Hotel demand forecasting models and methods using artificial intelligence: A systematic literature review

Modelos e métodos de previsão da procura hoteleira utilizando inteligência artificial: revisão sistemática da literatura

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Abstract

This systematic literature review (SLR) explores current state-of-the-art artificial intelligence (AI) methods for forecasting hotel demand. Since revenue management (RM) is crucial for business success in the hotel industry, this study aims to identify state-of-the-art effective AI-based solutions for hotel demand forecasting, including machine learning (ML), deep learning (DP), and artificial neural networks (ANNs). The study conducted an SLR using the PRISMA model and identified 20 papers indexed in Scopus and the Web of Science. It addresses the gaps in the literature on AI-based demand forecasting, highlighting the need for clarity in model specification, understanding the impact of AI on pricing accuracy and financial performance, and the challenges of available data quality and computational expertise. The review concludes that AI technology can significantly improve forecasting accuracy and empower data-driven decisions in hotel management. Additionally, this study discusses the limitations of AI-based demand forecasting, such as the need for high-quality data. It also suggests future research directions for further enhancing AI forecasting techniques in the hospitality industry.

Keywords: Artificial Intelligence, Hotel Demand Forecast, Revenue Management, Machine Learning, Artificial Neural Networks, Digital Transformation.

Resumo

Esta revisão sistemática da literatura (RSL) visa identificar os mais recentes métodos de previsão de procura de um hotel utilizando inteligência artificial (IA). Considerando a importância que a gestão da receita tem para o sucesso empresarial na industria hoteleira, este estudo visa identificar modelos e métodos eficazes baseados em IA para a previsão da procura, incluindo *Machine Learning*, *Deep Learning* e *Artificial Neural Networks*. Neste estudo foi realizada uma RSL utilizando o modelo PRISMA, tendo sido identificados 20 artigos indexados na Scopus e na Web of Science. No estudo são abordadas as lacunas na literatura sobre a previsão da procura baseada em IA, destacando-se a necessidade de maior clareza na especificação dos modelos; o impacto da IA na precisão do preço e no desempenho financeiro; e os desafios relativos à qualidade dos dados disponíveis e da capacidade computacional. A revisão conclui que a utilização de IA integrada nos modelos de análise pode melhorar significativamente a precisão da previsão, reforçando as decisões orientadas por dados na gestão hoteleira. Além disso, este estudo discute também as limitações associadas à previsão da procura baseada em IA, como a necessidade de dados de elevada qualidade. São sugeridas futuras linhas de investigação visando melhorar ainda mais as técnicas de previsão incluindo IA na indústria hoteleira.

Palavras-chave/Palabras clave: Inteligência Artificial, Previsão de Procura Hoteleira, Gestão da Receita, Machine Learning, Artificial Neural Networks, Transformação Digital.

1. Introduction

Following the deregulation of the U.S. aviation market in the 1970s, the initial objective of revenue management (RM) was to sell a fixed and perishable inventory optimally within a certain time horizon (Klein et al., 2020). The RM definition begins with the process of allocating the appropriate type of capacity to the appropriate type of consumer at the appropriate price to maximise the revenue or yield (Kimes, 1989a). An effective RM system will assist the company in determining how much of each type of inventory (airline seats, hotel rooms, or rental cars) to allocate to various types of demand (Kimes, 1989a). Despite this prominent impact and significance, formal yield management is still primarily viewed as a pricing and inventory management instrument (Kimes & Chase, 1998). Since the end of the last century, airlines and other transportation companies have considered RM systems and associated information technologies as crucial success factors for the future (McGill & van Ryzin, 1999). These systems enable them to optimise their revenue by dynamically adjusting their prices and capacity allocation to different types of demand (Huang & Zheng, 2023). With the help of these technologies, companies can make data-driven decisions and respond quickly to changing market conditions, which is essential in today's fast-paced business environment. The effective use of RM and associated technologies can lead to increased profitability and a competitive advantage for businesses. Lieberman (2003) argues that, as has long been known, achieving success with RM requires considerably more than the appropriate technology. A variety of managerial and organisational factors have a substantial impact on the level of RM programme benefits realised. One of those factors is the challenge of forecasting demand. Rajopadhye et al. (2001) argue that the dynamics of economic systems are characterised by increasing uncertainty, which is likely to result in financially costly errors in decision-making. Forecasting uncertain economic variables is thus a crucial activity for any organisation. Recently, a growing number of companies have acknowledged the significance of RM for their ability to increase their sales and profitability (Wirtz et al., 2003). Effective design and management of price, time, and volume can enable firms with limited capacity to use their available assets more profitably. Long-term success strategies with RM depend on the ability of the management to market and manage every available instant as a unique product while also considering the dynamic nature of the demand and competition (Kimes & Wirtz, 2015). Although the RM can be applied to different types of businesses, the hotel industry presents additional challenges because of its specificity. While some scholars and researchers compare airlines and hotels, Kimes (1989b) suggests that RM techniques developed for the airline industry are not always applicable to the hotel industry. Multiple-night stays, the multiplier effect of rooms on other hotel functions (like food and beverages), the booking lead times for various types of rooms, the lack of a distinct rate structure, and decentralised information systems are issues that the hotels' RM must address.

We have witnessed significant technological advancements during the past 20 years, including revolutionary hardware and software developments. In addition, we have seen the fusion of information, communication, and control technology-driven techniques and the cross-fertilisation of concepts. As a result, there has been a fundamental shift in the way in which businesses function and provide value to their consumers, a process known as "digital transformation", which involves integrating digital technology into all facets of the business (Doborjeh et al., 2022; Krajčík et al., 2023; Lincényi & Bulanda, 2023). The most recent advancement concerns the use of AI as the main enabler and facilitator of digital transformation (Kaynak, 2021; Ülkü, 2023). The term artificial intelligence (AI) consists of two words: artificial, which alludes to something created by humans, and intelligence, which corresponds to the capacity to think independently. However, there is no generalised, agreed definition of AI. In a recent study, Sheikh et al. (2023) try to define AI as "systems that display intelligent behaviour by analysing their environment and taking actions with some degree of autonomy to achieve specific goals". Bhushan (2021) suggests that AI is altering the way in which industries create economic value. In the scope of AI, several techniques can be found, such as machine learning (ML), deep learning (DP), and artificial neural networks (ANNs). ML is a set of algorithms usually trained with massive data sets through which a machine learns, repeating certain processes and gaining performance feedback on those processes (Bulchand-Gidumal, 2020). ML is one of the most exciting recent technologies in AI (Das et al., 2015) because it allows for quick improvement of the algorithms. Learning algorithms in many applications can ingest and process huge amounts of data and improve their predictions over time, making them more accurate and efficient. DP is an ML technique based on ANNs, in which the algorithm is provided with a large set of rules. With this technique, a model is given to the machine, allowing modifications based on examples and small instructions to make it stronger and more exact. Conversely, an ANN is a set of techniques that can be used in both ML and DP. This technique tries to imitate the connection of human neurons, bringing the machine's capacity closer to human intelligence (Bulchand-Gidumal, 2020).

As learned from the literature, there has been a paradigm shift towards simulated human intelligence, enabling machines of all types to interconnect, incorporate learning into the existing intelligence pool, and provide error-free solutions. RM systems for hotels can integrate AI to help manage the complex data and information that need to be processed, providing a more efficient and effective solution for hotel management. In hotel operations, as Nam et al. (2020) state, AI-based solutions are deemed to be intelligent enough to replace human activities completely while enhancing transaction speed and precision. In the strategic management decision field, AI can autonomously manage large amounts of complex data, search for patterns, and make timely decisions. With the support of AI, demand forecasting for hotels has gained better accuracy (Pereira & Cerqueira, 2022). Recently, AI-based algorithms have been able to analyse historical data, market trends, and even weather patterns to forecast the demand for hotel rooms, allowing hotel managers to optimise pricing and inventory management (Huang & Zheng, 2021; Pereira & Cerqueira, 2022; Viverit et al., 2023; Wang & Duggasani, 2020). This technology has the potential to revolutionise the hospitality industry by providing real-time insights into customer behaviour and preferences, enabling hotels to offer personalised experiences that drive customer loyalty and revenue growth (Caicedo-Torres & Payares, 2016).

