

Choi, Jeong-gil; Zhang, Yi-Wei; Nadzri, Nurulain Izzati Binti Mohd; Baymuminova, Nigora; Xu, Shi-Nyu

Article

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A Review of Forecasting Studies for the Hotel Industry: Focusing on results, contributions and limitations

Jeong-Gil Choi^a, Yi-Wei Zhang^b, Nurulain Izzati Binti Mohd Nadzri^c,
Nigora Baymuminova^{b†}, Shi-Nyu Xu^b

^aDepartment of Hotel Management, School of Kyung Hee University, Seoul, Republic of Korea

^bDepartment of Hotel Management, Graduate School of Kyung Hee University, Seoul, Republic of Korea

^cDepartment of Global Hospitality & Tourism, Graduate School of Kyung Hee University, Seoul, Republic of Korea

ABSTRACT

Purpose: The purpose of this study is to conduct a thorough review of the results, contributions, and limitations of forecasting studies in the hotel industry to uncover how those studies contribute to the body of knowledge and what limitations of those studies should be filled by future studies.

Design/methodology/approach: To uncover the overall trends and evolution of hotel forecasting findings, this study used a systematic literature review approach to ensure the strictness and transparency of the review process. To select a paper to be reviewed, two main review processes including keyword searching and citation counts of each paper were conducted. To assure the rigor of our first two procedures, this study took further steps including cross-checking the results of those studies and calculating the average citation per year of the selected studies. The selected papers were analyzed based upon their forecasting areas, the contribution of each paper by using citation score, frequency of using methodology or techniques, demographic characteristics of authors, and major trends of the forecasting studies.

Findings: This research has compiled a list of the most cited papers, as well as the average number of citations per year, the top list of the most used nations and subject areas which manifested the contribution to the body of literature in this study.

Research limitations/implications: Future research should consider using other platforms such as Web of Science (WoS) or Scopus to emphasize more the impact and value of the literature study. The outcome of this study will help other researchers to have a better understanding of the used models in forecasting the industry as well as to decipher the most and the least studied research areas in the forecasting hotel industry.

Originality/value: This study explored the overall development, contributions, and limitations of forecasting studies in the hospitality industry in an updated, thorough literature analysis. The themes and types of research that have already been studied can be seen by the researchers, as well as those that have not yet been explored.

Keywords: Review, Forecasting studies, Hotel industry

I. Introduction

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† Nigora Baymuminova

E-mail: nigorabay1998@gmail.com

The process of projecting or predicting actual data
for a future period or scenario is known as forecasting

(Otudi & Almaktoom, 2021). The success of a business depends on accurate forecasting (Wang, 2021). For instance, according to Wu et al. (2021), hotel revenue management relies heavily on demand forecasting. In terms of pricing and operation tactics, accurate demand predictions were the basis on which the tourism and hotel-related business choices were established (Wu et al., 2017). Forecasting is indeed an important aspect of practically every business, whether it's forecasting future demand, sales, or production (Klimberg et al., 2010).

Because of the importance of forecasting in the business, many types of research on this subject have been conducted to provide some grasp information or tools to use. There is no doubt that most of the published literature contributes to our body of knowledge and thus contributes to the progress of the business in practice. However, it is also true that not all published literature has value to be cited. Thus, this study raised questions about the significance of those published studies. Have those studies ever been conducted in the right direction and have those studies ever contributed to the industry? Are there any limitations to be filled?

There were some researchers focused on the published papers on forecasting in the hospitality and tourism industry by reviewing the literature (Choi et al., 2022; Ghalekhondabi et al., 2019; Goh & Law, 2011; Jiao & Chen, 2019; Li & Jiao, 2020; Lin & Song, 2015; Li & Wu, 2019; Prilistya et al., 2020; Song et al., 2019; Wu et al., 2017). For example, Wu et al. (2017) reviewed studies published from 2007 to 2015 on tourism and hotel demand modelling and forecasting by using journals from the science citation index and the social sciences citation index. The number of research focused on hotel demand is lower than those focused on tourism demand, according to this assessment. In addition, new trends in tourist and hotel demand modelling and forecasting were identified in the study. Another study by Prilistya et al. (2020) reviewed papers published from 2017 to 2019. They focused on 21 studies in tourism demand forecasts to give an organized analysis and identified certain remaining difficulties to be tackled. Recently,

a study by Choi et al. (2022) examined restaurant forecasting studies through a comprehensive assessment of 29 studies published between 1990 and 2021, discussing their strengths and limitations as well as suggested future research topics.

Even though these prior studies discussed the research trends and provided suggestions for further studies for forecasting topics, these studies only focused on the tourism and restaurant sectors and did not focus on whether there are any disparities in research trends and discoveries. In addition, prior research review papers mainly focused on statistical analysis including numbers of the specific method used in, a comparison of the usefulness of the methods. There was no explanation for their results, inputs of those studies and limitations to be filled by future studies. Therefore, it is very necessary to discover how those studies contribute to the body of knowledge and what limitations of those studies should be filled by future studies. The purpose of this paper is to fill the gap by doing a complete assessment of published papers' contributions and limitations. The result of this study is likely to help other research academics to have a better understanding of this topic and future studies in the context of forecasting the hotel industry.

