The Dynamic Pricing and Human Resource Analysis for a Guest House

A Final report for the BDM capstone Project

Submitted by

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Declaration Statement

I am working on a Project titled "**The Dynamic Pricing and Human Resource Analysis for a Guest House**". I extend my appreciation to **Garjiya Homestay**, for providing the necessary resources that enabled me to conduct my project.

I hereby assert that the data presented and assessed in this project report is genuine and precise to the utmost extent of my knowledge and capabilities. The data has been gathered from primary sources and carefully analyzed to assure its reliability.

Additionally, I affirm that all procedures employed for the purpose of data collection and analysis have been duly explained in this report. The outcomes and inferences derived from the data are an accurate depiction of the findings acquired through thorough analytical procedures.

I am dedicated to adhering to the principles of academic honesty and integrity, and I am receptive to any additional examination or validation of the data contained in this project report.

I understand that the execution of this project is intended for individual completion and is not to be undertaken collectively. I thus affirm that I am not engaged in any form of collaboration with other individuals, and that all the work undertaken has been solely conducted by me. In the event that plagiarism is detected in the report at any stage of the project's completion, I am fully aware and prepared to accept disciplinary measures imposed by the relevant authority.

I understand that all recommendations made in this project report are within the context of the academic project taken up towards course fulfillment in the BS Degree Program offered by IIT Madras. The institution does not endorse any of the claims or comments.

Signature of Candidate:

Name: Rahul Pathak

Date: August 5, 2025

1 Executive Summary

Located near Jim Corbett National Park, the **Garjiya Homestay,** guest house under study operates with six rooms (4 AC and 2 Non-AC) and caters primarily to tourists. Despite consistent occupancy, the owner faced two persistent challenges: (1) revenue instability due to subjective and negotiable pricing practices, and (2) high receptionist turnover driven by poor shift scheduling, static wages, and lack of growth opportunities. These problems limited both profitability and service consistency.

To address these issues, primary data was collected manually over a 12-month period (May 2024 – April 2025) from handwritten booking records, staff interviews, online reviews, and competitor rates. The data was cleaned and structured into Excel, capturing key variables such as check-in/out dates, room type, base/final prices, occupancy %, revenue, guest feedback, and employee satisfaction scores. A linear regression model was developed in Python using features like base price, season, room type, and occupancy to predict optimal final pricing.

The model achieved high performance ($R^2 = 0.93$, RMSE ≈ ₹150) and identified over ₹65,000 in missed revenue in 481 days due to underpricing. Simultaneously, HR analysis revealed all four receptionists resigned within a year, citing unfair schedules and low pay.

Recommendations include implementing model-based dynamic pricing and launching structured HR reforms. These measures are expected to enhance profitability, improve pricing consistency, and strengthen workforce retention — laying the foundation for sustainable growth.

2 Detailed Explanation of Analysis Process/Method

Data Collection

The data for this project was collected manually from **Garjiya Homestay** located near the Jim Corbett National Park. The data collection spanned a continuous period of 12 months — from **1st May 2024 to 30th April 2025** — covering the complete seasonal and operational cycle of the business.

Since the guest house maintained its records manually in handwritten registers, the first step was to digitize this data using **Microsoft Excel**. The digitization was performed meticulously to ensure accuracy and completeness. This process resulted in the creation of two primary structured datasets:

1. Booking Dataset:

This dataset was created by extracting details from daily guest logs and included:

- **Guest name, customer ID, and guest type (new/repeat)**
- **Check-in and check-out dates**
- **Room type (AC/Non-AC)**
- **Base price per night and final price charged**
- **Purpose of visit, group size, and total amount paid**
- **Bargaining indicator (Y/N/S), season tag, and booking date**
- **Derived fields like total nights stayed, occupancy %, and total revenue**

2. Employee Dataset:

This dataset was constructed based on **in-person interviews** conducted with the guest house **owner and manager**. It captured:

- **Employee ID, name, role, and department**
- **Job satisfaction scores and feedback on management relations**
- **Wage per month, tenure, and exit reasons (if applicable)**
- **Exit status (resigned, active, or deceased)**

3. Supporting Data:

To enrich the analysis:

- **Competitor pricing and customer ratings** were manually collected from **Google Maps** for five nearby guest houses.
- **Customer review text, ratings, and sentiment** were extracted from Google Maps.
- Based on this, a sentiment-labeled review dataset was constructed to analyze guest satisfaction and likelihood of recommendation.

