6 FORECASTING OF HOTEL REVENUE, BOOKINGS AND CANCELLATIONS THROUGH MACHINE LEARNING AND DEEP LEARNING

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Abstract

For managers, making the right decisions in a dynamic environment becomes critical. This study explores how forecasting methods convert reservation data into actionable information for decision-making in the hospitality industry. Based on data obtained from 5,087 accommodation facilities in Türkiye, this study forecast reservations, number of nights, cancellations, and revenue using deep learning model (LSTM) and machine learning models (linear regression, robust linear regression, artificial neural networks). Comparative analyses reveal that LSTM achieves the highest forecast accuracy and offers a valuable tool for managerial decision-making. This finding demonstrates the practical application of advanced forecasting methods, enabling managers to make more accurate decisions in dynamic and uncertain environments. The study also examines this issue using real data.

Keywords: *deep learning, machine learning, tourism industry.*

JEL Classification: *C53; C88; L83; M31.*

Highlights:

1. Introduction

In tourism and hospitality, demand forecasting plays a vital role. Recently, due to its impact on a wide range of organizational decisions, from tactical to strategic levels, accurate forecasting has become an increasingly important issue (Kourentzes *et al.,* 2017; Herrera *et al.,* 2024). However, demand forecasting is difficult in the hospitality industry, because of its complex and dynamic structure. Therefore, many studies have been conducted on tourism and hospitality demand forecasting using diverse methods such as statistical, econometric, artificial intelligence, and integrated models. Research shows that scholars have been working to find a better way to predict demand for tourism and hospitality, which should lead to more accurate predictions (Li *et al.,* 2020).

Demand forecasting and revenue management have a clear and important relationship (Tse and Poon, 2015). Revenue management (yield management) is described as “the application of information systems and pricing strategies to allocate the right capacity to the right customer at the right price at the right time” (Kimes and Wirtz, 2003). Revenue management has two primary roles: forecasting and optimization. The forecasting system allows demand to be forecasted using historical and current reservation data. Based on the demand forecast and remaining capacity, the optimization function ensures that room inventory is properly managed (Gayar *et al.,* 2011).

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The system is a complex and dynamic process. The concept has vital importance for businesses. A key aspect of revenue management depends on accurate demand forecasting (Mehrotra and Ruttley, 2006). Accurate demand forecasting also considers booking cancellations. Booking cancellation is a critical topic in terms of revenue management performance (Antonio *et al.,* 2017). There is scarce literature on cancellation forecasting, although booking cancellation is a very important topic (Sánchez-Medina and C-Sánchez, 2020). Forecasting influences managers' decisions. Given increasing competition, accurate forecasts for both the long and short term are essential for hotel managers. (Pan and Yang, 2017). Accurate demand forecasting is significant for both tourism businesses and national administrators, as it enables the formulation of appropriate policies aimed at reducing the uncertainty between tourism supply and demand.

The machine learning technique provides valuable benefits in fields such as booking, revenue management, and demand forecasting in the hospitality industry (Tanpanuwat, 2011; Herrera *et al.,* 2024). The purpose of this study is to determine the performance of machine learning and deep learning models for forecasting demand and revenue in the hospitality industry, and to compare the performance of these approaches. In particular, the study is significant in that it demonstrates how forecasting methods transform reservation data into actionable information to support decision-making in the hospitality industry. This study differs from previous studies in that it employs a combination of various machine learning techniques and the LSTM deep learning model to forecast hotel revenues, bookings, and cancellations. Additionally, the analysis is based on real data from 5087 distinct accommodation facilities located across various regions of Türkiye. The diverse range of facilities, encompassing varying sizes and characteristics, contributes to the uniqueness of this study compared to existing research.

2. Literature review

Tourism demand forecasting

Both qualitative and quantitative approaches can be used to predict tourist demand. Qualitative techniques, like the Delphi method and the consensus approach, rely on the discernment, experience, and insight of experts in the tourism sector. However, this approach is often criticized for its poor generalization capability (Witt and Witt, 1995). The quantitative method, in contrast, makes numerical predictions about the connections between various data points. Quantitative forecasting of tourism demand has developed through different models. There are three main types of these models: econometric, time series analysis, and machine learning (Song and Li, 2008) or methods that are either linear or nonlinear (Sapankevych and Sankar, 2009; Song and Li, 2008). Based on past trends, time series studies can predict how tourism will evolve in the future. A large body of literature has made use of these models (Zhang, 2003). These models identify trends, cycles, seasonality, and level shifts, as well as random variations (Song *et al.,* 2019). To determine which factors, cause others, econometric models are useful. Linear approaches are affected by the stability of historical patterns and economic structures (Song and Li, 2008) and they demonstrate that the level of certainty can be enhanced by the utilization of this form of limited sample data (Yang *et al.,* 2015). However, when it comes to forecasting performance, nonlinear approaches outperform linear approaches (Law, 2001; Li *et al.,* 2018; Zhang *et al.,* 2020). In particular, the LSTM model, as nonlinear model is best the statistical performance than other nonlinear models (Zhang *et al.,* 2020).

Tourism demand forecasting was primarily based on time series models and econometric models. In the late 1990s, artificial intelligence-based methods were implemented in tourism forecasting, and the methods have been widely used in the field since 2009 (Liu *et al.,* 2019). The methods based on artificial intelligence can be grouped into five categories: grey theory, fuzzy time series, rough set approach, support vector machines (SVMs), and artificial neural networks (ANNs) (Claveria *et al.,* 2015). The artificial neural network (ANN) model as an artificial intelligence-based method has appeared most frequently in recent literature. However, tourism and hotel demand forecasting have also used methods such as support vector regression (SVR), the rough set model, fuzzy system methods, genetic algorithms, and Gaussian process regression (GPR), but the methods have been applied less frequently (Wu *et al.,* 2017). In the past five years, tourism forecasting has seen the implementation of novel methods such as big data analysis, machine learning, and search engine data research (Liu *et al.,* 2019). Tourism demand studies compare method-performance profiles over time. Forecasting models have become more prevalent in recent years, and their accuracy has improved. No single method works well in all circumstances, and research continues (Song *et al.,* 2019).