II. Methodology

A. Key Literature Selection

It was vital to use a systematic literature review approach to ensure the strictness and transparency of this study's review process to uncover the overall trends and evolution of hotel forecasting findings. The advantage of the systematic literature review is that it offers clear and explicit procedures for researchers to find and evaluate the body of research relevant to a certain research issue (Tian et al., 2018). The following three processes comprised our data collection procedure. Firstly, Since the most prevalent data collection method for review papers has been keyword searching (Kim et al., 2018), this study

conducted keyword searching for the hotel forecasting studies in the major academic databases. In Google Scholar, this study searched for forecasting research using phrases like 'forecast' and 'hotel'. A total of 128,000 studies in the hospitality field were found using this search approach.

The second phase entails conducting a thorough review of all research to identify essential literature. A total of 125 forecasting hotel industry research papers from the year 1979 to 2021 were selected. For each research paper, this study calculated the citation counts. The total number of times an article was cited via the search engine was referred to as the citation count (Kim et al., 2018). The result list of Google Scholar displays the citation count for each article (Beel & Gipp, 2009), so this study used this search engine to identify the citation score for each paper. According to Chen & Zhang (2015), one of the most essential indicators for evaluating the impact of studies was the number of citations. This study chose papers that received more citations than the average value which is 28.9 for all research to assess the overall impact of the individual research. It is worth noting that this study also included papers published after 2016 although their citation counts were often low as these articles were published recently. From 125 research papers, this study chose a pool of 77 of the most significant hotel studies research based on this criterion.

To assure the rigor of the first two procedures, this study took further steps including cross-checking the results of those studies and removing 27 papers that have no comments on practical implications, limitations, and proposed studies. From this step, this study chooses 50 key literatures of works. However, since there were studies published in 2021 that do not have citations at all as these papers were recently published so this study calculated the quartile of average citations per year and removed 12 research papers that had a lower percentage of 25% (less than 1.375). Finally, 38 studies were selected as the final choices. Table 1 is the summary of the selected studies based on their citation counts, average citation per year, subject area and first authors' nations.

Table 1. Summary of 38 key forecasting studies on the hotel industry

No	Authors	Title	Subject area	Year	Citation times	Average citations per year	First authors' nations
1	Andrew et al.	Forecasting hotel occupancy rates with time series models: An empirical analysis	Room occupancy rates	1990	78	2.5	USA
2	Schwartz and Hiemstra	Improving the accuracy of hotel reservations forecasting: curves similarity approach	Room occupancy rates	1997	78	3.3	USA
3	Law	Room occupancy rate forecasting: a neural network approach	Room occupancy rates	1998	105	4.6	Hong Kong
4	Choi et al.	Forecasting industry turning points: the US hotel industry cycle model	Cyclical trends in the industry	1999	81	3.7	USA
5	Rajopadhye et al.	Forecasting uncertain hotel room demand	Demand	2001	120	6.0	USA
6	Brannas et al.	A new approach to modelling and forecasting monthly guest nights in hotels	Guest night	2002	100	5.3	Sweden
7	Choi	Developing an economic indicator system (a forecasting technique) for the hotel industry	Cyclical trends in the industry	2003	67	3.7	South Korea

Table 1. Continued

No	Authors	Title	Subject area	Year	Citation times	Average citations per year	First authors' nations
8	Weatherford and Kimes	A comparison of forecasting methods for hotel revenue management	Revenue management	2003	335	18.6	USA
9	Ghahia and Wang	Intelligent system to support judgmental business forecasting: the case of estimating hotel room demand	Demand	2004	69	4.1	USA
10	Law	Initially testing an improved extrapolative hotel room occupancy rate forecasting technique	Room occupancy rates	2004	57	3.4	Hong Kong
11	Schwartz and Cohen	Hotel revenue-management forecasting: Evidence of expert-judgment bias	Revenue management	2004	66	3.9	USA
12	Chen and Kachani	Forecasting and optimisation for hotel revenue management	Revenue management	2007	65	4.6	USA
13	Yüksel	An integrated forecasting approach to hotel demand	Demand	2007	70	5.0	Turkey
14	Wu et al.	Forecasting and evaluating the tourist hotel industry performance in Taiwan based on Grey theory	Cyclical trends in the industry	2008	46	3.5	Taiwan
15	Lim et al.	Forecasting h (m) oteI guest nights in New Zealand	Guest night	2009	71	5.9	New Zealand
16	Morales and Wang	Forecasting cancellation rates for services booking revenue management using data mining	Booking cancellation	2010	87	7.9	United Kingdom
17	Zakhary et al.	Forecasting hotel arrivals and occupancy using Monte Carlo simulation	Room occupancy rates	2011	104	10.4	Egypt
18	Pan et al.	Forecasting hotel room demand using search engine data	Demand	2012	172	19.1	USA
19	Yang et al.	Predicting hotel demand using destination marketing organization's web traffic data	Demand	2014	191	27.3	USA
20	Caicedo-Torres and Payares	A machine learning model for occupancy rates and demand forecasting in the hospitality industry	Room occupancy rates	2016	12	2.4	Columbia
21	Pereira	An introduction to helpful forecasting methods for hotel revenue management	Revenue management	2016	50	10.0	Portugal
22	Schwartz et al.	Hotel daily occupancy forecasting with competitive sets: a recursive algorithm	Room occupancy rates	2016	42	8.4	USA
23	Pan and Yang	Forecasting destination weekly hotel occupancy with big data	Room occupancy rates	2017	125	31.3	USA
24	Sierag et al.	A call for exploratory data analysis in revenue management forecasting: A case study of a small and independent hotel in The Netherlands	Revenue management	2017	6	1.5	Netherlands
25	Zhang et al.	Improving daily occupancy forecasting accuracy for hotels based on EEMD-ARIMA model	Room occupancy rates	2017	22	5.5	China

