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# Evaluation on the Accuracy of Artificial Intelligence (AI) Assisted Revenue Management Forecasting: Evidence from a Luxury Resort in Bali

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**Abstract:**
This study examines the accuracy of artificial intelligence-assisted forecasting in supporting hotel revenue management at Amarterra Villas Resort Bali Nusa Dua, a five-star luxury resort operating within Bali's premium leisure tourism market. The research was motivated by the growing need for hotels to improve forecasting reliability amid fluctuating demand, dynamic pricing conditions, and limited dedicated revenue management manpower. A descriptive quantitative research design with comparative forecasting accuracy analysis was applied using secondary operational data consisting of AI-generated forecasts and actual hotel performance records for Room Nights, Average Daily Rate (ADR), and Revenue. Forecasting accuracy was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Forecast Error (MFE), annual bias percentage, paired sample t-tests, and Pearson correlation analysis. The findings show that AI-assisted forecasting performed more accurately in predicting Room Nights than ADR and Revenue. Room Nights recorded relatively low forecast errors, with an MAE of 3.69, RMSE of 4.61, and MAPE of 11.65%, and the paired sample t-test indicated no statistically significant difference between forecasted and actual demand. In contrast, ADR and Revenue showed higher error values and statistically significant differences, indicating systematic underestimation in pricing and financial performance. Pearson correlation results further suggest that AI forecasts were useful in tracking general trends, although they remained less precise in predicting exact monetary outcomes.

**Keyword:** Evaluation, Artificial Intelligence, Revenue Management, Forecasting



## INTRODUCTION

Revenue management is a strategic issue in the hospitality industry because hotels operate with a relatively fixed, perishable, and time-sensitive room inventory. Unlike other products that can be stored and sold later, an unsold hotel room on a particular night represents a permanent loss of potential revenue. For this reason, decisions related to pricing, inventory allocation, market segmentation, and distribution channels must be made carefully and systematically. Revenue management should not be understood merely as an effort to increase occupancy or charge higher room rates, but as a managerial mechanism that aligns limited capacity with fluctuating demand through data-informed decision-making. Therefore, demand forecasting accuracy becomes a fundamental basis for hotels in determining pricing strategies, managing room availability, and sustaining revenue performance amid increasingly dynamic accommodation markets (Kimes & Thompson, 2005; Koupriouchina et al., 2014; Rodríguez-Algeciras et al., 2017; Selmi et al., 2018).

The digital transformation of the hospitality industry has further increased the complexity of revenue management because pricing decisions are no longer influenced solely by historical occupancy patterns. They are also shaped by price transparency on online travel agencies, rapidly changing booking behavior, online reputation, competitor promotions, and increasingly fragmented customer segments. This condition has shifted revenue management practices from periodic and conventional approaches toward more adaptive, real-time, and analytics-based decision-making processes.

Dynamic pricing, for instance, requires hotels to simultaneously interpret demand variation, price elasticity, and revenue opportunities so that rate decisions are not only oriented toward sales volume, but also toward optimizing revenue value per available room. Thus, the central issue in contemporary revenue management lies in the ability of hotels to process market data accurately and translate it into pricing and inventory decisions that are responsive to demand fluctuations (Abrate et al., 2019; Nair, 2019; Mitra, 2020; Guizzardi et al., 2021).

In recent developments, artificial intelligence has become an increasingly important approach in supporting revenue management because it can process large volumes of data, identify non-linear patterns, and generate more adaptive predictions than traditional forecasting methods. In the hospitality industry, AI is not only used for chatbots, service personalization, or automated customer interaction, but also for analytical functions such as demand forecasting, pricing intelligence, cancellation prediction, and operational decision support.

The ability of AI to learn from historical data and update predictive patterns based on market changes makes it highly relevant for hotels facing demand volatility, particularly in tourism destinations that are strongly affected by seasonality, events, tourist behavior, and competitive pressure. Therefore, AI should be positioned as a decision-support instrument that strengthens the capacity of revenue managers, rather than as a complete replacement for human managerial judgment (Nannelli et al., 2023; Bulchand-Gidumal, 2024; Zahidi et al., 2024; Kumawat et al., 2025).