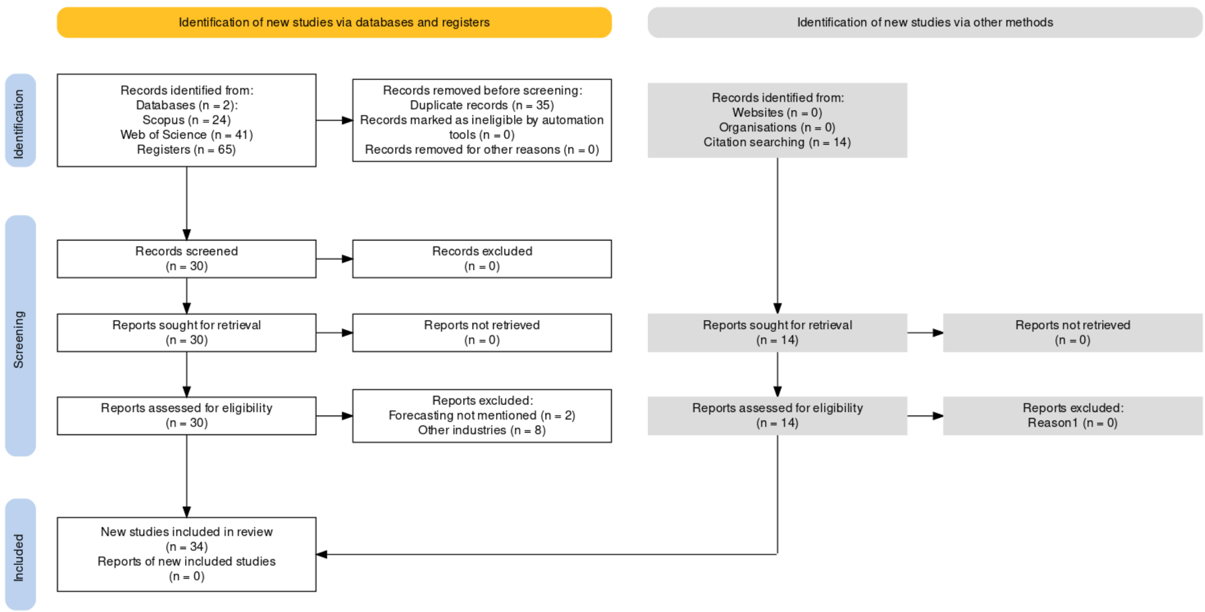
Considering the importance of demand forecasting for RM in the hotel industry and for business success, as well as the growing interest in AI solutions, a few papers have been published containing a systematic review of the literature and methods using AI-based tools in the context of tourism and hospitality (e.g., Doborjeh et al., 2022; Huang & Zheng, 2023; Wu et al., 2017). However, none of these papers focus only on hotel demand forecasting methods based on AI. For example, Wu et al. (2016) present a review of the literature about demand modelling and forecasting published between 2007 and 2015 in the fields of tourism and hospitality. Doborjeh et al. (2022) review AI methods in both hospitality and tourism, including models for demand forecasting and models for evaluating tourism destinations and measuring customer behaviour patterns. In a more recent work, Huang and Zheng (2023) conduct a literature review about the evolution of hotel demand forecasting over the past decades, including AI-based methods and well-known traditional models.

This study examines the state-of-the-art AI-based solutions used to forecast hotel demand, the statistical methods, and the kind of hotel data used in each methodology. Based on a systematic literature review (SLR) following the Prisma method, 20 papers were identified using specific keywords in two academic databases: Scopus and Web of Science. This research contributes to a more profound understanding of the statistical method AI results for each type of data analysed. Based on the previous issues identified, this paper focuses on the hotel industry and forecasting techniques using AI-based models, such as ML, DL, and other AI-based methods, comparing such models and looking for gaps and further research lines.

2. Methodology

The current SLR was based on the PRISMA model (Haddaway et al., 2022). PRISMA aims to ensure that the methods and outcomes of systematic reviews are described in sufficient detail to permit complete transparency. Flow diagrams in evidence synthesis enable the reader to quickly comprehend the core procedures used in a review and examine the attrition of irrelevant records during the review process. The review was conducted with two academic databases, Web of Science and Scopus, using specific keywords for data collection due to their widest coverage of academic journals. The search query was run in April 2023 with the following list of keywords: (TITLE-ABS-KEY (hotel AND revenue AND management) AND TITLE-ABS-KEY (demand) AND TITLE-ABS-KEY (forecasting) AND TITLE-ABS-KEY (artificial AND intelligence) OR TITLE-ABS-KEY (machine AND learning) OR TITLE-ABS-KEY (deep AND learning)). A total of 65 registries were identified, 41 in the Web of Science and 24 in Scopus, among which 30 duplicate records were found using the Rayaan software (Ouzzani et al., 2016) and 5 were ineligible because they were not connected with the research theme. After screening the 30 remaining records, a title and abstract review was conducted, following which 10 were excluded using two exclusion criteria (EC): EC1: forecasting words not mentioned (2); EC2: other industry studies (8). To support the literature review, 14 citations were searched for, identified for retrieval, and added to the review. The Prisma framework used is shown in Figure 1.

Figure 1
Prisma framework model



The full texts of the selected studies were downloaded and extensively reviewed to corroborate their relevance to the literature review topic. To demonstrate the recent interest in this theme and to justify this SLR, in Table 1, a chronological list of publications is presented.

Table 1: *Articles by year*

Year	Articles
2023	2
2022	5
2021	4
2019	6
2016	1

3. Results

3.1 Hotel revenue management demand forecasting

Demand forecasting is the process of making predictions or estimates about future observations of a target variable based on historical and present data. Hotel demand forecasting is the process of predicting, depending on the data available, reservations or occupancy rates for hotel rooms and other services but can also be used to predict other variables, like cancellations (Antonio et al., 2019) or no-shows, and to support pricing optimisation through dynamic rates (Zhang et al., 2019), maximising the revenue and profit. In the hospitality industry context, forecasting the demand is important for hotel managers and RM team to make inventory allocation and pricing decisions to maximise their revenues (Kaya et al., 2022; Zhang et al., 2019). Forecasting is a critical element in hotel planners' and managers' decision-making process, which involves the strategic allocation of hotel resources to maximise profitability. Indeed, it has been recognised that the use of accurate forecasting methods is vital to ensure better application of dynamic pricing to popular strategies like RM because errors in pricing will negatively affect a hotel's financial performance if the forecasting is not precise (Caicedo-Torres & Payares, 2016). In recent years, advances in ML and other AI-based methods have revolutionised the field of demand forecasting, allowing hotels to predict demand more accurately and adjust their pricing in real time (Huang & Zheng, 2023). Despite these advances, gaps remain in our understanding of how best to use these techniques.

