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A 2-Layered Game-Theoretic Deep Learning Model for Predicting Lodging Demand: SHAP and Nash Equilibrium

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Abstract

Forecasting tourism demand is critical for pricing and revenue management, yet most advanced machine learning models operate as “black boxes,” limiting interpretability and trust. This study introduces an explainable, game-theoretic hybrid deep learning framework for predicting short-term rental demand. This study incorporates game theory in two layers: a cooperative game and a competitive game. Using 729,888 daily observations from 1,852 Airbnb listings in Ann Arbor, Michigan, we compare traditional models (regression, SARIMAX) with advanced architectures (FCNN, LSTM, Transformer, and a Transformer–LSTM hybrid). Game theory is used in two layers: cooperative game (SHAP) and competitive game (classic Nash equilibrium). SHAP creates an explainable deep learning model to quantify each feature’s contribution. The best-performing model (FCNN) was further used to simulate a 3x3 pricing game between pairs within 4 submarkets. Results show that deep learning models significantly outperform traditional baselines, while SHAP-based feature attribution and clustering enhance transparency and strategic insight. The competitive games shed light on the characteristics and dynamics of each submarket. This research offers insights to revenue managers, policymakers, and operators.

1. Introduction

Forecasting demand in the tourism and hospitality industry is essential for strategic decisions related to pricing, revenue management, and resource allocation. The emergence of peer-to-peer platforms like Airbnb has introduced new opportunities and complexities in demand forecasting, given their distinct features such as host-driven supply, review-based trust mechanisms, and residential locations. Unlike traditional hotels, Airbnb listings exhibit heterogeneous demand patterns, which makes accurate forecasting vital for stakeholders, including hosts, urban planners, and tourism marketers. Traditionally, tourism demand forecasting relied on time-series models (e.g., ARIMA) and econometric regressions using macroeconomic indicators. While these models offered interpretability and reasonable performance under stable conditions, no single approach consistently outperformed others across all contexts(Binesh et al., 2024; Chinnaraju, 2025; Linardatos et al., 2020).

In the hospitality domain, researchers have progressed from univariate hotel occupancy forecasts to advanced algorithms incorporating spatial and temporal patterns (Ampountolas, 2019; Kouppriouchina et al., 2023; Wu et al., 2022). Deep learning techniques, such as Long Short-Term Memory (LSTM) networks, have become popular due to their ability to model long-term dependencies in sequential data. Studies like (Wang & Duggasani, 2020) demonstrated the effectiveness of LSTM in capturing irregular booking surges, while (Huang & Zhang, 2024) reported that Transformer-based models outperformed LSTMs in some scenarios. Originally developed for natural language processing, transformers use self-attention to learn complex dependencies without sequential constraints. Further improvements have been achieved using hybrid and ensemble models. For example, (He et al., 2022) introduced a SARIMA–CNN–LSTM hybrid that outperformed individual components, supporting evidence that combining models often enhances accuracy (Song et al., 2019).

However, as machine learning models become more complex, their interpretability diminishes. In tourism and hospitality, practitioners and decision-makers often value understanding the drivers of demand—not just the predictions themselves. Yet, many advanced forecasting models remain “black boxes,” providing little insight into how predictions are generated (Henriques & Pereira, 2024; Huang & Zhang, 2024; Wu et al., 2022; Zheng et al., 2020).

Moreover, property-level decisions are not made in isolation; they are strategic responses to competitor actions, local events, and shifting demand. Game theory provides a useful framework for modeling these interdependent behaviors, where individual hosts act as players competing for bookings under uncertainty. In this study, we leverage game-theoretic logic in both the feature design and the model interpretability layer, treating observed host and market attributes as strategic signals within a competitive environment. The following are the research questions of this study:

RQ1: How do deep learning models compare to traditional forecasting models in predicting Airbnb demand?

RQ2: Can SHAP-based feature attribution improve interpretability and model selection?

RQ3: What equilibria arise in 2-player pricing games when using ML-estimated demand?

Methodologically, it incorporates game theory at two levels: cooperative game and competitive game. Using Shapley Additive Explanations (SHAP) allows us to interpret feature importance as cooperative payoffs, while a 3x3 2-player game allows us to model pricing interaction between properties. This study is novel in its double-layered use of game theory. It is also novel in its use of the best-performing ML model to simulate the demand for each property in the competition. This is unlike prior studies that rely on static conditions.

By combining game theory’s strategic perspective with SHAP’s cooperative payoff logic, this study interprets forecasting features as strategic signals in tourism markets—each reflecting decisions made in anticipation of others. This new lens advances beyond accuracy-centered forecasting by providing a behaviorally and theoretically coherent explanation of why certain signals matter (strategic interaction) and how much they matter (marginal contribution). In doing so, it contributes to the broader tourism analytics literature that seeks to align machine learning interpretability with economic and behavioral reasoning, offering both theoretical depth and actionable insights for destination competitiveness, revenue management, and market adaptation.

2. Literature Review

Demand forecasting has long been recognized as a critical task in tourism and hospitality management, given its importance for revenue management, resource allocation, and strategic planning. Early research on tourism demand prediction, dating back several decades, predominantly employed classical time-series and econometric approaches (e.g., autoregressive models and regression analysis) to forecast tourist arrivals or hotel occupancy. No single model consistently outperforms all others across

all situations (González-Reverté & Díaz-Luque, 2024). The introduction of machine learning (ML) was an attempt to improve the predictability and adaptability.

2.1. Evolution of Forecasting Research

Early tourism demand forecasts often relied on univariate time-series methods like ARIMA (and its seasonal variants) or exponential smoothing and econometric models incorporating economic indicators (e.g., income, prices, exchange rates) as predictors. These traditional models provided interpretable results and were effective for relatively stable demand patterns. Even within this classical paradigm, no single statistical model works best in all scenarios (Ampountolas, 2025; Binesh et al., 2024; Li et al., 2025). Their influential review emphasized that forecasting performance is highly situation-specific, depending on destination, data frequency, and model assumptions. This realization spurred efforts to test a wider range of models in comparative studies. Indeed, the number of models evaluated per study has increased over the decades (on average ~ 2.5 models per study since the 1990s, compared to fewer than 2 in earlier decades). This era saw an influx of regression-based and ARIMA-based models (Pan & Yang, 2017). Still, many studies historically compared only a few methods that the researchers chose, which could bias conclusions to those specific contexts (Kim & Yeon, 2025).