Table 1. Continued

No	Authors	Title	Subject area	Year	Citation times	Average citations per year	First authors' nations
26	Konarasinghe	Forecasting foreign guest nights in hill country of Sri Lanka	Guest night	2018	6	2.0	Sri Lanka
27	Lee	Modeling and forecasting hotel room demand based on advance booking information	Demand	2018	31	10.3	USA
28	Zhang et al	Weekly hotel occupancy forecasting of a tourism destination	Room occupancy rates	2018	8	2.7	China
29	Aliyev et al.	Development of fuzzy time series model for hotel occupancy forecasting	Room occupancy rates	2019	9	4.5	Turkey
30	Ampountolas	Forecasting hotel demand uncertainty using time series Bayesian VAR models	Room occupancy rates	2019	13	6.5	USA
31	Assaf and Tsionas	Forecasting occupancy rate with Bayesian compression methods	Room occupancy rates	2019	14	7.0	USA
32	Rice et al.	Forecasting campground demand in US national parks	Demand	2019	28	14.0	USA
33	Zhang et al.	Forecasting hotel accommodation demand based on LSTM model incorporating internet search index	Demand	2019	16	8.0	China
34	Fiori and Foroni	Prediction accuracy for reservation-based forecasting methods applied in Revenue Management	Revenue management	2020	10	10.0	Italy
35	Lee et al.	A Machine Learning Approach to Improving Forecasting Accuracy of Hotel Demand: A Comparative Analysis of Neural Networks and Traditional Models	Demand	2020	3	3.0	USA
36	Phumchusri and Ungtrakul	Hotel daily demand forecasting for high-frequency and complex seasonality data: a case study in Thailand	Demand	2020	4	4.0	Thailand
37	Sánchez-Medina and Eleazar	Using machine learning and big data for efficient forecasting of hotel booking cancellations	Booking cancellation	2020	15	15.0	Spain
38	Schwartz et al.	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	Revenue management	2021	5	5.0	USA

B. Classifying Literature and Reviewing Process

To obtain a more targeted focus, this study classified the selected studies into six categories. Those categories were room occupancy rates, revenue management, hotel room demand, guest nights, booking cancellation, and cyclical trends of the industry (macro-level forecasting). Among the 38 articles, 12 articles were on room occupancy rates, 11 focused on demand, seven articles on revenue management, three articles on guest nights, two articles on booking cancellation and three articles regarding cyclical trends in the industry. This study reviewed the selected papers based upon their forecasting areas, the contribution of each paper by using citation score, frequency of using methodology or techniques, demographic characteristics of authors, and major trends of the forecasting studies.

III. Hotel Industry Forecasting

A. Studies on Forecasting Room Occupancy Rates

An earlier study by Andrew et al. (1990) which has been cited 78 times, investigated the Box- Jenkins model (BJM) and exponential smoothing model (ESM) to predict the occupancy rate. Based on their studies, both models exhibit a high level of predicted accuracy when fitted and tested using actual monthly occupancy rates. Thus, these models should be highly beneficial in actual hotel operations and other applications such as yield management because they were quite simple to implement. However, the data only included one hotel. Research by Schwartz & Hiemstra, (1997) which has been cited 63 times concentrated on the form of previous booking curves to construct an extrapolative forecasting model and compare four models which were the curves similarity model, the stepwise autoregression model (AR), high order polynomial model (HOPM) and weighted average of AR and HOPM predictions model (AR&HOPM) to predict the daily occupancy levels in a hotel. The curves

similarity model was significantly more accurate than the three benchmark models examined, according to the data from the result. These findings were noteworthy both statistically and practically. Nevertheless, the absence of a room variable rate was the limitation in all four models. A study which has already been cited 105 times by Law (1998) used artificial neural network (ANN), multiple regression and Naïve extrapolation to predict the occupancy room rate. The use of neural networks to estimate room occupancy rates surpasses multiple regression and Naïve extrapolation. This study demonstrated the viability of implementing a neural network forecasting model in a real-world hotel setting in Hong Kong. However, more dependent variables were needed to forecast more efficiently.

A study by Law (2004) that has been cited 57 times, proposed a new method for calculating future hotel occupancy rates by using the improved extrapolative room occupancy rate forecasting model (IERORFM) which was a new time-series model. The result indicated that IERORFM can anticipate with more accuracy than other comparable time-series forecasting models. However, it is unclear whether the technique can handle complex series. While the empirical results were promising, more research is needed to determine the model's general applicability. Zakhary et al. (2011) used the Monte Carlo simulation approach with other five comparative models from the time-series and pick-up approach to predict hotel arrivals and occupancy. For both arrival forecasting and occupancy challenges, as well as the daily and weekly forecasting difficulties, the suggested Monte Carlo model outperformed all the competing models. The proposed Monte Carlo model not only outperformed other competing forecasting models in terms of forecasting accuracy but also has other useful features, such as the ability to obtain densities for any variable of interest. This study has been cited 104 times.

Caicedo-Torres & Payares (2016) examined several machine learning techniques to construct models to forecast daily occupancy. Results proved that the ridge regression model with quadratic features outperforms the other models tested on the reservations data set. The findings were encouraging indicating that machine

learning algorithms can be used to help handle problems like occupancy rates and demand predictions. This method required little statistical expertise from the hotel staff which was the limitation of this study. This research paper has been cited 12 times. To forecast hotel daily occupancy, a study which has been cited 42 times by Schwartz et al. (2016) used a genetic algorithm and simple linear regression model. The results of the simulated scenario analysis, as well as the empirical tests of the field study data, all support the idea that this unique approach was most likely to improve the accuracy of hotel daily occupancies, and hence improve revenue management practice performance. Although implementing the forecasting paradigm may be viable, further research is required before it is clear how to do so.