3.2 Hotel demand forecasting methods based on artificial intelligence

Several forecasting methods associated with AI solutions were identified in the literature review. A mix of statistical methods and AI models was also found. The traditional statistical methods used to forecast hotel demand are time series analysis and econometric models. The methods within the time series analysis category include the moving average, which consists of calculating averages of demand over a specified period to smooth out fluctuations, and exponential smoothing, which assigns exponentially decreasing weights to past demand observations to give more importance to recent data. In the exponential smoothing subcategory, we can find a wide range of methods, such as the Holt and Holt–Winters method. Another traditional method is the autoregressive integrated moving average (ARIMA), which combines autoregressive, differencing, and moving average components to model and forecast time series data. The ARIMA model is often implemented through the Box–Jenkins approach, also known as the ARIMA Box–Jenkins methodology. This methodology provides a systematic framework for identifying, estimating, and validating a suitable ARIMA model for a given time series. SARIMA is commonly used to extend the ARIMA method to account for seasonality in data analysis (Antonio et al., 2019; Kaya et al., 2022; Pereira & Cerqueira, 2022; Phumchusri & Ungtrakul, 2020; Salamanis et al., 2022; Schwartz et al., 2021; Wang & Duggasani, 2020). In the econometric category of models, we can find, for example, the autoregressive distributed lag model, error correction model, and vector autoregression (VAR) (Viverit et al., 2023).

With the evolution of technology and computer capabilities, ML algorithms have been used to mix traditional statistical models with ML, building a new approach to forecasting hotel demand (Doborjeh et al., 2022). This approach involves the use of large amounts of data to train algorithms, allowing them to learn patterns and make predictions with greater accuracy. By combining traditional statistical methods with machine learning (Huang & Zheng, 2023), hotels can improve their forecasting accuracy and make more informed pricing and inventory management decisions. Some of the ML models identified are ANNs (Ampountolas, 2021; Caicedo-Torres & Payares, 2016; Huang & Zheng, 2021; Kaya et al., 2022; Sánchez et al., 2020; Sánchez-Medina & C-Sánchez, 2020), used to simulate the human brain system by using artificial layers (Doborjeh et al., 2022). ANNs have demonstrated good results as a model for managing nonlinear data; however, they do not demonstrate the same results in capturing long-term time dependence (Huang & Zheng, 2023). To support the weakness of ANNs, long short-term memory (LSTM) (Huang & Zheng, 2021; Salamanis et al., 2022; Wang & Duggasani, 2020; Wu et al., 2022) is a type of recurrent neural network (RNN) architecture that can capture the temporal dependencies in hotel reservation data (Huang & Zheng, 2023). A support vector machine (SVM) (Sánchez et al., 2020; Sánchez-Medina & C-Sánchez, 2020), used with the support vector regression (SVR) extension (Pereira & Cerqueira, 2022; Phumchusri & Ungtrakul, 2020), allows users to map the data into a higher-dimensional space and identify the hyperplane that best fits the training data, permitting nonlinear relationships between predictors and demand. The random forest (RF) (Pereira & Cerqueira, 2022; Sánchez-Medina & C-Sánchez, 2020) is used to construct an ensemble of decision trees and aggregate their predictions to forecast the demand. These trees can capture nonlinear relationships and interactions among predictors, making them suitable for complex demand patterns. The gradient boosting machine (GBM) (Ampountolas, 2021; Sánchez et al., 2020) creates an ensemble of weak prediction models iteratively, learning from previous mistakes. Models like XGBoost (Antonio et al., 2019) or LightGBM are popular implementations of gradient-boosting algorithms. Linear regression (LR), as a foundational statistical model, contains various extensions for flexible and strong modelling. Ridge regression, kernel ridge regression (Caicedo-Torres & Payares, 2016), and lasso regression (Pereira & Cerqueira, 2022) are used for data regularisation. Due to some limitations of the traditional forecasting models, other AI-based statistical approaches have been used to complement them and improve their accuracy. The Cross-Industry Standard Process for Data Mining (CRISP-DM) (Antonio et al., 2019), clustering booking curves (Viverit et al., 2023), deep factorisation Machine (DeepFM), Seq2Seq (Zhang et al., 2019), K-means clustering (Kaya et al., 2022), generic algorithm (GA) (Sánchez-Medina & C-Sánchez, 2020), multi-layer perceptron, and radial basis function networks (Caicedo-Torres & Payares, 2016) are other ML models mentioned in the literature reviewed. Some articles propose extra background methods to fine-tune the data collected. Several methods and models are identified that can be used for different purposes, and the choice of method should depend on the specific research question and available data. It is important to consider each approach's strengths, limitations, and results carefully before selecting a method or model for analysis. A more in-depth analysis will be applied to this study later.

3.3 Hotel data set

As mentioned earlier, the forecasting method used will depend on the kind of variable that should be predicted and the forecasting horizon (Koupriouchina et al., 2014). Several variables can be set to forecast, such as occupancy, reservations, prices, and cancellations, which can be forecasted in the hotel business to assist the revenue manager's decision-making. For each variable, a set of data should be collected and processed to apply the corresponding method or model. Caicedo-Torres and Payares (2016) argue that occupation forecasts can be grouped into two categories: historical reservation models and advanced reservation models. The historical reservation model focuses on the time series modelling problem to understand historical patterns and predict the future. The advanced reservation model uses the concept of "pick-up", adding a certain number of future bookings to existing reservations on the books in a certain advanced period of days. According to the literature review, six data types are used to perform forecasting: room occupation (Ampountolas, 2021; Ampountolas & Legg, 2021; Antonio, de Almeida, et al., 2019, 2019; Caicedo-Torres & Payares, 2016; Chen et al., 2023; Huang & Zheng, 2021; Kaya et al., 2022; Pereira & Cerqueira, 2022; Phumchusri & Ungtrakul, 2020; Sánchez et al., 2020; Schwartz et al., 2021; Viverit et al., 2023a; Wang & Duggasani, 2020; Webb et al., 2020), room reservations (Ampountolas, 2021; Antonio, de Almeida et al., 2019; Caicedo-Torres & Payares, 2016; Kaya et al., 2022; Salamanis et al., 2022; Sánchez-Medina & C-Sánchez, 2020; Viverit et al., 2023a; Wang & Duggasani, 2020), room cancellations (Antonio, de Almeida, et al., 2019, 2019; Rakesh et al., 2022; Sánchez-Medina & C-Sánchez, 2020), online reviews (Wu et al., 2022), social media keywords (Ampountolas & Legg, 2021), and prices (Kaya et al., 2022; Wang & Duggasani, 2020; Zhang et al., 2019). Due to the interconnection between data sets, some scholars and researchers use a mixed-data approach to achieve more accurate forecasting results. This involves combining multiple data types and analysing them together to gain a more comprehensive understanding of the factors influencing hotel demand. Additionally, ML algorithms can be applied to these mixed data sets to improve the accuracy of forecasting models further (Viverit et al., 2023b). A hotel data set used in forecasting demand comparisons is presented in Table 2 to offer a better understanding.