By the 2000s and 2010s, researchers began introducing artificial intelligence (AI) and machine learning techniques, such as support vector machines, random forests, gradient boosting, as well as artificial neural networks (ANNs), and other ML models (Das et al., 2021; Li et al., 2020; Pereira & Cerqueira, 2021, 2022; Sanchez-Medina & C-Sanchez, 2020; Zhang et al., 2020; Zhu et al., 2021). While these models showed superior performance, they introduced new challenges related to interpretability and transparency.

2.2 Advanced models

Over the past five years, there has been a marked expansion in research applying machine learning (ML) and deep learning (DL) to hotel-level demand forecasting and short-term rental occupancy prediction. Recent studies can be grouped into several streams: deep learning models, hybrid models, and ensemble models.

2.2.1 Neural Networks

Artificial Neural Network (ANN)-based models have been a cornerstone of machine learning applications in tourism forecasting since the 2000s. An ANN can approximate complex nonlinear functions, making it suitable for capturing patterns in demand data that linear models miss. Many studies have documented ANNs outperforming traditional methods in tourism/hospitality contexts. For example, (Claveria et al., 2015a) showed that a neural network could improve hotel demand forecast accuracy by modeling nonlinear relationships in historical data. Similarly, Schwartz et al. (2021) demonstrated that machine learning (including neural nets) can enhance the accuracy of revenue management forecasts when combined appropriately with human judgment. Pure ANN models have some limitations for time-series

forecasting: they do not inherently account for temporal order or sequence dependence. Therefore, while Recurrent Neural Network (CNNs) have been used (and are still used as baseline ML models for demand prediction), they are often supplemented or replaced by sequence-based deep learning models for time-dependent data (Binesh et al., 2025). CNNs are designed to handle sequence data by maintaining internal state (memory) across time steps. The most popular RNN variant in tourism demand forecasting is the Long Short-Term Memory (LSTM) network, which addresses the vanishing gradient problem of basic RNNs and can learn long-term dependencies. LSTM models have seen extensive application in tourism and hospitality forecasting in the past five years, such as LSTM-based RNN to forecast hotel reservations (Wang & Duggasani, 2020), and LSTM-based models for long-term tourism demand forecasting (Salamanis & et al., 2022). Despite this rapid adoption, these models often lack transparency and fail to incorporate the complex competitive behaviors and contextual factors that increasingly influence accommodation demand (Binesh et al., 2024; Chinnaraju, 2025).

2.2.2 Transformers and Attention-Based Models

The most recent wave of innovation involves Transformer architectures, originally developed for natural language processing, now adapted for time-series forecasting. Transformers use self-attention mechanisms to capture long-range dependencies without the sequential bottleneck of RNNs. Huang and Zhang (2024) appear to be among the first to apply a transformer (specifically an inverted Transformer or "iTransformer") to tourism demand data, demonstrating improved accuracy on daily tourist visit forecasts compared to RNN benchmarks. Transformer models are relatively new in the hospitality and tourism context. While promising, Transformer applications in hospitality remain nascent and narrowly focused on accuracy, leaving critical gaps in scalability, transparency, and integration with market-level dynamics (Li et al., 2024).

2.2.3. Hybrid models

Given the strengths and limitations of individual models, hybrid approaches combining statistical and deep learning techniques have emerged as a dominant trend. Studies show that hybrid models often outperform single-method approaches by leveraging complementary strengths (Henriques & Pereira, 2024). He et al. (2022) introduced a SARIMA–CNN–LSTM model that significantly outperformed each component (Kim, 2025). In contexts, Gunter, Önder, and Zekan (2020) modeled Airbnb demand in New York City using a spatial panel data approach. A notable recent contribution is Gunter et al. (2024), who modeled and forecasted Airbnb occupancy across 43 European countries during the COVID-19 pandemic. Despite these advances, recent reviews note persistent limitations in the literature. The 2024 systematic review by Henriques and Pereira points out challenges such as inconsistent model specification, limited transparency regarding feature engineering and data granularity, and a lack of studies linking improved forecast accuracy to actual financial or pricing outcomes (i.e., few studies demonstrate how better occupancy forecasts translate into improved revenue management).

Moreover, most existing models remain primarily focused on enhancing predictive accuracy, with limited attention to interpretability or theoretical grounding in decision-making behavior (Chinnaraju, 2025). Only

a few studies explicitly connect predictive performance to the strategic mechanisms that shape tourism markets—such as pricing competition, adaptive behavior among service providers, and travelers' responses to uncertainty (Binesh et al., 2024; Nikseresht, 2025). Most hybrid models remain black boxes, prioritizing predictive performance over interpretability and failing to connect forecasts with strategic decision-making mechanisms such as pricing competition or market adaptation (Henriques & Pereira, 2024; Nikseresht, 2025).

2.3. Game Theory and Explainable AI

A common concern of ML models is the "black-box" complex; these models are hard to interpret and understand. In recent years, the focus on explainable models has increased. An explainable model is one that combines ML with interpretability. Tourism markets function as complex adaptive systems characterized by strategic interdependence among destinations, service providers, and travelers. Hotels, short-term rental hosts, and tour operators adjust pricing, amenities, and capacity in anticipation of competitors' strategies, while travelers coordinate booking decisions and trip timing under uncertainty about price fluctuations, availability, and destination conditions (Ampountolas, 2025; Binesh et al., 2025). Such behavior reflects core principles of game theory, where agents act strategically based on others' anticipated moves, leading to equilibria shaped by competitive and cooperative interactions.

Within this theoretical tradition, the Shapley value, originally proposed by Shapley (1953), provides a mathematical framework to assess each participant's marginal contribution to a cooperative outcome. The SHapley Additive exPlanations (SHAP) method is built on this concept (Lundberg & Lee, 2017), which extends the Shapley logic to machine learning interpretability by assigning each feature in a model its proportional "payoff" to a predicted output. In tourism forecasting and market analytics, this approach allows researchers to decompose predictions into fair, theoretically grounded attributions, revealing how factors such as competitor pricing, event timing, accessibility, and traveler sentiment contribute to overall demand and occupancy outcomes (Binesh et al., 2024; Choudhury & Goswami, 2012; Stier et al., Procedia Computer Science/2018).