The paper of Pan & Yang (2017) used autoregressive moving average exogenous (ARMAX) and Markov switching dynamic regression (MSDR) to determine the most effective model strategy for projecting weekly hotel occupancy with big data sources. In terms of accurate predictions, the results revealed that ARMAX models outperformed MSDR models. Nevertheless, there was a limitation where the amount of big data that was chosen was limited. This study has been cited 125 times by other research papers. A study from Zhang et al. (2017) which has been cited 22 times by other researchers, used autoregressive integrated moving average (ARIMA) and ensemble empirical mode decomposition (EEMD) as the models for forecasting the occupancy rates. The result found that EEMD-ARIMA outperformed the common ARIMA method in terms of forecasting accuracy, especially for short-term forecasting. Thus, the EEMD-ARIMA model was suitable for predicting daily occupancy in individual hotels. However, the model might be difficult for those unfamiliar with it.

Similarly, another research by Zhang et al. (2018) also used the ARIMA and EEMD with intrinsic mode functions (IMFs) for weekly hotel occupancy forecasting. The result showed that the EEMD-ARIMA model has a higher impact on more stable time series. This study demonstrated that the modified EEMD-ARIMA model delivers more accurate forecasting results with

fewer standard deviations than the EEMD-ARIMA model for medium-term forecasting (26 weeks) of hotel occupancy of a tourism destination. However, in the short term, the EEMD-ARIMA model failed to predict accurately. This study has been cited eight times. The research paper from Aliyev et al. (2019) which has been cited nine times, used the fuzzy time-series approach which was developed by analyzing 40 months' time-series data and applying fuzzy c-means clustering algorithm to forecast the hotel occupancy. Intensive computer simulations have revealed that a fuzzy model with seven clusters and four inputs can deliver the best forecasting answer. Thus, computer investigations have shown that this model was more accurate for the problem of hotel occupancy. Although this study had no limitations, it would be ideal if the researchers could go into further detail about the implications and suggestions for improvement for future studies. To forecast the occupancy rate, a study from Assaf & Tsionas (2019) which has been cited 14 times, introduced two novel nonlinear compressed Vector autoregression (VARs) with ANN and a non-parametric VAR based on priors from the Gaussian Process was also used. The empirical results show that the new compressed VARs outperformed the alternative models in almost every forecast horizon from 1 to 36 months and that their accuracy was maintained throughout nearly all forecast horizons. However, other factors that may affect the occupancy rate of hotels within the area were not taken into account in the study.

Overall, most of the studies in this section compared each model to find the best forecasting model. Besides that, most of the studies were using time-series and econometrics models for almost two decades which showed that these models were still dominating in forecasting room occupancy rates studies. The study by Pan & Yang (2017) had the most average citation value per year which was 31.2 times compared to all selected studies which proves the individual impact in terms of the amount of citation per year.

B. Studies on Forecasting Demands

Rajopadhye et al. (2001) which has been cited by 120 times used the Holt-Winter method & Monte Carlo Simulation to forecast uncertain hotel demand. Although neither the long-term forecast (LTF) nor the short-term forecast (STF) can provide a credible estimate of demand on their own, a weighted aggregate appeared to be useful in some instances. However, this empirical research did not support the model and the study's flaw was that it was based on the analysis of simulated cancellations and simulated arrivals. Ghahia & Wang (2004) used the intelligent system to support judgmental forecast and knowledge (IS-JFK) and fuzzy IF-THEN rules to estimate the hotel room demand. The usefulness of IS-JFK has been proved through problem scenarios and simulated results based on actual hotel data. However, to make IS-JFK mature and implementable in many sorts of hotel properties more study is needed as this study focused only on hotels catering to business travellers. This study had 69 times cite score.

To see demand changes in the hotel industry, Yüksel (2007) used two Delphi-based panels which were the variables determination panel and the environmental monitoring panel as well as the analytical hierarchy process (AHP). Even though the adjustment panel seems to get close to the actual figures, the process should be performed numerous times with actual department managers as panelists. Nevertheless, flexibility, dynamism, openness, understandability, and ease of application were some of the benefits of an AHP-based adjustment approach. However, the use of classic forecasting adjustment principles with paired comparisons on a nine-point scale presents certain challenges. This study has been cited 70 times. The study from Pan et al. (2012) that has been cited 172 times employed three autoregressive-moving-average (ARMA) family models and their ARMAX counterparts to foresee the demand for hotel rooms by using the search engine data. The study revealed that the significance of search engine data in supporting accurate demand prediction for hotel rooms was validated when all three ARMAX models regularly outperformed their ARMA equivalents. However, this study only focused on one tourist city

with five specific tourism-related queries. To forecast hotel demand for the destination using web traffic volume data of destination marketing organization (DMO), Yang et al. (2014) used ARMA, autoregressive moving average exogenous (ARMAX) and threshold autoregressive (TAR) model. The result showed that the ARMAX model was particularly useful as the hotel demand was strong. The study also demonstrated that web traffic data can be used to forecast hotel room demand in the short term. This study has been cited by 191 times so far.