Table 2: *Hotel Data Set Used*

Authors	Hotel Data Set Used
Caicedo-Torres & Payares, (2016); Viverit et al. (2023)	Reservation and historical room occupancy
Pereira & Cerqueira (2022); Phumchusri & Ungtrakul, (2020); Sánchez et al. (2020)	Historical room occupancy
Salamanis et al. (2022); Sánchez-Medina & C-Sánchez, (2020); Webb et al. (2020)	Historical room reservation
Ampountolas & Legg (2021)	Social media keywords and historical occupancy
Antonio, De Almeida, et al. (2019)	Reservations, Occupancy and Cancelations history
Wu et al. (2022)	Hotel Reviews and hotel demand
Antonio, de Almeida, et al. (2019)	Historical Occupancy Rate and Cancelations
Zhang et al. (2019)	Predicted room-nights, Total number of rooms, ADR, REVPAR, Base price
Kaya et al. (2022)	Historical rate occupancy, Reservations and Hotel features
Schwartz et al. (2021)	Historical Occupation Rates and Forecasting Records
Wang & Duggasani (2020)	Number of bookings, and average room rate
Ampountolas, 2021; Huang & Zheng (2021)	Daily Demand Observations
Chen et al. (2023)	Personal Name Records (PNR)

Additional information is used to improve the forecasting results in some of the mixed methods mentioned. Wu et al. (2022) combine customer reviews from two popular online platforms with the historical hotel demand for specific dates to analyse the impact on forecasting demand using the LSTM and ARIMAX methods. Antonio et al. (2019b) combine hotel reservations and cancellations using the Cross-Industry Standard Process Model (CRISP-DM), a data-mining method, to predict future hotel cancellations. Another complex example is the dynamic price prediction research from Zhang et al. (2019), in which 759 hotels in China are utilised and divided into two datasets to forecast the rates in the off-season and peak season using a comparative competitor analysis base price setting. Salamanis et al. (2022) research the impact of weather on hotel reservation cancellations, combining historical time series hotel data on reservations, cancellations, and weather conditions in a DL methodology using an LSTM layer. These are some examples showing how complex a forecasting model can be and the kind of data used to perform the model.

3.4 Target forecast objectives

As mentioned earlier, the data collected from hotel databases or external sources can be used to improve the accuracy of forecasts of variables of interest for maximising revenue. In the literature review, two targets were identified. i) Cancellation prediction was found in six studies (Antonio et al., 2019; Chen et al., 2023; Rakesh et al., 2022; Sánchez et al., 2020; Sánchez-Medina & C-Sánchez, 2020): along this research line, the aim of the investigation focuses on finding the best forecasting method to predict future cancellations since this event can contribute negatively to more accurate forecasts and revenue performance. ii) Occupation forecasts were found in six studies (Ampountolas, 2021; Caicedo-Torres & Payares, 2016; Huang & Zheng, 2021; Kaya et al., 2022;

Viverit et al., 2023; Wu et al., 2022). Occupation forecasts for better price prediction were found in one study (Zhang et al., 2019). As suggested by the author, due to the development of digital and computer reservation systems, forecasting for dynamic pricing is another big challenge in hotel RM. To resolve this issue, a new forecasting model is proposed using DeepFM and Seq2eq, two ML models, one combining DL and factorisation and the other a type of NN architecture for sequence-to-sequence learning tasks, and a data-driven dynamic pricing methodology to recommend a more rational price than revenue managers' rule-based technique. In the role of RM, occupation forecasting is the most important for better operational and tactical decisions (Wang & Duggasani, 2020). Therefore, it is crucial for hotels to invest in advanced technology and data analysis tools to forecast the hotel demand accurately and adjust their prices accordingly. Additionally, RM strategies should consider external factors, such as competition and market trends, to stay ahead of the game.

3.5 Comparative studies of forecasting methods

Seven papers comparing forecasting methods based on the traditional statistical approach or comparing hybrid models using traditional and ML models were identified. Schwartz et al. (2021) explore the interactions between two methods of accuracy enhancement: forecast combination and human learning. Pereira and Cerqueira (2022) analyse two short-term hotel demand forecasting methods for lead times up to 14 days ahead. The paper focuses on ML models, such as support vector regression, random forest, and ANNs, and compares them with traditional statistical methods, such as seasonal naive and exponential smoothing methods for double seasonality. The study aims to provide insights into the potential benefits of using ML models in hotel demand forecasting for RM. Wang and Duggasani (2020) propose two LSTM models for forecasting hotel reservations and compare their performance with that of traditional ML algorithms. The authors aim to address the limitations of the existing ML techniques in modelling the sequential dependence of bookings over time and to demonstrate the effectiveness of LSTM models in predicting the demand for hotel rooms. Phumchusri and Ungtrakul (2020) propose hotel daily demand forecasting models using both time series models and ML techniques. The article aims to investigate the use of the transformation of time series data as an input variable for forecasting hotel demand. It also compares the forecasting accuracy of different methods and provides insights into their strengths and weaknesses. Salamanis et al. (2022) propose introducing a DL-based approach for forecasting long-term tourism demand. The authors suggest two different models based on the long short-term memory network (LSTM), which can incorporate data from exogenous variables, such as weather-related parameters, to generate accurate long-term predictions. The proposed models are evaluated using real data from three hotels in Greece and compared with traditional statistical models. Ampountolas (2021) aims to compare the forecasting performance of three different models (SARIMAX, NN, and GARCH) in predicting the daily hotel demand. Webb et al. (2020), whose study focus is on evaluating the efficacy of advanced booking methods in RM for hotels located near national parks in the USA, aim to compare the accuracy and effectiveness of various statistical and ML models in forecasting the demand in the advanced booking environment and to identify best practices for RM in this context. These studies suggest that incorporating ML techniques into RM can lead to more accurate and efficient forecasting, ultimately resulting in increased business revenue and profitability. Therefore, companies need to consider implementing these hybrid models in their RM strategies.

3.6 Artificial intelligence forecasting advantages

ML is one of the most fascinating recent AI technologies. Many applications that we use daily involve learning algorithms, which allow the software to adapt and improve over time (Doborjeh et al., 2022). By incorporating ML into RM, businesses can make more accurate predictions about customer behaviour and adjust their pricing accordingly. This approach can lead to increased profits and a competitive advantage in the market. However, several kinds of ML techniques are available, and it is important for businesses to choose the one that best fits their needs. Some ML techniques are supervised learning, unsupervised learning, and reinforcement learning (Das et al., 2015). Each technique has its strengths and weaknesses, and businesses should carefully consider which one to use based on their specific goals and data. Additionally, they should ensure that they have high-quality data to feed into the ML algorithms to achieve the best results. As mentioned by scholars and researchers regarding the data used in forecasting hotel RM, some of these techniques, like demand forecasting and pricing optimisation, can be applied to predict and support revenue managers' decisions. Several models and methods have been applied. In the review chapter on forecasting results, we aim to identify the ML model that can best predict hotel demand. However, after screening the data, it is suggested that the best model depends on the data available and the problem being addressed. Nevertheless, ANNs, support vector machines, and linear regression are some of the most prominent hotel demand forecasting methods (Huang & Zheng, 2023). The complex relationships between the input variables and the intended output can be captured effectively by ANNs (Ampountolas, 2021; Ampountolas & Legg, 2021; Caicedo-Torres & Payares, 2016; Huang & Zheng, 2021; Kaya et al., 2022; Pereira & Cerqueira, 2022; Phumchusri & Ungtrakul, 2020; Sánchez et al., 2020; Sánchez-Medina & C-Sánchez, 2020). Support vector machines are a form of supervised ML that can efficiently identify the optimal linear boundary between distinct data classes (Pereira & Cerqueira, 2022; Phumchusri & Ungtrakul, 2020; Sánchez et al., 2020; Sánchez-Medina & C-Sánchez, 2020). Using historical data, linear regression is a straightforward but effective technique for forecasting demand (Salamanis et al., 2022; Sánchez-Medina & C-Sánchez, 2020; Webb et al., 2020; Wu et al., 2022).

