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Forecasting hotel room prices when entering turbulent times: a game-theoretic artificial neural network model

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Abstract

Purpose – This study aims to propose a risk-induced game theoretic forecasting model to predict average daily rate (ADR) under COVID-19, using an advanced recurrent neural network.

Design/methodology/approach – Using three data sets from upper-midscale hotels in three locations (i.e. urban, interstate and suburb), from January 1, 2018, to August 31, 2020, three long-term, short-term memory (LSTM) models were evaluated against five traditional forecasting models.

Findings – The models proposed in this study outperform traditional methods, such that the simplest LSTM model is more accurate than most of the benchmark models in two of the three tested hotels. In particular, the results show that traditional methods are inefficient in hotels with rapid fluctuations of demand and ADR, as observed during the pandemic. In contrast, LSTM models perform more accurately for these hotels.

Research limitations/implications – This study is limited by its use of American data and data from midscale hotels as well as only predicting ADR.

Practical implications – This study produced a reliable, accurate forecasting model considering risk and competitor behavior.

Theoretical implications – This paper extends the application of game theory principles to ADR forecasting and combines it with the concept of risk for forecasting during uncertain times.

Originality/value – This study is the first study, to the best of the authors' knowledge, to use actual hotel data from the COVID-19 pandemic to determine an appropriate neural network forecasting method for times of uncertainty. The application of Shapley value and operational risk obtained a game-theoretic property-level model, which fits best.

Keywords Revenue management, ADR, Price, Forecasting, Artificial neural network, Machine learning, LSTM, Game theory, Risk

Paper type Research paper

This paper is derived from the first author's PhD dissertation.

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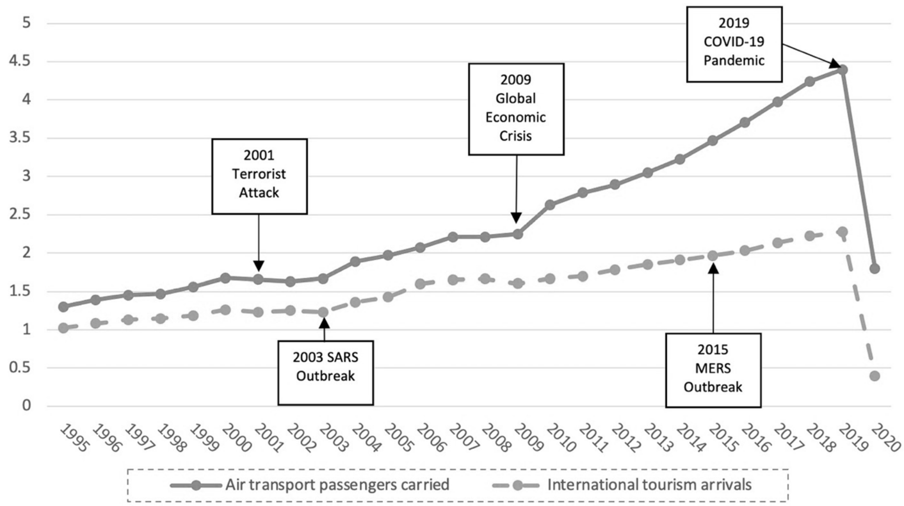
Introduction

Times of worldwide disruption from disease and terror, such as SARS in 2003, swine flu in 2009, MERS in 2015 and the September 11 terrorist attack in 2001, show that none had led to the catastrophic decline in tourism demand as did COVID-19 (Figure 1). As a result of the COVID-19 pandemic, hotel occupancy rates in the USA fell to 40.3% in November 2020, which was the lowest rate since the height of the Great Depression in 1933 (Broadstock *et al.*, 2021; Gössling *et al.*, 2020). RevPAR dropped by more than 47.5% to an average of $45.48 (STR, 2021). Although ten significant epidemic outbreaks occurred over the past 56 years (Škare *et al.*, 2021), each coinciding with economic turmoil, hotel revenue management models have ignored the element of risk (Koenig and Meissner, 2015). Under normal circumstances, this seems appropriate, but during highly volatile times, incorporating a risk measure that permits "control of the probability that total revenues fall below a minimum acceptable level" makes sense (Levin *et al.*, 2008).

While forecasting tourism recovery has received ample research attention (Zhang *et al.*, 2021), work on hotel revenue management forecasting amid COVID-19 is still scarce. Zhang and Lu (2022) combined an autoregressive distributed lag model with a compound scenario method to generate five-year baseline forecasts and scenarios of hotel room demand in Hong Kong toward ten source markets in three hotel price categories. Wu *et al.* (2022) specify a mixed data sampling model to analyze the impact of the COVID-19 pandemic on Macau's average hotel occupancy. Their critical insight is that incorporating high-frequency big data sources to update short-term hotel occupancy rate forecasts can increase forecasting effectiveness. These studies are valuable at the aggregate (destination) level but do not prescribe and analyze revenue management forecasts and scenarios at the property level. Huang *et al.* (2022) evaluate a deep learning model that incorporates graph-structured data to simultaneously forecast the daily demand of multiple hotels. Their study is novel, as it is the first to include price and online rating data, thereby examining competitive effects on hotel demand forecasting at a regional level. Ampountolas and Legg (2021) combined the segmented boosting method with social media text analysis to enhance demand forecast



Source: World data: Authors' own creation

Figure 1.
Global crises and tourism (in billions)

accuracy at multiple time horizons. The practical value of the study is high, and their machine learning approach outperforms widely used traditional methods.