The accuracy of demand forecasting is influenced by booking cancellations (Antonio *et al.,* 2019). A number of studies have examined the forecasting of booking cancellations in different industries such as the airline industry (Iliescu, 2008; Lemke, Riedel and Gabrys, 2013; Petraru, 2016), the hotel industry (Morales and Wang, 2010; Antonio *et al.,* 2017, 2019; Falk and Vieru, 2018), the restaurant industry (Huang *et al.,* 2013; Tse and Poon, 2017), and the railway industry (Azadeh, 2013; Cirillo *et al.,* 2018). Forecasting of booking cancellations has used different algorithms in these studies. Antoni *et al.* (2017) found that the decision forest algorithm was the best for booking cancellations and tree-based decision algorithms or SVMs had lower performance. Antonio *et al.* (2019) have confirmed that hotel booking cancellations can be forecasted with high accuracy using machine learning models.

Machine learning and deep learning

Machine learning is used for clustering, classification, and regression. However, it is also used for revenue management, operational analytics, and customer experience development in the hospitality industry (Ganga *et al.,* 2018). Machine learning is typically classified into four categories (Tripathy *et al.,* 2019). Supervised learning happens on a set of data points consisting of some input x and a corresponding output value y (Engelen and Hoos, 2020). The problems of supervised predictive modelling can typically be divided into two types of problems. These are i) regression, and ii) classification (Hastie *et al.,* 2001). Semi-supervised learning is concerned with using both labelled and unlabeled data to perform certain learning tasks. Unsupervised learning does not provide a specific output value; instead, it tries to identify the underlying structures in the input data (Engelen and Hoos, 2020). Reinforcement learning does not necessitate detailed teaching signals from a human, and it is anticipated to be implemented in robots (Hosokawa *et al.,* 2014). The techniques give a computer the ability to carry out a task through generalized approaches (Witten and Frank, 2002). Machine learning has different algorithms. These algorithms have advantages and disadvantages compared to each other (Darapaneni *et al.,* 2019). Machine learning models are not required to make any assumptions about the data (e.g. distribution and probability). Furthermore, their adaptability and non-linearity make them suitable for non-linear forecasting (Li *et al.,* 2018; Song and Li, 2008). In the tourism industry, machine learning models are widely used for forecasting studies (Li *et al.,* 2018).

Tourism demand forecasting has been conducted using a variety of machine learning models. For example, neural networks are used in some forecasting studies (Chen *et al.,* 2012; Hassani *et al.,* 2015, 2017; Lin *et al.,* 2018). However, support vector regression has been used in some studies (Chen and Wang, 2007; Hong *et al.,* 2011). Some forecasting studies have used multiple models and compared their performance (Burger *et al.,* 2001; Antoni *et al.,* 2017).

Deep learning is a sub-category of machine learning and is a commonly used technique (Zheng *et al.,* 2021). There are different network structures of deep learning, such as DBN, RNN, and DNN and they are used in studies for different aims (image recognition, speech recognition, financial forecasting etc.). Similarly, these models have advantages and disadvantages compared to each other. For instance, traditional RNNs are unable to acquire or retain long-term memories (Zhang *et al.,* 2020). To solve this problem, LSTM was developed by Hochreiter and

Schmidhuber (1997). LSTM outperforms traditional deep learning techniques in forecasting (Hochreiter and Schmidhuber, 1997). Deep learning approaches such as the LSTM model remain in their incipient stage within hospitality and tourism research despite considerable efforts in business (Zhang, 2019; Zheng *et al.,* 2021). It is still scarce in the tourism and hospitality literature (Zheng *et al.,* 2021). It should be used for tourism demand forecasting (Xie *et al.,* 2021). The study focuses on machine learning and deep learning approaches for forecasting of booking, cancellations, and revenue.

3. Material

In the study, classical machine learning and deep learning models were used to forecast the number of bookings, the number of nights, the number of cancellations, and the amount spent using the data obtained from a travel agency. The dataset used in the experiments was collected from a travel agency, with data from 18 regions, 34 features, and 5,087 accommodation facilities. Table 1 shows the descriptive statistical results of the features in the dataset obtained from a travel agency. The integrity and reliability of the dataset used in the study were evaluated through a comprehensive data preprocessing procedure prior to proceeding to the modeling phase. Prior to modelling, the dataset was screened for missing values and anomalous observations. Missingness analysis using the isnull().sum() function indicated that no variable contained missing data; therefore, no imputation procedure was required. Because reservation, cancellation, and revenue data may exhibit skewed and heavy-tailed distributions, outlier assessment was not based solely on the Z-score criterion. In addition to descriptive statistics, a robust distribution-aware evaluation was performed using the interquartile range (IQR) framework to identify extreme observations. However, observations detected as potential outliers were not automatically removed, since in hotel demand data such cases may represent rare but operationally meaningful events rather than measurement errors. Therefore, the final preprocessing strategy preserved these observations unless they were deemed inconsistent with the data generation process. To reduce the influence of extreme values during model training, robust scaling was preferred over conventional min–max normalization. Accordingly, numerical variables were transformed using RobustScaler, which scales features based on median and interquartile range, making the learning process less sensitive to atypical observations.

Table 1. Descriptive statistical results of the dataset

Features	mean	std	min	max
Region	9,997248	4,786844	1	18
HotelType	6,064871	5,103194	1	26
NumberofRooms	69,610773	290,609865	0	11013
LeadTime	14,671313	25,89064	-1	305
NumberofPeoples	138,508158	552,516289	0	20917
Commission	4597,03291	15824,8694	0	614118,7
Cost	267,795068	1025,03367	0	38344,68
CallCenter	0,134246	0,171979	0	1
Nonused	10,405937	45,339881	0	1851
Adwords	0,080867	0,120584	0	1
Trivago	0,323996	0,259454	0	1

Features	mean	std	min	max
EuroMessage	0,003812	0,030276	0	1
GoogleJenerik	0,051719	0,102578	0	1
Otelz	0,118338	0,178071	0	4
Affilate	0,019017	0,063922	0	1
OtherChannels	0,097086	0,135488	0	1
RmcWebPush	0,002909	0,032134	0	1
GooglePerfist	0,0032	0,033892	0	1
GoogleDinamikFeed	0,032665	0,077704	0	1
GoogleDinamik	0,069604	0,13008	0	1
GoogleDisplay	0,001338	0,021979	0	1
NeredeKal	0,032967	0,094273	0	1
Facebook	0,00008	0,001946	0	0,1
Instagram	0,000297	0,005171	0	0,2
RTBHouse	0,010073	0,045935	0	1
OtelSiteleriAdwords	0,002161	0,024931	0	1
ZeoAdwords	0,002335	0,030968	0	1
TripAdvisor	0,011082	0,053013	0	1
Criteo	0,001764	0,013029	0	0,5
CustomerScore	7,975379	1,074724	1	10
NumberofNights	115,440928	403,755517	0	14999
Amount_spent	31155,7	107608,4	0	4094847
NumberofBooking	64,754865	272,29371	0	10205
NumberofCancel	17,936701	58,377805	0	2250