3.7 Analyses of forecasting methods by models, results, and limitations

This chapter examines the application of various statistical methods and ML algorithms for forecasting hotel outcomes. By comparing and contrasting these methods, we hope to shed light on their advantages, disadvantages, and potential for improving forecasting accuracy in the hospitality industry. Forecasting is a critical activity for dynamic pricing strategies in RM, and errors in pricing will negatively affect hotel financial performance if forecasting is not precise (Caicedo-Torres & Payares, 2016). Strategic planning and decision-making rely heavily on accurately forecasting hotel results in the highly competitive hospitality industry. Forecasting assists hotel managers in anticipating demand patterns, optimising pricing strategies, allocating resources efficiently, and maximising revenue and visitor satisfaction (Phumchusri & Ungtrakul, 2020). Historically, statistical methods have been used to predict hotel performance; however, with the advent of ML techniques, new opportunities for more accurate and sophisticated forecasting models have emerged. From the literature reviewed, a comparison was made to establish a relationship between the methodology used (statistical and AI models), the targeted forecast, the results, and the limitations. To better understand and compare, the articles were divided by forecast target: demand, cancellations, and prices. Table 3 compares the studies that concern demand forecasting; Table 4 presents studies that forecast booking cancellations; and Table 5 contains studies that predict pricing recommendations.

Table 3: *Forecasting demand studies*

Authors	Article	Study Objective	Methodology used (Statistical and AI Models)	Results conclusion	Limitations
Caicedo-Torres & Payares (2016)	A machine learning model for occupancy rates and demand forecasting in the hospitality industry	Explore the potential of ML for improving demand forecasting	Ridge Regression, Kernel Ridge Regression, Multi-layer Perceptron and Radial Basis Function Networks	Results show a Ridge regression model outperforms the other models considered	Not set
Wu et al. (2022)	Are customer reviews just reviews? Hotel forecasting using sentiment analysis.	Adding sentiment variables into hotel demand forecasting	Long Short-Term Memory (LSTM) model, ARIMA, Autoregressive integrated moving average with exogenous variables (ARIMAX), Linear support vector machine	The incorporation of Sentiment indices improve accuracy for short-term forecasts of 1-7 days.	Sentiment analyses not improve forecast accuracy for long-term demand
Huang & Zheng (2021)	Novel deep learning approach for forecasting daily hotel demand with agglomeration effect.	Develop a DL model using the agglomeration effect among hotels in forecasting demand comparing with ARIMAX, VAR and LSTM	RNN, LSTM, DLM-ST, Bayesian optimisation, ARIMAX, VAR	The MAPE result is significantly lower than the MAPEs of the other models tested, including ARIMA, LSTM, and VAR.	Forecasting is based on historical data.
Kaya et al. (2022)	Demand forecasting model using hotel clustering findings for hospitality industry	Develop a demand forecasting model using clustering findings comparing with other models	K-means Clustering, Hotel Embedding, Attention-LSTM, Seq2One, Spectral Clustering, Random Forest Regressor, Gradient Boosting Regressor, Extra Trees Regressor, XGBoost, Regressor, Gated Recurrent Unit	Attention LSTM model that uses feature embeddings outperforms other models	The demand forecast model may not be applicable to all types of tourism destination and hotels and the model accuracy may depend on data quality and quantity.
Ampountolas & Legg (2021)	A segmented machine learning modeling approach of social media for predicting occupancy.	Develop a modelling framework that incorporates text mining via DL with qualitative social media data to improve demand forecast	ARIMA, Exponential Smoothing, Random Forest, Gradient Boosting, NN, Hierarchical Clustering Tied	The results show that the proposed model outperforms traditional time series models in terms of forecasting accuracy	The sentiment analysis is based only on Twitter. The data was collected only from one main hotel chain and in USA.
Viverit et al. (2023)	Application of machine learning to cluster hotel booking curves for hotel demand forecasting.	The study proposes a data-driven approach for hotel demand forecasting that combines big data sources, ML algorithms, and traditional forecasting methods. It aims to improve accuracy by clustering booking curves and incorporating big data sources.	Clustering Booking Curves, Additive pickup method	The results using ML models outperformed traditional exponential smoothing methods. Additionally, the study found that a DL model performed better than time series (ARIMA model), econometric (Vector Autoregression model), and other LSTM models	Highly computational resources and expertise are required to implement effectively.

Schwartz et al. (2021)	Enhancing the accuracy of revenue management system forecasts: The impact of machine and human learning on the effectiveness of hotel occupancy forecast combinations across multiple forecasting horizons.	The study aims to investigate whether the capacity of forecast combinations to improve accuracy changes as learning occurs	Moving Average, Exponential Smoothing, and Holt–Winters Exponential Smoothing, ML models not specified	This study compares 3 experiments A controlled academic based experiment A recorded human and machine generated forecasts from a hotel. And an RMS vendor with machine generated forecasts and user overrides recorded. The results are not conclusive.	The three studies results seem that in some cases forecasting machine and human overrides may improve forecast accuracy, however is not conclusive.
Pereira & Cerqueira (2022)	Forecasting hotel demand for revenue management using machine learning regression methods	The study aims to provide insights into potential benefits of using ML models in hotel demand forecasting comparing 22 methods for short-term forecasting for lead times up to 14 days ahead.	Naïve, ARIMA, Theta, Exponential Smoothing, Holt-Winters, Tbats, Rule-based Regression, Support Vector Regression, Principal Components Regression, Projection Pursuit Regression, Partial Least Squares, Generalized Boosted Regression, Extreme Gradient Boosting, Random Forest, Gaussian Process, Multivariate Adaptive Regression, Lasso, Dynamic Ensemble	ML methods outperform classical statistic methods. ADE fits the best performance comparing all other methods in Short-term forecasting. Support Vector Regression, Partial Least Squares and Principal Components Regression fits better results in Long-term forecasting	Under certain circumstances, like a pandemic scenario all the models should be re-tested to validate the accuracy under strong external stress.
Wang & Duggasani (2020)	Forecasting hotel reservations with long short-term memory-based recurrent neural networks.	The study compares two LSTM forecasting models with traditional ML techniques.	NN, Feedforward neural networks (FNN), multi-layer perceptron (MLP), Deep Neural Network (DNN), Convolutional Neural Network (CNN), Long Short-term Memory (LSTM)	Mostly LSTM models outperformed ML algorithms	Should be used more neural layers and add more diverse data to improve the forecasting accuracy.
Phumchusri & Ungtrakul (2020a)	Hotel daily demand forecasting for high-frequency and complex seasonality data: a case study in Thailand	The study proposes compare different methods of hotel demand forecasting using advanced time series and ML techniques	Holt-Winters, Box-Jenkins, Box-Cox transformation, ARMA errors, BATS, TBATS, ANN, SVR	ML techniques outperform advanced time series methods BATS and TBATS.	ADR was unavailable for the study and can explain hotel daily occupancy. Transformed regression data cannot explain time series seasonality or trend.
Salamanis et al. (2022)	LSTM-Based Deep Learning Models for Long-Term Tourism Demand Forecasting.	The objective of the study is to propose and evaluate the effectiveness of DL-based models, demonstrate the potential of LSTM-based models for hotel demand forecasting using exogenous variables	Naïve Forecasting model, Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), Holt-Winters Exponential Smoothing, Multi-layer Perceptron, Bayesian Ridge Regression LSTMB, LSTMX	LSTM-based models were able to generate more accurate long-term predictions by incorporating data from exogenous variables such as weather-related parameters compared with those without	A large amount of data is required for better train the model. Factors such seasonality and holidays are not take into account.
Ampountol as 2021)	Modeling and Forecasting Daily Hotel Demand: A Comparison Based on SARIMAX, Neural Networks, and GARCH Models	The study compares three different models (SARIMAX, NN and GARCH models) in predicting hotel demand for different forecasting horizons	Seasonal Naïve Method, Holt-Winters' Triple Exponential Smoothing, ARIMA, SARIMAX, ANN-MLP, GARCH Models	In general, GARCH Models outperformed all the compared models	Different dataset and hotel locations should be tested to validate the model.
Webb et al. 2020)	Revenue management forecasting: The resiliency of advanced booking methods given dynamic booking windows	The study compares accuracy and effectiveness of various statistical and ML models in forecasting demand	Additive pickup, Multiplicative pickup, Linear regression, Log-Linear Regression, Polynomial Curve Fit, Curves Similarity, Multi-Layer Perceptron	The results show how reservations accumulate over time increase accuracy. In advance booking, using past curve data may help forecast accurately.	The study only used four properties near national parks in US. Other locations should be considered with different target markets.