Recent studies have demonstrated that even modest improvements in forecast accuracy can yield substantial financial benefits for tourism operators, particularly in volatile contexts such as pandemics or economic downturns (Binesh et al., 2025). While deep learning and hybrid models have improved forecasting accuracy, they remain largely black boxes and fail to capture strategic interdependencies among market players. Moreover, existing studies treat properties or destinations homogenously, regardless of their intrinsic differences (Binesh et al., 2024; Nikseresht, 2025; Salamanis & et al., 2022). This gap motivates our study, which integrates explainable AI and game theory into a unified forecasting framework, using machine learning predictions to inform competitive pricing simulations and equilibrium analysis. By bridging predictive accuracy with strategic insight, this research advances both methodological rigor and practical relevance for dynamic tourism markets.

3. Methodology

3.1 Data Overview

The data was collected from Ann Arbor, Michigan, from January 2021 to December 2022. A total of 729,888 observations from 1,852 distinct properties were analyzed. The dataset contained 22 features, such as property type, listing details, guest capacity, amenities, and location-specific attributes (e.g., zip code, latitude, longitude). Temporal features such as date, event indicators (e.g., holidays, local events), and market demand were also included. Preprocessing steps involved handling missing data, scaling features for consistency, and encoding categorical variables. Supply and demand in this context are calculated using the 'Status' of property listings. Both statuses, "Available" and "Booked," count as supply. If a property is Available, it has a demand value of 0, meaning there is no demand for that property. If a property is booked, it has a demand value of 1, indicating that it is in demand.

3.2 Feature engineering

Feature engineering in this study centered on identifying and transforming variables most relevant to forecasting demand. 22 features were included in the base model (Table 3). This is a mix of location-based and property-specific characteristics (such as the number of bedrooms and guest capacity). These engineered features were designed to capture complex, non-linear relationships as well as spatial and temporal dependencies within the dataset.

3.3 Models Tested

Three scenarios were tested (base model, SHAP, SHAP extended). To create a comprehensive comparison, we tested several traditional models (linear regression, SARIMAX) against DL models (Long Short-Term Memory (LSTM), Transformer, Fully Connected Neural Network (FCNN), and a Combined Model (Transformer + LSTM) (Supplementary Materials, Table A1). The combined model integrates the strengths of both LSTM and Transformer to enhance predictive accuracy. Various combinations of weights were experimented with, including LSTM 50% - Transformer 50%, LSTM 40% - Transformer 60%, LSTM 30% - Transformer 70%, LSTM 70% - Transformer 30%, and LSTM 60% - Transformer 40%. Among these, the best results were achieved with a weight distribution of LSTM 30% and Transformer 70%, optimizing the model's performance and predictive accuracy.

The dataset was randomly split into 80% training and 20% testing. A random seed was used for reproducibility. A fully connected neural network with two hidden layers of 512 and 128 neurons using sigmoid activation. The LSTM model had 5 hidden layers, 128 each, binary classification with logit loss, and sigmoid evaluation. The transformer model uses 4 heads, 2 encoder layers, and 2 decoder layers, a dropout rate of 0.1, and a feed-forward dimension of 2048. All the deep learning models were trained using the Adam optimizer (β_1=0.9, β_2=0.999) with a learning rate of 0.001. The binary cross-entropy loss function was used. The batch size of 64 and epoch of 10 were used for all models. 5-fold cross-validation was used for all models.

3.4 Performance Metrics

To evaluate the results, we used multiple metrics, which is consistent with previous studies highlighting the importance of incorporating various measures (Binesh et al., 2025). Given the binary nature of the demand, we used precision, F1 score, ROC AUC, accuracy, and recall (Fernández-Delgado et al., 2014).

3.5 Game theoretic analysis

This study applies game-theoretic reasoning at two levels: First, cooperative game theory is used at the feature level through SHapley Additive exPlanations (SHAP) to quantify the marginal contribution of each input variable to predicted demand. Second, we model pricing interaction between properties in a competitive game, in which hosts independently select pricing strategies and receive payoffs that depend on both their own decisions and those of their competitors. Figure 1 shows an overview of this study.

FIGURE 1.

3.5.1 SHAP values

To enhance interpretability and address the "black box" nature of advanced machine learning models, we used SHAP (SHapley Additive exPlanations) values to quantify the contribution of each feature to the predicted demand outcomes. Rooted in cooperative game theory, SHAP provides a unified, model-agnostic framework that fairly attributes the marginal contribution of each input variable to a model's prediction (Lundberg & Lee, 2017).

This approach is particularly well-suited for tourism and hospitality applications, where interpretability is essential for stakeholder trust and actionable decision-making (Doborjeh et al., 2021; Nam & et al., 2020). For each model, absolute SHAP values were averaged across all observations to determine global feature importance. The mean SHAP score served as a threshold to guide feature selection in Scenarios 2 and 3 of the study. In scenario 2, only the features that had an absolute SHAP value over the threshold were retained in the model, while in scenario 3, the next four features with the highest absolute SHAP were also included.

3.5.2 Competitive Game within Clusters

In this study, we tested two types of games, Bertrand and Stackelberg. The Bertrand games are the classic Nash Equilibrium, where players act simultaneously. The Stackelberg games are a situation where one player acts first and the second player responds. First, we clustered our data into submarkets. K-means clustering was used as it has shown promising results in analyzing lodging data (Lee et al., 2020). For creating the clusters, we used the location-based data to make sure competitors in each

cluster are within 5 5-mile radius, as well as property-based data such as number of bedrooms, bathrooms, price, to make sure clusters contain properties of a similar class.

The optimal number of clusters (k) was determined using the elbow method, which plots the total within-cluster sum of squares (inertia) against the number of clusters. The x-axis represents the number of clusters (k), and the y-axis shows the inertia, which quantifies the variance within each cluster. The elbow method identifies the point where adding more clusters results in diminishing improvements in variance reduction (Van Der Donckt et al., 2023). This "elbow" point represents the most appropriate k value, balancing model simplicity with clustering effectiveness (Rokach & Maimon, 2005).