A key limitation of these forecasting studies, however, is that they assume that hotels are risk neutral, an assumption most forecasting studies make (Bitran and Caldentey, 2003). However, other industries such as energy (Luo *et al.*, 2020), medicine (Tyrer *et al.*, 2004) and geography (Kasiyanchuk *et al.*, 2015) have long used risk-induced forecasting models. Moreover, previous studies focus on demand forecasting, with little attention to average daily rates (ADR) forecasting (Binesh *et al.*, 2021; Qiu *et al.*, 2021), even though demand, duration of stay and occupancy are affected by room rates (Zheng *et al.*, 2020). Additionally, competitors' prices are largely ignored, a common limitation of forecasting studies (Moncarz and Kron, 2010), even though they are used in the real world (Mohamed, 2020).

We propose a risk-induced game-theoretic hotel room price (ADR) forecasting model. We evaluate five traditional time-series models – naive (same-time/last year), moving average, exponential smoothing, autoregressive integrated moving average (ARIMA) and regression – against a novel artificial neural network (long-term, short-term memory [LSTM]) model to forecast hotel ADR using Smith travel research (STR) data from three properties from January 1, 2018, to August 31, 2020. The study's main contribution is to test a risk-induced hotel property-level price forecasting model during a pandemic. We do so by introducing the element of operational risk via Shapley value to the literature on hotel forecasting.

Literature review

Forecasting methods

Forecasting is a challenge for hotels, as many are too small to invest in a revenue management software (Sierag *et al.*, 2017). Less than one in every ten hotels uses a revenue management system (Webb *et al.*, 2020), and even with such a system, these systems lack the sophistication of other industries. A guest's spa booking data tends to be recorded in a database separate from room booking and/or email marketing data. This limits the hotels' ability to determine customer lifetime value, something that airlines can easily generate (Giousmpasoglou *et al.*, 2021).

The role of revenue managers in determining hotel pricing is crucial but can also lead to customers perceiving it as unfair (Meatchi *et al.*, 2021). When hotels set prices that are perceived as unrealistic or unfair by consumers, it can lead to a shift in demand towards peer-to-peer accommodation options (Sainaghi, 2021), as consumers may view peer-to-peer options as more affordable (Chi *et al.*, 2021). Nevertheless, many hotels still use traditional price forecasting models, like the naive (same-time/last year) method (Pereira, 2016). Additionally, forecasted prices tend to be adjusted (i.e. overridden) based on qualitative methods rather than quantitative pricing models (Ampountolas, 2021; Koupriouchina *et al.*, 2023). For forecasting, several studies use moving average and exponential smoothing methods (Kimes, 2003). A major shortcoming of moving average models, however, is their slow response to rapid changes in the data (Johnston *et al.*, 1999). Moving average methods do not respond well to fluctuations in price and overlook the complex relationships in hotel data (Al Shehhi and Karathanasopoulos, 2020). Also, the moving average does not respond well to seasonal fluctuations (Chu, 2009), while due to its nature, the hotel operations data are seasonal. Additionally, hotel revenue management studies have started to use ARIMA-based models (Zheng, 2014).

ARIMA models, however, neglect the complex nonlinear nature of data (Zheng *et al.*, 2020). They are less effective in capturing sudden changes in the data values, leading to significant increases in forecast error (Wang *et al.*, 2010). While ARIMA is adept at modeling trends, it is sensitive to outliers and limited in forecasting extreme values (Al Shehhi and Karathanasopoulos, 2020). Moreover, identifying the correct ARIMA model can be difficult and usually computationally strenuous. ARIMA-based models also neglect the complex nonlinear nature of data; ARIMA models assume the data are stable and ignore external factors (Zheng *et al.*, 2020). The hotel industry is vulnerable to external factors such as economic changes and pandemics (Zheng *et al.*, 2020). Traditional models such as ARIMA are not effective in capturing turning points with can lead to significant errors in forecasting (Wang *et al.*, 2010). See Appendix for more information on these models.

In times of uncertainty, pricing plays a crucial role in the operations and survival of hotels (Zaki, 2022). Given the unprecedented nature of the events in the hospitality industry in the wake of the pandemic, new forecasting methods are needed to address ongoing changes and challenges, like neural networks (Ampountolas and Legg, 2021; Webb *et al.*, 2020). Machine learning algorithms, particularly LSTM, can address this issue by assigning the appropriate weights to data based on its chronological order. In this method, data that happened at a farther point in the past is assigned a lesser weight compared to more recent data (Zhu *et al.*, 2021). Unlike traditional methods, machine learning models are good at detecting the complex nature of data and any sudden changes (Wang and Duggasani, 2020). For instance, Ampountolas and Legg (2021) showed that machine learning models surpass traditional methods such as the naïve approach and ARIMA models in forecasting hotel occupancy during COVID-19. LSTM models, an advanced type of recurrent neural networks, have been used in various fields such as finance (Ferdiansyah *et al.*, 2019) and medicine (Islam *et al.*, 2020). Despite their potential, the application of LSTM models in hospitality literature is limited. Among those few studies, Wang and Duggasani (2020) compared the performance of LSTM models with six alternative machine learning models to predict the actual reservations; the LSTM models improved the accuracy of the prediction by 3%.

Zheng *et al.* (2020) also showed that LSTM was more accurate than ARIMA, support vector regression and naïve models in predicting hotel room rates. Another major shortcoming of traditional and ARIMA models is that they assign the same weight to data points, while in many settings, the more recent data points are stronger predictors of the model compared to the older data points (Zheng *et al.*, 2020). However, LSTM models have disadvantages such as complexity, the limit on the length sequence and being prone to overfitting (Gers *et al.*, 2002). In some instances, traditional forecasting models outperform neural networks and LSTM models (Ampountolas, 2021; Arceda *et al.*, 2020). (See Appendix for more information). Therefore, the following hypotheses are proposed:

H1a. An LSTM price forecasting model is more accurate than a naïve model.

H1b. An LSTM price forecasting model is more accurate than a moving average model.