The final structured dataset enabled comprehensive analysis for both pricing optimization and workforce evaluation, ensuring a strong foundation for model development and decision-making.

Data Cleaning and Preprocessing

Given that the original data was recorded manually in handwritten registers, the quality and consistency of the raw data posed a significant challenge. Therefore, data cleaning and preprocessing were crucial steps to ensure analytical accuracy and model readiness. The process was carried out using Microsoft Excel for the initial data preparation and Python for final transformation and model training.

1. Handling Missing Values:

Several important fields were found to be incomplete due to manual entry errors. In particular:

- The Total_Amount field was missing in some cases and was logically inferred using the formula:
  Total_Amount = Final_Price_Per_Night × Number_of_Nights Stayed where Number_of_Nights was calculated from the difference between check-in and check-out dates.
- For entries with missing occupancy-related values, information was derived from the daily occupancy sheet by matching dates.

2. Avoiding Duplicates and Assigning Unique Identifiers:

Since guest names were manually written and prone to inconsistency (e.g., abbreviations or misspellings), the risk of duplication was high. To address this:

- A manually generated Customer_ID system was introduced, based on full names and booking dates.
- Entries were checked to avoid repeat records, especially in the case of recurring guests or group bookings.

3. Creating Derived Columns:

Several new variables were engineered to enhance analysis and enable predictive modeling:

- Occupancy_% was calculated by comparing rooms booked against total available rooms for each date, sourced from the occupancy dataset.
- Revenue per day was computed using the check-in date, length of stay, and final price.

4. Final Preparation for Modeling:

Before training the ML model, the cleaned dataset was processed using Python:

- Categorical variables (Room_Type, Season) were One-Hot Encoded using ColumnTransformer.
- Missing or inconsistent rows were dropped.
- The final dataset used for modeling included features such as:
    - Base_Price_Per_Night
    - Occupancy_%
    - Room_Type
    - Season
    - and target variable: Final_Price_Per_Night

The entire cleaning process ensured that the data was not only consistent and complete but also structured in a way that supported reliable analysis and model training. This foundation was critical for accurate predictions and insightful recommendations later in the project.

Feature Engineering

Most of the features required for analysis were manually created due to limited structured input data. For example:

- **Customer_ID** was self-generated
- **Season** was assigned manually based on check-in dates
- **Occupancy_%** was joined from a separate sheet based on date mapping
- Additional sheets like **Competitor Pricing**, **Reviews**, and **Exit Feedback** were compiled from online sources and owner interviews

This hands-on derivation ensured maximum context awareness and tailored modeling inputs for the guest house.

Tools and Analysis Workflow

1. **Excel-Based Analysis:** Used for descriptive analysis and business insights:

- **PivotTables**: To summarize revenue by room type and seasonal trends

- **Charts**: Bar charts, pie charts, and line markers were used to show occupancy, revenue, satisfaction levels
- **Conditional Formatting**: Applied to highlight low satisfaction or peak seasons
- Customer reviews were also classified manually for sentiment tagging

2. **Python-Based Predictive Modeling:** A **Multiple Linear Regression** model was created using:

- Independent variables: Base_Price_Per_Night, Occupancy_%, Room_Type, and Season
- Target: Final_Price_Per_Night

Mathematical Formulation:

$$\text{Final\_Price} = \beta 0 + \beta 1 \cdot \text{Base\_Price} + \beta 2 \cdot \text{Occupancy\%} + \beta 3 \cdot \text{Room\_Type} + \beta 4 \cdot \text{Season} + \varepsilon$$

Performance:

- R^2 Score: 0.93
- RMSE: ₹150.43

The model was visualized through **Actual vs Predicted Scatter Plot** and residual patterns. Python's Pipeline and ColumnTransformer were used to preprocess categorical variables with OneHotEncoding.

Justification of Methods and Tools

- **Excel** was chosen for its accessibility and interactive business analytics capabilities. It enabled the owner and team to understand seasonal revenue trends, room-wise contribution, and satisfaction levels.
- **Python** provided the modeling strength to build and validate a regression framework, helping in pricing decisions. LinearRegression was selected due to its interpretability, ease of implementation, and suitability for limited data size.