Next, a series of 3x3 2-player games was performed. Within each cluster, we analyze **pairwise non-cooperative pricing interaction** by randomly selecting two properties to participate in a discrete pricing game (Osborne & Rubinstein, 1994). Each property acts as an independent player and chooses one of three pricing strategies (**Low, Medium, or High**) defined based on the within-pair quantile bands (20th, 50th, and 80th). Pricing decisions are made either **simultaneously**, corresponding to a **Bertrand pricing game**, or **sequentially**, corresponding to a **Stackelberg leader–follower game**. By restricting strategic interaction to properties within the same cluster, the analysis ensures that competitors face comparable demand conditions, pricing environments, and degrees of substitutability, consistent with the notion of localized competition in short-term rental markets (Zervas et al., 2017; Lee et al., 2020). Payoffs are defined as **expected revenue**, calculated as the product of the predicted booking probability and the selected price level. Booking probabilities are generated using the best-performing forecasting model (FCNN) (Vives, 1999; Cachon & Netessine, 2006). This approach makes the data analysis rely on data rather than static assumptions.

4. Results

The models were evaluated using various feature selection strategies, with performance assessed through precision, recall, F1-score, accuracy, and ROC AUC. Next, clustering was used to improve predictive accuracy. The results highlight key insights into the effectiveness of different models under varying conditions. Table 1 shows the scenarios tested in this study. Across all three scenarios, model performance varied based on the feature selection strategy, demonstrating the impact of feature selection on predictive accuracy.

TABLE 1

4.1 Study 1: DL Models used for Predicting Demand

4.1.1 Scenario 1: Full Feature Set

When all 22 features were included, the Fully Connected Neural Network (FCNN) exhibited the strongest predictive performance, achieving the highest precision (92.50%), F1-score (93.21%), and accuracy

(89.59%). The ROC AUC score of 95.48% further reinforced FCNN's superior ability to differentiate between high-demand and low-demand properties. LSTM followed closely, while the Transformer model also demonstrated strong results. In contrast, traditional models such as Linear Regression and SARIMAX underperformed significantly, indicating their limitations in capturing the intricate patterns governing Airbnb demand.

4.1.2 Scenario 2: Feature Selection Based on Shapley Scores

Restricting the feature set to only those with Shapley scores above the average altered the ranking of model performance. The Transformer model emerged as the most effective, achieving an F1-score of 93.11%, a precision of 91.08%, and an accuracy of 89.08%. These results suggest that a more selective approach to feature inclusion enhances generalization, reducing potential overfitting and improving the model's predictive robustness. The FCNN model, while still performing well, exhibited a slight decline in accuracy (87.23%) and F1-score (91.74%), further underscoring the importance of targeted feature selection. Table 2 shows the Shapley value results for each model.

TABLE 2

4.1.3 Scenario 3: Expanded Feature Selection Strategy

Incorporating the most relevant Shapley features alongside the next four most significant variables resulted in a shift in model rankings. FCNN regained its top position, yielding an F1-score of 89.96%, a precision of 90.37%, and an accuracy of 86.66%. The ROC AUC score of 93.67% reaffirmed its capacity to effectively distinguish demand fluctuations. The Transformer model remained a strong performer, with a ROC AUC score of 91.48%, though its overall accuracy was slightly lower than FCNN. These results suggest that expanding the feature set beyond the highest-ranked Shapley features can enhance FCNN's predictive performance while maintaining competitive results for the Transformer model. Table 3 shows the summary of the models tested in each scenario.

TABLE 3

4.2 Study 2: 2-player Games within clusters

In the second study, we use the best overall DL model (FCNN) to simulate demand for a series of 2-player games. First, we used k-means clustering to create organic groups of players (properties) competing in the same market. In game theory, heterogeneous agents often adopt different strategies based on their resource levels, location, or market position (Özçini et al., 2023). Similarly, short-term rental properties vary in size, price, and location, which creates implicit competitive tiers. Clusters were generated based on all numerical attributes in the dataset, such as the number of bedrooms, bathrooms, maximum guests, latitude, longitude, cleaning fees, and more. Using a single attribute, such as "Listing

Type," would have oversimplified the clustering process and missed key patterns driven by other important features.

FIGURE 2

The elbow method was used to determine the optimal number of clusters (Figure 2) (Syakur et al., 2018). The elbow graph shows that k=4 is the optimal number of clusters (Table 5). This finding was later confirmed with the silhouette test. Figure 3 shows the booking rate versus price for each cluster. Cluster sizes range from 44 to 1,223 properties, indicating both niche and mass-market segments. Cluster 2 constitutes the largest group, accounting for approximately two-thirds of all properties. Listings in this cluster show low average booking rates (3.1%) and low average prices (approximately $148), with minimal price dispersion and near-zero correlation between price and demand. This pattern suggests that pricing variations within this segment have limited influence on occupancy outcomes. Cluster 3 is a high-demand segment, characterized by the highest average booking rates (39.5%) and substantial price dispersion. The positive correlation between price and demand in this cluster shows meaningful price sensitivity, suggesting that pricing strategies play a significant role in shaping booking outcomes. This cluster shows strong responses to demand, which makes it the competitive core of the market. Clusters 1 and 4 capture high-price segments with distinct demand dynamics. Cluster 1 consists of high-priced listings (average price exceeding $1,200) with incredibly low booking rates and limited price variation. In contrast, Cluster 3 combines similarly soaring prices with substantially higher average booking rates and extreme heterogeneity in pricing behavior. The low correlation between price and demand in Cluster 3 suggests that factors other than price—such as quality, reputation, or uniqueness—play a dominant role in driving bookings.