H1c. An LSTM price forecasting model is more accurate than a simple exponential smoothing model.

H1d. An LSTM price forecasting model is more accurate than ARIMA.

Competitor effects

Limited studies have looked at the role of competitors in hotel pricing and forecasting. Steed and Gu (2009) used a survey-based study to investigate the factors that influence hotel budgeting and forecasting; they showed that competitor assessment was one of the top factors that hotel managers consider. Aznar *et al.* (2019) created two indices from STR's

STAR Report and used game theory to predict the price change in competition between hotels and Airbnb. Similarly, Tran *et al.* (2016) extracted two indices from STAR reports to implement in a game-theoretic framework with two players. The outcome of the game was to forecast when hoteliers should change their prices. However, with the exception of Huang *et al.* (2022), neither of these studies provided an exact price point that the price should be changed to and instead provided two strategies, either increase or decrease the price. Their study forecasted demand rather than price, and their forecasting model only considered price and online ratings.

Game theory and Shapley value

Von Neumann and Morgenstern (1953) developed game theory to explain how people react to uncertain situations to maximize their benefits. Game theory deals with a situation where two or more players must make decisions, and the outcomes of those decisions will impact all players. Game theory has been used in a wide range of disciplines, including marketing (Abedian *et al.*, 2021) and finance (Sezer *et al.*, 2020). In marketing, game-theoretic frameworks have been used in pricing strategy (Aviv and Pazgal, 2005) and channel distribution management (Yan, 2008).

The evolution of the booking environment and accessibility of the booking process has provided travelers with the convenience of booking from anywhere at any time (Martin-Fuentes and Mellinas, 2018). This creates a challenge to properly forecast the demand and price for hotel rooms, such as overestimation/underestimation of demand and price (Webb *et al.*, 2020). Game theory could capture these unique characteristics as well as changes in booking patterns caused by a new entrant in the market and provide a framework that addresses this gap (Schwartz, 1997).

Game theory allows researchers to study competitors in the same market. The competitive market structure is a key determining factor in dynamic pricing (Chung, 2000). The player strategy can change based on what the player learns during the game. The evolving nature and adapting of the players' strategy based on the course of the game makes the neural network a compatible model to combine with game theory (Schwartz, 1997). Dixit and Skeath (1999) suggested the use of game theoretic forecasting when looking ahead to situations where multiple decision-makers will interact strategically. Arenoe *et al.* (2015) proposed a game-theoretically founded approach to conjoint analysis to determine equilibrium room rates under differentiated price competition in an oligopolistic hotel market. Game theory has been used for forecasting in practical contexts. For example, Decision Insights Inc. (which works with Fortune 500 companies) used game theory to predict the outcome of political events that influence business activities (Goodwin, 2002).

In the recent years, game theory has been used in hospitality in a limited way. Lim and Shanthikumar (2007) created a pricing model by using stochastic differential games and used relative entropy as the constraint to account for uncertainty. In their model, uncertainty was defined as the difference between the base model (nominal probability) and the robust model (two-player zero-sum stochastic differential game). Arenoe *et al.* (2015) used game theory and utility maximization theory with discrete-choice analysis to find the optimal pricing for two resorts. Another study applied game theory to the hotel distribution channel mix (Dolasinski *et al.*, 2019). Game theory and prospect theory were combined by Constantino *et al.* (2016), who created a neural network forecast model of tourism demand. Similarly, Aznar *et al.* (2019) provided a game-theoretic model to investigate the dynamic between Airbnb and hotels. Schuster and Yamaguchi (2010) conducted a theoretical investigation on the application of game theory to neural networks. They applied the dynamics of game theory to a neural network and illustrated a game-theoretic neural network in which each neuron is a player. Metzler (2002) argues that a player's memory operates similarly to a neural network and further illustrates that the minority game dynamics generate a time series.

Shapley (1953) introduced the Shapley value, a mathematical approach to estimating the expected marginal contribution of a covariate in a model. Shapley value is a solution concept in game theory that involves distributing the gains and costs to players in a coalition (Choudhury and Goswami, 2012). To compare the Shapley values, one should first fit a model including the covariate "i" and another model without the covariate. The difference between the two models' prediction of the model's main variable of interest "x" is the marginal contribution of that covariate. In the case of more than one covariate, the main model without the covariate was compared to all the variations of all the possible subsets of covariates. The final covariate contribution is the weighted average of all marginal contributions, which is a cumbersome method. Lundberg and Lee (2017) proposed a more efficient variation of the Shapley value by approximating the effect of removing covariates with Shapley values less than the threshold on the performance of the model. Stier *et al.* (2018) used the Shapley value to separate the relevant from irrelevant neurons of a neural network. In their study, a coalitional game between neurons in the neural network was created (where neurons form coalitions), and the Shapley value was calculated using the average contribution of each neuron to the coalition. The same study further showed that in the final model (following removing the neurons with low contribution), the neural network was significantly improved. Therefore, the following hypotheses are proposed:

H2. A game-theoretic LSTM model is more accurate than an LSTM model that ignores competitor pricing.

H3. A risk-induced game-theoretic forecast model is more accurate than a risk-neutral LSTM model.

Methodology

Data

Data were obtained from STR, a leading company in hotel performance data (STR, 2021). Three anonymous data sets came from three hotels in the USA, classified by STR as upper-midscale, operating in three different locations (urban, interstate and suburb). The data sets included daily occupancy rate, ADR, supply (capacity), demand and RevPAR, for the period January 1, 2018, to August 31, 2020. The period before March 11, 2020 (the date the WHO declared the COVID-19 pandemic) is labeled as "pre-pandemic" (Cucinotta and Vanelli, 2020) and from March 11, 2020, as "during the pandemic." Many scholars believe that the US market was hit on this date (Beckman and Morse, 2020; Fuchs *et al.*, 2021). While there are some differentiations but the common date to define the pandemic period in the US-based literature is March 11, 2020 (Ghannadian and Vahlberg, 2022). In many parts of the USA, travel resumed after May 2020, which continued to grow until the end of the summer season in August (AAA, 2021). The period from July to August 2020 was the summer season and marked the travel campaign initiated in different countries, such as "Viva Las Office" in the USA (MGM, 2020).