Nevertheless, many hotels, particularly independent properties and small to medium-sized hotels, still rely on conventional forecasting methods such as historical averages, simple trend analysis, manual pickup, and managerial intuition. Although these approaches are relatively easy to apply, they are often insufficient to capture sudden changes in booking patterns, variations in booking windows, relationships among market segments, and the influence of external factors on demand. The revenue forecasting literature shows that forecasting accuracy is a crucial component of revenue management because prediction errors may affect pricing decisions, room allocation, distribution strategies, and potential revenue outcomes. In other words, weaknesses in forecasting do not only influence the accuracy of demand estimates, but also affect the overall effectiveness of the revenue management strategy implemented by hotels (Pereira, 2016; Lee, 2018; Webb et al., 2020; Pereira et al., 2022).

Several recent studies indicate that machine learning and deep learning models have strong potential to improve hotel demand forecasting accuracy because they are able to process historical patterns, booking curves, spatial-temporal features, hotel characteristic clustering, and complex relationships across data variables. Models such as neural networks, long short-term memory, transformers, and attention-based forecasting are capable of identifying demand patterns that are not always linear and not always repeated in a stable manner over time.

This is especially important in the resort industry because demand is influenced not only by price and room availability, but also by destination characteristics, length of stay, leisure travel patterns, international booking behavior, and market sensitivity to holiday seasons and external conditions. Accordingly, AI-based forecasting offers both scientific and practical opportunities to overcome the limitations of traditional statistical methods, particularly when hotels operate in rapidly changing market environments (Huang & Zheng, 2021; Kaya et al., 2022; Viverit et al., 2023; Zheng et al., 2024).

In addition to internal historical hotel data, the development of big data analytics has expanded the sources of information that can be used to understand hotel demand. Data from online reviews, digital reputation, customer comments, online prices, booking behavior, and distribution platform activities can serve as important signals for hotels in projecting future demand. In this context, AI enables unstructured data such as customer reviews and digital sentiment to be transformed into more measurable indicators that support forecasting and service performance evaluation.

However, the use of big data in hospitality still requires caution because large data volumes do not automatically guarantee prediction quality unless they are supported by appropriate variable selection, model validation, managerial interpretation, and a strong understanding of the hotel business context. Therefore, studies on AI forecasting need to consider the relationship between historical operational data, digital market signals, and the practical needs of revenue management at the property level (Lyu et al., 2022; Cai et al., 2024; Zhang et al., 2024; Guo et al., 2026).

Table 1. Position of the Study within the Literature on AI-Based Revenue Forecasting in Hospitality

| No. | Aspect of discussion | Position of Previous Literature | Relevance to This Study |
|---|---|---|---|
| 1 | Hotel revenue management | Previous studies emphasize price optimization, inventory allocation, segmentation, and distribution as key mechanisms for maximizing revenue from limited room capacity. | It provides the conceptual basis that forecasting directly influences rate decisions and room allocation. |
| 2 | Conventional forecasting | Historical and statistical models are widely used, but they tend to be limited in capturing volatility and non-linear demand patterns. | It explains the need for an AI-based approach to examine possible improvements in forecasting accuracy. |

| No. | Aspect of discussion | Position of Previous Literature | Relevance to This Study |
|---|---|---|---|
| 3 | AI and machine learning | AI models have been shown to process large datasets, identify complex patterns, and update predictions more adaptively. | It supports the research approach in evaluating forecasting accuracy using commercially available AI tools. |
| 4 | Big data in hospitality | Digital data such as online reviews, OTA prices, and customer behavior can become strategic sources of information for hotels. | It strengthens the argument that modern forecasting does not depend solely on internal historical data. |
| 5 | Research gap | Empirical studies using operational data from luxury resorts remain limited, particularly in relation to commercially available AI tools for Room Nights, ADR, and Revenue. | It confirms the originality of this study in the context of Amarterra Villas Resort Bali Nusa Dua as a luxury resort property. |