FIGURE 3

For each cluster, we analyzed the Bertrand pricing (Nash Equilibrium) and Stackelberg pricing (leader-follower game) between property 1 (P1) and property 2 (P2) (Table 4). In cluster 1, examining P2's payoff function shows that its **best response is High pricing regardless of P1's price choice**. Anticipating this response, P1 maximizes its own payoff by selecting High as well. Reversing leadership roles yields the same outcome. In Cluster 2, P1 earns an expected revenue of approximately **142.8**, while P2 earns approximately **40.2**. Given P2's low price, P1 strictly prefers the highest price level. Conversely, given Property 1's price choice, P2 strictly prefers the lowest price level, as any deviation to medium or high pricing leads to a near-complete loss of bookings. In cluster 3, properties were highly saturated in demand, which made it hard to find a pair of properties to run a meaningful game. After analyzing the data output, we decided to use two properties that had enough daily observations (516) and varied in booking and pricing variance. The results show a Low/High equilibrium for P1 and P2, respectively. In Cluster 4, best-response analysis yields a **unique pure-strategy Nash equilibrium** at **(High, High)**, with expected revenues approximately **(0.71, 33.45)** for (P1, P2). The equilibrium is supported by **dominant strategies** for both properties: each maximizes expected revenue at the highest price band given any

rival choice. In all four clusters, the **Stackelberg Pricing (Leader–Follower) results were the same as the Nash Equilibria.** We therefore find **no first-mover advantage** in this pair.

TABLES 4 & 5

5. Discussion

Deep learning models consistently outperformed traditional statistical baselines (Claveria et al., 2015b; Huang et al., 2024; Wang & Duggasani, 2020). However, the relative performance of models varied depending on the feature selection and enhancement strategy used. This finding echoes previous studies that show the importance of feature selection and data representation.

In Scenarios 1 and 3, FCNN achieved the highest overall performance (F1 = 93.21% and AUC = 95.48%). This outcome indicates that FCNNs, though not inherently designed for sequence modeling, can deliver strong results when provided with a rich set of well-engineered features (Henriques & Pereira, 2024; Pereira & Cerqueira, 2022). In Scenario 2, the Transformer model emerged as the top performer (F1-score = 93.11%). This suggests that attention-based architectures are adept at extracting meaningful patterns from compact, high-quality inputs (Wu et al., 2024).

Although the hybrid Transformer–LSTM model consistently delivered strong results, it did not outperform the top models in any scenario. This may point to inefficiencies in feature weights or overlapping information between the two architectures. Nevertheless, its close performance shows it can be a promising substitute (He et al., 2022).

Furthermore, incorporating Shapley values significantly enhanced the interpretability of our models, which addresses a notable gap identified in previous research (Binesh et al., 2024; Doborjeh et al., 2021). Key variables such as Cleaning Fee, Price, Bathrooms, and geospatial indicators like Latitude and Distance to Stadium consistently emerged as influential predictors across models. These findings provide clear, actionable insights for both Airbnb hosts and urban policy planners, offering interpretable decision levers grounded in data. While earlier studies, such as (Wu et al., 2024), demonstrated interpretability through attention mechanisms in specific models like the Temporal Fusion Transformer, our approach extends this transparency across a broader set of model architectures.

Beyond identifying important features, Shapley-based analysis also revealed underlying nonlinear relationships. For example, the interaction between spatial variables and pricing data points to intricate geospatial-economic patterns within Airbnb markets. This finding aligns with insights from spatial econometrics (Aznar et al., 2019; Hong & Yoo, 2020; Kim & Yeon, 2025), but extends them through a machine learning lens. Our findings offer a more flexible and scalable approach to understanding location-driven demand dynamics.

Our 2-player games showed that in Cluster 1 (high prices, low booking rate), both properties gained the best revenue at a higher price. Although alternative scenarios generate higher outcomes, they remain

unstable. This result reflects a defensive pricing equilibrium, meaning players might have a price match policy. This scenario is also common in markets when a new player enters the market, and the existing players reduce their prices to make the market less attractive for the new entrant (Moorthy & Winter, 2006). For cluster 2, P1 functions as a high-price listing, monetizing periods of strong demand even at elevated prices. Property 2, by contrast, can only sustain demand at the lowest price level and effectively operates as a budget or fallback option. This equilibrium outcome reflects a form of endogenous price segmentation; players choose their market segment (such as high quality, high value, etc.). This means that in this cluster, the hosts filter out the guests based on their willingness to pay. Unlike the cluster-1 pair, where strategic interaction arose from mutual substitution, the cluster-2 (low price and low booking rate) pair exhibits asymmetric pricing roles. The changes in property prices appear to be caused by sudden changes in demand rather than changes in the competitors' strategy (Friberg & Martensen, 2001).

In cluster 3 (highest booking rate, moderate prices), the Nash equilibrium suggests a high/low strategy. Meaning when P2 goes higher in prices, P1 maximizes payoff at low, and when P1 goes low, P2 maximizes payoff at high. This cluster is a classic example of inelastic demand; regardless of price, properties always have high demand. This shows that cluster 3 is distinctly different than the other clusters, due to highly saturated demand, asymmetric price elasticity. This condition creates a market where consumers react more strongly to price increases than to price decreases. This means, when prices increase, consumers feel a "loss" (Tellis, 1988).The cluster-4 (very high prices, strong booking rate) pair behaves as a high–high market segment, where listings mutually benefit from high demand. Both listings can monetize higher price bands without lowering their price. The equilibrium reflects the consumers' sensitivity to higher prices, meaning that when both players keep their prices high the consumers' adverse reaction to a rise in prices minimizes (Kopalle & Shumsky, 2010).

The results of the Stackelberg test were the same as the Nash equilibrium in all scenarios. This means that the first-mover advantage is absent in this pairwise market, not because of flat demand or weak identification, but because pricing incentives are strictly ordered for players. This means that (price = marginal cost); both players are motivated to set their prices at their marginal costs. These conditions happen under two circumstances: first, when players have a small capacity and cannot dominate the market, and second, when all firms are rational and fully informed about their opponents' costs and strategies (Bernard et al., 2016). In Airbnb's listings, the first case is a better representation of the realities of the market. No single player has the capacity to fully dominate the market. Therefore, it would be interesting to test these dynamics among hotels, or between hotels and Airbnb as a whole in future studies.

6. Contributions and implications

This study contributes to the literature on demand forecasting in several ways. First, it is among the first studies to introduce game-theoretic reasoning into tourism accommodation forecasting, treating host and market level attributes as strategic signals rather than isolated predictors. We integrate deep

learning, game theory, and explainable artificial intelligence (XAI) within a unified forecasting framework. By embedding Shapley Additive Explanations (SHAP)—grounded in cooperative game theory—the study provides an approach to quantifying each feature's marginal contribution to the predicted outcome. Unlike traditional feature selection or correlation-based methods, SHAP conceptualizes prediction as a cooperative process, where model features act as "players" contributing to a shared payoff. This framing ensures that feature importance is interpreted both statistically and theoretically, aligning machine learning outputs with established behavioral logic in tourism markets (Lundberg & Lee, 2017).