Each method directly tackled the **core business problems**:

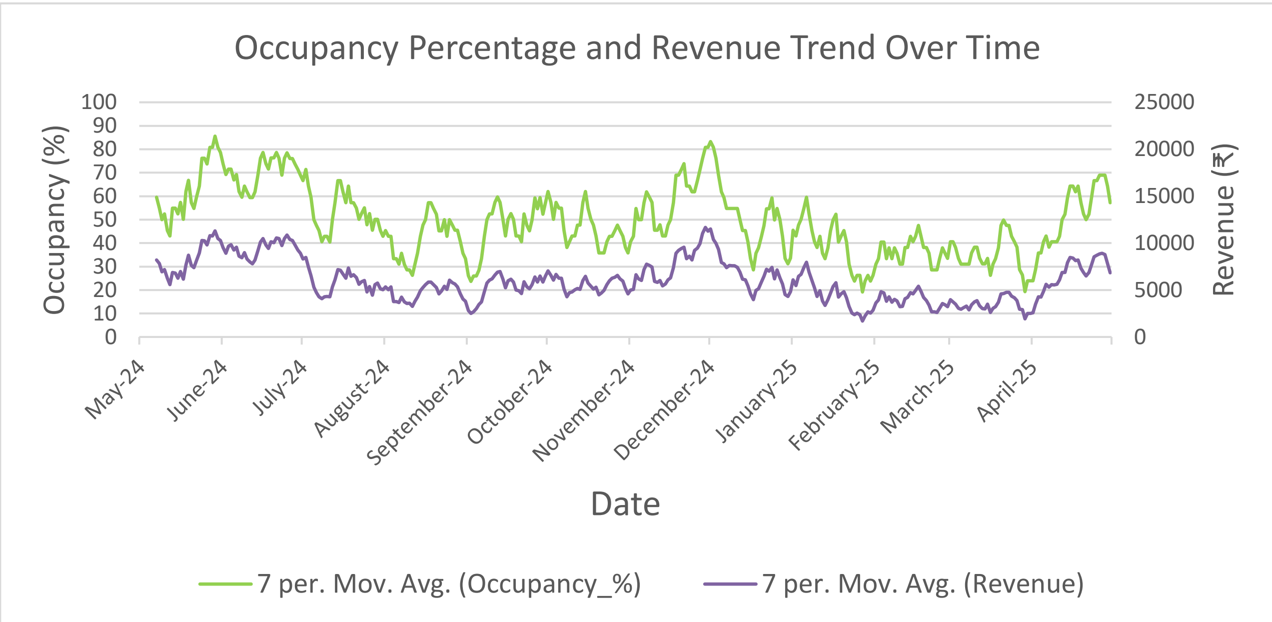
- Unpredictable pricing → solved via price prediction model
- High attrition → addressed using employee sentiment analysis and satisfaction scoring

This structured pipeline created a bridge between operational decision-making and data-backed insights, laying the groundwork for long-term revenue optimization and workforce stability.

Results and Findings

Figure 1: Occupancy Percentage and Revenue Trend Over Time

This dual-axis line chart presents the 7-day moving average of both occupancy percentage (green line) and total daily revenue (purple line) across a full year, from May 2024 to April 2025. The purpose of this visualization is to uncover demand patterns and understand their relationship with earnings.



Key Insights:

- **Peak Occupancy Periods:** Occupancy rates consistently crossed 90% during June and December, aligning with the summer vacation rush and peak wildlife tourism season. These months reflect naturally high demand, likely driven by school holidays and favorable travel conditions.
- **Mismatch Between Occupancy and Revenue:** In several high-occupancy periods, revenue did not rise proportionally. For example, June showed 90%+ occupancy but moderate revenue — suggesting that manual pricing or excessive bargaining diluted revenue potential despite strong demand.