Model

We developed three LSTM models based on an artificial recurrent neural network used in the field of deep learning. Unlike standard neural network models, the LSTM models have feedback connections that give more weight to the most recent observations and can map out several inputs and outputs (Wang and Duggasani, 2020). The detailed model architecture can be found in the supplementary material. The neural network models were evaluated against naive (same-time/last year), moving average, exponential smoothing and ARIMA. The definition of the baseline models can be found in Supplementary material.

Following Stier *et al.* (2018) approach, competitors' ADR is introduced to the model to capture the game theoretic dynamic between players. Using the Shapley value, the contribution of each competitor to the final ADR prediction is measured. Shapley value is a solution concept in cooperative game theory. More information on Shapley value and it application in this study can be found under supplementary material section. Two measures for risk were used: Value at risk (VaR) and Conditional VaR (CVaR). VaR was introduced into the models by estimation of historical values of RevPAR. The detailed information on risk measures in this study can be found under supplementary material.

Analytical approach

Data analysis was done in R and MATLAB. Following Fildes and Ord's (2002) and Koupriouchina *et al.*'s (2014) guidelines, the models' efficiency is evaluated by comparing multiple error statistics. To capture the characteristics of the error distribution, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE) and mean squared error (MSE) were calculated. Following Lewis's (1982) guidelines, these error statistics were considered highly accurate if they were below the 10% threshold (Chu, 2009).

Results

Model comparisons

As Table 1 shows, differences in ADR before and after March 11, 2020, and for the entire period. It can be seen that COVID-19 caused great fluctuations in ADRs. While room rates for all three hotels were extremely volatile during the pandemic, from mid-2020, the fluctuations tended to stabilize, and ADR partially returned to pre-pandemic levels in properties A and B. However, the ADRs were not fully recovered and were still below the prior to pandemic prices. ADR and demand dropped significantly after COVID-19 started in March 2020 for all three properties. In property A, demand gradually increased after April 2020. While in property B, this increase happened later in May 2020. As for property C, demand gradually increased after June 2020. It should be noted that property A experienced the least reduction in demand, whereas properties B and C were severely affected.

Table 2 shows the forecasting errors for all model tests for three properties. Overall, the LSTM models show consistent results with different subsets of data, producing high-accuracy results in all three properties compared to the traditional models. LSTM-2, in particular, is the most accurate across the four different accuracy measures. This implies that with the addition of occupancy rates, day of the week, supply (capacity) and demand, forecasting errors have been reduced. This is consistent with expectations that more diverse data improve the forecast accuracy of a neural network (Ampountolas and Legg, 2021; Huang *et al.*, 2022).

Figures 2–4 show that before COVID-19, all properties responded to the changes in the market close to their competitors. However, after COVID-19 started, we can see that properties diverged in their strategy and response. This is evident in all properties, particularly in properties B and C. Property A and its competitors reach closer to the pre-pandemic levels by August 2020.

Table 1.
Descriptive analysis of properties A, B and C

	Mean Before	Mean After	Mean Total	SD Before	SD After	SD Total	Min Before	Min After	Min Total	Max Before	Max After	Max Total
Property A	($n = 970$)											
ADR	100.76	91.64	99.14	11.97	9.76	12.12	66.90	78.34	66.9	161.93	168.52	168.52
Demand	67.85	54.45	65.46	18.17	11.94	17.97	16.00	22.00	16.00	97.00	91.00	97.00
Supply	96.00	96.00	96.00	0.00	0.00	0	96.00	96.00	96.00	96.00	96.00	96.00
RevPAR	72.40	52.24	68.80	24.69	14.78	24.49	14.27	26.06	14.27	130.83	117.05	130.83
Property B	($n = 972$)											
ADR	252.96	117.45	228.90	57.54	34.19	74.96	126.19	34.66	34.66	567.92	244.72	567.92
Demand	183.63	43.52	158.73	34.68	40.66	64.46	41.00	1.00	1.00	209.00	183.00	209.00
Supply	202.90	207.00	203.62	14.17	0.00	12.95	154.00	207.00	154.00	207.00	207.00	207.00
RevPAR	233.51	26.53	196.76	74.53	28.25	104.80	26.73	0.17	0.17	445.99	191.75	445.99
Property C	($n = 972$)											
ADR	117	99.75	113.79	25.08	20.22	25.13	70	45.70	45.70	234.71	316	315.74
Demand	61	34.91	56.50	16.99	22.95	20.74	9	3.00	3.00	82.00	84	84.00
Supply	82	82	82.00	0.00	0.00	0.00	82	82	82.00	82	82	82.00
RevPAR	90	44	81.73	38.79	32.09	41.48	10	3	2.76	146	316	315.74