Source: Author, 2026

Although the literature has extensively discussed AI, big data, and hotel demand forecasting, a research gap remains in the use of actual operational data from luxury resort properties, particularly in evaluating the accuracy of commercially available AI tools that can be practically used by hotels. Most previous studies have focused on conceptual models, large-scale hotel chains, simulations, or the development of specialized algorithms that are not always easy to adopt by properties with limited human resources in revenue management. In practice, many hotels require forecasting solutions that are simpler, more efficient, and usable without requiring advanced technical expertise. At this point, Amarterra Villas Resort Bali Nusa Dua represents a relevant research context because, as a five-star resort within the Marriott brand ecosystem, it faces high forecasting accuracy demands while also needing to consider resource efficiency in daily revenue management practices (Altin et al., 2017; Millauer & Vellekoop, 2019; Ivanov et al., 2021; Yolcu et al., 2025).

Based on this background, this study aims to analyze the extent to which artificial intelligence can produce accurate forecasting based on the resort's historical data, particularly within the context of revenue management in a luxury resort property in Bali. The focus of this research is not merely on AI as a technology, but on its capacity as a practical decision-support tool for estimating demand, supporting rate decisions, and strengthening revenue management effectiveness when specialized human resources in analytics remain limited. Therefore, this article seeks to provide a scientific contribution by empirically examining the forecasting accuracy of commercially available AI tools, while also offering practical value for hotels that require forecasting methods that are more efficient, affordable, and relevant to operational needs. Accordingly, the main research question addressed in this study is: "How accurate is the demand forecasting of the resort based on historical data using commercially available AI?"

## RESEARCH METHOD

This study employed a descriptive quantitative research design with comparative forecasting accuracy analysis to evaluate the performance of AI-assisted revenue management forecasting at Amarterra Villas Resort Bali Nusa Dua. A quantitative design was considered appropriate because the study examined numerical hotel performance indicators and measured the extent to which AI-generated forecasts corresponded with actual operational outcomes. The descriptive approach was used to present the characteristics of forecasted and realized data, while comparative analysis was applied to assess differences between predicted and actual values across selected performance indicators. Accordingly, this method enabled the study to evaluate forecasting reliability in a structured and measurable manner within the context of hospitality revenue management (Creswell & Creswell, 2018; Bryman, 2016).

The population of this study consisted of operational performance records from Amarterra Villas Resort Bali Nusa Dua, a five-star luxury villa resort under the Marriott brand and positioned within Bali's premium leisure tourism market. The resort primarily serves high-spending international leisure travelers, honeymooners, and luxury free independent travelers, with demand patterns strongly influenced by seasonality, special events, and global travel trends. A purposive sampling technique was applied by selecting specific periods in which both AI-generated forecast data and actual performance data were available. This technique was relevant because the study required data units that met specific analytical criteria, particularly the availability of matched forecasted and realized values within the same business dates. The sample therefore comprised daily and monthly hotel performance data within the designated forecasting horizon, allowing direct comparison between predicted and realized hotel performance (Saunders et al., 2019; Hair et al., 2019).

This study examined two main variables. The independent variable was the AI-generated forecast of hotel performance, while the dependent variable was the actual realized hotel performance. Both variables were measured using numerical indicators consisting of room nights, Average Daily Rate (ADR), and room revenue. Room nights were measured as the total number of occupied room nights per day, while ADR was calculated by dividing total room revenue by the total number of rooms sold. Revenue was measured as total daily room revenue generated from sold rooms, excluding ancillary revenue such as food and beverage income. Forecasted and actual values were matched according to identical business dates to ensure comparability and consistency in measurement.