Before model development, the observations were sorted chronologically according to the forecasting timeline, and no random shuffling was applied. To prevent temporal leakage, all preprocessing steps were performed within each training fold only. Specifically, RobustScaler was fitted using the training subset and then applied unchanged to the corresponding out-of-sample evaluation subsets. In the same way, feature selection was carried out only on the training portion of each fold, and the selected variables were subsequently used for the corresponding out-of-sample evaluation subsets.

4. Method

Long short-term memory networks (LSTM)

The LSTM model was developed by Hochreiter and Schmidhuber in 1997 and has been further refined in conjunction with other studies (Hochreiter and Schmidhuber, 1997). LSTM relies on a recurrent neural network (RNN) architecture, which has a very good ability to learn long-term dependencies and remember the values in the model randomly (Hochreiter and Schmidhuber, 1997). This model has a special structure, designed to overcome the long-term dependency problem, allowing it to forget unnecessary information. The LSTM model is based on previous information used by RNNs. LSTM units are usually implemented within blocks. These blocks contain multiple gates for controlling the flow of information. Logistic functions are used to compute the value of these gates between 0 and 1 (Cho *et al.,* 2014). The architecture of the LSTM comprises three gates: the input gate, forget gate, and output gate. These gates include a block input, constant error carousel, activation function and peephole connections (Greff *et al.,* 2017). First, with the help of the activation (σ) function, such as sigmoid, SoftMax, ReLU, the information to be forgotten is determined. Equation 1 produces a number between 0 and 1 with the help of the sigmoid activation function (σ) by taking W_f input gate weight matrices, X_t current time step input, h_{t-1} previous LSTM cell output values and b_f bias values as input (Yao *et al.,* 2015, Koutnik *et al.,* 2014).

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{1}$$

Following Equation 1, the cell's new information is determined in two steps. Equation 2 identifies the component to be updated by the input, while Equation 3 generates a vector for all possible values from the new input.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$C_t = tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

In the last step, Equation 4 is used to forget information about the old input and to add new information by using the new input. The results are obtained by applying the *tanh* function to the sigmoid activation function that was determined for the forecasting (Greff *et al.,* 2017). In this way, the forecasting is performed.

$$C_t = f_t * C_{t-1} + i_t * C_t \tag{4}$$

The LSTM model is a deep neural network architecture designed to effectively capture short-term and long-term dependencies in time series data. The final LSTM architecture was determined through a structured hyperparameter search over candidate configurations differing in the number of LSTM layers, hidden units, dropout rates, batch sizes, and epochs. Based on the average performance across the time-ordered validation folds, a single-layer LSTM configuration provided the best balance between forecasting accuracy and generalization. Accordingly, the final model consisted of one LSTM layer followed by a fully connected output layer for continuous prediction. The optimal hidden-unit size and training settings were selected according to the configuration reported in Table 3. The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. This architecture was preferred because it captured temporal dependencies effectively while avoiding the additional complexity and overfitting risk associated with deeper LSTM alternatives.

The final LSTM configuration was selected after comparing simpler and deeper alternatives within a predefined hyperparameter space. This design choice reflects a progressive model selection strategy in which lower-complexity architectures were evaluated first, and additional layers or units were introduced only when they improved validation performance without increasing overfitting risk.

Linear regression

Linear regression identifies relationships between dependent and independent variables. If a current relationship is linear, it is defined as a linear regression, otherwise it is defined as a nonlinear regression. A simple linear regression is applied to forecast variables with a normal distribution using another variable with a normal distribution. However, forecasting a variable using more than one variable with a normal distribution is expressed as the multiple linear regression model. The purpose of linear regression is to help us understand how dependent variables change when independent variables change. In this regard, it is used to reveal the causal relationship between the variables. For a proper linear regression, dependent variables must be continuous or sequential. Independent variables, on the other hand, must be numeric or categorical. In this way, Equation 5 is used to reveal the relationship between the dependent variable and the independent variables using the optimal regression line. Linear regression is used to find the optimal hyperplane using the data (Kılıç, 2013).

$$y = b_0 + b_1 x_1 \tag{5}$$

In Equation 5, *y* refers to the dependent variable, and x_1 refers to the independent variable for the simple linear regression model. In the equation, the value b is a measure of error expressed proportionally in regression coefficients. This value refers to the average change that can occur in the dependent variable when the independent variable decreases or increases (Poole and O'Farrell, 1971, Dawson-Saunders, 1994, Montgomery *et al.,* 2012). In our study, multiple linear regression analysis was used in the analysis since there was more than one independent variable. The multiple linear regression model used is shown in Equation 6.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + e_i \tag{6}$$

In Equation 6, *β* refers to a constant value, and *e* refers to the random error in a multiple linear regression model. In a multiple linear regression model, it must be expressed numerically between dependent and independent variables. Our main goal is to obtain a regression coefficient *β* that can give the value closest to the ideal result (*y*). For this purpose, the ordinary least squares method is used for forecasting (Gabralı and Aslan, 2020).

Robust linear regression

Regression analysis is used to identify existing relationships between dependent variable and independent variables. In the linear regression method, the forecasting is performed using the assumptions generated by the least squares method. However, if the assumptions are false, it performs a misleading forecast that is not true, indicating that the assumptions of the least squares are not always reliable for forecasting. Robust linear regression is an alternative method designed to avoid being affected by assumption errors that may occur in the least squares method. The robust linear regression model is applied as in Equation 7.

$$y = X_w + t + n \tag{7}$$

In Equation 7, X_w are the input values, *t* is the sparsity vector corresponding to the outlier value within the dataset *t*, and *n* is the background noise. Since it is used independently of the inputs, the *n* expression is considered Gaussian noise (Xue *et al.,* 2011). By not accepting outlier values normally, as in linear regression models, it works very precisely, especially with outlier values. In the robust linear regression model, a breakdown point and influence function are used to measure performance (Donoho, 1983). The breakdown point refers to the ratio of outliers that the dataset can contain before performing the forecasting. A smaller ratio indicates higher forecasting accuracy.