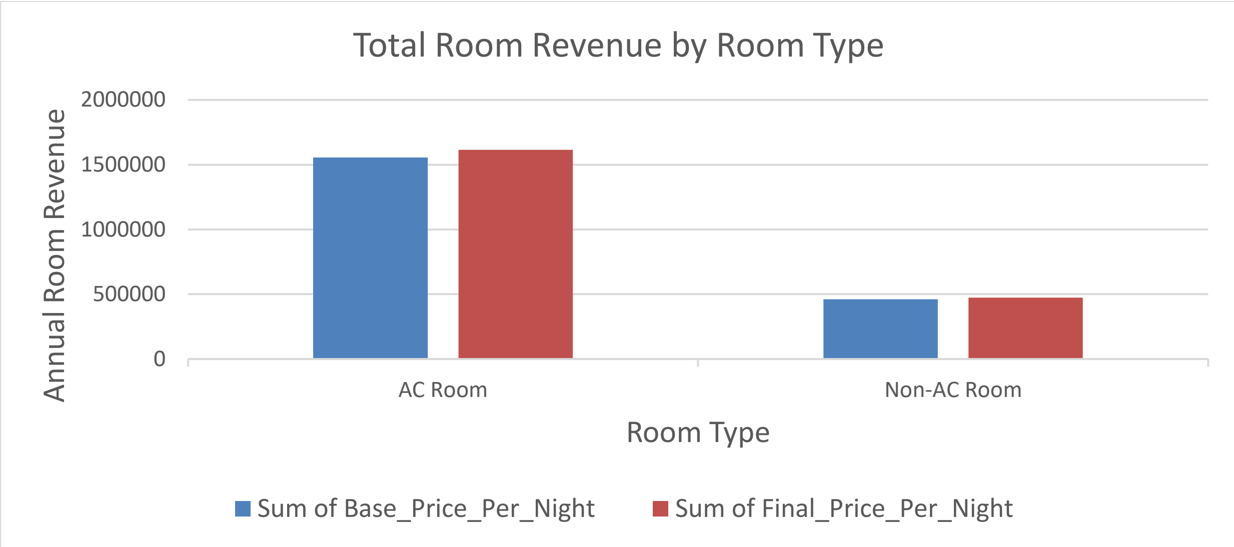
- **Seasonal Lows in August–September:** A steep drop in both occupancy and revenue during monsoon months (August–September) confirms the impact of seasonal demand dips. This off-season trend indicates the need for more aggressive promotions or discounted packages to attract visitors.
- **Revenue Rise in Late Season (March–April):** Despite only moderate occupancy (around 60–70%), revenue began to climb again in March and April. This could point to successful upselling strategies, increased room rates, or fewer discounts given — a positive trend worth reinforcing.

Strategic Implications:

- **Dynamic Pricing Opportunity:** The guest house should implement season-aware pricing strategies. Room rates can be raised during high-demand months like June, December, and April to capitalize on full occupancy and willingness to pay.
- **Revenue Optimization in Mid-Occupancy Months:** In periods where occupancy is average (e.g., October or February), the business can still boost revenue through room-type upgrades, bundled services (e.g., meals, safari tours), and strategic upselling.
- **Off-Season Planning:** August and September require targeted offers, such as flat discounts for direct bookings or tie-ups with travel agencies to maintain base-level occupancy and avoid empty rooms.
- **Avoid Over-Bargaining:** Where occupancy is already high, the focus should shift from filling rooms to maximizing revenue per room. Avoiding unnecessary discounts and using model-driven pricing can reduce revenue leakage.

Figure 2: Total Room Revenue by Room Type

This **clustered column chart** presents the total revenue generated by different room types — comparing **base prices (blue bars)** with **final prices (red bars)** for both **AC Rooms** and **Non-AC Rooms**. The visualization helps in understanding which room category contributes more to overall income and how pricing flexibility varies between categories.



Key Insights:

- **AC Rooms as Revenue Drivers:** AC rooms generated more than ₹16 lakh in revenue over the year, which is over three times higher than the revenue generated from Non-AC rooms. This indicates that AC rooms are the primary income stream for the guest house.
- **Higher Price Differentials in AC Rooms:** The gap between base and final price is significantly wider for AC rooms, reflecting greater pricing flexibility. It suggests that AC rooms are often upsold successfully, possibly due to higher guest expectations or peak demand during summer and holiday seasons.
- **Limited Upselling in Non-AC Rooms:** For Non-AC rooms, the base and final prices are often nearly identical, indicating low negotiation or value addition. This may result from low perceived value, seasonal disinterest, or customer price sensitivity in that category.