Data were collected through documentation by obtaining historical records, forecast outputs, and actual performance data from the hotel's internal revenue management systems. The study relied exclusively on secondary quantitative data to maintain objectivity and consistency in the analytical process. Data analysis was conducted using comparative quantitative techniques, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Forecast Error (MFE) to evaluate forecasting accuracy. In addition, paired sample t-tests were used to examine whether significant differences existed between forecasted and actual values, while Pearson correlation analysis was applied to assess the strength of the relationship between AI-generated forecasts and realized hotel performance. Missing values were excluded only when both forecast and actual records were unavailable, while extreme outliers caused by exceptional operational closures were reviewed and retained only when they were operationally justified.

## RESULTS AND DISCUSSION

### 1. Overall Forecasting Performance of AI-Assisted Revenue Management

The empirical findings indicate that AI-assisted forecasting at Amarterra Villas Resort Bali Nusa Dua demonstrates relatively strong accuracy in predicting room night demand, but weaker performance in forecasting Average Daily Rate (ADR) and total room revenue. This pattern suggests that AI forecasting is more reliable when estimating demand volume than when predicting financial outcomes that are influenced by pricing behavior, market positioning, and managerial decisions. Room Nights recorded a Mean Absolute Error (MAE) of 3.69, a Root Mean Squared Error (RMSE) of 4.61, and a Mean Absolute Percentage Error (MAPE) of 11.65%. These results show that, on average, the AI forecast missed approximately 3.7 room nights per day, which is operationally acceptable for a resort-scale property.

In contrast, the forecasting performance for ADR and Revenue showed larger deviations. ADR recorded a MAE of IDR 694,641, an RMSE of IDR 928,524, and a MAPE of 12.82%. Meanwhile, Revenue recorded a MAE of IDR 37,064,882, an RMSE of IDR 47,101,741, and a MAPE of 20.88%. These results indicate that while the AI model can reasonably predict demand volume, it faces greater difficulty in estimating rate and revenue outcomes. This is understandable because ADR and Revenue are not only shaped by historical demand patterns, but also by competitor pricing, promotional campaigns, market mix, negotiated rates, and manual revenue management decisions.

The findings also reveal a consistent under-forecasting pattern across all variables. The Mean Forecast Error (MFE) values were negative for Room Nights, ADR, and Revenue, indicating that forecasted values tended to be lower than actual realized performance. The MFE for Room Nights was −0.26, while ADR recorded an MFE of IDR −161,283 and Revenue recorded an MFE of IDR −8,749,089. At the annual level, Room Nights showed a very small bias of −0.78%, while ADR and Revenue showed larger annual bias rates of −2.91% and −4.58%, respectively. This indicates that the AI forecasting system was generally conservative, especially in estimating pricing and revenue performance.

Overall, these results suggest that AI-assisted forecasting provides useful support for revenue management, particularly in demand forecasting. However, its performance becomes less accurate when the forecast involves variables affected by pricing strategy and managerial discretion. Therefore, AI should be understood as a decision-support tool rather than a fully autonomous forecasting mechanism. Human revenue managers remain important in interpreting forecast outputs, adjusting rate strategies, and incorporating external market intelligence that may not be fully captured by the AI model.

### 2. Forecast Accuracy Based on Error Measurement Indicators

Forecast accuracy was evaluated using four main statistical indicators: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Forecast Error (MFE). These indicators were used to compare AI-forecasted data for 2025 with actual hotel performance data from the same year. The comparison was conducted across three core hotel performance variables, namely

Room Nights, ADR, and Revenue. Each metric provides a different perspective on forecasting accuracy, ranging from the average size of forecast error to the direction of forecasting bias.

Mean Absolute Error (MAE) was used to measure the average absolute difference between forecasted and actual values. This indicator is useful because it provides a practical measure of daily operational error. The formula used is as follows:

$$MAE = (1/n)\, \Sigma\, |F_t - A_t|$$

Where:
$F_t$ = AI-forecasted value on day t
$A_t$ = actual value on day t
n = number of observations, namely 365 days

The MAE results show that Room Nights had an average daily error of 3.69 room nights, ADR had an average daily error of IDR 694,641, and Revenue had an average daily error of IDR 37,064,882. These findings indicate that demand forecasting error was relatively small, while pricing and revenue forecasting errors were more substantial. The larger revenue error reflects the combined effect of inaccuracies in both demand and rate estimation.