Second, the study extends the application of game-theoretic reasoning beyond interpretability. Using the FCNN model's output as predicted demand, a 3x3 2-player game was conducted between 4 random pairs. This two-layer use of game theory—cooperative (SHAP) and competitive —offers a richer and more realistic representation of how agents behave and interact in tourism environments.

Third, unlike prior studies that rely on static assumptions, we use outputs from the best-performing ML model to feed real-time demand estimates into a pricing game. This novel approach allows a dynamic payoff calculation and equilibrium analysis.

Fourth, methodologically, the study enhances forecasting accuracy and interpretability by combining Transformer and LSTM architectures with feature selection based on Shapley values and cluster-informed inputs. This hybrid structure allows the model to simultaneously capture temporal dependencies, spatial variations, and strategic interdependencies among properties, advancing beyond previous black-box deep learning models that emphasized prediction over explanation.

Finally, the research contributes to the growing body of work on explainable AI in tourism forecasting, demonstrating that predictive precision and interpretability are not mutually exclusive goals. By showing how complex models such as Transformers can be rendered transparent through SHAP and clustering, this study fosters greater trust, accountability, and decision-making value for both researchers and industry practitioners (Doborjeh et al., 2021).

In terms of practical implications, the findings of this study can be used by revenue managers and revenue management system developers. In highly saturated markets, price changes have low marginal returns. As such, it is recommended to focus on other revenue management strategies such as minimum stays, cleaning/turnover, and listing quality. In a competitive core market, pricing rules can be beneficial (e.g., if rival is High, we stay High; if rival is Low, we still stay High/Low). Our results showed that the leader did not have an advantage. As such, being the first to set the price is not advisable, and instead, properties can focus on positioning. Currently, the use of AI in revenue management remains limited. One reason is the "black box" nature of ML models, which makes it hard to quantify their impact. Incorporating SHAP creates a solution to rectify this issue by creating actionable, explainable models and outcomes.

7. Limitations and future research

This study focused on a single urban Airbnb market, limiting generalizability. Future work could test these models across multiple markets to test their generalizability. We tested several traditional and ML models. However, many models remained unexplored. Future research can test other models, such as gradient boosting, and other forms of transformer architecture. While we included some external factors, such as events and holidays, future studies can expand the external factors. We used pre-existing data; future studies may use real-time data, which can capture the dynamic nature of short-term rental markets. Due to the study length constraints, we only looked at 1 pair per cluster; future studies can look at 5 or 10 pairs randomly selected from each cluster. K-means clustering was used for this analysis; future studies may test other clustering methods and compare the results. The feature selection for the clusters (e.g., external factors such as weather and inflation) can also be modified in future studies to compare the results.

Declarations

Author Contribution

Binesh supervised the project from creation and ideation to completion. Kushi worked on data analysis the other authors helped with editing and writing the manuscript.

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Declaration of InterestThe authors report no conflict of interest.Declaration of generative AI and AI-assisted technologies in the writing processDuring the preparation of this work, the author(s) used Grammarly in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.FundingThis study was not funded.

Data Availability

The data was purchased from air DNA.

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Tables

Table 1: The best models and features

Case	Best Model	Features
Case 1: Full Feature Set	FCNN	‘Property Type’, ‘Listing Type’, ‘Bedrooms’, ‘Bathrooms’, ‘Max Guests’, ‘Overall Rating’, ‘Number of Reviews’, ‘Security Deposit’, ‘Cleaning Fee’, ‘Minimum Stay’, ‘Football’, ‘Event’, ‘Holiday’, ‘Zip Code’, ‘Latitude’, ‘Longitude’, ‘Distance Stadium’, ‘Distance Town’, ‘Occupancy Rate’, ‘Price’
Case 2: Shapley-Based Feature Selection	Transformer	‘Bedrooms’, ‘Bathrooms’, ‘Max Guests’, ‘Cleaning Fee’, ‘Price’, ‘Zip Code’, ‘Latitude’, ‘Distance Town’, ‘Occupancy Rate’
Case 3: Expanded Shapley Feature Selection	FCNN	‘Bathrooms’, ‘Price’, ‘Latitude’, ‘Longitude’, ‘Distance Town’, ‘Distance Stadium’, ‘Occupancy Rate’, ‘Bedrooms’, ‘Max Guests’, ‘Security Deposit’, ‘Listing Type’

Table 2: Models tested and cases (The best model in each case is bolded in parentheses)

Case 1: Full Feature Set (**FCNN**)						
Performance Metric	LSTM	Transformer	Combined Model	**FCNN**	SARIMAX	Linear Regression
Precision	91.71%	91.41%	87.01%	**92.50%**	78.59%	78.13%
F1-Score	93.08%	92.75%	92.48%	**93.21%**	86.91%	87.12%
Accuracy	89.29%	88.71%	87.65%	**89.59%**	77.56%	76.98%
ROC AUC	95.27%	82.76%	84.69%	**95.48%**	69.99%	53.12%
Recall	95.10%	94.08%	98.29%	**94.11%**	92.74%	97.61%
Case 2: Shapley-Based Feature Selection (**Transformer**)						
Performance Metric	LSTM	**Transformer**	Combined Model	FCNN		
Precision	85.32%	**91.08%**	82.71%	90.43%		
F1-Score	89.96%	**93.11%**	89.54%	91.74%		
Accuracy	83.76%	**89.08%**	82.22%	87.23%		
ROC AUC	86.41%	**82.49%**	88.49%	81.29%		
Recall	95.80%	**95.22%**	98.84%	91.85%		
Case 3: Expanded Feature Selection (**FCNN**)						
Performance Metric	LSTM	Transformer	Combined Model	**FCNN**		
Precision	86.84%	85.23%	83.08%	**90.37%**		
F1-Score	89.99%	88.54%	89.62%	**89.96%**		
Accuracy	84.23%	85.12%	83.01%	**86.66%**		
ROC AUC	88.14%	91.48%	89.27%	**93.67%**		
Recall	95.75%	92.07%	97.19%	**89.55%**		