The study from Lee (2018) that has been cited 31 times examined the key features of booking arrivals and propose a better forecasting method based on stochastic models of booking arrivals by utilizing the non-homogeneous Poisson process (NHPP), Multivariate distributions and Poisson mixture models. Poisson mixture models outperformed the benchmark model as well as the typical NHPP model, based on estimation results on actual hotel reservation data. Thus, the empirical investigation indicated that utilizing inter-temporal correlations in the dynamic updating method could greatly enhance the precision of short-term forecasting of hotel room demand. However, arrival behaviours may vary depending on the visiting patterns of each industry in the issue. The study from Ampountolas, (2019) which has been cited 13 times, applied the Bayesian technique to estimate a probability distribution of projected hotel demand uncertainty using the VAR model and vector error correction model (VECM). The results were assessed using a new metric for forecasting accuracy, mean arctangent absolute percentage error (MAAPE). The forecast results confirmed the Bayesian model's ability to increase forecasting performance significantly. In terms of error rates, the findings implied that MAAPE exceeds other available accuracy measures. However, there were limitations where the data set was limited and MAAPE was a new measure that will require further research utilizing various forecasting methods.

The next study that has been cited 28 times by Rice et al. (2019) forecasted demand for campgrounds in US national parks by using time-series models and neural network autoregression (NNAR) as an

additional machine learning strategy and the k-nearest neighbours (KNN) algorithm was introduced. According to the findings of this study, seasonal autoregressive integrated moving average (SARIMA) was the most cost-effective and practical solution. However, the dataset was rather limited which only includes data for campsite bookings made through recreation.gov or for same-day reservations entered by campground management. A study by Zhang et al. (2019) which has been cited 16 times, developed a deep learning framework to address the problem of hotel demand prediction. Overall, the long short-term memory model (LSTM) model better fitted the dynamic characteristics of the passenger flow, while all of the benchmark models had a slightly poor fit performance. In comparison to benchmark models, the experimental results indicated that LSTM increased model predictive ability to varying degrees demonstrated satisfactory prediction ability and powerful generalization, and could also imitate the dynamic characteristics of the passenger flow. Other sources of information representing the dynamic nature of hotel lodging requests will need to be expanded in future studies.

Lee et al. (2020) compared the predicting capabilities of neural networks which were backpropagation multilayer perceptron (MLP) models against those of traditional approaches that can predict daily hotel demand. The neural network technique outperforms standard forecasting models, including advanced time-series models. As a result, neural network models may be able to capture non-linear and complicated correlations concealed in everyday hotel demand with greater flexibility. However, daily demand behaviour may be a more complicated phenomenon than a single sort of data can capture. Therefore, future research could involve a comparison of alternative neural network topologies. This research paper has been cited three times. Phumchusri and Ungtrakul (2020) used both time-series and machine learning methods to forecast models for a case study of a four-star hotel in Phuket, Thailand. The results showed that ANN outperforms other models, with a MAPE of 8.96%. However, the lack of daily independent data was the primary weakness of this study. This study

has been cited four times.

A crucial component of managing hotel income is demand forecasting Lee (2018). Overall, forecasting methods such as time series and econometrics were still the most used method used for forecasting demand studies. It was also worth noting that the artificial intelligence based models (AI) such as ANN and MLP as well as LSTM models were also being vastly used by researchers as this model had been showing positive results in the forecasting hotel demand study such as the study by (Phumchusri & Ungtrakul, 2020; Zhang et al., 2019). Even though IS-JFK and Poisson mixture models were not the most selected models in this section, it is recommended for future studies to explore more about these models as both models also gave encouraging results. The study from Yang et al. (2014) received the most citation count which showed its impact than other studies in the forecasting hotel demand section.

C. Studies on Forecasting Revenue Management

The research of Weatherford and Kimes (2003) compared the forecasting models for hotel revenue management to determine the most accurate method by using the data from Choice Hotels and Marriott Hotels. Moving average, univariate: exponential smoothing, pickup and regression models were used for this research. The pickup methods and regression yielded the lowest error from the preliminary results utilizing the Choice Hotel data. The most robust models were exponential smoothing, pickup, and moving average models, according to a more in-depth analysis using Marriott Hotel data. Hotels can use their revenue management systems more effectively and profitably if they utilized these models. However, the study of combination forecasts utilizing the five robust approaches outlined here should be done in the future to discover any extra forecast accuracy. This study has been cited the most from other selected research papers in this study which was 335 times. Mean absolute deviation (MAD) was used by Schwartz and Cohen (2004) to forecast hotel revenue management

with expert-judgement bias. The result showed that the managers who used a slow computer and an interactive chart made the most changes. Thus, the findings shed insight on the impact of computer-user interface design on decision-maker performance. However, this study included only a small number of participants and did not systematically examine how the interface design would influence the revenue manager's decision. This study has been cited 66 times by other studies.

Chen and Kachani (2007) used Classical and Advanced Pickup, Linear Regression, Simple Exponential Smoothing with $\alpha = 0.35$, Advanced Pickup + Exponential Smoothing with $\alpha = 0.15$ as well as Advanced Pickup + Exponential Smoothing with $\alpha = 0.35$ to forecast and optimization for hotel revenue management in their study. According to the result, simple exponential smoothing proved to be the most reliable strategy in terms of predicting accuracy and optimization performance. However, to further test the use of partial versus full history for hotel projections, more study with large data is required and more advanced models such as multiple regression models might help to get more precise forecasts. This research paper has been cited 65 times. The study conducted by Pereira (2016) which has been cited by other studies 50 times, used various methods to provide new time-series forecasting methods that can be used to predict hotel revenue management. Instead of utilizing the naive technique, the author suggested using the model that consists of Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS) and a combination of the TBATS and the double-seasonal holt-winters (DSHW) model to develop disaggregated projections of the hotel daily occupancy over a forecast horizon up to eight weeks ahead, which this model also outperformed the majority of the other models based on an in-depth analysis of the empirical research results. Thus, the modelling framework presented here was a promising tool to implement in revenue management systems' forecasting modules. However, further empirical evidence about the framework's applicability and correctness would be beneficial to all parties.

