Prediction of Booking Trends and Customer Demand in the Tourism and Hospitality Sector Using AI-Based Models

A Case Study of Major Hotel Chain

Siham Rekiek[1]*, Hakim Jebari[2], Kamal Reklaoui[3]
Intelligent Automation and BioMedGenomics Laboratory, University Abdelmalek Essaâdi, Morocco[1]
Innovative Systems Engineering Laboratory, University Abdelmalek Essaâdi, Morocco[2]
Innovation and Engineering Research Laboratory, University Abdelmalek Essaâdi, Morocco[2, 3]

***Abstract*—Accurate demand forecasting is critical for optimizing operations in the tourism and hospitality sectors. This paper proposes a robust multi-algorithmic framework leveraging four advanced models of Artificial Intelligence (LSTM, Random Forest, XGBoost, and Prophet) to predict booking trends and customer demand. In contrast to traditional approaches, this study incorporates external factors such as competitors' pricing strategies, local events, and weather patterns, offering a more holistic view of demand drivers. Using a comprehensive dataset from a leading hotel chain, we systematically compare the performance of these models, providing detailed evaluations. The findings offer actionable insights for hotel managers, demonstrating how predictive analytics can inform revenue management, improve operational efficiency, and enhance marketing initiatives. These results contribute to the evolving field of demand forecasting, offering practical recommendations for data-driven decision-making in the tourism and the hospitality sector.**

Keywords*—Artificial Intelligence; decision-making; long short-term memory; XGBoost; Random Forest; Prophet; tourism; hospitality; demand forecasting; booking trends; customer

I. Introduction

The tourism and hospitality sector is one of the most important sectors in the world economy. The application of Artificial Intelligence has transformed this sector and other sectors [1, 2], and its support is used to enhance service quality and productivity. As more AI technologies such as machine learning, natural language processing and robotics become readily available [3], tourism and hospitality businesses can leverage them to innovate their business processes in marketing, customer service, inventory management or revenue optimization [4, 5].

Hotels, as well as other tourism service providers, face the predicament of obtaining an equilibrium between demand and supply. Overestimating the demand often lead to an overstaffing situation and waste of resources. Conversely, underestimating demand can cause a high opportunity cost of unattended customer demands and potential loss in revenue due to lack of supply. Traditional methods were designed for forecasts in those conditions where this information is close enough such as mid-term city-wide events; however, when confronted with short-term rare event related increases at a hotel caused by conferences, festivals or sudden extreme weather changes these approaches quickly outperformed given the need to incorporate variables with diverse scales as well as volatile derivatives along nonlinearity. Artificial Intelligence introduces flexible modeling that provides this improvement on classical estimation models allowing one to learn from more different sources because it can consider many exogenous factors simultaneously while capturing nonlinear relations among them.

The main problem addressed by this paper is the challenge of accurately predicting customer demand in the tourism and hospitality industry using traditional methods, which fail to account for the complexity and volatility of real-world scenarios. Hotels often experience difficulties in adjusting to sudden demand changes, leading to either overstaffing or missed revenue opportunities. The inadequacy of current forecasting approaches to include critical external factors such as competitors' pricing, local events, and unpredictable weather patterns further compounds the issue. Therefore, there is a need to develop and evaluate AI-based multi-algorithmic models capable of addressing these complexities.

This research aims to answer the following key questions:

- How can AI-based multi-algorithmic models improve the accuracy of demand forecasting in the tourism and hospitality sector?
- What is the comparative performance of advanced AI techniques such as LSTM, Random Forest, XGBoost, and Prophet in predicting booking trends?
- How do external factors, like competitors' pricing, local events, and weather conditions, influence customer demand in the hospitality industry?
- What actionable insights can hotel managers derive from AI-powered demand forecasting to optimize revenue management and operational efficiency?

The objectives of this paper are:

- To develop a comprehensive multi-algorithmic forecasting framework that combines advanced AI models (LSTM, Random Forest, XGBoost, and Prophet) for predicting booking trends and customer demand.

- To incorporate external factors such as competitors' pricing, local events, and weather patterns into the predictive models to improve forecast accuracy.
- To systematically compare the performance of these AI models using a real-world dataset from a leading hotel chain in Morocco.
- To provide practical recommendations for hotel managers on how to use predictive analytics for better decision-making in revenue management, operational efficiency, and marketing.

The significance of this research lies in its potential to revolutionize demand forecasting in the tourism and hospitality sector through the use of AI. By developing more accurate and responsive forecasting models, this study can help hotel managers optimize their resource allocation, avoid overstaffing or under-booking, and enhance overall profitability. Furthermore, the integration of rarely considered external factors into the predictive models addresses the limitations of traditional approaches, making this research highly relevant for both academics and industry practitioners. The findings from this research can also be extended to other industries, such as retail and transportation, where demand forecasting plays a crucial role.

The paper is structured as follows: Section II provides a literature review, Section III presents the models and experimental setup, Section IV outlines the experimentation and results, Section V offers a discussion, and Section VI details future research directions, with the conclusion presented in Section VII.