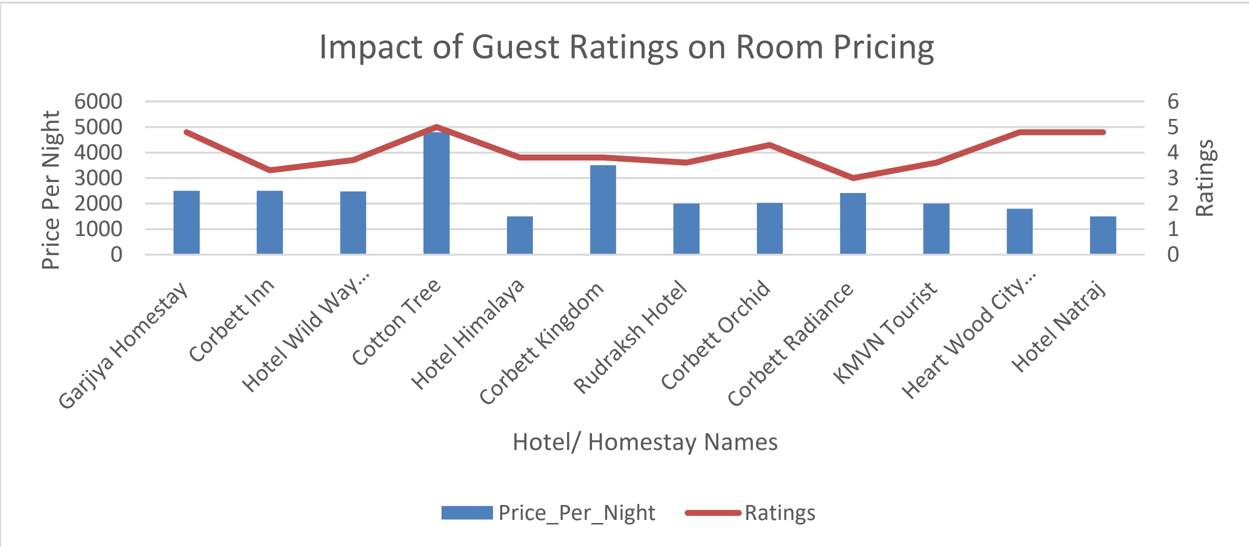
Strategic Implications:

- **Expand AC Room Inventory:** Given their high revenue yield and pricing flexibility, the guest house should consider **increasing the proportion of AC rooms**. This could be done by upgrading existing infrastructure or converting underperforming Non-AC rooms.
- **Targeted Upselling for Non-AC Rooms:** Non-AC rooms can be made more profitable by **bundling value-added services** like complimentary breakfast, pickup/drop facilities, or safari experiences. This can enhance perceived value without altering the core room offering.
- **Leverage Pricing Model Differently for Each Room Type:** While dynamic pricing can be used aggressively for AC rooms to maximize revenue during peak times, **Non-AC**

room pricing should focus on package deals and off-season offers to drive volume and enhance utilization.

Figure 3: Impact of Guest Ratings on Room Pricing (Competitor Benchmarking)

This **dual-axis chart** benchmarks the guest house's room pricing and reputation against 12 nearby competitors. The **bars** represent each competitor's **price per night**, while the **line graph** displays their **average customer rating**, as sourced manually from **Google Maps**. The aim is to assess whether room rates across the local market align with guest satisfaction levels, and to identify potential mispricing or under positioning.



Key Insights:

- **Top Performer with Premium Pricing:** Cotton Tree, priced at ₹4800 with a perfect 5.0 rating, positions itself at the top tier of the market, likely due to luxury amenities and prime location.
- **Our Guest House is Undervalued:** Garjiya Homestay, the guest house under study, is priced at ₹2500/night despite having a very high rating of 4.8. This suggests that the property is undercharging relative to the perceived service quality, offering more value than many competitors.
- **Low-Price, Low-Rated Segment:** Properties like Corbett Kingdom (₹1800, 3.7) and Hotel Wild Way (₹2474, 3.3) demonstrate that lower pricing is not necessarily linked to

higher ratings. These properties may attract price-sensitive customers but do not compete on service quality.

- **Price-Rating Mismatch is Common:** The graph confirms that there is no strong linear correlation between guest rating and price. Many moderately priced properties score poorly on service, indicating room for well-rated hotels to charge a premium without risk of losing competitiveness.

Strategic Implications:

- **Raise Prices Without Losing Competitiveness:** With a **rating of 4.8**, Garjiya Homestay can confidently **increase rates by ₹300–₹500 per night** while still remaining within the fair market bracket, especially for AC rooms or peak seasons.