Sierag et al. (2017) used the nonhomogeneous Poisson method to demonstrate how a real-life hotel can get new forecasting insights by investigating and analyzing data from its revenue management system. This study provided evidence for the nonhomogeneous Poisson structure of the probability distribution that demand follows which was a critical feature for forecasting modelling that was commonly assumed but not described in the hotel forecasting literature. However, this study was not without limitations as the information was gathered only from a single hotel. This study has been cited six times in other research papers. A study by Fiori and Foroni (2020) that has been cited 10 times, proposed a stochastic framework for a class of pickup forecasting methods by using simple reservation-based methods (stochastic pickup). The result showed that the proposed prediction intervals (PIs) appeared to be well-calibrated and narrow enough to provide meaningful data to hotel executives. However, the results of this empirical investigation were restricted to the current data set which was the limitation.

The article from Schwartz et al. (2021) examined the interplay between two established approaches of accuracy enhancement which were forecast combinations and learning, in the context of hotel revenue management systems based on three distinct investigations. The first study was using a typical academic classroom setting associated with a novice-forecasting context while the second study was a professional setting using estimates from a single hotel's revenue management team during a two-year timeframe and the third was the main study that focused on examining a massive data collection that includes 900 hotels and 694 forecasters, yielding 1322 distinct hotel employee pairs. The first two preliminary studies support the notion that as learning occurs, the effectiveness of forecast combination in generating more accurate forecasts was reduced whereas the main study's findings indicate that learning has a positive effect on longer forecasting horizons but the learning does not affect the effectiveness of forecast combinations in short-term horizons (21 days or less). Thus, the result of this has significant ramifications for hotel revenue management. However, while the data suppliers

claimed that the forecasting algorithms utilized have a learning component, this study was unable to validate that aspect since the data sources refused to reveal essential details which was the limitation of this study. This research paper has been cited five times by other researchers.

Among other studies in all subject areas, the study from Weatherford and Kimes (2003) received the most citation count which was 335 times which also proves the impact of the individual study. Overall, the method used was mostly time-series and econometrics models. This showed that compared to other models, time-series and econometrics were indeed the best choices to do a forecasting study. Besides that, the study by Schwartz and Cohen (2004) was the only study that used both quantitative and expert judgements methods to forecast revenue management.

D. Studies on Forecasting Guest Night

The first study was by Brannas et al. (2002) developed an integer-valued moving average model by the cross-sectional and temporal aggregation to forecast monthly guest nights in hotels in Sweden & Norway. Both the mean check-in and the check-out probability indicated notable seasonal patterns, according to this study's findings. Thus, in terms of goodness-of-fit, models based on differenced series were recommended. However, future study is suggested to use a larger scale as this study indicated there was a limited comparison with an ARIMA model. This study has been cited 100 times by other studies. The next study was by Lim et al. (2009) which has been cited 71 times, forecasted the guest night in hotels and motels in New Zealand. For this study, the researchers used The Holt-Winters and Box-Jenkins ARMA models to forecast the guest night. The results of this study demonstrate that relatively basic models, such as the Holt-Winters approach and ARMA, can forecast better than the statistically complex box-Jenkins seasonal ARMA model. However, future research is needed to know whether it makes sense to aggregate combined forecasts of a variable that has been disputed.

Konarasinghe (2018) used the SARIMA and other time-series models for forecasting guest nights. The SARIMA strategy was highly successful in this research, while the other approaches were not. The study's findings demonstrated that SARIMA was capable of estimating occupancy visitor nights in Sri Lanka's Hill Country. A wave-like pattern, on the other hand, may contain both seasonal and cyclical variations which the SARIMA was unable to distinguish which was the limitation of this study. Thus, this study suggested that the Circular Model be tested using de-trended data to determine if it improves predicting. This research paper has been cited eight times.

The majority of these studies in the forecasting guest night section utilized the time-series models and these models showed promising results in each study. According to Lim (2009), the industry can benefit from using the simple time-series model such as The Holt-Winters as the forecasts can be obtained at a low cost for effective planning because of their substantial practical value and utility. The study from Brannas et al. (2002) has been cited 100 times by other studies in this subject area.

E. Studies on Forecasting Booking Cancellation

The study that has been cited 87 times by Morales and Wang (2010) predicted cancellation rates for service booking revenue management by using the passenger name record (PNR) data mining model. According to the result of this study, PNR data mining models were far more accurate than seasonal average cancellation (SAVG) and average cancellation (AVG), lowering error by more than 20% on average over the seven-time points. The outcomes of this study, which used data mining to forecast cancellation rates using two-class probability estimate methods, were encouraging. Nevertheless, this was a difficult task because the relative relevance of variables varies over time, therefore the analysis of cancellation drivers must be coordinated across different periods along the booking horizon. Machine Learning techniques with ANN and genetic algorithm (GA) were used

to predict hotel cancellations more accurately for the recent study by Sánchez-Medina and C-Sánchez (2020). The result of this study showed that machine learning approaches such as ANN optimized with GA that was used in this case resulted in a cancellation rate of up to 98%. However, in terms of the proposed methodology's limitations, due to forecasts being based on historical data, abrupt changes in the market may not be reflected in the model initially. This study has been cited 15 times by other studies.