Table 3: Shapley values for each model

Feature	Transformer	LSTM	Combined model (Transformer + LSTM)	FCNN
Bedrooms	-0.062*	-0.421	-0.469	-0.431
Bathrooms	0.038*	-0.977*	-0.839*	-0.722*
Max Guests	0.134*	-0.164	-0.13	-0.192
Overall Rating	-0.001	0.003	0.001	0.001
Number of Reviews	0.001	-0.019	-0.001	-0.021
Security Deposit	0	0.199	0.28	0.319
Cleaning Fee	0.0605*	1.247*	1.088*	0.099
Price	0.030*	0.915*	0.650*	0.583*
Football	0	-0.304	-0.034	-0.001
Event	0	0.52	0.025	0.001
Holiday	0	1.092*	0.092	0.065
Zip code	0.036*	-1.096*	-0.960*	-0.076
Latitude	0.034*	-1.124*	-2.591*	-3.862*
Longitude	0.017	1.717*	1.730*	1.811*
Distance Town	0.027*	-0.413	-0.886*	-1.091*
Distance Stadium	0.007	1.023*	-2.416*	-1.443*
Property Type	-0.012	1.713*	0.071	0.001
Listing Type	-0.013	-0.913*	0.07	0.121
Occupancy Rate	-0.031*	-0.823*	-0.652*	-0.792*
Minimum Stay	0.001	0.820*	0.001	0.022
Absolute Average Score	0.025	0.775	0.649	0.582

Table 4: Payoff matrix for Cluster 1 (rows = s1, cols = s2) * indicates Nash Equilibrium, bold number for one player show a possible best solution that is unstable

P1/P2	Low	Medium	High
Cluster 1			
Low	(239.63 , 599.89)	(151.24 , 664.31)	(93.36 , **728.17**)
Medium	(523.43 , 401.74)	(350.89 , 437.12)	(225.80 , 470.51)
High	(**981.50** , 97.66)	(722.36 , 103.49)	**(500.36 , 108.53)***
Cluster 2			
Low	(83.95 , 39.75)	(55.71 , 0.31)	(32.11 , 0.00003)
Medium	(113.40 , 40.15)	(83.31 , 1.37)	(52.75 , 0.00014)
High	**(142.78 , 40.24)***	(114.94 , 5.61)	(80.61 , 0.00064)
Cluster 3			
Low	(17.84, 3.44)	(18.60, 4.01)	**(19.37, 4.63)***
Medium	(14.92, 3.05)	(15.57, 3.56)	(16.24, 4.11)
High	(12.27, 2.71)	(12.81, 3.16)	(13.38, 3.65)
Cluster 4			
Low	(1.367 , 29.396)	(0.802 , 33.967)	(0.470 , 38.847)
Medium	(1.684 , 27.268)	(0.988 , 31.519)	(0.580 , 36.062)
High	(2.055 , 25.276)	(1.206 , 29.227)	**(0.707 , 33.452)***

Table 5: Cluster Statistics and Characteristics

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
n	203	1,233	382	44
Average booking rate	3.8%	3.1%	39.5%	17.5%
Average price	$1,216	$148	$209	$1,251
Price standard deviation	$42	$15	$85	$557
Price-demand correlation	0	0	0.192	-0.02
Characteristic	Expensive, low booking rate	Low-end, oversupply	Core market	High demand luxury
Nash Equilibrium	High/High	High/Low	Low/High	High/High
Interpretation	Defensive pricing	Endogenous price segmentation	Demand saturated	Rival price has limited impact on demand