II. Literature Review

A. Artificial Intelligence Technologies in Tourism and Hospitality

Artificial Intelligence technologies (machine learning, natural language processing, robotics, computer vision, augmented reality and blockchain) are increasingly employed within tourism and hospitality to produce service customer and efficient operations [5, 6]:

1) Machine learning is an algorithm able to learn from and provide recommendations or predictions depending on data is machine learning. Utilization of machine learning in tourism as well as hospitality is numerous. It can be used to predict customer preferences [7], to dynamically optimize the pricing of hotel rooms [8] as well as to optimize marketing efforts. Machine learning algorithms can analyze booking patterns and generate, based on these data, personalized travel recommendations for customers [9]. In addition, machine learning can also support inventory decision-making by demand forecasting and adjusting stocks when required [10].

2) Natural language processing is a subfield of Artificial intelligence which is focused on the interaction between computers and humans using the natural language. In tourism and hospitality, NLP is applied for chatbots and virtual assistants to answer instantly customers' questions or provide personalized recommendations [10, 11]. Furthermore, NLP helps analyzing customer feedbacks or reviews in order to extract information about customer satisfaction or points of weaknesses [12]. For instance, NLP algorithms are able to deal with huge amounts of unstructured data coming from social media or online reviews to extract trends and sentiment [13].

3) Robotics: Designing and operating machines for tasks which were previously done by humans is called robotics. Robots are used in the travel and hotel industry for chores like room cleaning, baggage handling, and check-in systems [13]. Robots may save labor expenses, improve operational efficiency, and provide visitors with an original and unforgettable experience [14, 15]. Robots with artificial intelligence, for instance, can negotiate difficult surroundings, communicate with visitors, and do highly exact jobs [16].

B. Emerging Artificial Intelligence Technologies

Beyond the well-established applications, several emerging Artificial Intelligence technologies hold promises for further transforming the tourism and hospitality sector such as Computer Vision, Voice Recognition, Augmented Reality and Blockchain:

1) Computer vision is an approach to artificial intelligence which permits machines to study and interpret visual input It is utilized in a variety of tourism-related applications. Hotels, for instance, are leveraging computer vision to ensure security by early detecting potential threats through surveillance systems [17] and facilitating automated check-ins and check-outs using facial recognition [18] as well as monitoring cleanliness and maintenance of hotel properties [19]. Computer vision is also applicable in the marketing context whereby it can capture customer demographics information as well as behaviours in retail spaces for effective product placement and promotions [20].

2) Voice recognition technology helps AI systems to understand and react to human voices. Recently, this technology is also been employed in hotel rooms. Guests can use their voice to control the room features such as lights, temperature or entertainment systems. Voice recognition promises higher convenience and guest personalization [19, 20]. Voice-activated assistants inform guests about services of the hotel, local restaurants etc., interesting spots and current weather [21]. Voice control may also help in speeding up check-in/check-out processes by reducing the time needed for filling paperwork at the front desk [22].

3) Augmented reality consists of enriching the real world with digital information. In the field of tourism, a visitor can be guided in an interactive way during his/her visit to a landmark or point of interest, or interact with virtual characters that will increase their knowledge about historic events or monuments. When booking a hotel room, customers may do a virtual tour in which they experience the look and feel of the room through AR before taking a final decision [21, 22]. Similarly, when eating out at a restaurant, an AR system could provide a 3D visualisation of menu items and related dietary information on top of printed food menus or directly projected onto restaurant tables so as to help people make more informed choices [23]. AR has been used by destination managers to offer potential visitors immersive experiences advertising by letting them explore landscapes and other interest features without leaving home or office [24].

4) Blockchain technology which is known for secure and transparent nature can be used in multiple applications of tourism and hospitality. Blockchain can improve security and transparency of transactions, supply chain management, and veracity of customer reviews [25]. Blockchain technology may be used for safe creation of immutable transaction ledger that can reduce intermediaries, double selling frauds and ensure the integrity in booking and payment process [26]. Furthermore, blockchain could allows sharing data between various travel industry constituents securely [27].

C. Traditional Demand Forecasting Methods

Traditional demand forecasting techniques such as linear regression, ARIMA (Autoregressive Integrated Moving Average) and exponential smoothing have been used for a long time in tourism and hospitality sector. These techniques are easy to implement and interpret but lack the ability to capture the complexities among variables. For example, linear regression models assume that independent variables and demand have a linear relationship which may not be true in practical case-study environments. ARIMA models are better than linear regression but are not able to incorporate external factors like weather, events or competitor’s prices. Many research papers have proved that traditional models fail to give promising results when it comes to accurately predicting hotel demand. The research in [28] states that ARIMA model provides inaccurate predictions when data exhibits high seasonality due to events as well as irregular patterns of demand especially during peak stays. The study in [29] suggests sophisticated forecasting methods with enhanced performances exhibiting non-linear patterns of multiple determinants.

D. Artificial Intelligence for Demand Forecasting

Artificial Intelligence (AI) has become a powerful tool to predict demand, especially in industries where demand is affected by multiple internal and external factors. Contrary to conventional models, AI techniques are capable of dealing with complex and non-linear relationships, while learning automatically from historical data. The most frequently used AI algorithms for demand prediction include the following.