Table 4: Forecasting *Cancelations studies*

Authors	Article	Study Objective	Statistical and ML models used	Results conclusion	Limitations
Antonio, et al. (2019)	Big Data in Hotel Revenue Management: Exploring Cancellation Drivers to Gain Insights into Booking Cancellation Behavior.	The study aims to evaluate the performance of ML learning models in predicting booking cancellations and no-shows	Cross-industry standard process model for data mining (CRISP-DM)	The AUC values are considered to indicate fair-to-good or excellent model results, depending on the value	Very complex prediction equation, which does not allow the models to be depicted.
Antonio, De Almeida, et al. (2019)	An automated machine learning based decision support system to predict hotel booking cancellations.	The study objective was to develop a prototype system that can predict hotel booking cancellations with high accuracy and precision	CRISP-DM, XGBoost, Grid-search, Random-search, Time Series, Convenience Splitting	The results demonstrated a satisfactory model's precision	This model suggests some constraints in terms of obtaining complete information about all bookings and contacting a large number of customers within a limited amount of time
Chen et al. 2023)	Prediction of hotel booking cancellations: Integration of machine learning and probability model based on interpretable feature interaction.	The study compares two studies to predict hotel booking cancellations and no-shows using Bayesian nested logit model.	Bayesian networks (BN), Lasso Regression, AAN, XGB	Both studies mentioned high accuracy rates for their prediction models. One study reported an accuracy rate of 91% for their ML model, while the other study reported an accuracy rate of 80% for their probability model. These high accuracy rates suggest that the models are effective in predicting hotel booking cancellations	One study acknowledges that their dataset only includes hotels from Portugal, which may limit the generalizability of their findings to other regions. The other study notes that their probability model assumes independence between cancellations, which may not always be the case in real-world scenarios.
Sánchez-Medina & C-Sánchez 2020)	Using machine learning and big data for efficient forecasting of hotel booking cancellations	The study aims to identify the reasons that lead customers to cancel their hotel bookings and to develop a model that can predict which customers are likely to cancel their bookings.	Tree decision-based, C5.0, Random Forest, Support Vector Machine, ANN, Genetic Algorithm	Results show that the proposed methodology for forecasting hotel booking cancellations using ML techniques is effective. The model achieved a cancellation rate of up to 98%, which is higher than previous studies in the area.	One limitation is that the model relies on historical data and may not be able to account for sudden changes in market conditions or other unforeseen events. Another limitation is that the model requires a certain level of technical expertise to implement and maintain, which may be a barrier for some hotels
Sánchez et al. (2020)	Identifying critical hotel cancellations using artificial intelligence.	The study objective is to develop a forecasting model that can predict the likelihood of hotel reservation cancellations based on customer characteristics and historical reasons for cancellations using several supervised learning algorithms.	C5.0, Support Vector Machine (SVM), ANN, and GBM for tree boosting ensemble	Ensemble technique successfully improves the individual techniques achieving up to 14% of AUC above the lowest value and also reaching balanced specificity and sensitivity	The model relies on historical records. If sudden changes happen the model needs to be re-trained.
Rakesh et al. 2022)	Hotel Booking Cancelation Prediction using ML algorithms.	The study objective is to predict hotel booking cancellations using ML models and to develop interactive reports to provide users with information on country-wise bookings and cancellations, as well as future predictions based on the experience gained from the ML models	Linear regression, K-Nearest Neighbor, Decision Tree, Naïve Bayes Classifier	Not set	Not set

Table 5: *Forecasting pricing studies*

Authors	Article	Study Objective	Results conclusion	Statistical and ML models used	Limitations
Zhang et al. (2019)	Deep learning based dynamic pricing model for hotel revenue management.	The study aims to develop a data-driven dynamic pricing system for hotel rooms that can provide more rational price suggestions compared to a rule-based pricing strategy made by revenue managers.	The proposed method (DeepFM+seq2seq) outperforms all other models in both off-season and peak-season occasions by a large margin	SES, MA, Additive Holt-Winters, Multiplicative Holt-Winters, Prophet, XGBoost, seq2seq, and DeepFM+seq2seq	The system assumes the prices as the only factor affecting the demand. Does not take into account other external factors such weather, events, holidays and others.

3.8 Recommended future research

Grounded on the analysed articles, Table 6 presents in the main future lines of research proposed by the authors. The table summarises the topics mentioned in the various articles and the authors who suggested them. The identified future lines of research pave the way for new research possibilities and contribute to the advancement of knowledge in the field. The systematisation of these suggestions allows a broad and organised view of the directions that studies can follow.

Table 6: *Future lines of research*

Recommend Future Research (number of studies)	Authors
Apply the proposed or tested methods in different locations or hotel types (7)	Ampountolas & Legg (2021); Viverit et al. (2023); Phumchusri & Ungtrakul (2020a); Salamanis et al. (2022); Ampountolas (2021); Webb et al. (2020); Sánchez-Medina & C-Sánchez (2020)
Incorporate external factors, like weather conditions, events, or economic indicators, to improve accuracy of forecasts (6)	Wu et al. (2022); Huang & Zheng (2021); Pereira & Cerqueira (2022); Wang & Duggasani (2020); Sánchez-Medina & C-Sánchez (2020); Phumchusri & Ungtrakul (2020a)
Use novel data sources and variables, such as social media or search data (4)	Kaya et al. (2022); Ampountolas & Legg (2021); Chen et al. (2023); Huang & Zheng (2021)
Combine historical data with advanced booking data, as well as cancellation data (4)	Huang & Zheng (2021); Antonio, De Almeida, et al. (2019); Chen et al. (2023); Sánchez-Medina & C-Sánchez, 2020)

4. Discussion

The study's analysis shows that AI techniques, such as ML and DP, systematically outperform traditional models when used to forecast hotel demand. These techniques allow the use of different data sources, improving the accuracy of hotel demand forecasting. However, the quality and quantity of the available hotel data are critical issues in producing these results. Conversely, computational knowledge is required to apply complex AI techniques, which can be difficult for most hotel companies. Most of the proposed models using AI techniques revealed superiority compared to traditional techniques. The hotel sample's locations, available in Table 7, are another restriction to the promotion of a correct comparison due to their heterogeneity since they present different seasonality patterns, target markets, cultures, and customer behaviours, among other reasons.