Table 2. Errors for all the model tests using properties A, B and C

Error measure	LSTM-1	LSTM-2	LSTM-3	Naive	ES	MA	ARIMA	Reg/ARI	Best
Property A									
RMSE	11.026	4.467	10.139	15.002	7.537	8.182	7.670	9.816	LSTM2
MAPE	10.550	4.511	5.912	500.894	4.422	5.030	4.611	350.248	ES
MSE	171.509	21.697	99.96	210.043	9945.549	66.947	58.812	96.361	LSTM2
MAE	9.630	4.343	6.193	11.931	4.468	5.055	4.630	7.215	LSTM2
Property B									
RMSE	35.599	28.485	30.309	54.123	37.0381	44.914	18.473	21.012	ARIMA
MAPE	10.98	8.970	9.130	203.350	13.290	16.127	9.991	365.955	LSTM2
MSE	1267.300	111.398	918.634	2100.134	1908.156	2017.259	341.257	441.497	LSTM2
MAE	27.084	22.340	23.205	45.934	26.182	33.293	10.521	14.063	ARIMA
Property C									
RMSE	12.004	11.343	11.118	23.560	18.265	19.900	37.671	17.759	LSTM3
MAPE	7.422	6.381	6.970	212.357	8.801	9.907	13.716	604.129	LSTM2
MSE	144.090	128.673	123.613	2670.819	13608.870	396.012	1419.088	315.37	LSTM3
MAE	8.111	7.098	7.753	17.543	10.4139	11.688	26.741	11.328	LSTM2

Notes: The three LSTM models were evaluated with 10 repeated validation tests. Naive = same time last year); ES = exponential smoothing; MA = moving average; Reg/ARI = regression with ARIMA on residuals

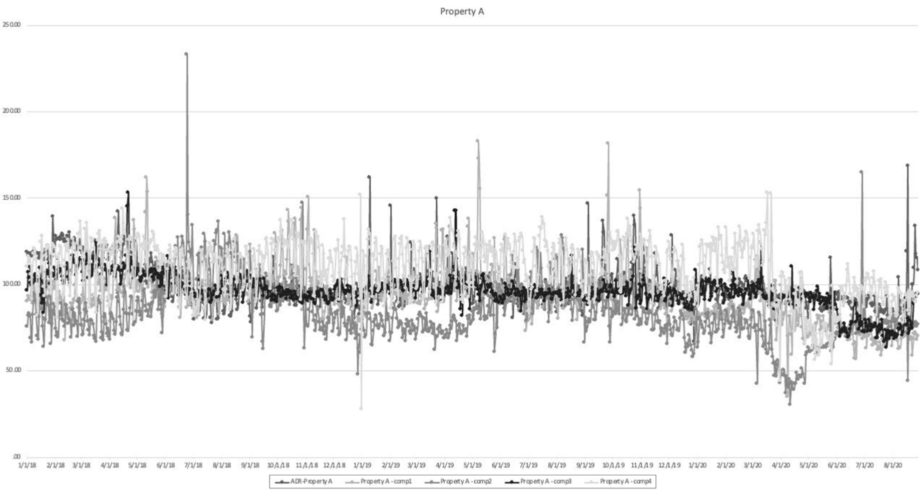


Figure 2.
ADR of property A and its competitors

Source: Authors' own creation

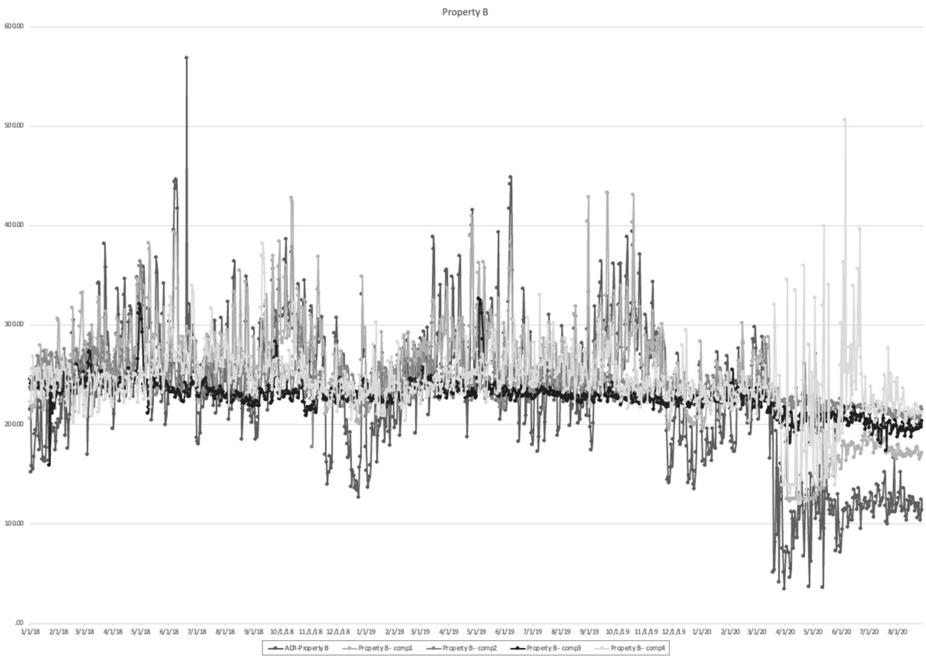
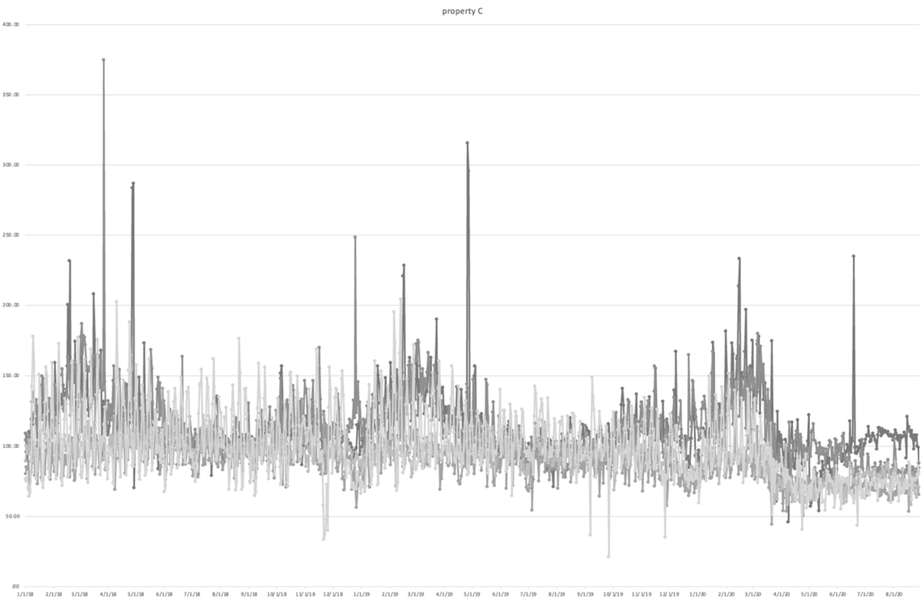