Artificial neural network

Artificial neural networks (ANN) are used to collect information from data and make comparisons with unseen samples based on this information to make decisions about these samples using previously learned information (Schalkoff, 1997, Yöntem *et al.,* 2019, Adem *et al.,* 2019; Kılıçarslan *et al.,* 2021; Kılıçarslan *et al.,* 2020). The ANN model is a system focused on the mathematical modeling of neurons and on imitating neurons in the human brain using computers (Karahan, 2015). Artificial neurons consist of three parts: dendrites, axons and synapses. Artificial neural networks attract the attention of many researchers due to their training ability, non-linearity, adaptability, fault tolerance, and generalization capability. Thus, they stand out with their ability to be used in diverse areas for solving complex problems. There are three layers - input, hidden and output - in an artificial neural network. Equation 8 shows the neural network function.

$$y = f(W_x + b) \tag{8}$$

The input layer transfers data to the cells in the hidden layer without any changes on the data received from outside. In accordance with the system designed in the ANN model, sigmoid SoftMax and ReLU activation functions were used to improve the performance of the architecture by calculating the net output value of the network as shown in Equation 8. The input layer consists of the input neurons, corresponding to the features of the samples. In Equation 8, *y* refers to the output, *f* is activation function, *W* denotes weights, *x* refers to the input data, and *b* is the constant bias value. Weights (*W*) are the parameters used to adjust the impact of inputs on outputs. The most critical point in the network is that the optimum weight values need to be computed by spreading error according to the training set. The hidden layer, the number of layers, and the number of neurons in the architecture can vary depending on the problems. In this layer, the learning process is performed using the Equation 8 through forward calculations and backward error propagation algorithms. Since the derivatives are important in the backpropagation, the activation function selected in the study should be a function that is easy to find its derivative. For the solution of complex problems, number of layers and neurons is increased. After all these operations, class information or labels of the values to be learned are computed and presented in the output layer. After completing the training process, the dataset provided for testing is used for forecasting with the final weight values (Uğur and Kınacı, 2006).

The final ANN architecture was selected through a structured hyperparameter search over candidate configurations that varied in the number of hidden layers, neurons, dropout rates, batch sizes, and learning rates. Based on the average performance across the time-ordered validation folds, the single-hidden-layer configuration provided the best balance between predictive accuracy and generalization. Accordingly, the final ANN model consisted of one hidden layer with 10 neurons and employed the sigmoid activation function. The network was trained using the back-propagation algorithm to minimize prediction error. This relatively simple architecture was preferred because it yielded more stable forecasting performance than deeper ANN alternatives under the chronological validation setting.

The selected structure provided the best trade-off between predictive accuracy and generalization on temporally ordered validation subsets.

Temporal Data Splitting and Leakage Prevention

Because the study addresses a forecasting problem, model development and evaluation were conducted using a strictly chronological time-series protocol rather than random train-test splitting. First, all observations were ordered according to their temporal sequence. Then, in each fold, the earlier 70% of the data were used for model training, while the immediately following 30% were reserved for out-of-sample evaluation. This rolling-origin chronological validation procedure was repeated across five temporal folds in order to obtain a more robust and realistic assessment of predictive performance.

To prevent temporal leakage, no random shuffling was applied at any stage of the analysis. In addition, all preprocessing operations that could introduce future information into the learning process were performed using only the training portion of each fold. Specifically, the RobustScaler transformation was fitted on the training data only, and the resulting scaling parameters were then applied unchanged to the corresponding evaluation subset. In the same way, feature selection was also carried out within each training fold only; Fisher Score rankings were computed using the training partition, and the selected features were subsequently transferred to the corresponding evaluation data. Thus, no information from future observations was used during preprocessing, feature selection, model fitting, or model comparison. For the LSTM model, input sequences were generated separately within each temporal fold after chronological splitting, ensuring that no sequence crossed the boundary between the training and out-of-sample evaluation periods.

This evaluation design provides a leakage-aware and statistically consistent framework for forecasting hotel revenue, booking quantity, and cancellation quantity, while also ensuring that performance estimates better reflect real-world deployment conditions.

Fisher score

The feature selection methods identify optimal features by removing unnecessary features from the dataset. In this way, they ensure data compression and reduce computational complexity (Kılıçarslan *et al.,* 2019). The feature selection method is a preprocessing step used in machine learning before the classification or forecasting process is carried out. In the study, the Fisher-Score algorithm, one of the statistical information-based filtering methods, is used for feature selection. Fisher-score is a filter-based feature selection method developed by Stork *et al.* in 2001 (Stork *et al.,* 2001). Fisher-Score performs feature selection by calculating the score associated with the mean and standard deviation values according to attributes in the input dataset, as in Equation 9 (Budak, 2018).