1) Decision trees and Random Forests: These algorithms can be applied with any type of data (Numerical or Categorical), moreover it provides feature importance ranking that could help understand the impact of each factor on influencing the demand [30].

2) Support Vector Machines (SVM): SVM are efficient in high dimensional space and have been applied for hotel occupancy prediction as well. However, performance of SVM is parameter sensitive and scaling dependent [31].

3) Artificial Neural Networks (ANN): Artificial neural networks have been used for demand forecasting because of its ability to learn nonlinear and complex patterns, but the ANNs demand huge amounts of quality data and computational requirements [32].

4) Deep learning: LSTM is a recurrent neural network type [33] that is well-suited to time series forecasting problems due to their ability in handling long-term dependencies in data [34].

E. Influencing Factors in Tourism Demand Forecasting

Several studies emphasized the need to include external factors in forecast models, thus improving their prediction capacity.

1) Seasonality: The study in [35] investigates the seasonality of tourism and its implication on booking pattern. Hotels in popular tourist areas often face high demand during holidays and school breaks.

2) Competitor pricing: The study in [36] found that many customers compare prices on several platforms before booking, so competitor pricing is likely to have an impact on customer booking behaviour.

3) Local events: The study in [37] showed that large local events such as conferences, music festivals or sports tournaments can generate a peak of demand in the short-term so being able to integrate event-based information will greatly benefit forecasting.

4) Weather conditions: The research in [38] pointed out that the weather conditions significantly impact the hotel demand in leisure destination, especially for outdoor tourism activity.

III. Models and Experimental Setup

Based on the literature study and preliminary experiments, the following Artificial Intelligence models have been selected for further evaluation.

A. Long Short-Term Memory (LSTM)

LSTM, a special kind of recurrent neural network (RNN), is very popular in time series prediction since it can learn long-term and short-term dependency. LSTM networks maintain memory over time by using gated cells to control the flow of information.

1) Architecture: In this study, the LSTM model consists of 2 hidden layers each with 128 LSTM units, followed by a dense layer with single neuron for regression output. Dropout regularization was used to prevent overfitting.

2) Training: Adam optimizer with learning rate of 0.001 is used and mean squared error is taken as loss function. Early stopping based on validation performance is done after training for 50 epochs.

3) Feature selection: LSTM model uses lag features along with other booking related internal features, weather data and few indicators to include external influence in the model and temporal patterns.

B. Random Forest

Random Forest is an ensemble learning method. Building multiple decision trees at training and outputting the average prediction of all the individual trees can reduce overfitting and improve model generalizability.

1) Feature importance: Random Forest provider a feature importance ranking which indicate are the most important variables driving booking demand. In this research room pricing, competitor rates, and local events were found to be the most important features.

2) Hyperparameters: The model was tuned by grid search with number of trees (n_estimators) set to 500, maximum depth set to 10 and minimum samples per leaf set to 5.

C. XGBoost

XGBoost is an optimized implementation of gradient boosting that will increase the speed and performance of the model. It builds decision trees one at a time, trying to reduce the errors from the last iteration. It also handles missing data.

1) Boosting rounds: The model was set to do 100 boosts/rounds with early stopping enabled so it doesn't overfit.

2) Regularization: L1 and L2 regularization terms are added to the objective function to prevent overfitting, especially when there are some noisy features such as competitor pricing data.

D. Prophet

Prophet is a time-series forecasting algorithm developed by Facebook to make fast and accurate predictions on non-linear trends, seasonality and holiday effects. It is very useful in the tourism industry because there are a lot of seasonal patterns and event-triggered peak or drop demand. Some of the key features are:

1) Seasonality components: You can easily model multiple seasonality components with Prophet (i.e. weekly and yearly) which makes it great for predicting hotel bookings as they have very clear seasonalities.

2) Holiday and event handling: In Prophet's model special event indicators are added to account for local festivals, conferences, etc, that cause demand to surge.

IV. Experimentation and Results

A. Data Collection and Preprocessing

The dataset used in this study is a real-world hotel booking dataset obtained from an internal data source of a well-known Major hotel chain in Morocco. The data collected ranged from 2015 to 2023. It includes:

1) Booking data: These captures booking date, room type, length of stay, booking channel and information on cancellations and no-shows.

2) Customer data: This captures nationalities, age, range and purposes of travel (business/leisure).

3) Pricing data: The room price at the time of booking, the discount applied to booking for prepayment or another reason, and variations in prices due to changes in demand, seasonality and other reasons.

4) Competitor data: Pricing data of competitor hotels fetched from 3rd party aggregators and web scraping.

5) External data: Weather conditions (Temperature, Precipitation), local event schedules (Conferences, Festivals).

External data such as weather information, and local events' data were also added to the dataset considering the impact of these factors on customer demand. Data preprocessing was performed in order to make sure that the dataset is suitable for analysis:

1) Handling missing data: Missing values in customer demographics were imputed with median or mode imputation. Missing weather or competitor pricing data were filled with interpolation.

2) Outlier detection and removal: Outliers in room rates, booking lengths and cancellations were detected using the Inter Quartile Range (IQR) method and capped within a reasonable range to avoid any distortion in the model.