In general, the methods that were used in these studies should be implemented by the revenue managers as the result to forecast cancellation rates were encouraging. These studies emphasized how the models used can also help the management to obtain information ahead of time, allowing them to develop suitable overbooking policies and cancellation policies as well as to assist in gaining a better understanding of the reasons for cancellation.

F. Studies on Forecasting Cyclical Trends in the Industry

Choi et al. (1999) focused on forecasting industry turning points in the US hotel industry by using the cycle study model. The result of this study showed that unless there were significant changes in the trends, the next peak will be in 1996 or 1997. Once it reached its peak, the hotel sector began to decline rapidly and the general business cycles did not provide a clue for the hotel industry cycle. Furthermore, the findings reveal that every four or five years, the hotel industry has a significant increase (boom) and the growth cycle was a short-term change in the hotel industry's overall performance. Thus, the findings of this study give practitioners and researchers in the hotel business important guidelines for getting the most out of the cycle study. Nevertheless, there was a limitation in this study no matter which technique was utilized, there can be no guarantee of an accurate prognosis. Therefore, the findings of this study must be interpreted in conjunction with other data and with a thorough understanding of the business context.

This study has been cited 81 times by other researchers. Choi (2003) aimed to create an economic indicator system for the hotel business in the United States to forecast the industry's growth and turning points by using the national bureau of economic research (NBER) turning point criteria and statistical correlation method. The result of the study showed that with a 67% accuracy, the leading indicator system predicted the peaks of the hotel growth cycle by one year and the lagging indicator system also performed well. The indicator system's performance revealed that it has a lot of potential as a forecasting approach. However, the study was not without limitations where "random" or short-lived changes in economic mobility might make cyclical variations very sensitive. This research paper has been cited 67 times.

In the next study that has been cited 46 times, Wu et al. (2008) used the grey system theory to forecast and evaluate the tourist hotel industry. The results of this study show that the four-point Grey model (1,1) was the best model for predicting future output value. Thus, this research exposes the best hotels' different competitive advantages and methods, such as their ideal location, higher price, and higher occupancy rate. However, there was still a limitation where the capacity to obtain secondary data limits indicator selection, which affects total performance ratings and the importance of government policy was not considered in this study.

Overall, this section focused on the cyclical trends of the hotel industry as a whole such as forecasting the turning point of the hotel industry and evaluating the tourist hotel industry. Besides that, all of these studies highlighted how the models used can help lodging businesses in terms of evaluating the performance of tourist hotels, business important guidelines for getting the most out of the cycle study and enabling to monitor as well as locate the elements linked with hotel business cycle turning points. Furthermore, as all of these research papers' citation counts were above the average value, it showed how impactful all these research papers were to other researchers.

IV. Conclusion and Discussion

In this study, prior research papers in hotel forecasting were categorized and reviewed according to forecasting areas to characterize the development of forecasting studies in the hotel industry. By reviewing 38 pieces of literature regarding hotel industry forecasting, this study summarized the overall selected research papers from the year 1990 to 2021 based on their results, contributions and limitations. Firstly, there was a trend that appeared among all the research papers such as to search for the best forecasting model in their studies. Secondly, to improve the prediction of accuracy, many scholars examined various forecasting models to come up with new forecasting methods. Next, more combined and hybrid models were used by the researchers to ensure an excellent result. Throughout the whole papers that were reviewed, even though models such as the time-series and econometrics were the most used model for forecast study but other models such as the AI-based models like ANN and SVR, the LSTM models are worth to be noted as well for future studies as these models showed a promising positive result. Law (1998) mentioned that it would be worthwhile to investigate a neural network such as ANN to forecast room occupancy rates with such high accuracy in locations with nonstable or low room occupancy rates. Not only that, a more recent study from Phumchusri and Ungtrakul (2020) proved that ANN could produce high levels of forecasting accuracy and outperformed other time series models and causal models which this finding can be applied to the case study of hotel's future planning for the expected number of left-over

rooms, allowing them to more efficiently distribute to their discounted online travel agent. In terms of booking cancellation as well, ANN optimized with GA resulted in a prediction of a 98% cancellation rate. This proposed methodology enabled the researchers to determine not just cancellation rates, but also which customers were most likely to cancel. Future studies should consider machine learning models, as well as the results from the selected studies, which showed that machine learning techniques may be utilized to aid with issues like occupancy rates and demand forecasts, which was encouraging as well.

Nevertheless, even though these selected studies showed how their selected models were giving mostly positive and promising results but there were still limitations that were found in these studies so more future studies need to be done. For example, inventing a new method might be a challenging task as more and more research is needed and some of the models that were utilized might be difficult for those who were unfamiliar with models thus limiting their adoption and usage.

The citation times were utilized as a barometer of each paper's contribution to the body of literature in this study. Table 2 showed the top five research papers with the most citations. These articles were published between 2003 and 2017, and the most cited article was by Weatherford and Kimes (2003) article regarding the comparison of forecasting methods for hotel revenue management with a total of 335 citations. The second article was from Yang et al. (2014) with a total of 191 citations on predicting hotel demand. The next article was followed by the study regarding forecasting hotel room demand by Pan et al. (2012) which had the citation 172 times and Pan and Yang

Table 2. Top 5 key works of literature sorted by citation times

No.	Author	Title	Year	Citation times
1	Weatherford and Kimes	A comparison of forecasting methods for hotel revenue management	2003	335
2	Yang et al.	Predicting hotel demand using destination marketing organization's web traffic data	2014	191
3	Pan et al.	Forecasting hotel room demand using search engine data	2012	172
4	Pan and Yang	Forecasting destination weekly hotel occupancy with big data	2017	125
5	Law	Room occupancy rate forecasting: a neural network approach	1998	105

(2017) on forecasting destination weekly hotel occupancy with 125 citations in the fourth place. The fifth place was the paper published by Law (1998) regarding room occupancy rate forecasting using a neural network approach which has been cited 105 times.