$$F(x_a) = \frac{|\mu_a^+ - \mu_a^-|}{\sigma_a^+ - \sigma_a^-} \tag{9}$$

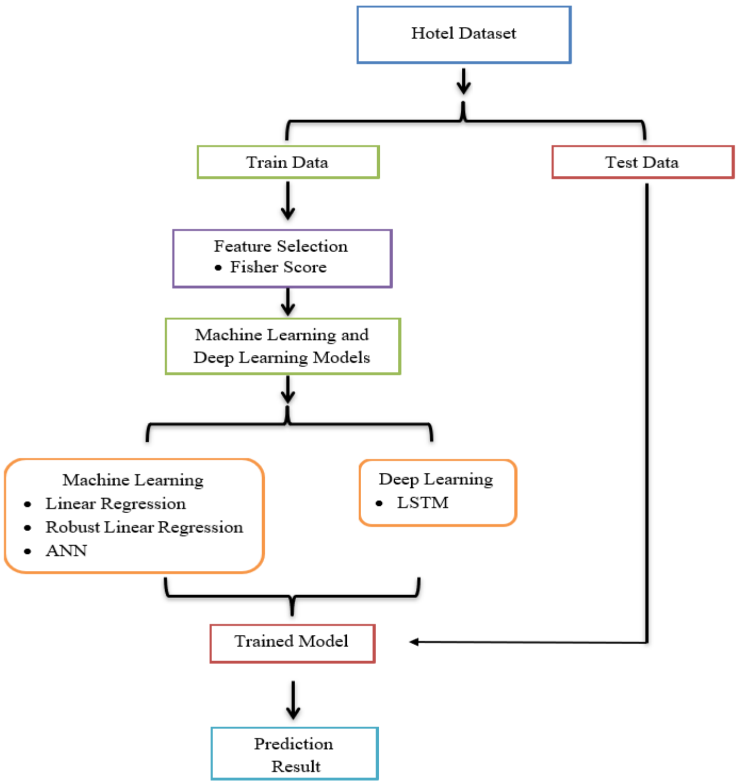
In Equation 9, the $+$ and $-$ symbols refer to two different class problems, the μ_a values refers to the arithmetic mean of different classes, and the σ_a values refer to the standard deviation values of different classes. The score values computed using Equation 9 are sorted from large to small. After sorting, the desired number of attributes is selected starting from the highest score. If the computed score is high, the mean differences between classes are expected to be high, and the standard deviations to be low (Budak, 2018, Bolón-Canedo *et al.,* 2014).

The feature selection process offered substantial practical advantages by employing the Fisher Score algorithm to systematically eliminate variables with limited predictive power, thereby reducing dataset complexity and improving computational performance. This procedure not only expedited model training but also strengthened the system's resilience against overfitting, ensuring more reliable predictions across diverse scenarios. Equally important, the analysis identified critical operational drivers particularly available room inventory and occupancy duration that directly shape booking patterns and revenue outcomes. These insights enable hotel managers to focus their monitoring efforts and strategic planning on the metrics that truly matter, enabling for more targeted data collection practices and decision-making processes aligned with the factors that demonstrably influence business performance.

5. Results

In this study, annual revenue, booking quantity and cancellation quantity (dependent variables) were forecasted separately using independent variables such as region, number of hotel type, number of rooms, number of guests, cost, commission payments and booking rates. Within each temporal fold, Fisher Score was computed using only the training partition, and the top-ranked predictors were then used for model development and out-of-sample evaluation. Table 2 presents the resulting feature importance patterns across the forecasting tasks. Then, linear regression, robust linear regression, artificial neural networks and the LSTM deep learning model were used to forecast the dependent variables. The application and block diagram of the models proposed are shown in Figure 1.

Figure 1. Machine learning and deep learning models



As shown in Figure 1, Fisher Score analysis was performed within each temporal training fold to identify the most significant features affecting each dependent variable, and the resulting rankings are summarized in Table 2.

Table 2. Application of the Fisher Score Method for the most significant feature selection

Amount Spent		Number of Booking		Number of Cancellation	
Features	**Fisher score**	**Features**	**Fisher score**	**Features**	**Fisher score**
Commission	0.76	Number of unused rooms	0.73	Number of unused rooms	0.68
Cost	0.72	Number of customers	0.70	Number of nights per room	0.66
Number of nights per room	0.65	Number of room	0.65	Number of customers	0.61
Number of unused rooms	0.64	Number of nights per room	0.61	Cost	0.57

As shown in the Fisher Score analysis applied to three different dependent variables in Table 2, the analysis reveals that the most significant features affecting the annual revenue of hotels are the commission fees, cost, number of nights per room and the number of unused rooms, respectively. Significant features affecting the booking quantity value were the number of unused rooms, the number of customers, the number of rooms, and the number of nights per room. The most significant features affecting the number of cancellations are the number of unused rooms, the number of nights per room, the number of customers, and the cost values, respectively. Looking at Table 2, it is seen that the number of unused rooms and the number of nights per room affect the result more than other features when forecasting each of the three dependent variables.

Hyperparameter selection for the ANN and LSTM models was conducted in a structured manner rather than relying solely on ad hoc trial-and-error procedures. Model development started with relatively simple architectures, and complexity was gradually increased only when performance gains were observed on the time-ordered validation folds. For the ANN model, the search space included the number of hidden layers (1–3), the number of neurons in the hidden layer (10, 32, 64, 128), batch sizes (10, 32, 64), and learning rates (0.001, 0.0005). For the LSTM model, the search space covered the number of LSTM layers (1–4), hidden units (32, 50, 64, 100), dropout rates (0.10, 0.20, 0.30), batch sizes (10, 16, 32, 64), and epochs (10, 25, 50, 100). A random search strategy was employed to efficiently evaluate candidate configurations under computational constraints, and the final architectures were selected based on average performance across the time-ordered splits. The results showed that single-layer ANN and LSTM configurations yielded more stable forecasting performance than deeper alternatives. Accordingly, the final ANN model used one hidden layer with 10 neurons and a sigmoid activation function, while the final LSTM configuration is reported in Table 3. This procedure allowed the study to balance model complexity, generalization ability, and computational efficiency. It was observed that performance accuracy was higher in the single-layer ANN and LSTM models than in 2-or 3-layer models. The ANN model's hidden layer comprises 10 neurons, with activation performed using the sigmoid function and training carried out using the back-propagation algorithm. The parameters used in the LSTM model are shown in Table 3.

Table 3. The parameters and values of the LSTM Model

LSTM Parameters	Values
Number of layers	1
Number of neurons	100
Fully connected layer	50
Dropout value	0.1
Number of Epoch	100
Batch size	10
Optimization method	'adam'
GradientThreshold	1
Learning rate	0.005

To ensure the reliability of the results and to prevent temporal leakage, a time-series cross-validation procedure based on rolling-origin chronological splits was employed (Kohavi, 1995; Hastie et al., 2009). In each fold, the observations were kept in chronological order, with the earlier 70% used for model training and the immediately following 30% used for out-of-sample evaluation. This procedure was repeated across five temporal folds, and the average performance metrics are reported in Table 4. In addition, all preprocessing steps, including scaling and feature selection, were fitted using only the training portion of each fold and then applied unchanged to the corresponding evaluation subset, thereby preventing information from future observations from influencing model development. This evaluation design provides a leakage-aware and statistically consistent assessment of forecasting performance.