Root Mean Squared Error (RMSE) was used to measure the square root of the average squared forecast errors. This indicator gives greater weight to larger errors, making it useful for identifying whether certain days experienced substantial forecasting deviations. The formula used is as follows:

$$RMSE = \sqrt{[(1/n)\, \Sigma(F_t - A_t)^2]}$$

The RMSE results show that Room Nights recorded an RMSE of 4.61, ADR recorded an RMSE of IDR 928,524, and Revenue recorded an RMSE of IDR 47,101,741. Since the RMSE values were higher than the MAE values for all variables, the results indicate the presence of several days with larger forecast deviations. This pattern is particularly visible in Revenue, where the relatively high RMSE suggests periodic spikes in forecasting error, most likely during peak demand periods, disrupted market conditions, or days with significant pricing adjustments.

Mean Absolute Percentage Error (MAPE) was used to measure forecast error as a percentage of actual values. This metric is useful because it allows comparison across variables with different measurement scales. The formula used is as follows:

$$MAPE = (100/n)\, \Sigma\, |(F_t - A_t) / A_t|$$

The MAPE results show that Room Nights recorded 11.65%, ADR recorded 12.82%, and Revenue recorded 20.88%. The Room Nights and ADR values fall within a moderate and operationally acceptable range, indicating that the AI forecast can still provide useful guidance for demand and pricing direction. However, the Revenue MAPE exceeded 20%, suggesting lower accuracy at the revenue level. This confirms that forecasting total revenue is more complex because it combines both demand volume and pricing accuracy. Mean Forecast Error (MFE) was used to identify the direction of forecast bias. Unlike MAE and RMSE, which measure the magnitude of error, MFE indicates whether the forecast tends to overestimate or underestimate actual performance. The formula used is as follows:

$$\text{MFE} = (1/n)\ \Sigma(F_t - A_t)$$

The MFE results show negative values across all variables: −0.26 for Room Nights, IDR −161,283 for ADR, and IDR −8,749,089 for Revenue. These negative values indicate that the AI forecasts tended to underestimate actual performance. The under-forecasting bias was relatively small for Room Nights but more meaningful for ADR and Revenue. This suggests that the forecasting system was conservative, especially in predicting pricing outcomes and revenue potential. Annual bias was also calculated to evaluate whether the AI model systematically underestimated or overestimated yearly performance. The formula used is as follows:

$$\text{Annual Bias } \% = [(\Sigma F - \Sigma A) / \Sigma A] \times 100$$

The annual bias results show that Room Nights had a bias of −0.78%, ADR had a bias of −2.91%, and Revenue had a bias of −4.58%. These findings reinforce the conclusion that demand forecasting was highly accurate at the annual level, with less than 1% deviation. However, the under-forecasting of Revenue by approximately 4.6% suggests that the AI model may underestimate financial performance, particularly when actual market conditions allow the hotel to achieve stronger pricing or revenue outcomes than initially predicted.

3. Statistical Significance of Forecast and Actual Differences

To examine whether the differences between forecasted and actual values were statistically significant, a paired sample t-test was conducted. This test compared AI-forecasted data and actual data for the same business dates in 2025. The paired sample t-test was appropriate because each forecasted value was directly paired with its corresponding actual value. The test was applied to Room Nights, ADR, and Revenue to determine whether the mean difference between forecasted and realized performance was statistically meaningful. The formula used for the paired sample t-test is as follows:

$$t = \bar{d} / (s^d / \sqrt{n})$$

Where:
$\bar{d}$ = mean of daily differences between forecasted and actual values
$s^d$ = standard deviation of the differences
$n$ = number of observations, namely 365 days

Based on Table 1, the paired sample t-test shows that Room Nights had a p-value of 0.277, which is greater than 0.05. This means that there was no statistically significant difference between forecasted and actual Room Nights. Therefore, the AI-generated demand forecast can be considered statistically reliable in estimating room night volume. The relatively low daily error and non-significant mean difference indicate that the AI model performed well in capturing overall demand.

