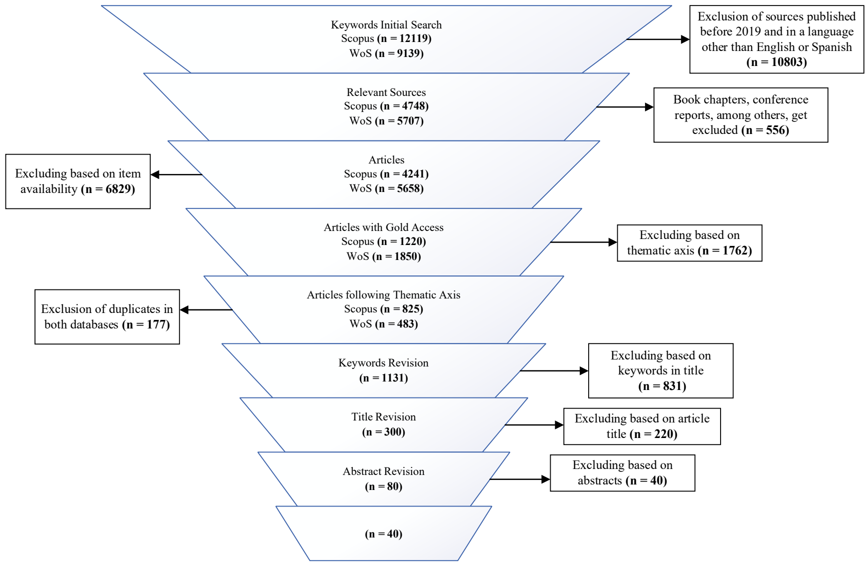

Figure 1. Prism Diagram

As it shows on Figure 1, a total of 21,258 sources were found using the searching set on the established databases. Following the exclusion criteria, the number of sources drop to 10,455 after applying the date and language criteria, of which only 9,899 happen to be in article format. Just 3,070 have a gold access and 1,762 happen to not follow the thematic axis. Duplicates turn out to be 177 sources to take out, then is the selection through keywords that leave us with 300 sources. Finally, 40 sources were selected due to their title and abstract being the most appropriate when it comes to contributing to the investigation. A content analysis was made to identify the forecasting methods used with the most frequency.

5. Results and Discussion

5.1 Title of the magazine

There are five magazines; Forecasting, Journal of Tourism Futures, International Journal of Advanced and Applied Sciences, Procedia Computer Science and Complexity that cover more than 35% of the articles selected for this research. Forecasting contributing the most with five of its articles serving into the analysis (Figure 2).

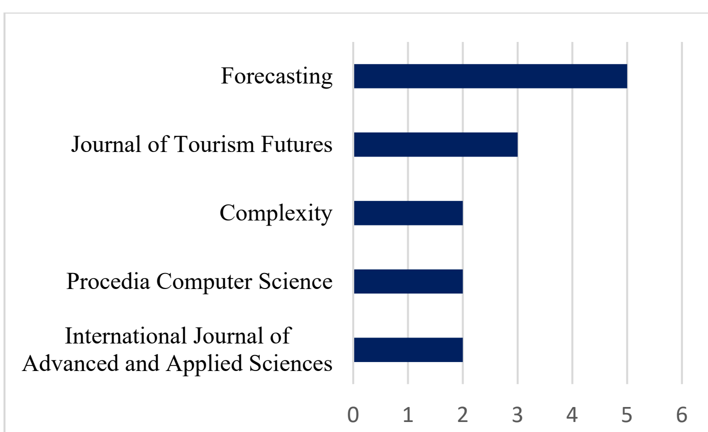

Figure 2. Articles by title of the magazine

5.2 Database
The current systematic review obtains 21 articles from the database Scopus, a representation of 53% of the articles used for this research. The remaining 47% comes from the database Web of Science (Figure 3).

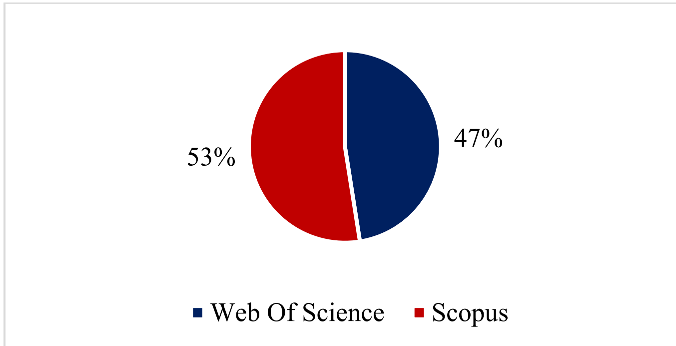

Figure 3. Articles per database

5.3 Year of publication
Year 2021 and 2022 happens to be the period were most useful articles got published, bringing in a 58% of sources used for this research. There seems to be a steady increase when it to contribution per year, yet in 2023 this trend gets put on a hold as the entire year wasn't considered (Figure 4).