3) Normalization and standardization: Continuous variables like room rates and customer ages were normalized using Min-Max scaling, while categorical variables like booking channels and room types were one-hot encoded.

B. Feature Engineering

Feature Engineering was an important factor to increase the predictive power of the Artificial Intelligence models. The following new features have been created:

1) Lag features: booking data from the last 7, 14 and 30 days before each reservation were used to create lag features so the model could account for trends and seasonality

2) Event indicators: Binary indicators have been constructed to identify the occurrence of major local events (festivals, sports tournaments, meetings etc.), which are expected to impact short-term demand positively.

3) Weather features: Features including temperature (in Celsius and Fahrenheit), humidity, and precipitation were updated, as the weather conditions have a significant differentiating impact in some specific leisure destinations in particular.

4) Price competitiveness: A variable which measures the difference between hotel's room rate and its competitor was defined to consider the effect of competitive pricing on demand.

C. Data Experimental Setup

The dataset was partitioned into training (80%) and testing (20%), datasets using data from 2015 to beginning 2021 as the training data and data from beginning 2022–early 2023 as testing dataset. To tune hyperparameters and validate the models, a 5-fold cross-validation step was used. After building each model, their performance was further examined using both the training and testing datasets to evaluate their generalization capacity.

- Training Set: 2015-2021
- Testing Set: 2022-2023

D. Evaluation Metrics

Several performance metrics were used to assess the accuracy and reliability of the models:

- Mean Absolute Percentage Error (MAPE): A percentage-based measure of prediction accuracy, useful for comparing models across different scales.
- Root Mean Square Error (RMSE): A common measure of the magnitude of prediction errors.
- R-squared (R^2): Represents the proportion of variance in the dependent variable explained by the independent variables.

E. Results Analysis

The performance metrics of the models (LSTM, Random Forest, XGBoost, and Prophet) are summarized in Table I.

TABLE I. PERFORMANCE METRICS OF THE MODELS

Model	Metrics		
	MAPE (%)	*RMSE (%)*	*R^2*
LSTM	5.42	12.34	0.92
Random Forest	6.18	13.27	0.89
XGBoost	5.75	12.88	0.90
Prophet	7.12	14.22	0.87

The results show that:

- The LSTM model outperforms all models with the capability to capture both short-term and long-term demand dependencies. Based on the results, this model has an MAPE of 5.42% and $R^2 = 0.92$ which indicates highest accuracy among all developed models.
- Both Random Forests and XGBoost have relatively similar performance where Random Forests performs better in feature importance analysis while not delivering good performance in temporal prediction.
- Prophet was the weakest by far on both performance measures, not great at short-term fluctuations, but pretty comfortable with seasonality.

F. Feature Importance Analysis

Understanding the factors that affect customer demand is important before beginning any predictive modeling. This statement becomes more relevant and challenging in Tourism and Hospitality due to high level of competition as well as dynamic nature of sector. We used four different models Long Short-Term Memory, Random Forest, XGBoost and Prophet to understand which factors are affecting customer demand prediction the most. In such highly competitive industry, identifying these key features can help organizations allocate resources appropriately, make effective pricing decisions and create popular marketing campaigns. This section explores all such important features identified by each model along with explaining their impact on customer demand in detail.

1) Room pricing and discounts: Pricing is an important driver of customer booking behavior and all the four models recognized it as one of the predictors to influence demand.

a) LSTM Analysis:

- Long-term Trends: LSTM being suited for capturing long-term dependencies in time-series data proved that room pricing and discount strategies were highly influential in long-run. Price fluctuations, especially discounts, contributed a variance of 30% in the model prediction.
- Seasonality and Discounts: LSTM was able to learn from the data how room prices interact with the seasonal demand patterns, especially in high-peak seasons where discounts are an important strategy influencing customer decision-making. Special offers, promoting events, or early-bird discounting are particularly important during this period.

b) Random Forest insights:

- High Contribution to Variance: The model Random Forest hat is based on decision trees, clearly indicates that the pricing of rooms and discount offered are the most important variables since it contributed 34% to the overall variance of booking. As an ensemble method, Random Forests are also particularly suitable for feature importance calculation and they are therefore highly exposed to differences in prices between regions or market segments.
- Price Sensitivity: Most important it showed that especially customers in the budget segment and the mid-range segment react very elastic to price changes. If a hotel makes even small increases there will be considerable cuts in bookings.

c) XGBoost insights: XGBoost indicated that the price of rooms interacts with other features, such as competitor's price and lead time. The price of rooms together with a discount offered contributes to 32% of demand forecasting. Hence, this model is better at capturing the interaction effect between price of the room and the discount offered.

d) Prophet's perspective: The Prophet provided a surrogate model for seasonality which revealed room price is not the highest contributing feature. But it still accounts for around 25% of demand variability when the seasonally room prices are adjusted. And also, during holidays and festive seasons room pricing contributes disproportionately.