Figure 3.
ADR of property B and its competitors

Source: Authors' own creation

H1a–H1d addresses the applicability of neural network forecasting models as compared to traditional methods of forecasting. For these hypotheses, the results indicate that *H1a* is supported for all LSTM models; all three LSTM models perform better than the naive (same-time/last year) model. *H1b* is supported for LSTM-2; the model outperforms moving average



Source: Authors' own creation

Figure 4.
ADR of property C and its competitors

models. This hypothesis, *H1b* however, is partially supported by LSTM-3. LSTM-3 does not outperform moving average models for hotel A. Moreover, *H1b* is rejected for LSTM-1. LSTM-2 is more accurate than exponential smoothing, which supports *H1c*. However, this hypothesis *H1c* is partially supported for LSTM-1 and LSTM-3, as these models do not outperform the moving average model for hotel A. Finally, LSTM-2 and LSTM-3 are more accurate than ARIMA, which supports *H1d*. LSTM-2 is the best model and defeats ARIMA for data sets from properties A and C. For property B, LSTM-2 is close in accuracy to the ARIMA model and shows higher accuracy than the ARIMA model for two of the error measures. Still, the hypothesis *H1d* is rejected for LSTM-1. That is, property A shows the least fluctuations in ADR, and traditional models appear to work better for this property. However, for properties B and C with more volatile ADRs, the machine learning models outperform the traditional models. For property C (the most volatile), none of the traditional methods were the 1st or 2nd most accurate model. Considering all error measures from all three properties, the most accurate model under volatile conditions is LSTM-2.

Game theory

Using the Shapley values for LSTM-3, it was analyzed which competitor contributed most to the forecast. Table 3 shows the Shapley values and the threshold for each property. The thresholds were calculated using $\theta_s = 0.25$ an average of the absolute values of the Shapley values.

As none of the competitor ADRs reached the significant threshold for property A, no further analysis was performed for this hotel. In Property B, lagged ADR of the property is shown to have less impact on the model predictions than competitors' ADR. This may be because that property saw the most fluctuations in price. Also, the ADR of Competitor 3 is the least contributor to the final model with a Shapley value of −0.121. A subsequent LSTM

Table 3. Shapley values and thresholds

	Shapley value	Threshold
Property A		
ADR lag	12.501*	0.802
OCC	5.102*	
Demand	−5.090*	
DOW	4.763*	
Supply	0.11	
ADR 1	0.453	
ADR 2	0.162	
ADR 3	−0.264	
ADR 4	−0.41	
Property B		
ADR lag	1.020*	1.064
OCC	−1.245*	
Demand	5.861*	
DOW	2.789*	
Supply	1.04*	
ADR 1	17.890*	
ADR 2	7.932*	
ADR 3	−0.121	
ADR 4	0.401*	
Property C		
ADR lag	−12.465*	0.733
OCC	5.870*	
Demand	0.145	
DOW	0.040	
Supply	0.106	
ADR 1	−6.278*	
ADR 2	−0.370	
ADR 3	0.782*	
ADR 4	0.346	

Note: *Variables that their absolute value of Shapley values is above the threshold

model after retaining Competitors 1 and 2 and removing Competitors 3 was generated. The new model outperformed LSTM-2. This shows that when competitors contributed more to the model, the model performed better than LSTM-2 without competitors.

In property C, the ADR of Competitor 1 contributed the most after the lagged ADR. Supply and day of the week showed to have the least impact on the final model. A consequent LSTM model after retaining Competitors 1 and 3 and removing Competitors 2, 4, day of the week and supply was generated. The new accuracy measures are reported in Table 4. This further suggests the possibility that the competitors of the properties were not

Table 4. LSTM model after Shapley value-Property B

Error measure	LSTM-1	LSTM-2	LSTM-3	Shapley LSTM-3
RMSE	35.599	28.485	30.309	28.010
MAPE	10.980	8.970	9.130	8.540
MSE	1267.300	111.3982	918.634	21.651
MAE	27.084	22.340	23.205	10.510

the main competitors. As can be seen, when the competitor ADR had a higher impact on the neural network model outcome, the accuracy of the model was improved and suppressed than that of LSTM-2 and all the traditional models.

For property C, removing the competitors with the lowest Shapley values made LSTM-3 the most accurate of all the models. This further strengthens the argument that choosing the right competitors is key (Schwartz and Webb, 2022) and could improve the ADR forecast model. The findings support *H2*, a game-theoretic neural network model is more accurate than a neural network model that ignores the competitors for hotels B and C after adjusting the predictors of the model using Shapley values.