Evaluation Criteria

The mean absolute error (MAE) shows the absolute error between the actual values and the forecasted values. The fact that the MAE value approaches zero indicates that the model's forecasting ability is good (Ekinci and Erdal, 2015).

$$MAE = \frac{\sum_{i=1}^{n}|x-x'|}{n} \tag{10}$$

Equation 10 defines *x* as the actual value, *x'* as the forecasted value, and *n* as the number of observations. The Root Mean Squared Error (RMSE) is computed by dividing the sum of the squared errors of a dataset by the number of data points and then taking the square root of this result (Lee, 2014).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x-x')^2}{n}} \tag{11}$$

Equation 11 computes the squares of the errors, which means that large errors in the dataset have a significant impact on the mean and the overall measurement. When evaluating forecasting problems, the RMSE value should typically be less than 10% of the dependent variable's average value (Lee, 2014).

Relative absolute error (RAE) shows the relative absolute error between actual values and forecasted values as a percentage.

$$\mathrm{RAE} = \frac{\sum_{i=1}^{n}\left|\frac{(\mathrm{x}-\mathrm{x}')}{x}\right|}{n} x100 \tag{12}$$

The forecasting ability of the model increases as the RAE value given by Equation 12 approaches zero.

Theil's U statistic measures the relative forecasting accuracy of a model compared to a naive benchmark model (Theil, 1966). A value of *U* < 1 indicates that the proposed model outperforms the naive forecast:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{x}-\mathrm{x}')^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}+\sqrt{\frac{1}{n}\sum_{i=1}^{n}\mathrm{x}'^2_i}} \tag{13}$$

The Mean Absolute Percentage Error (MAPE) provides an intuitive percentage-based measure of forecasting accuracy:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{x}-\mathrm{x}'}{x}\right| \tag{14}$$

Lower values of Theil's U and MAPE metrics given in Equations 13 and 14 indicate higher model accuracy and stability across predictions. MAE, RMSE, RAE, Theil's U and MAPE values obtained from these experiments applied to the dependent variables are presented in Table 4.

As shown in Table 4, the LSTM method was found to be the most successful among the four forecasting models (Linear Regression, Robust Regression, ANN, and LSTM) for predicting annual revenue, booking quantity, and cancellation quantity. This superiority arises from LSTM's ability to capture nonlinear temporal dependencies in sequential hotel booking data, which cannot be efficiently modeled by conventional approaches. Theil's U values for all three dependent variables are below 1, confirming that each model performs better than the naive benchmark, with the LSTM model exhibiting the lowest U values. Similarly, MAPE results align with the RMSE, MAE, and RAE metrics, further validating the superior accuracy and stability of the LSTM framework across revenue, booking, and cancellation forecasts. In particular, the results of annual revenue and booking quantity forecasting are more accurate than those of cancellation quantity forecasting. This can be explained by the higher stochasticity and imbalance in cancellation data—factors such as last-minute customer behavior changes, external travel restrictions, or price fluctuations introduce additional uncertainty. Overall, these findings highlight both the robustness of the proposed model and the intrinsic difficulty of cancellation prediction compared to other forecasting targets. The results obtained from the test dataset for each dependent variable and forecasted by the most successful model, the LSTM, are shown in Figures 2, 3 and 4.

Table 4. Forecasting evaluation criteria and results of methods applied to dependent variables

Dependent Variables	Evaluation Criteria	Linear Regression	Robust Regression	ANN	LSTM
Annual Revenue	MAE	1933.55	1536.42	1624.32	1483.24
	RMSE	10580.53	10675.42	10324.62	9875.85
	RAE (%)	5.11	5.89	4.98	4.81
	MAPE (%)	7.42	6.08	5.86	5.12
	Theil's U	0.86	0.82	0.79	0.74
Number of Bookings	MAE	2.36	2.06	1.97	1.88
	RMSE	7.30	6.42	6.28	6.03
	RAE (%)	2.89	2.76	2.61	2.52
	MAPE (%)	4.35	4.01	3.78	3.42
	Theil's U	0.84	0.79	0.77	0.73
Number of Booking Cancellations	MAE	7.37	6.77	6.02	5.33
	RMSE	20.10	20.00	18.67	16.05
	RAE (%)	36.75	35.22	33.48	29.88
	MAPE (%)	12.64	11.93	10.72	9.58
	Theil's U	0.91	0.88	0.83	0.78

As shown in Figures 2, 3 and 4, the LSTM deep learning model was the most successful method based on the annual revenue amounts, booking quantities and cancellation quantities of the dataset of 5,087 hotels and 31 features. Error values in the number of booking cancellations are higher than in the other two dependent variables. This indicates that different features should also be collected to increase the success rate of forecasting of booking cancellations. As a result of the experimental studies, the error value and error ratio were found to decrease when an artificial neural network was used, despite the linearity between dependent variables and independent variables. Accordingly, the LSTM deep neural network method was applied, and it was found that MAE values decreased to 1,483.23 in annual revenue, to 1.88 in the booking quantity forecast, and to 5.33 in the booking cancellation quantity. The study used the Fisher Score method to forecast the dependent variables of the annual revenue amount, booking quantity, and booking cancellation quantity. The most effective features were found to be the number of rooms and the number of nights per room. This is an expected result. To examine whether the observed differences in forecasting accuracy among the models were statistically significant, the Diebold–Mariano (DM) test was applied using the absolute forecasting errors. The test results showed that the LSTM model significantly outperformed the Linear Regression, Robust Regression, and ANN models ($p < 0.05$) across all three dependent variables (revenue, bookings, and cancellations).

These findings confirm that the superior performance of the LSTM model is statistically significant rather than a random outcome.