2) Competitor pricing: Competitor pricing was also identified as a main component, reinforcing the view that price competition matters in the hotel industry.

a) LSTM Analysis:

- Real-Time Fluctuations: The LSTM model captures real-time fluctuations of competitor prices (prices of other hotels), which in fact affect the booking demands in short-term horizon. The competitor price directly contributed 20% to the demand variation as reflected by LSTM, meaning that customer's choice is largely influenced by competitor price, especially under high competition environment.

- Temporal Sensitivity: customers frequently make comparisons (between hotels) on real-time prices, and LSTM has indicated sensitivity on short-term changes of bookings.

b) Random Forest insights:

- Market Dynamics: Random Forest identified competitor pricing as the second most important feature contributing 22% of variance in bookings. The model indicated that real-time competitor rate monitoring, especially in markets with high hotel density, is of utmost importance.

- Dynamic Pricing Strategies: Given the importance of competitor pricing; demand predictions and revenue can be greatly improved using dynamic pricing algorithms where prices are adjusted based on competitor behaviour.

c) XGBoost insights: XGBoost highlighted that competitor pricing had a 21% contribution to the prediction. With the ability of the model to handle non-linear interactions, it became apparent how perplexing customers respond to both its prefered hotel's price and its competitors' price. Competitive rate was especially important during promotional period.

d) Prophet's perspective: In Prophet, where more seasonality is captured, competitor pricing also had an important role but with 15% contribution in demand changes. the price competition impact demand changes during high traffic days such as weekend and public holiday.

3) Local Events: Local events—festivals, conferences, concerts etc. were identified as a major short-term booking demand driver.

a) LSTM Analysis:

- Event-driven spikes: The LSTM model was able to capture short-term event-related spikes of bookings demand contribution ~25% of booking variance. This feature is most important for hotels in proximity to the places where event take place and experiencing huge increases of demand over particular periods (externalities).

- Seasonality of Events: The model was able to learn long term seasonal patterns which are caused by periodic events such as annual festivals, or trade shows and make use of this information in the forecast of the demand surge.

b) Random Forest insights:

- Short-Term Variations: Random Forest reported the local events contributes 18% to the variance of bookings and it is an important feature for booking rate prediction close future, which means our hypothesis based on anticipation of events is supported.

- Geographical Sensitivity: The result also showed that the geographical variation is a specific feature, which means hotels located in the central city or spots with high tourist volume showed higher responsiveness with respect to this feature.

c) XGBoost Insights: XGBoost showed that 19% of the accuracy in predicting demand comes from local events. Hotels need to consider the size and popularity of events, as smaller local events don't have as large an effect as major conferences or festivals.

d) Prophet's perspective: Prophet considers holidays and events in its seasonality component and assigned 23% to event-related changes in demand. It performs especially well with recurring events like national holidays and effective in forecasting demand for event-heavy periods.

4) Weather conditions: Weather conditions, particularly in regions dependent on outdoor activities, significantly influenced booking behavior.

a) LSTM Analysis: LSTM was able to capture long term weather patterns including seasonal differences and short terms weather conditions such as storms or heatwaves. This feature contributed 15% to the variance by the model for predicting demand, especially for destinations with outdoor activities like beach resorts or ski lodges.

b) Random Forest insights: Random Forest showed that weather conditions contributed 15% of the variance in customer demand. It wwas able to capture how a certain event characterized by extreme weathers (hurricanes, heatwaves) led to sudden shift of booking's trend.

c) XGBoost Insights: XGBoost identified that weather is responsible for 13% of the variation in demand, especially in places where the overall experience is very much linked to the weather. The non-linear impact of weather was well captured by this model (i.e., some slight changes in temperature can create huge deviations in demand).

d) Prophet's perspective: Prophet attributes 18% of the total variance in demand to features related with weather. This model was also able to better incorporate both short-term as well as cyclical effects associated with weather on long-term forecasts.

5) Booking lead time: Furthermore, booking lead time which is the duration between a customer making a booking until their actual check-in date was detected as an important feature among all the models.

a) LSTM analysis: LSTM model that is capable of handling sequential data, revealed that 12% of the predictive power of the obtained model is due to this feature (booking lead time). The model captured long-term patterns in customers' booking behaviour such early bookings for holiday and last-minute reservations for business.

b) Random Forest insights: Random Forest indicated that booking lead time contributed 10% to the total variance and showed how different types of customers (e.g., leisure versus business) has different patterns of booking lead times.

c) XGBoost Insights: XGBoost indicated that booking lead time contributed 11% to the model performance and that the interaction between booking lead time with room price is important because earlier bookers often get lower prices as an incentive for them to book early, which influencing booking behavior.

d) Prophet's perspective: Prophet found that lead time was responsible for 9% of the total forecast, particularly in predicting holiday demand, capturing how far ahead customers typically book during peak travel periods.

6) Comparison of model performance in feature importance

- LSTM: proficient for capturing long term dependencies and interplay between seasonal factors, pricing and lead time.
- Random Forest: Best adapted to understand the importance of features relatively across different customer segments and geographies.
- XGBoost: Works well at capturing complicated, non-linear feature interactions (e.g. pricing vs. local events).
- Prophet: Primarily heavily relied on seasonality and event driven demand, works better with time series (predictable recurring patterns).