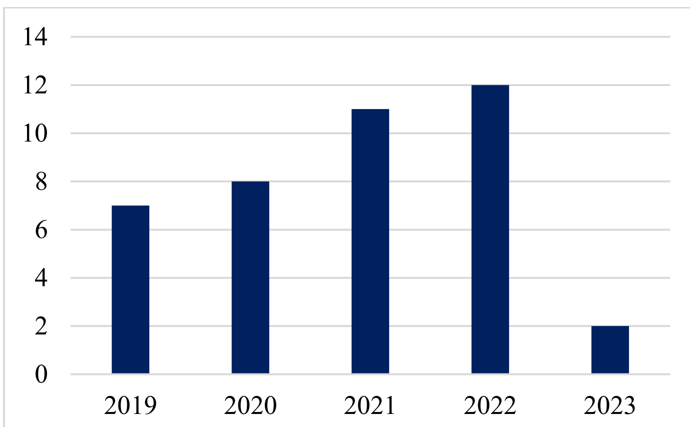

Figure 4. Articles by year of publication

5.4 Country of publication
China, Vietnam, Morrocco, Malaysia and the United Arab Emirates are the countries with the most contribution to this research in terms of articles published reaching a 48% of all sources utilized. China alone has a 23% of sources published (Figure 5).

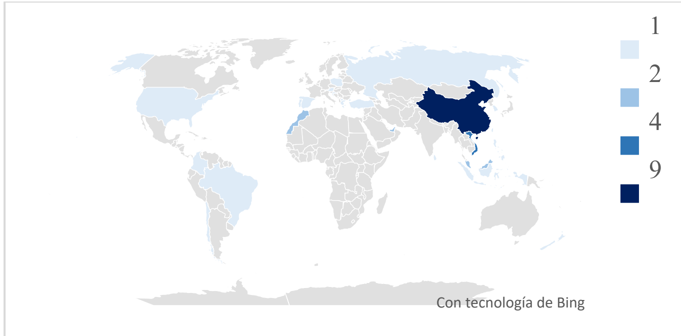

Figure 5. Articles by country of publication

5.5 Forecasting tool

Artificial Neural Networks (ANN) is the most used model with a frequency of 9 times, followed by the Seasonal Autoregressive Integrated Moving Averages (SARIMA) and Support Vector Regression (SVR) being used 7 times each (Figure 6).

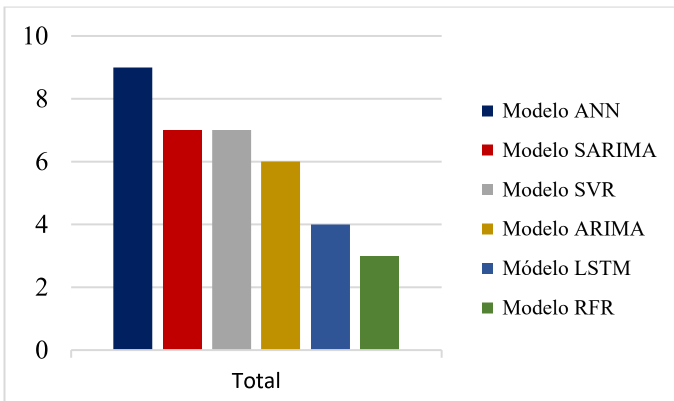

Figure 6. Most frequently used forecasting models

The forecasting model known as ANN, as used by Álvarez-Díaz et al. (2018), Andariesta & Wasesa (2022), Mtapuri & Giampiccoli (2020), Gregorić & Baldigara (2020), Nguyen et al. (2021), Nhat et al. (2021), Ren et al. (2021), Saba et al. (2022) and Wang (2022), has properties that allows it to feed itself from multiple webs of communication, and from it come to a conclusion of a dependent prediction.

Some other authors opted for the ARIMA model, such as Andreeski & Mechkaroska (2020), Gunter et al. (2020), N. Nguyen et al. (2019), N. Nguyen et al. (2020), Ouassou & Taya (2022), Yao et al. (2021). The ARIMA model is often used to predict future values inside of a data sequence, it helps with short term predictions across an area that requires at least 40 data points in history.

Instead, the SARIMA model, as used by Abellana et al. (2021), Álvarez-Díaz et al. (2018), Colther & Arriagada-Millaman (2021), Hossen et al. (2021), Thushara et al. (2019), Zhang et al. (2022); introduces seasonal multiplicity into the ARIMA model and is mostly used to forecast across literature with reasonable and precise predictions.
Another model used frequently is Support Vector Regression (SVR), as by Abellana et al. (2021), Andariesta & Wasesa (2022), Feng et al. (2022), Mishra et al. (2021), Ouassou & Taya (2022), Ren et al. (2021), Yao et al. (2021). Its ability to work well when modeling non-lineal data by mapping in a high-dimensional space makes de SVR model a good alternative when forecasting demand.