Table 2. Paired T-test Results

| Variable | t-Statistic | p-Value |
|---|---|---|
| Room Nights | −1.089 | 0.277 |
| ADR | −3.365 | 0.00085 |
| Revenue | −3.607 | 0.00035 |

Source: Research Result, 2026

In contrast, ADR and Revenue showed statistically significant differences between forecasted and actual values. ADR recorded a p-value of 0.00085, while Revenue recorded a p-value of 0.00035. Both values are below 0.001, indicating strong statistical evidence of systematic differences between the AI forecasts and actual realized outcomes. These findings confirm that the AI model was less reliable in forecasting pricing and revenue performance than in forecasting demand volume.

The significant underestimation of ADR and Revenue can be explained by the nature of pricing decisions in luxury hospitality. Unlike room demand, which is often influenced by booking pace, seasonality, and historical occupancy patterns, ADR is shaped by revenue manager interventions, competitor rate changes, market positioning, promotional strategies, and customer willingness to pay. Revenue forecasting is even more complex because it combines both demand uncertainty and pricing uncertainty. As a result, even when the model can forecast demand reasonably well, revenue forecasts may still deviate when actual pricing decisions differ from forecast assumptions.

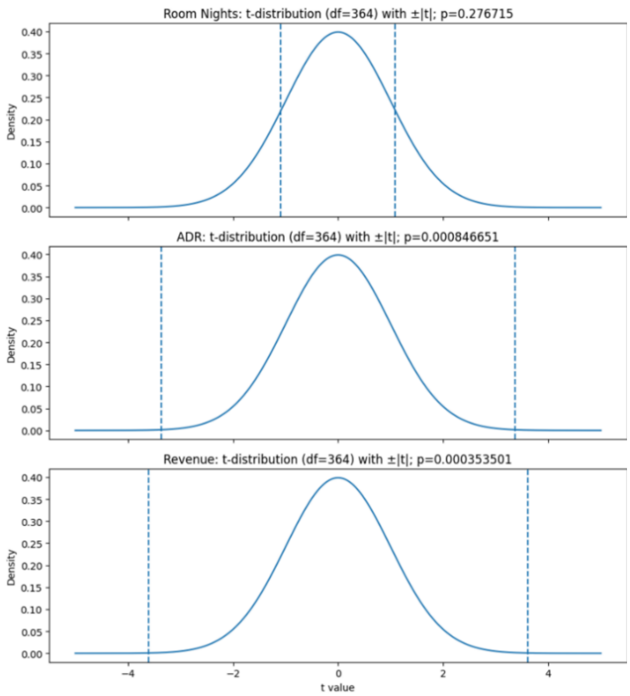


Figure 1. Paired Sample t-Test (Forecast vs Actual)
Source: Research Result, 2026

Figure 1 illustrates the comparison between forecasted and actual values based on the paired sample t-test. The figure supports the statistical results by showing that the gap between forecasted and actual Room Nights was relatively small, while larger deviations appeared in ADR and Revenue. This visual pattern confirms that AI-assisted forecasting performs better for demand estimation than for financial forecasting. Therefore, revenue managers should use AI-generated forecasts as a starting point for analysis, while still applying managerial judgment when making pricing and revenue decisions.

4. Pearson Correlation between Forecasted and Actual Performance

Pearson correlation analysis was conducted to measure the strength and direction of the relationship between AI-generated forecasts and actual hotel performance. This analysis is important because a forecasting model may still be useful even when it contains bias, as long as it can follow the general direction of market movement. In revenue management, a model that tracks demand and pricing trends can support decision-making, although further calibration may be required to improve absolute accuracy. The Pearson correlation coefficient was calculated using the following formula:

$$r = \Sigma[(F_t - \bar{F})(A_t - \bar{A})] \;/\; \sqrt{[\Sigma(F_t - \bar{F})^2 \, \Sigma(A_t - \bar{A})^2]}$$