By utilizing the strengths of each model, this holistic feature importance study reveals insightful knowledge about the determinants of customer demand for Tourism and Hospitality. Such information can assist practitioners in making better-informed decisions based on data analytics in managing operations as well as developing pricing and marketing strategies.

7) Model interpretability and feature engineering: Incorporation of external data with local events and weather data lead to significant improvement in models, hence proving the need of feature engineering. Creation of lag variables for room price and competitor rates were also found useful in capturing price dependency booking pattern by models.

Apart from predictions, Random Forest and XG Boost provided insights on feature importance which was advantageous for hotel managers/planners as they targeted the most influential factors when modifying their pricing or marketing strategies. Knowledge about demand drivers would permit hotels to make better decisions on promotions, dynamic pricing and allocation of resources.

V. Discussion

A. *Implications for Revenue Management*

The accuracy of booking demand prediction can bring significant impacts on revenue management. Hotels indeed have the opportunity to adjust room prices dynamically when they expect high demand, and reduce the number of vacant rooms when they face lower booking likelihood. In addition, hotels can also be more effective with their pricing strategies when they understand their rivals better in the market to capture those customers sensitive with price, while maintaining profitability.

The results from this study show that indeed, there is an important impact of dynamic pricing policies on the hotel revenues since through including the competition pricing, local events data and weather data in forecasting models hotels may obtain more accurate information about the expected future demand.

B. *Impact on Operational Efficiency*

Accurate forecasts of customer demand can lead to improvements in operational efficiency through optimized staffing, inventory management, and marketing efforts. For instance, during peak periods of demand hotels might want to staff positions so as to ensure the best possible guest experiences while they simultaneously have an incentive to reduce labor costs during low demand periods. More generally, using demand forecasts for managing food and beverage (F&B) inventory can alleviate both waste issues and problems with stocking out of items which are in high demand from guests.

The findings derived from this study would provide skills for hotels where those allocations shall be made appropriately not only reduce operation costs but also increases customer satisfaction.

C. *Limitations of the Study*

While the models developed in this study have very high accuracy, there are a several of limitations that need to be acknowledged:

- External Events: Unpredictable external events like political instability, pandemics, and natural disasters can significantly change booking behavior thus making it difficult to accurately forecast the demand.
- Generalization: Models built in this study have been developed using data from a single hotel chain meaning that they are not generalizable across hotels or regions. In future research, this could be made more applicable across hotel types e.g., boutique or budget hotels.

VI. Future Work

A. *Expanding Model Generalization to Different Hotel Types*

Future research needs to further develop generalizable predictive models for different types of hotel properties – i.e., budget accommodations, luxury resorts and boutique hotels – in diverse geographic regions to obtain more robust findings that can better meet the varied requirements of the hospitality industry within market segments.

B. *Integration of Macroeconomic Indicators*

Future research should also examine whether relevant macroeconomic indicators (e.g. exchange rates, fuel prices and unemployment rates) would strengthen their predictive power as they affect travel decision making; for example, during economic recessions, customers would more likely choose cheaper boutique or budget accommodations or engage in local tourism activities, while during economic booms, customers might prefer luxury hotels or overseas trips.

C. Addressing Extreme Events in Forecasting

The challenge of such approaches is how the model deals with out of sample events like a pandemic or for example in the case of an earthquake which impacts generates considerable damages, but not demand.

Future work should see if there are ways that models can be improved to deal more effectively with these types of events, potentially through hybrid methods where ML and traditional scenario planning are used together and where rare but significant events are easier captured on the supply side.

D. Cross-Industry Applications

While this research paper concentrates on the tourism and hospitality industry, there is potential for the methodologies and models developed to be used in other industries where accurate demand forecasting is of high importance; for example, retail, airlines or car rentals. The extension of these predictive models would be beneficial to those industries that experience dynamic patterns of demand and are influenced by similar market drivers.

E. Leveraging Hybrid AI Approaches and Hybrid Metaheuristics for Enhanced Demand Forecasting

Future research should also investigate the potential of hybrid AI approaches and hybrid metaheuristics to enhance the efficiency and accuracy of demand forecasting models. By hybridation of various optimization techniques—such as metaheuristics methods and hybridation of AI models like LSTM, Random Forest, XGBoost, and Prophet, researchers can develop robust frameworks that effectively tackle complex, dynamic demand patterns. Hybrid metaheuristics can optimize model parameters and search for better solutions in complex environments, improving the overall performance [39]. Additionally, the insights gained from this hybrid methodology is applied across different sectors, allowing for improved operational strategies in industries facing different challenges [40, 41].

VII. Conclusion

Accurate prediction of booking trend and customer demand in tourism and hospitality industry is essential for revenue maximization, operation optimization, and customer satisfaction. This paper revealed that how Artificial Intelligence models like LSTM, Random Forest, XGBoost as well as Prophet can be utilized to build robust demand forecasting model by incorporating internal and external factors. The results underline the significance of dynamic pricing, the effect of event related demands' influx, and the role of competitor's price in molding customers' responses.

Data-driven decision making enables hotels to forecast changes in demands more accurately which facilitates improved resources allocation plans as well as pricing strategies resulting higher profitability and better guest experience.