Table 7: *Studies per country*

Hotel Sample Countries	Number of studies
USA	4
China (including Macau and Hong Kong)	4
Portugal	3
Spain	3
Colombia	1
Italy	3
France	1
Turkey	1
Thailand	1
Greece	1
Not set	2

The literature review suggests testing different AI-based forecasting models with the available hotel data and the specific variables to be targeted to ensure a better forecasting model selection. In conjunction with some learning models and statistical methods, a specific AI technique, whether it belongs to the ML or the DL domain, can serve a specific hotel but not others. This attests to the challenge of forecasting the demand in the hospitality industry. The best model designs for demand forecasting are unclear, and numerous possibilities exist. In addition, the inclusion of auxiliary information in the forecasting models, such as social media sentiments (Ampountolas & Legg, 2021), customer review keywords (Wu et al., 2022), or exogenous variables such as weather or temperature (Salamanis et al., 2022), implies the use of more complex data analysis, which AI techniques can handle. The shift towards high-frequency forecasting using high-quality data sources, such as big data from the Internet (e.g., web search data and social media data), reflects tourists' preferences and real-time decision-making (Wu et al., 2022). The emergence of novel DL approaches, such as the DL model with spatial and temporal correlations, and the use of sentiment analysis of customer reviews can improve prediction performance (Huang & Zheng, 2021; Wu et al., 2022). The application of ML algorithms to cluster historical booking curves and forecast occupancy will soon provide a practical solution for RM decision-making processes, especially considering the uncertainty brought about by the COVID-19 pandemic (Viverit et al., 2023). Additionally, despite the importance of hotel demand forecasting for efficient resource allocation and appropriate pricing strategies, research in this area has been limited compared with tourism demand forecasting. There is no single "best" demand forecasting methodology for the hospitality industry as accuracy can vary depending on the property demand behaviour and forecasting horizon. However, there is a consensus in the literature that accuracy in demand forecasts is crucial to the success of RM systems, and more accurate demand forecasts can lead to higher revenue. The choice of forecasting methodology depends largely on the circumstances, such as market or reservation patterns that are property-specific. It can be burdensome for practitioners to forecast the demand using numerous independent variables, so selecting and refining those variables is recommended. It is important to note that new economic and non-economic variables can be added to the model to improve the forecasting performance. The literature suggests that the best forecasting methodology will vary depending on the specific circumstances and data available. Hotel typification is an identified gap within the studies. Typifying the hotel features, location, or seasonality can help better understand the forecasting model that best fits each type (urban, rural, resort, etc.). Comparing forecasting methods based on different hotel types can create some bias in the results and conclusions.

4.1 *Theoretical Implications*

The study makes a theoretical contribution by conducting a systematic literature review to identify the current state of the art of AI methods for forecasting hotel demand. It provides insights into the effectiveness of AI-based solutions, including machine learning (ML) and artificial neural networks (ANNs), for demand forecasting in the hotel industry. The study highlights AI technology's potential to significantly improve forecasting accuracy and facilitate data-driven decisions for hotel management. By comparing traditional forecasting models with AI-based algorithms, the study sheds light on their advantages, disadvantages, and potential for improving forecasting accuracy in the hospitality industry. The study emphasises the importance of incorporating accurate hotel demand forecasts into revenue management (RM) to make better pricing decisions, leading to increased profits and a competitive advantage in the market. Overall, the study contributes to the theoretical understanding of AI-based demand forecasting in the hotel industry, highlighting the potential benefits and challenges associated with the use of AI techniques. It also suggests future research directions to enhance further the effectiveness of AI techniques in revenue management and forecasting in the hospitality industry.

4.2 Practical Implications

Good accuracy demand forecasting for RM is vital for all practitioners, scholars, and researchers. This result implies a daily decision driver for hotel managers and RM teams. More accurate demand forecasts support better decisions that improve both operational and financial success in the hotel business. An accurate forecasting model is necessary in a dynamic and competitive distribution environment where dynamic pricing relies on daily decision-making. Conversely, an accurate forecast of the occupancy rate allows hotel managers to plan better issues such as inventory, supplies, and workforce(Caicedo-Torres & Payares, 2016). The results reveal that AI-based forecasting models tend to outperform traditional models. For this reason, we think that all practitioners, whether they are hotel managers, revenue managers, or revenue management system developers, should move one step ahead and start learning, implementing, and using AI-based forecasting models of hotel demand.

5. Conclusions

Based on the systematic literature review conducted for this study on hotel demand forecasting models and methods employing AI, it can be concluded that AI-based solutions offer promising tools for improving the accuracy of hotel demand forecasting. Combining traditional statistical methods with AI-based approaches can considerably enhance the accuracy of forecasting, allowing hotels' management to make more precise and informed decisions. However, there are still limitations and gaps that require further investigation. The lack of standardisation in data collection and analysis methods across studies is a limitation that makes it difficult to compare their results. In addition, the majority of the reviewed studies concentrate on developed countries and larger hotels. Therefore, the results may not be applicable to small hotels or hotels in developing nations. Future research should concentrate on developing standardised data collection and analysis methods to correctly compare results from various studies. In addition, future research should investigate the applicability and efficacy of AI-based forecasting models in different-sized hotels and in different regions to determine whether the models' applicability is limited. The review also highlighted the need to investigate the effect of external factors, such as macroeconomic indicators and environmental events, on the accuracy of hotel demand forecasting.

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References

Ampountolas, A. (2021). Modeling and forecasting daily hotel demand: a comparison based on SARIMAX, neural networks, and GARCH models. *Forecasting*, 3(3), 580–595. doi.org/10.3390/forecast3030037

Ampountolas, A., & Legg, M. P. (2021). A segmented machine learning modeling approach of social media for predicting occupancy. *International Journal of Contemporary Hospitality Management*, 33(6), 2001–2021. doi.org/10.1108/IJCHM-06-2020-0611

Antonio, N., de Almeida, A., & Nunes, L. (2019). An automated machine learning based decision support system to predict hotel booking cancellations. *Data Science Journal*, 18(1). doi.org/10.5334/dsj-2019-032

Antonio, N., de Almeida, A., & Nunes, L. (2019). Big data in hotel revenue management: exploring cancellation drivers to gain ınsights ınto booking cancellation behavior. *Cornell Hospitality Quarterly*, 60(4), 298–319. doi.org/10.1177/1938965519851466

Bhushan, S. (2021). The impact of artificial intelligence and machine learning on the global economy and its implications for the hospitality sector in India. *Worldwide Hospitality and Tourism Themes*, 13(2), 252–259. doi.org/10.1108/WHATT-09-2020-0116

Bulchand-Gidumal, J. (2020). Impact of artificial ıntelligence in travel, tourism, and hospitality. In *Handbook of e-Tourism* (pp. 1–20). Springer International Publishing. doi.org/10.1007/978-3-030-05324-6_110-1

Caicedo-Torres, W., & Payares, F. (2016). A machine learning model for occupancy rates and demand forecasting in the hospitality ındustry. *In Lecture Notes in Computer Science* (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 10022 LNAI (pp. 201–211). Springer Verlag. doi.org/10.1007/978-3-319-47955-2_17

Chen, S., Ngai, E. W. T., Ku, Y., Xu, Z., Gou, X., & Zhang, C. (2023). Prediction of hotel booking cancellations: Integration of machine learning and probability model based on interpretable feature interaction. *Decision Support Systems*, 170, 113959. doi.org/10.1016/j.dss.2023.113959

Claveria, O., Monte, E., & Torra, S. (2015). A new forecasting approach for the hospitality industry. *International Journal of Contemporary Hospitality Management*, 27(7), 1520–1538. doi.org/10.1108/IJCHM-06-2014-0286

Das, S., Dey, A., Pal, A., & Roy, N. (2015). Applications of artificial ıntelligence in machine learning: review and prospect. *International Journal of Computer Applications*, 115(9), 31–41. doi.org/10.5120/20182-2402

Doborjeh, Z., Hemmington, N., Doborjeh, M., & Kasabov, N. (2022). Artificial intelligence: a systematic review of methods and applications in hospitality and tourism. *International Journal of Contemporary Hospitality Management*, 34(3), 1154–1176. doi.org/10.1108/IJCHM-06-2021-0767

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020 : An R package and shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and open synthesis. *Campbell Systematic Reviews*, 18(2). doi.org/10.1002/cl2.1230

Huang, L., & Zheng, W. (2021). Novel deep learning approach for forecasting daily hotel demand with agglomeration effect. *International Journal of Hospitality Management*, 98. doi.org/10.1016/j.ijhm.2021.103038