Figure 2. Annual revenue amount with LSTM forecasted

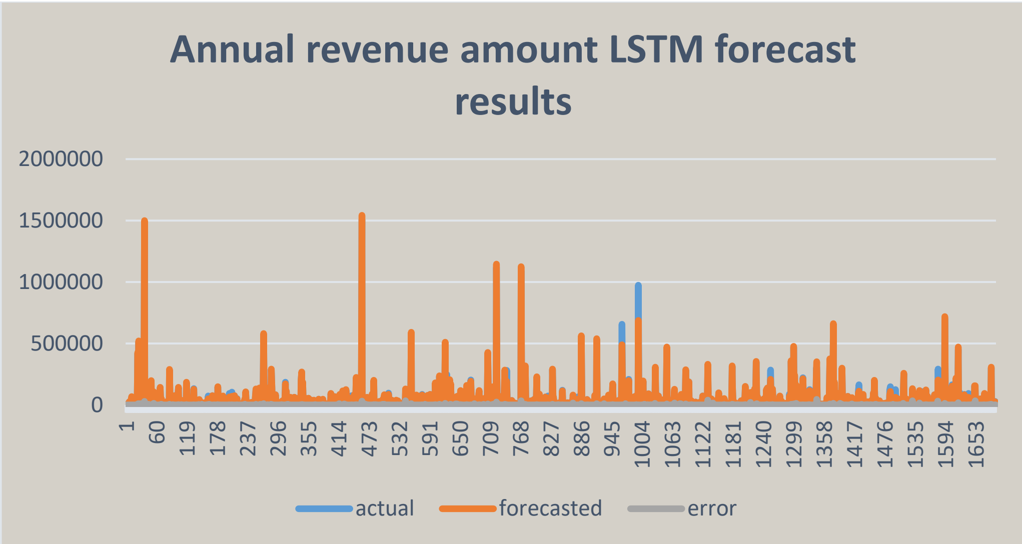


Figure 3. The booking number with LSTM forecasted

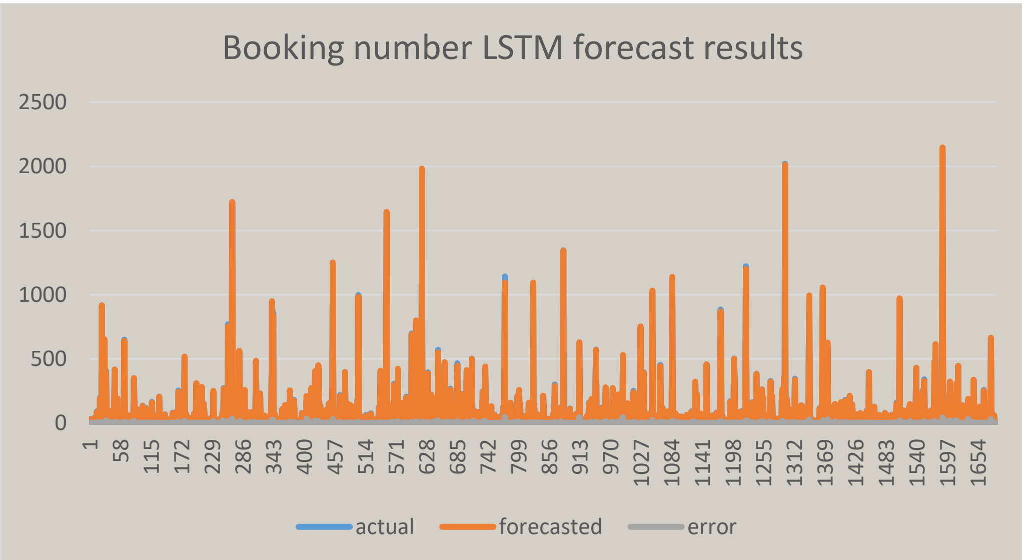
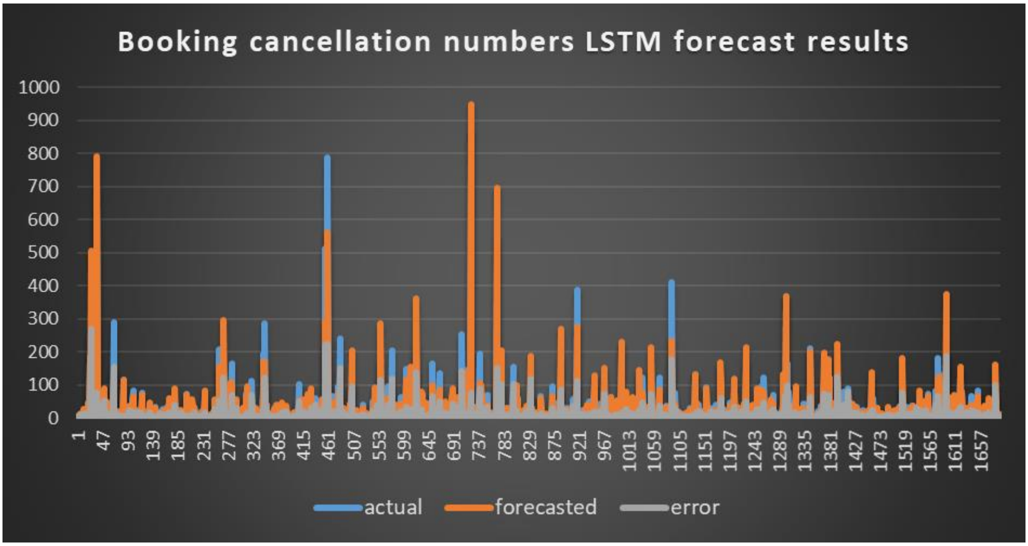


Figure 4. Booking cancellation numbers with LSTM forecasted



6. Discussion and conclusion

The importance of international tourism has increased in the world economy, and industries have allocated resources and invested in this sector. (Jiao and Chen, 2019). Naturally, forecasting has become an important challenge for practitioners and researchers (Song, Qiu and Park, 2019). Tourism demand forecasting has been examined using time-series, econometric and AI models. The accuracy of forecasting is based traditionally on the goodness of the set of features. A good selection of indicators leads to higher accuracy. The selection requires extensive human effort in traditional approaches (Coshall and Charlesworth, 2011). However, modern approaches require minimal human effort. Some studies using modern approaches have shown that advanced machine learning algorithms are better for booking, booking cancellation, and revenue forecasting (Antonio *et al.,* 2017; Falk and Vieru, 2018; Huang *et al.,* 2013). Thus, artificial intelligence methods have drawn increasing attention to improving forecasts in recent years. Motivated by the limited number of studies on tourism forecasting in Türkiye, the research has yielded insights into the field of hospitality business forecasting, particularly as it pertains to hotel reservations, cancellations, and revenue. This study analyzes the forecasting performance of machine learning models (linear regression, robust linear regression, and ANN) and a deep learning model (LSTM) and compares these forecasting approaches at the country level. According to the findings, the LSTM model is the best model for revenue, bookings, and cancellations in the empirical results. In addition, statistical validation using the Diebold–Mariano test confirmed that the forecasting improvements achieved by the LSTM model were statistically significant ($p < 0.05$). The success of the LSTM model may be attributed to two factors: first, deep learning models mimic the way the human brain works, and second, LSTM's attention mechanism automatically identifies a set of influential features at each time step (Law *et al.,*2019).