Advancing the predictive modelling capabilities in tourism and hospitality through this research will support smarter, efficient management to cope with changing industry dynamic.

The relevance of this research in the community, more particularly to the tourism and hospitality industry, is very high. This research develops a powerful multi-algorithmic AI-driven framework to forecast hotel booking trend and customer demand accurately. It allows hotel managers to make better decisions concerning their hotel operations. The use of external factors regarding competitors' pricing, local events, weather conditions tend to make more reliable demand predictions which lead to smarter revenue management decisions, increase efficiency in operations and target marketing efforts more effectively. Such a data-driven approach will help both business organizations' bottom-line and practitioners within other domains applying predictive analysis realize its potential towards making accurate business-related forecasting. Making informed decisions through such research could support sustainable growth and continuous delivery of quality service in the community.

The study's limitations include the impact of unpredictable external events, such as political instability, pandemics, and natural disasters, which can significantly alter booking behavior and make accurate demand forecasting challenging. Additionally, the models were developed using data from a single hotel chain, limiting their generalizability to other hotels or regions.

Future research aims to enhance the generalization of predictive models across various hotel types and geographic regions, improving their relevance across market segments. Incorporating macroeconomic indicators such as exchange rates and unemployment rates can increase predictive accuracy by considering external factors influencing travel behavior. Moreover, addressing extreme events like pandemics or natural disasters remains a challenge, but hybrid models that integrate artificial intelligence with traditional scenario planning could offer better solutions. Extending these models to industries such as retail, airlines, and car rentals would also prove beneficial due to their similar demand dynamics.

Acknowledgment

The Ministry of Higher Education supports this project, Scientific Research and Innovation, the Digital Development Agency (DDA), and the National Center for Scientific and Technical Research (CNRST) of Morocco. APIAA-2019-KAMAL.REKLAOUI-FSTT-Tanger-UAE.

References

[1] N. Gouiza, H. Jebari, and K. Reklaoui, "Integration for IoT-Enabled Technologies and Artificial Intelligence In Diverse Domains: Recent Advancements and Future Trends," Journal of Theoretical and Applied Information Technology, vol. 102, no. 5, 2024, pp. 1975-2029.

[2] N. Gouiza, H. Jebari, and K. Reklaoui, "IoT in Smart Farming: A Review," in Proceedings of the International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD'2023), M. Ezziyyani, J. Kacprzyk, V. E. Balas, Eds., Lecture Notes in Networks and Systems, vol. 930, Springer, Cham, 2024, pp. 142-153.

[3] D. Buhalis and R. Leung, "Smart hospitality – Interconnectivity and interoperability towards an ecosystem," International Journal of Hospitality Management, vol. 71, 2018, pp. 41-50.

[4] S. Ivanov and C. Webster, "Adoption of robots, artificial intelligence and service automation by travel, tourism and hospitality companies – a cost-benefit analysis," International Journal of Contemporary Hospitality Management, vol. 31, no. 7, 2019, pp. 2530-2552.

[5] C. Morosan, “Hospitality and tourism consumers' adoption of artificial intelligence: Building a theoretical framework,” Journal of Hospitality and Tourism Technology, vol. 9, no. 1, 2018, pp. 33-52.

[6] World Tourism Organization, “AI in Tourism: The Role of Artificial Intelligence in Enhancing the Travel Experience,” UNWTO, 2019.

[7] Lufthansa Group, “Optimizing Flight Operations with AI,” Lufthansa Technical Report, 2019.

[8] J. W. Creswell, Research Design: Qualitative, Quantitative, and Mixed Methods Approaches, Sage Publications, 2013.

[9] Radisson Hotel Group, “Personalizing Guest Experiences with AI,” Radisson Industry Report, 2019.

[10] Visit Orlando, “AI-Driven Destination Marketing,” Visit Orlando Industry Report, 2019.

[11] AccorHotels, “AI in Customer Feedback Analysis,” AccorHotels Industry Report, 2019.

[12] B. Silverstein and H. Dong, “AI in Hospitality: Leveraging AI for Personalized Guest Experiences,” Hospitality Technology, vol. 28, no. 3, 2018, pp. 15-22.

[13] C. K. Anderson and S. Han, “The Impact of Artificial Intelligence on Hotel Pricing and Revenue Management,” Cornell Hospitality Quarterly, vol. 60, no. 2, 2019, pp. 146-157.

[14] B. A. Sparks and K. Weber, “AI-Driven Service Innovation in Hospitality,” Journal of Service Management, vol. 29, no. 3, 2018, pp. 420-441.

[15] U. Gretzel and D. R. Fesenmaier, “Leveraging AI for Tourism Marketing: Insights from the Industry,” Tourism Review, vol. 73, no. 2, 2018, pp. 215-225.

[16] S. Melián-González, J. Bulchand-Gidumal, and C. González, “The Role of Artificial Intelligence in the Tourism Industry,” Tourism Management Perspectives, vol. 31, 2019, pp. 120-128.

[17] Y. Li and Y. Mao, “AI in the Hospitality Industry: A Review and Research Agenda,” Journal of Hospitality Marketing & Management, vol. 28, no. 9, 2019, pp. 1197-1219.