Where:
$F_t$ = forecasted value on day t
$A_t$ = actual value on day t
$\bar{F}$ = mean of forecasted values
$\bar{A}$ = mean of actual values

The results show that Room Nights had a Pearson correlation coefficient of 0.419, ADR had a coefficient of 0.613, and Revenue had a coefficient of 0.618. The Room Nights correlation indicates a moderate relationship between forecasted and actual values. This means that although the AI model produced relatively small forecast errors for Room Nights, it did not always follow day-to-day demand fluctuations perfectly. Therefore, it is important to distinguish between forecast error and correlation strength. A low MAE and MAPE show that the average forecast deviation was operationally small, while a moderate correlation indicates that daily movement patterns were not always fully synchronized.

ADR and Revenue showed stronger directional relationships, with correlation coefficients above 0.60. These values indicate that the AI model was reasonably capable of following general pricing and revenue trends, even though the absolute forecast errors were larger. In other words, the model could recognize the direction of changes in ADR and Revenue, but it still struggled to estimate the exact monetary values. This finding is important because it shows that AI forecasts may still have value for strategic decision support, especially when used to identify trend direction, market movement, and potential revenue opportunities.

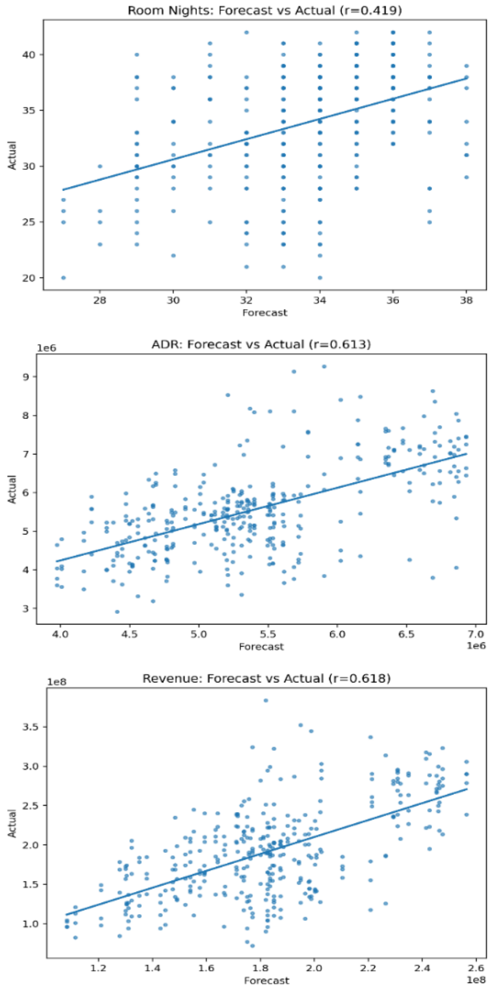


Figure 2. Scatter plots illustrating the Pearson correlation between forecasted and actual values for room nights, average daily rate (ADR), and revenue
Source: Research Result, 2026

Figure 2 presents the scatter plots showing the relationship between forecasted and actual values for Room Nights, ADR, and Revenue. The scatter plot pattern supports the correlation results by indicating a moderate relationship for Room Nights and stronger directional relationships for ADR and Revenue. However, the spread of points also suggests that the model did not consistently produce highly precise forecasts at the daily level. This reinforces the conclusion that AI forecasting is informative for identifying general trends but still requires human interpretation and calibration for execution-level revenue management decisions.

5. Discussion and Managerial Implications

The findings confirm that AI-assisted forecasting performs better in predicting Room Nights than ADR and Revenue. This result is logical because room night demand is more directly related to historical occupancy, seasonality, booking pace, and recurring travel patterns. These variables are generally easier for machine learning models to identify and predict. In contrast, ADR and Revenue are more sensitive to managerial pricing decisions, competitor reactions, promotional strategies, market segmentation, negotiated rates, and sudden changes in demand conditions.