Value at risk

Table 5 shows a significant change in the accuracy of the models after the introduction of risk. This supports *H3*, stating that a risk-induced game-theoretic forecast model would outperform a risk-neutral neural network model. CVaR outperformed VaR in property C, which is also the most turbulent property in terms of data fluctuations. CVaR produced comparable model accuracy results to VaR in property B. However, VaR proved to generate more accurate results in property A. This could be due to the distribution of property A's data (thin tail, absence of good tail model) (Sarykalin *et al.*, 2008). Nonetheless, both measures improved the accuracy of the model compared to the risk-neutral model. As such, we conclude that hotels should indeed consider and include risk in forecast models. This finding strengthens the capabilities of risk-induced models during times of uncertainty.

Discussion

Considering that studies focusing on hotel room prices are limited, in this study we developed and tested a novel game theoretic risk-induced machine learning model to predict the hotel ADR during times of uncertainty. Our findings offer strong evidence that machine learning and game theory could be used to improve price forecasting in revenue management. This supports studies that highlighted the application of game theory to pricing (Han and Bai, 2022). The results indicate that LSTM models outperform traditional methods in turbulent times. Our findings support previous research showing traditional methods' shortcomings in times of uncertainty (Guillet and Chu, 2021). Assaf and Tsionas (2019), who also combined risk with neural networks, showed that neural networks outperform all of the traditional models, including ARIMA and moving average. Our results contradict other studies that traditional forecasting models outperformed neural networks and LSTM models (Ampountolas, 2021; Arceda *et al.*, 2020; Lin *et al.*, 2011). LSTM-2 and LSTM-3 are more accurate than the ARIMA models (probably one of the most commonly used forecasting models), which support previous literature on the shortcomings of ARIMA. While ARIMA is adept at modeling trends, it is sensitive to outliers and is limited in forecasting extreme values (Al Shehhi and Karathanasopoulos, 2020). ARIMA models assign the same weight to data points, while in many settings, the more recent data points are stronger predictors of the model than the older data points (Zheng *et al.*, 2020).

Error measure	LSTM-1	LSTM-2	LSTM-3	Shapley LSTM-3
RMSE	12.004	11.343	11.118	11.133
MAPE	7.420	6.380	6.970	6.301
MSE	144.090	128.673	123.613	123.948
MAE	8.111	7.098	7.753	7.444

Table 5. LSTM model after Shapley value-Property C

The results suggest that a risk-induced game-theoretic neural network model is more accurate than the risk-neutral model. The selection of risk measures depends on the characteristics of the property data and circumstances. However, given the mathematical superiority of CVaR and its capability to measure loss over a threshold (Maillard, 2018), we recommend opting for CVaR if revenue managers do not have the resources to examine the data structure. It should be noted that property A, which shows the least fluctuations in ADR, is also the property that traditional models tend to work best. Yet, in properties B and C with more unpredictable ADRs, the machine learning models outperform the traditional models. For the most volatile property (C), the LSTM models outperform all traditional methods. This supports previous findings that LSTM models can better detect and learn complex dynamics and produce low forecasting errors, i.e. an ability to better capture fluctuations and sudden changes in data (Zheng *et al.*, 2020). Overall, our results show that during times of uncertainty, the accuracy of traditional methods severely deteriorates, as they do not perform well with rapid fluctuations (Law and Au, 1999; Zheng *et al.*, 2020). This echoes previous results that neural networks are superior to traditional forecasting models (Law and Au, 1999).

These findings support the applicability of game theory to hotel revenue management forecasting (Aznar *et al.*, 2019) and previous work on the application of game theory with neural networks (Choudhury and Goswami, 2012). It should be noted that the data were anonymous (i.e. STR statistically choose the competitive set based on nine factors that most influence competitor dynamics). We cannot verify if the competitors chosen were the right competitor set for each property. Our findings support that choosing the right players for a game theoretic problem is one of the key steps (Tran *et al.*, 2016); in properties B and C where competitors' Shapely values were above the threshold, including them in the model improved the accuracy of the model.

Theoretical implications

Considering the limited number of studies on forecasting ADR, this research adds a much-needed contribution to forecasting literature. It demonstrates that deep learning forecasting models can be applied to forecasting ADR and that even a simple LSTM model can outperform traditional methods. This study supports previous work demonstrating the better performance of machine learning forecasting models than the traditional methods (Pereira and Cerqueira, 2021), particularly in times of uncertainty (Zheng *et al.*, 2020).

While previous studies are dedicated to demand forecasting and occupancy rate (Brannas *et al.*, 2002), hotel room price has been under researched. During normal times, demand, duration of stay and occupancy rate can be influenced by hotel room rates, and demand-based pricing is common practice among revenue managers (Al Shehhi and Karathanasopoulos, 2020; Chattopadhyay and Mitra, 2019). Nevertheless, during COVID-19, the drop in demand was independent of price (Guillet and Chu, 2021). In times of uncertainty, pricing decisions can significantly impact the recovery process (Herédia-Colaço and Rodrigues, 2021). Therefore, this study adds to the ongoing research on hotel room price forecasting by proposing and testing a novel model to predict ADR.

This paper introduces a new way to include the competitive dynamics between hotels in the same market. We show that game theory can provide valuable insights and support for the application of pricing strategies in the hotel industry (Han and Bai, 2022). By incorporating game theory principles, hotels can develop more effective and strategic pricing strategies that consider the behavior of their competitors and customers. While previous studies have examined these factors separately (Assaf and Tsionas, 2019; Arenoe *et al.*, 2015), to the best of our knowledge, no previous study has investigated how these two concepts can be combined to address the challenges of forecasting price in times of uncertainty.