The LSTM model was used by Laaroussi et al. (2023), Li (2022), Nguyen-Da et al. (2023), Ouassou y Taya (2022); its use is mainly to avoid long term dependency problems, it can also be used to predict data by analyzing time series.

At last, there is Random Forest Regression (RFR), which used by Andariesta & Wasesa (2022), Feng et al. (2019), Mishra et al. (2021). RFR consists in following a decision tree where the most common branch is the most prone to happen possibility.

6. Discussion

This section provides a reasoning and understanding of the obtained results. We will go through each of them and try to understand why they emerged. Starting the journal, Forecasting gets a great collection of articles that contribute to the theme research, as the journal is an advanced forum for forecasting-related studies (Forecasting, n.d.).

The article quantity per year show numbers related to tourism sector that aims to reach pre-pandemic levels by increasing tourist arrivals and monetary equivalency. China being the country with the most publications in this research makes sense when considering their recent boost in tourism, from having the harshest travel restrictions and sealing off their borders to fully reopening them recently in 2023 (Hong & Che, 2023).

Regarding the techniques, we found a diversity of these. Starting with the hybrid R/SSVR-ARIMA approach, the ARIMA model performs a linear fit to the residual time series predicted by the SVR, resulting an improved predictive ability (Yao et al., 2021). According to Ouassou & Taya (2022), ARIMA outperforms AI-based techniques; however, ARIMA can’t outperform a hybrid model.

Thushara et al. (2019), concluded that SARIMA model is more suitable for forecasting total tourist arrivals in Sri Lanka as it considers the seasonality in the data. Abellana et al. (2021), worked with SVR-SARIMA hybrid approach to forecast tourism demand in the Philippines, and found that the sensitivity of the proposed model to the direction and trend change inherited from SARIMA, which proved to be highly sensitive to said aspects. SARIMA provides robust forecasts that are slightly less accurate than computational approaches, but their implementation is simpler and faster (Álvarez-Díaz et al., 2018).

An SVR-SARIMA hybrid significantly improves the individual forecasts of SVR and SARIMA; the contribution of SVR being the ability to reduce errors in magnitude, something recommended when working with non-linear data such as tourism demand (Abellana et al., 2021). SVR also works for short-term prediction, due to the inclusion of the “decomposition and integration” strategy that makes the model more effective (Feng et al., 2022).

The ANN model, when combined with evolutionary equations, outperforms SARIMA in predicting international tourist arrivals with a high degree of accuracy (Álvarez-Díaz et al., 2018). According to Andariesta & Wasesa (2022), the ANN model has better performance when fed with both qualitative and quantitative information. In addition, it improves its efficiency in time series forecasting and finds its best architecture when implemented with genetic algorithms, according to Nhat et al. (2021).

A study carried out by Nguyen-Da et al. (2023), indicates that Long Short-Term Memory (LSTM) when implemented in a hybrid arrangement with Convolation Nerual Network (CNN), improves performance compared to using both models individually; and can be optimized by fine-tuning hyperparameters.

According to Mishra et al. (2021), Random Forest Regression (RFR) proves to work well on small databases, otherwise it is vulnerable to being overfed and creating false associations due to random noise.

When comparing this research to the one focused in the weather forecasting sector by Jaseena & Kovoor (2022); we come across some similarities within the results, one of them being ANN the most frequent tool when it comes to forecasting, as well as hybrid models being the more reliable for it.

The authors demonstrate that the efficiency of predictions relies on available data and the application of various techniques. Through the analysis of the various results obtained from this research, as well as the analysis of the tools mentioned in the articles utilized for this study, the main objective of this review has been completed.

7. Conclusion

After reviewing the articles, we concluded that a journal such as Forecasting would have the most relevant articles for the scope of the research. The number of contributions per year would naturally increase as the industry tries to recover from the effects of the pandemic. Similarly, countries heavily impacted by the pandemic would search for new tools and resources to improve their performance in the affected sectors. China is a prime example of such a country.

This article analyzed the more frequently used models for forecasting tourism demand within a base of 40 articles. The following conclusions in relation to the tools reviewed were reached: statistical models, such as ARIMA, ANN and SARIMA, as well as models based on artificial intelligence, such as SVR, RFR and LSTM, happen to be the most useful when forecasting tourism demand. Likewise, there is evidence that the models can be improved, if they are implemented with a model from the other category, as such being a hybrid model. This partnering of models has been proven to be more effective than both categories on their own, achieving a more accurate forecast of the demand.

A few recommendations for future research are the use of a sample bigger than 40 articles, to obtain more accurate results as to which models are the most frequently used when forecasting tourism demand. Finally, an important recommendation when it comes to analyzing forecasting models, is to consider the inclusion of multiple variables such as economic, political and social events. Because if not, the analysis would end up reaching the wrong conclusion.

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