[18] J. Wang and J. Lee, “Computer Vision and Its Applications in the Hotel Industry,” International Journal of Hospitality Management, vol. 73, 2018, pp. 81-90.

[19] K. Patel and A. Brown, “Voice Recognition Technology in Hotels: Enhancing Guest Experience,” Journal of Hospitality Technology, vol. 12, no. 1, 2019, pp. 28-35.

[20] R. Singh and M. Clark, “AI-Powered Voice Assistants in the Hospitality Industry,” Journal of Hospitality and Tourism Technology, vol. 9, no. 4, 2018, pp. 414-430.

[21] Y. Park and H. Lee, “Augmented Reality in Tourism: Enhancing Visitor Experience,” Tourism Management Perspectives, vol. 31, 2019, pp. 69-77.

[22] S. Lee and J. Kim, “The Role of Augmented Reality in Hotel Marketing,” Journal of Travel & Tourism Marketing, vol. 37, no. 3, 2020, pp. 295-310.

[23] K. Johnson and P. Hall, “AI Applications in Customer Service: A Case Study of Major Hotel Chains,” Journal of Hospitality and Tourism Insights, vol. 2, no. 2, 2019, pp. 123-135.

[24] S. Williams and D. Brown, “The Use of Chatbots in Enhancing Hotel Customer Service,” Journal of Hospitality Marketing & Management, vol. 27, no. 7, 2018, pp. 799-813.

[25] R. Thomas and K. Smith, “Real-Time Customer Support: The Role of AI in Travel Agencies,” International Journal of Information Management, vol. 48, 2019, pp. 129-137.

[26] M. Johnson and P. Jackson, “AI-Powered Concierge Services: Case Studies from the Hospitality Industry,” Journal of Hospitality and Tourism Technology, vol. 11, no. 1, 2020, pp. 47-63.

[27] D. Green and E. Clarke, “Voice-Activated Assistants in Hotels: Enhancing Guest Experience,” Journal of Hospitality Technology, vol. 13, no. 1, 2019, pp. 14-23.

[28] A. Singh, M. Kumar, and R. Jain, "Challenges in time series forecasting for hotel bookings: Limitations of ARIMA model," J. Hosp. Tour. Res., vol. 43, no. 4, 2019, pp. 567-584.

[29] Y. Chen, J. Wang, and L. Zhang, "Enhancing demand forecasting in the hotel industry using advanced machine learning models," Int. J. Forecast., vol. 36, no. 3, 2020, pp. 850-861.

[30] L. Breiman, “Random Forests,” Mach. Learn., vol. 45, no. 1, 2001, pp. 5-32.

[31] W. S. Noble, “What is a support vector machine?” Nat. Biotechnol., vol. 24, no. 12, 2006, pp. 1565-1567.

[32] G. Huang, "Artificial neural networks for hotel demand forecasting: A review of applications and challenges," J. Hosp. Res., vol. 78, 2021, pp. 123-135.

[33] H. Jebari, M. H. Mechkouri, S. Rekiek, and K. Reklaoui, “Poultry-Edge-AI-IoT System for Real-Time Monitoring and Predicting by Using Artificial Intelligence,” International Journal of Interactive Mobile Technologies, vol. 17, no. 12, 2023, pp. 58-70.

[34] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to Sequence Learning with Neural Networks,” in Advances in Neural Information Processing Systems, 2014, pp. 3104-3112.

[35] W. Geerts, "The impact of seasonality on hotel booking patterns in tourist destinations," Tour. Manag., vol. 56, 2016, pp. 186-195.

[36] F. Martín-Fuentes, S. Mateu, and J. Salinas, "The role of competitor pricing in customer booking behavior: A study on hotel price comparison websites," Int. J. Hosp. Manag., vol. 71, 2018, pp. 67-74.

[37] R. Santos, A. Costa, and P. Pereira, "Impact of large local events on hotel demand forecasting," Tour. Manag., vol. 74, 2019, pp. 153-162.

[38] G. Chiappa, M. Baggio, and F. G. Del Chiappa, "The influence of weather on hotel demand for outdoor leisure activities: A time series analysis," Ann. Tour. Res., vol. 83, 2020, pp. 102931.

[39] H. Jebari, S. Rekiek, S. R. Elazzouzi, and H. Samadi, “Performance comparison of three hybridization categories to solve multi-objective flow shop scheduling problem: A case study from the automotive industry,” International Journal of Advanced Computer Science and Applications, vol. 12, no. 4, 2021, pp. 680–689.

[40] Jebari Hakim, Siham Rekiek, and Kamal Reklaoui, “Solving the Job Shop Scheduling Problem by the Multi-Hybridization of Swarm Intelligence Techniques,” International Journal of Advanced Computer Science and Applications, vol. 13, no. 7, 2022, pp. 753–764.

[41] Hakim Jebari, Siham Rekiek, Kamal Reklaoui, "Improvement of Nature-Based Optimization Methods for Solving Job shop Scheduling Problems," International Journal of Engineering Trends and Technology, vol. 71, no. 3, 2023, pp. 312-324.