Perhaps the most important contribution of this study to theory is the application of Shapley value, a game theoretic concept in a revenue management context. We showed that Shapley values are different for each competitor, as well as models based on stable versus turbulent data. Adding risk and Shapley value improves the model accuracy significantly in turbulent times. Our model closely resembles Zheng *et al.* (2020). However, our model extends the body of literature on price forecasting by adding competitor price and risk to the model. Most prior game-theoretic studies in revenue management have focused on two competing hotels (Aznar *et al.*, 2019; Tran *et al.*, 2016). This study is unique in its ability to include an unlimited number of competitors in the proposed model. While we relied on the comp set identified by STR, recent research has highlighted the shortcomings of these comp sets (Schwartz and Webb, 2022; Webb and Schwartz, 2017), showing that one should not simply rely on preidentified comp sets. Moreover, we intend to propose a flexible model that is not property dependent. As such, it is important to add other hotels other than the comp sets for pricing decisions. Thus, we propose a flexible property-independent model that can be adapted to any property. The proposed model can easily be used in any timeframe regardless of the forecast window; it could also be used with a large data set, such as real-time online travel agency (OTA) data.

The proposed models advance revenue management research by combining a game theory concept (Shapley value) with a neural network model. This combination has been previously implemented in other fields, such as engineering (Stier *et al.*, 2018). However, to our knowledge, this is the very first time that these concepts have been combined in a hotel price forecasting setting. This study advances the body of literature on revenue management by proposing an artificially intelligent model that could potentially improve its accuracy over time.

The findings provide new insights into the impact of COVID-19 on hotel ADR forecasting. Many studies have highlighted the unprecedented nature of the pandemic and its impact on hospitality and tourism. Particularly, they highlighted the lack of preparation for similar incidents (Giousmpasoglou *et al.*, 2021), and the insufficiency of the current models to address pricing in times of uncertainty (Han and Bai, 2022). Nonetheless, limited studies focused on hotel room pricing. It demonstrates that machine learning models improve forecasting accuracy during favorable times. These models considerably outperform the traditional models during turbulent times by accounting for volatile fluctuations and uncertainty. This study also highlights the importance of robust price forecasting models during volatile times such as the pandemic. Accurate price forecasting provides valuable information for hoteliers to make timely decisions to maximize resource exploitation and revenue. Accurately forecasting room rates during difficult and turbulent times is crucial because inaccurate estimates can result in negative economic outcomes. Our findings also provide novel insight into why time-series models do not perform well in turbulent times. We also exhibit why traditional models can outperform machine learning models and vice versa and that game theory helps us understand how competitors' actions affect hotel pricing during turbulent times.

Practical implications

Practically, this study provides a new forecasting model that can be used by hotel revenue managers. The results highlight the different responses of each property to COVID-19. This paper shows that hotel managers may need to critically reassess their competitor set (Schwartz and Webb, 2022). The results also show that the traditional methods particularly are not efficient in hotels with rapid fluctuations of demand and ADR, because LSTM models perform more accurately for these hotels. This highlights the importance of adopting new price forecasting methods that address changes in the market. Our results show that the traditional methods are less accurate for volatile cases. Therefore, the proposed models are more accurate alternatives to use in times of uncertainty.

Finally, the results of this study address an important characteristic of the modern hospitality industry; the accessibility of booking processes from anywhere at any time (Martin-Fuentes and Mellinas, 2018). Machine learning algorithms are highly effective due to the fact that they can learn from experience (Das *et al.*, 2021). These models have also been shown to be more effective in addressing rapid changes (Zheng *et al.*, 2020). The proposed models can potentially be used to address these challenges and potentially be used to forecast other parameters, e.g. affective forecasting (Lajante *et al.*, 2021).

Limitations and future research

This project was limited by the amount and size of the data. The model was evaluated in the USA and only focused on 3 upper-midscale hotels with 12 competitors over 3 corresponding comp sets. Future studies may look at bigger samples of various hotel types as well as the rates of larger comp sets and compare the results with different regions (Enz *et al.* (2016). Moreover, this study was based on data from a limited time period. Future research may test the proposed models in times beyond the timeframe of this study. Future studies may investigate the dynamics between competitor hotels and other lodging options such as Airbnb in the same market. Also, this paper only focused on predicting ADR. Future studies can replicate the model for other hotel performance metrics such as RevPAR and occupancy. Future studies can use other estimation methods for VaR, such as Monte Carlo simulation. Finally, other proxies of risk can be used, such as the Bayesian approach to risk analysis.

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Supplementary material

The supplementary material for this article can be found online.

Appendix

Model	Definition	Formula	Source
Naive (same time/ last year)	Price of the same room the same time, last year		Weatherford and Kimes (2003)
Moving average	Projects the last m records of ADR into the future (m is the forecast horizon)	Say, the forecast horizon is 1 week, then $m = 1$. $f_i = \frac{1}{m}\sum_{k=1}^{m} ADR_{i-7k}$	Ellero and Pellegrini (2014)
Exponential smoothing	Uses a smoothing factor (α) between 0 and 1, where α controls the rate that the influence of the previous observation on the forecast decreases exponentially	$f(ADR)_i = \alpha ADR_{i-7} + (1-\alpha) f(ADR)_{i-7}$ Where $0 < \alpha < 1$	Ellero and Pellegrini (2014)
ARIMA models	Time-series data to better understand the data and/or to predict the future	An ARIMA model is shown as ARIMA(p, d, q), where p, d and q are auto regressive, integrated and moving average parts of the model, respectively	Yuksel (2007)
Regression with ARIMA on residuals	The regression part forecasts the variable using the predictors such as a regression, whereas the ARIMA on residuals addresses the autocorrelation between residuals		Mohamed (2020)

Table A1. Baseline model definitions

Layers	LSTM-1	LSTM-2	LSTM-3
Input	Lagged ADR	Lagged ADR Occupancy DOW Supply Demand	Lagged ADR Occupancy DOW Supply Demand Competitor 1 ADR Competitor 2 ADR Competitor 3 ADR Competitor 4 ADR
Hidden	100	100	100
Output	ADR	ADR	ADR

Table A2. Structure of the LSTM models

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