Besides that, the average citation times each year must be examined. This was because each publication was published in a different year, meaning that each time was different. As a result, disclosing the average citation times articulates each paper's true contribution and demonstrates the significance of the article's influence as an individual study. However, many of the studies that were published in 2021 do not have citations since these papers were recently published thus many studies were removed due to this reason when the quartile of the average citation per year was calculated. Table 3 showed the top five works of literature that were ranked based on their average citation per year. The study from Pan and Yang (2017) has the most average citation per year followed by the study from Yang et al. (2014). Next was the paper by Pan et al. (2012) in third place and Weatherford and Kimes (2003) in fourth place. The fifth place goes to the study by Sánchez-Medina & C-Sánchez (2020). It was worth noting as well that the studies from first to fourth place were also ranked in the top five most-cited research papers.

Furthermore, by reviewing all of these studies, most of the first author's nation was from the United States of America (USA) which was 18 articles, followed by China which were three articles and Turkey as well as Hong Kong with a total of two articles. As for the rest of the selected studies, each

country published only one research paper. It can be shown that the USA was the country that published the most and the earliest articles on hotel forecasting, indicating the prominence of American academic study. Table 4 summarizes all the first-author nations in the selected studies.

Table 5 showed the top ranking of the research papers in each subject that has the most citation counts. The table shows that the study from the subject area of revenue management was ranked first place, demand in second place and followed room occupancy rates. Next, in fourth place was guest night followed by booking cancellation and lastly cyclical trends of the industry. Furthermore, it can be seen from Table 5 that Revenue Management was the most interesting research area in predicting future trends of the hotel industry among scholars than five other subject areas namely Demand, Room Occupancy Rates, Guest Night, Booking Cancellation and Cyclical Trends of the Industry.

The outcomes of this study can help to expand hotel forecasting research, giving researchers and hotel managers more options to solve problems that will occur which were related to the subject area. This study will help other researchers better understand which subject area or any models remain unexamined by looking at the overall result, contributions, and limitations of forecasting studies in the hotel industry.

Table 3. Top 5 key works of literature sorted by average cited per year

No	Author	Title	Year	Average citation per year
1	Pan and Yang	Forecasting destination weekly hotel occupancy with big data	2017	31.25
2	Yang et al.	Predicting hotel demand using destination marketing organization's web traffic data	2014	27.29
3	Pan et al.	Forecasting hotel room demand using search engine data	2012	19.11
4	Weatherford and Kimes	A comparison of forecasting methods for hotel revenue management	2003	18.61
5	Sánchez-Medina and Eleazar	Using machine learning and big data for efficient forecasting of hotel booking cancellations	2020	15.00

Table 4. Number of key works of literature sorted by first authors' nations

Nations	Number of articles	Authors and years
USA	18	Ampountolas, 2019; Andrew et al., 1990; Assaf & Tsionas, 2019; Chen and Kachani, 2007; Choi et al., 1999; Ghalia and Wang, 2004; Lee, 2018; Lee et al., 2020; Pan et al., 2012; Pan and Yang, 2017; Rajopadhye et al., 2001; Rice et al., 2019; Schwartz & Cohen, 2004; Schwartz et al., 2016; Schwartz et al., 2021; Schwartz and Hiemstra, 1997; Weatherford & Kimes, 2003; Yang et al., 2014
China	3	Zhang et al., 2017; Zhang et al., 2018; Zhang et al., 2019
Turkey	2	Aliyev et al., 2019; Yüksel, 2007
Hong Kong	2	Law, 1998; 2004
Spain	1	Sánchez-Medina & Eleazar 2020
Sri Lanka	1	Konarasinghe, 2018
Italy	1	Fiori & Foroni, 2020
South Korea	1	Choi, 2003
United Kingdom	1	Morales & Wang, 2010
New Zealand	1	Lim et al., 2009
Netherlands	1	Sierag et al., 2017
Columbia	1	Caicedo-Torres & Payares, 2016
Egypt	1	Zakhary et al., 2011
Portugal	1	Pereira, 2016
Sweden	1	Brannas et al., 2002
Thailand	1	Phumchusri & Ungtrakul, 2020
Taiwan	1	Wu et al., 2008

Table 5. Top key works of literature sorted by each subject area

No	Authors	Title	Subject area	Year	Citation times
1	Weatherford and Kimes	A comparison of forecasting methods for hotel revenue management	Revenue management	2003	335
2	Yang et al.	Predicting hotel demand using destination marketing organization's web traffic data	Demand	2014	191
3	Pan and Yang	Forecasting destination weekly hotel occupancy with big data	Room occupancy rates	2017	125
4	Brannas et al.	A new approach to modelling and forecasting monthly guest nights in hotels	Guest night	2002	100
5	Morales and Wang	Forecasting cancellation rates for services booking revenue management using data mining	Booking cancellation	2010	87
6	Choi et al.	Forecasting industry turning points: the US hotel industry cycle model	Cyclical trends of the industry	1999	81

V. Limitation and Further Research

The limitation of this study is using citation counts

generated by Google Scholars only. Future research should consider using other platforms such as Web of Science (WoS) or Scopus to emphasize more the impact and value of the literature study. Future studies

should focus on investigating the least studied subject area such as Cyclical Trends of the Industry to have a better contribution to the body of knowledge of literature.

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