The conclusions drawn from this research are strongly supported by the experimental findings and extend beyond the reported accuracy improvements. The proposed LSTM-based framework not only enhances forecasting precision but also advances methodological development in tourism analytics by demonstrating the effectiveness of sequential deep learning in complex, real-world hotel operations. The integration of Fisher Score feature selection with LSTM further reduces model complexity and improves interpretability, providing actionable insights for revenue and booking management. Consistent results across all evaluation metrics (MAE, RMSE, RAE, MAPE and Theil's U) reinforce the robustness of the findings, indicating that the observed improvements in LSTM forecasting accuracy are not metric-dependent but structurally reliable across different performance measures.

According to the findings, commission fees paid by hotels have the greatest impact on annual revenue. High commission fees for each room sold also reduce profit margins. Therefore, optimizing commission costs is essential for economic performance. A similar assessment should be made regarding the cost element. Costs are the second most significant factor in estimating annual revenue. Therefore, cost optimization will contribute to improved economic performance. Furthermore, estimating the number of unused rooms and the number of nights per room is critical. The fact that these factors play a prominent role in determining a business's annual revenue, booking volume, and cancellation rate indicates that capacity utilization in the accommodation sector is the foundation of economic performance and the most critical factor for its improvement. A low-capacity utilization rate in hotels retains fixed costs while decreasing revenue. High capacity or occupancy rates, on the other hand, both increase a business's revenue and contribute to overall tourism revenue. At this point, businesses can achieve more effective demand management by accurately estimating capacity utilization rates and implementing a dynamic pricing strategy based on these estimates. Effective demand management of businesses positively affects their profitability. Collectively, these outcomes emphasize the significance of data-driven modeling in supporting both strategic and tactical decision-making processes within the hospitality industry.

Theoretical implications

There are important theoretical implications in terms of forecasting tourism demand. The study proposes a novel and feasible method to forecast hospitality booking, booking cancellation, and revenue. Moreover, the study presents some of the algorithms that have demonstrated performance. Thus, the study could encourage researchers to use these algorithms. Unlike much prediction research focusing on a single performance measure, this study used five performance measures to evaluate the model: MAE, RMSE, RAE, MAPE, and Theil's U. The study extends the previous literature through hospitality sector application of machine learning and deep learning models.

This research advances beyond existing LSTM and machine learning applications in tourism forecasting (e.g., Law *et al*., 2019; Zhang *et al.,* 2020; Herrera et al., 2024). This study contributes to literature in three ways. First, it simultaneously examines hotel operational flows (bookings and cancellations) and financial indicator (revenue) using on real-world evidence. Second, the empirical analysis provides a broader geographic sample, encompassing thousands of Turkish accommodation establishments. This strengthens both the robustness of the findings and their transferability to various hospitality contexts. The third contribution is methodological: it offers a rigorous comparative evaluation of traditional machine learning approaches and LSTM architecture, thereby providing practitioners with a clear understanding of when to employ each technique. The study extends the limited literature on the hotel and tourism industry and proposes a method of forecasting hotel bookings, cancellations, and revenue.

Practical implications

Managers can make better decisions with a reliable and accurate forecast. Depending on forecasts, managers can develop a proper policy or pricing strategy (Sánchez-Medina and Sánchez, 2020). In addition, businesses, governments, and organizations will be able to make better use of limited resources through accurate forecasts (Wu *et al.,* 2017). For an accurate demand forecast, booking cancellation is vital. Cancellation forecasts could be used as an input in revenue management (Antonio *et al.,* 2019). Revenue management refers to the management of all revenue sources within businesses. Revenue management has shifted from tactical revenue management to strategic revenue management (Guillet, 2020). Revenue management is a complex and dynamic process. Positive results do not occur in the short term. Revenue management should be considered an integrated management practice (Haddad, 2015).

There is a strong relationship between attaining revenue management objectives and accurate forecasts. Based on accurate forecasts, businesses can arrange daily demand daily forecasts. In other words, their ability to dynamically monitor tourist flows will be enhanced by an accurate forecast. Moreover, they can apply a dynamic pricing approach and proper staff scheduling. In essence, the tourism sector might benefit from more accurate predictions in terms of developing more effective marketing strategies and generating more revenue. In addition, managers can plan crowd management and consequently increase their competitiveness. Similarly, governments may develop a more appropriate advance strategy and ensure better service to visitors.

The study has important practical implications for industry managers. Managers should take into account the salient factors affecting revenue, reservations, and cancellations, and design their strategies (personnel, pricing, product supply, communication, channels, etc.) based on these factors, enabling businesses to use their resources more economically and reduce their opportunity costs. We propose a novel and feasible method to forecast tourism bookings, cancellation, and revenue. Besides, the study provides an important forecasting tool for both tourism managers and decision makers. The forecasting tool can be used to forecast other tourism areas, such as flight bookings, tourist flows, etc.

Limitations and future research directions

The study is limited in some ways. The study is based on forecasting bookings, booking cancellations, and revenue in the hospitality sector. We use three machine learning models (linear regression, robust linear regression, and ANN) and a deep learning model (LSTM). While the LSTM model has advantages, it also has some limitations, such as its sensitivity to hyperparameter settings, high computational requirements, and the need for extensive data preprocessing. Therefore, future research could expand on the findings of this study by using alternative architectures (e.g. transformer-based deep learning models and attention-focused networks) or hybrid architectures (e.g., integrating CNN and LSTM or BiLSTM layers). Furthermore, future research could improve the model's robustness and accuracy by using ensemble learning and optimization-focused approaches The study could be expanded to include additional research on tourism forecasting in other countries, as it was conducted in Türkiye. In addition, the identification of anomalous observations represents another area that could be explored in future research. Although the present study evaluated extreme values within their operational context and retained rare but meaningful events, more advanced anomaly detection techniques could provide additional insights. In particular, density-based methods such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and Local Outlier Factor (LOF) may be useful for identifying multivariate anomalies in complex hotel demand data. Future studies may also investigate reconstruction-based approaches, such as LSTM autoencoders, for automated anomaly detection.

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