Figures

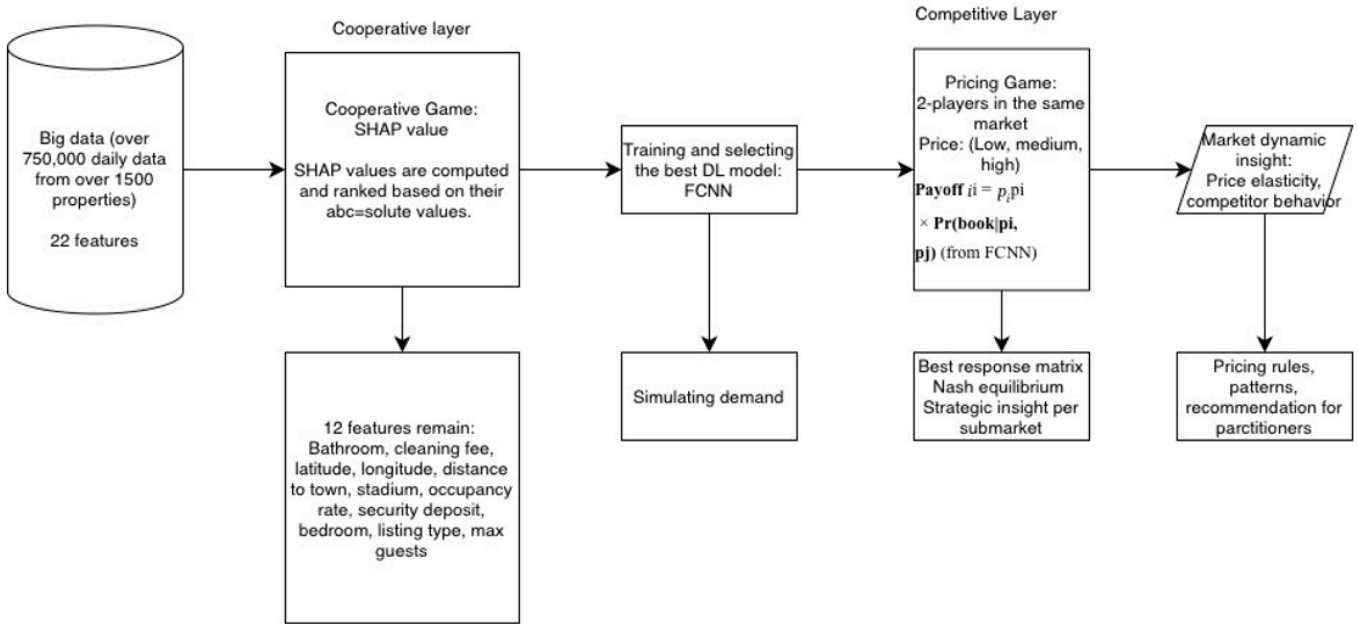


Figure 1

Overview of the study

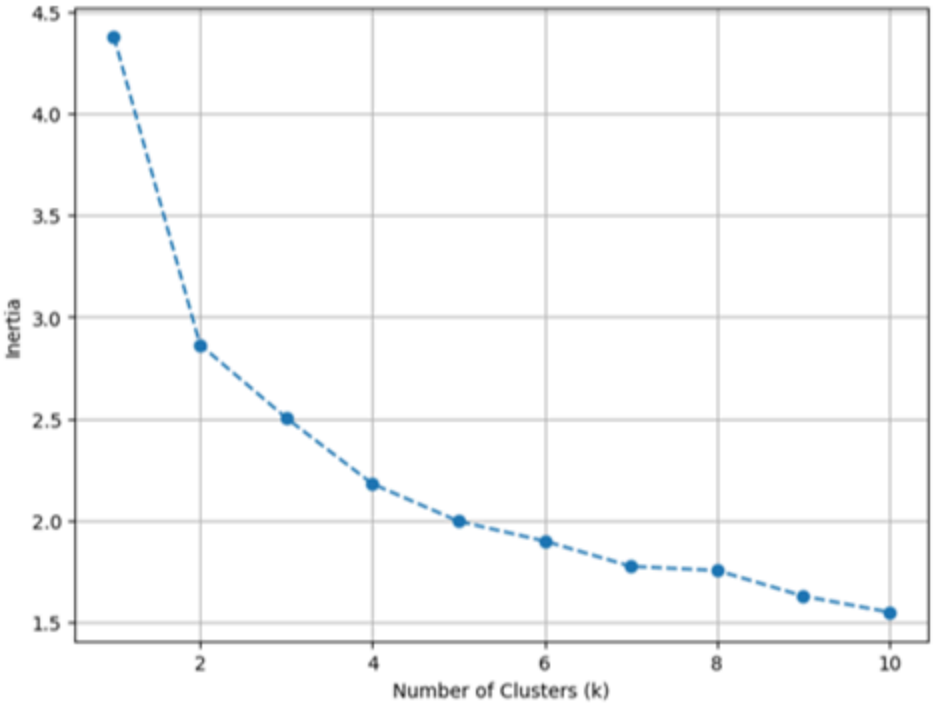


Figure 2

Elbow diagram

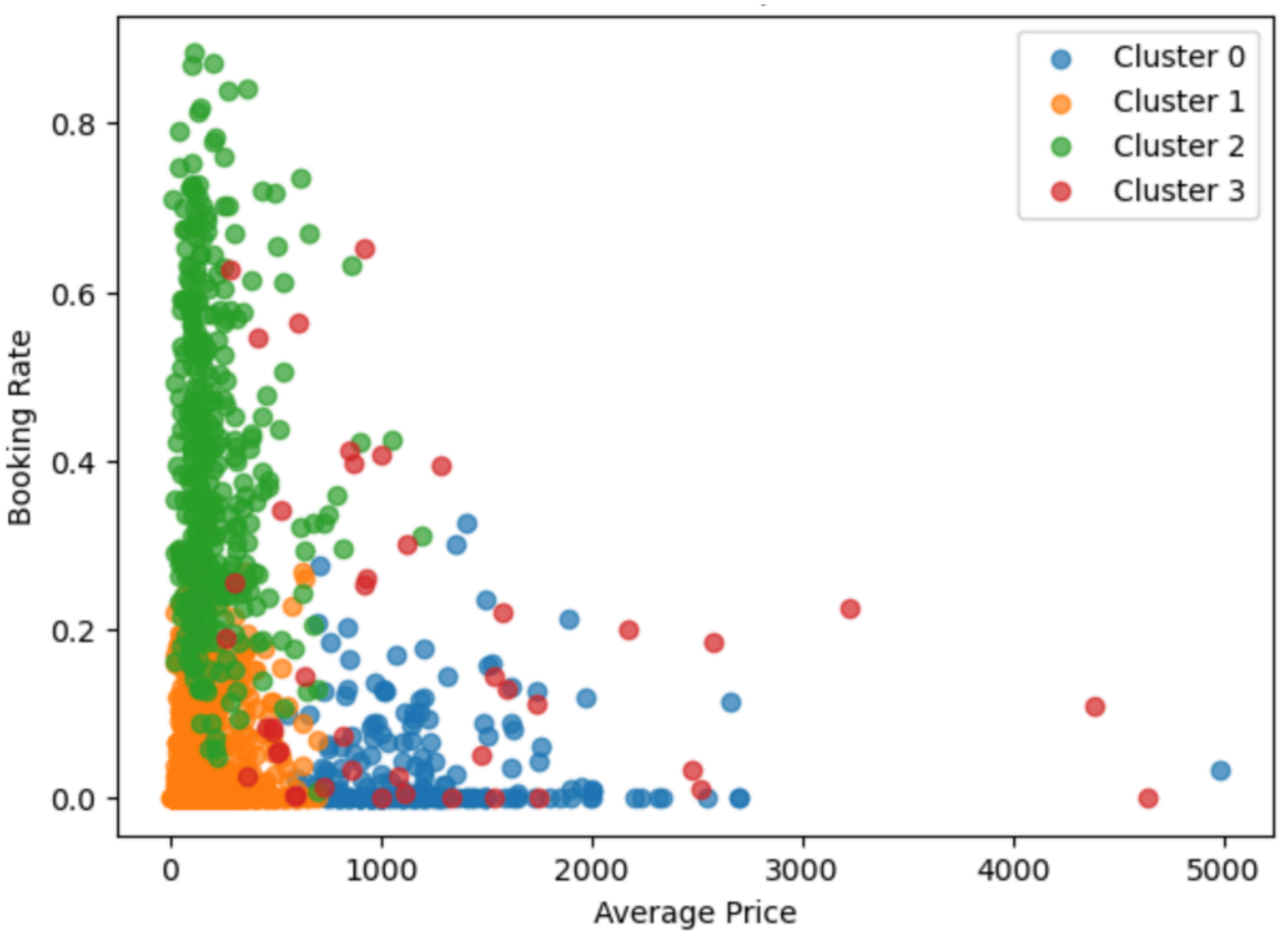


Figure 3

Clusters’ booking rate vs demand