Huang, L., & Zheng, W. (2023). Hotel demand forecasting: a comprehensive literature review. *Tourism Review*, 78(1), 218–244. doi.org/10.1108/TR-07-2022-0367

Kaya, K., Yılmaz, Y., Yaslan, Y., Öğüdücü, Ş. G., & Çıngı, F. (2022). Demand forecasting model using hotel clustering findings for hospitality industry. *Information Processing & Management*, 59(1), 102816. doi.org/10.1016/j.ipm.2021.102816

Kaynak, O. (2021). The golden age of Artificial Intelligence. *Discover Artificial Intelligence*, 1(1), 1. doi.org/10.1007/s44163-021-00009-x

Kimes, S. E. (1989a). The basics of yield management. *Cornell Hotel and Restaurant Administration Quarterly*, 30(3), 14–19. doi.org/doi.org/10.1177/0010880489030003

Kimes, S. E. (1989b). Yield management: A tool for capacity-considered service firms. *Journal of Operations Management*, 8(4), 348–363. doi.org/10.1016/0272-6963(89)90035-1

Kimes, S. E., & Chase, R. B. (1998). The strategic levers of yield management. *Journal of Service Research*, 1(2), 156–166. doi.org/10.1177/109467059800100205

Kimes, S. E., & Wirtz, J. (2015). Revenue management: advanced strategies and tools to enhance firm profitability. *Foundations and Trends® in Marketing*, 8(1), 1–68. doi.org/10.1561/1700000037

Klein, R., Koch, S., Steinhardt, C., & Strauss, A. K. (2020). A review of revenue management: Recent generalisations and advances in industry applications. *European Journal of Operational Research*, 284(2), 397–412. doi.org/10.1016/j.ejor.2019.06.034

Koupriouchina, L., Van der Rest, J. P., & Schwartz, Z. (2014). On revenue management and the use of occupancy forecasting error measures. *International Journal of Hospitality Management*, 41, 104–114. doi.org/10.1016/j.ijhm.2014.05.002

Krajcik, V., Novotny, O., Civelek, M. & Semradova Zvolankova, S. (2023). Digital literacy and digital transformation activities of service and manufacturing SMEs. *Journal of Tourism and Services*, 26(14), 242-262. doi:10.29036/jots.v14i26.551

Lieberman, W. H. (2003). Getting the most from revenue management. *Journal of Revenue and Pricing Management*, 2(2), 103–115. doi.org/10.1057/palgrave.rpm.5170055

Lincényi, M.& Bulanda, I. (2022). Use of marketing communication tools in tourism in accommodation facilities during the COVID-19 pandemic. *Journal of Tourism and Services*, 26(14), 25-44. doi:10.29036/jots.v14i26.440

McGill, J. I., & van Ryzin, G. J. (1999). Revenue management: research overview and prospects*.* *Transportation Science*, 33(2), 233–256. doi.org/10.1287/trsc.33.2.233

Nam, K., Dutt, C. S., Chathoth, P., Daghfous, A., & Sajid Khan, & M. (2020). The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges*.* *Electronic Markets*, 31, 553–574. doi.org/10.1007/s12525-020-00442-3/Published

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan: a web and mobile app for systematic reviews. *Systematic Reviews*, 5(1), 210. doi.org/10.1186/s13643-016-0384-4

Pereira, L. N., & Cerqueira, V. (2022). Forecasting hotel demand for revenue management using machine learning regression methods. *Current Issues in Tourism*, 25(17), 2733–2750. doi.org/10.1080/13683500.2021.1999397

Phumchusri, N., & Ungtrakul, P. (2020). Hotel daily demand forecasting for high-frequency and complex seasonality data: a case study in Thailand. *Journal of Revenue and Pricing Management*, 19(1), 8–25. doi.org/10.1057/s41272-019-00221-6

Rajopadhye, M., Ben Ghalia, M., Wang, P. P., Baker, T., & Eister, C. V. (2001). Forecasting uncertain hotel room demand. *Information Sciences*, 132(1–4), 1–11. doi.org/10.1016/S0020-0255(00)00082-7

Rakesh, M. V., Kumar, S. P., Yogitha, & Aishwarya., R. (2022). Hotel booking cancelation prediction using ML algorithms. *Proceedings of the 2nd International Conference on Artificial Intelligence and Smart Energy,* ICAIS 2022, 466–471. doi.org/10.1109/ICAIS53314.2022.9742843

Salamanis, A., Xanthopoulou, G., Kehagias, D., & Tzovaras, D. (2022). LSTM-based deep learning models for long-term tourism demand forecasting. *Electronics*, 11(22), 3681. doi.org/10.3390/electronics11223681

Sánchez, E. C., Sánchez-Medina, A. J., & Pellejero, M. (2020). Identifying critical hotel cancellations using artificial intelligence. *Tourism Management Perspectives*, 35, 100718. doi.org/10.1016/j.tmp.2020.100718

Sánchez-Medina, A. J., & C-Sánchez, E. (2020). Using machine learning and big data for efficient forecasting of hotel booking cancellations. *International Journal of Hospitality Management*, 89, 102546. doi.org/10.1016/j.ijhm.2020.102546

Schwartz, Z., Webb, T., van der Rest, J.-P. I., & Koupriouchina, L. (2021). Enhancing the accuracy of revenue management system forecasts: the impact of machine and human learning on the effectiveness of hotel occupancy forecast combinations across multiple forecasting horizons. *Tourism Economics*, 27(2), 273–291. doi.org/10.1177/1354816619884800

Sheikh, H., Prins, C., & Schrijvers, E. (2023). Artificial ıntelligence: definition and background (pp. 15–41). *Springer, Cham*. doi.org/10.1007/978-3-031-21448-6_2

Ülkü, A. (2023). Artificial intelligence-based large language models and integrity of exams and assignments in higher education: the case of tourism courses. *Tourism & Management Studies*, 19(4), 21-34. https://doi.org/10.18089/tms.2023.1904

Viverit, L., Heo, C. Y., Pereira, L. N., & Tiana, G. (2023a). Application of machine learning to cluster hotel booking curves for hotel demand forecasting. *International Journal of Hospitality Management*, 111, 103455. doi.org/10.1016/j.ijhm.2023.103455

Wang, J., & Duggasani, A. (2020). Forecasting hotel reservations with long short-term memory-based recurrent neural networks. *International Journal of Data Science and Analytics*, 9(1), 77–94. doi.org/10.1007/s41060-018-0162-6

Webb, T., Schwartz, Z., Xiang, Z., & Singal, M. (2020). Revenue management forecasting: The resiliency of advanced booking methods given dynamic booking windows. *International Journal of Hospitality Management*, 89, 102590. doi.org/10.1016/j.ijhm.2020.102590

Wirtz, J., Kimes, S. E., Theng, J. H. P., & Patterson, P. (2003). Revenue management: resolving potential customer conflicts. *Journal of Revenue and Pricing Management*, 2(3), 216–226. doi.org/10.1057/palgrave.rpm.5170068

Wu, D.C., Song, H. and Shen, S. (2017). New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 1, pp. 507-529. doi.org/10.1108/IJCHM-05-2015-0249

Wu, D. C., Zhong, S., Qiu, R. T. R., & Wu, J. (2022). Are customer reviews just reviews? Hotel forecasting using sentiment analysis. *Tourism Economics*, 28(3), 795–816. doi.org/10.1177/13548166211049865

Zhang, Q., Qiu, L., Wu, H., Wang, J., & Luo, H. (2019). Deep learning based dynamic pricing model for hotel revenue management. *2019 International Conference on Data Mining Workshops (ICDMW)*, 2019-November, 370–375. doi.org/10.1109/ICDMW.2019.00061