In luxury resort operations, pricing decisions are often adjusted manually by revenue managers based on brand positioning, competitor intelligence, market demand, guest profile, and expected willingness to pay. These managerial interventions may not be fully captured by a closed forecasting system that relies primarily on historical and structured data. As a result, the AI model may produce conservative pricing forecasts even when actual market conditions allow the property to achieve higher ADR and Revenue. This explains why the model produced more accurate demand forecasts but showed systematic underestimation in financial indicators.

The relatively strong performance of AI in Room Nights forecasting suggests that AI can be used as a valuable tool for demand planning, staffing preparation, inventory control, and operational coordination. Accurate demand forecasting helps the hotel estimate occupancy levels, prepare room allocation strategies, and anticipate operational needs. However, the weaker accuracy in ADR and Revenue forecasting indicates that AI should not be used as the only basis for pricing decisions. Instead, revenue managers should combine AI-generated forecasts with competitor rate shopping, market intelligence, promotional planning, and strategic pricing judgment.

The results also suggest that AI forecasting tools need continuous calibration. Because the model tended to under-forecast ADR and Revenue, hotel management should review whether the forecasting system sufficiently incorporates pricing decisions, market events, competitor actions, and luxury demand behavior. Regular evaluation of forecast bias can help the hotel identify whether the model consistently underestimates or overestimates performance. This process is particularly important for owner reporting, budgeting, and strategic planning, where revenue expectations must be realistic and financially reliable.

In practical terms, commercially available AI forecasting tools can offer a cost-effective solution for hotels with limited dedicated revenue management manpower. For a property such as Amarterra Villas Resort Bali Nusa Dua, AI can support faster analysis, reduce manual forecasting workload, and improve the consistency of demand estimation. However, the findings also show that AI forecasts should be interpreted carefully, especially when applied to ADR and Revenue. The role of human revenue managers remains essential in adjusting forecasts based on contextual knowledge, market conditions, and strategic business objectives.

Overall, this study demonstrates that AI-assisted forecasting has meaningful value in hotel revenue management, particularly for demand forecasting. The model produced operationally acceptable Room Nights forecasts and showed useful directional tracking for ADR and Revenue. Nevertheless, the significant differences between forecasted and actual ADR and Revenue indicate that AI forecasting still requires managerial oversight. Therefore, the most appropriate use of AI in this context is as a hybrid decision-support system that combines algorithmic forecasting with human revenue management expertise.

## CONCLUSION

This study concludes that AI-assisted forecasting has meaningful potential to support revenue management practices at Amarterra Villas Resort Bali Nusa Dua, particularly in predicting room night demand. The empirical results show that AI-generated forecasts were relatively accurate in estimating Room Nights, as indicated by low forecast error values and the absence of a statistically significant difference between forecasted and actual demand. This finding demonstrates that AI can effectively identify historical demand patterns, seasonality, and booking tendencies, making it useful for operational planning, inventory control, and demand-based decision-making in a luxury resort environment.

However, the study also finds that AI forecasting was less accurate in predicting Average Daily Rate and total room revenue. The higher MAE, RMSE, and MAPE values for ADR and Revenue, combined with statistically significant differences between forecasted and actual values, indicate that AI still has limitations in capturing pricing complexity and revenue outcomes. These limitations are mainly caused by the influence of managerial pricing adjustments, competitor actions, promotional strategies, market segmentation, negotiated rates, and changing guest willingness to pay. Therefore, while AI can support forecasting efficiency, it cannot fully replace human judgment in pricing and revenue optimization decisions.

Overall, this study contributes to hospitality revenue management literature by providing empirical evidence on the practical use of commercially available AI forecasting tools in a luxury resort context. The findings suggest that AI should be applied as a hybrid decision-support system that combines algorithmic forecasting with managerial expertise. For hotels with limited dedicated revenue management manpower, AI can offer a cost-effective and efficient tool for improving demand forecasting and supporting strategic decision-making. Nevertheless, continuous model calibration, market intelligence integration, and human interpretation remain essential to improve forecasting accuracy for ADR and Revenue in future revenue management practices.

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