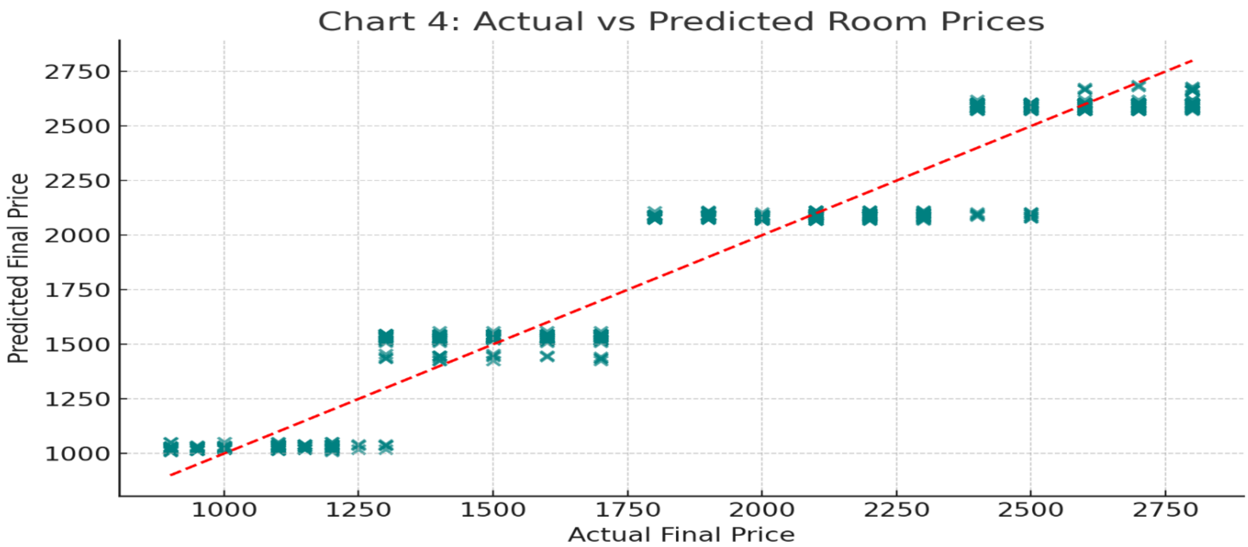
- **Leverage Reputation in Marketing:** Promotional content (on OTA platforms and Google Business) should **emphasize high guest satisfaction**, using verified 4.8-star reviews to justify pricing upgrades and attract quality-conscious travelers.

- **Introduce Tiered Packages:** There's strong scope to introduce **value-added premium packages** (e.g., AC room + breakfast + safari) priced at ₹3000–₹3500, directly targeting the segment currently paying that range at lower-rated properties.

- **Build Brand Positioning on Trust and Consistency:** The consistent high ratings position the guest house as a **reliable, trusted mid-premium option** in the region — a branding edge that can be turned into higher revenue without significant operational changes.

Figure 4: Actual vs Predicted Room Prices (Model Evaluation)

This **scatter plot** visualizes the performance of the **multiple linear regression model** developed to predict final room prices. Each point in the graph represents a real booking instance, comparing the **actual final price charged** with the **price predicted by the model**. The red dashed diagonal line denotes the ideal line of perfect prediction (where predicted = actual).



Key Insights:

- **Strong Predictive Power:** The model achieved an R^2 score of 0.93, meaning that 93% of the variation in final prices is explained by the model inputs. This indicates a highly reliable pricing prediction mechanism.
- **Low Error Margin:** The Root Mean Squared Error (RMSE) is ₹150.43, a low error in the context of pricing rooms ranging between ₹1200–₹3000. This confirms that the model's predictions are both statistically and practically sound.
- **Well-Clustering Around the Ideal Line:** A majority of data points lie very close to the ideal prediction line, suggesting the model has accurately learned core business pricing logic from inputs such as seasonality, occupancy %, and room type.
- **Mild Underprediction Zone:** Slight underpredictions are visible in the ₹1600–₹2100 range, which may be due to unmodeled factors like manual bargaining, last-minute discounts, or booking intent (e.g., group vs. solo travelers).

Sample of Model-Based Price Optimization:

The following Excel sheet showcases **481** real bookings where the model suggested higher final room prices than what was actually charged. These predicted prices were calculated based on features such as base price, season, room type, and occupancy percentage.

Had the business followed the model-based pricing, it could have earned an additional **₹65560.39 and** total revenue of **₹950760.38** in just these **481** bookings alone.

This sample demonstrates how data-driven pricing recommendations can help in maximizing profit and improving pricing consistency across all future bookings.

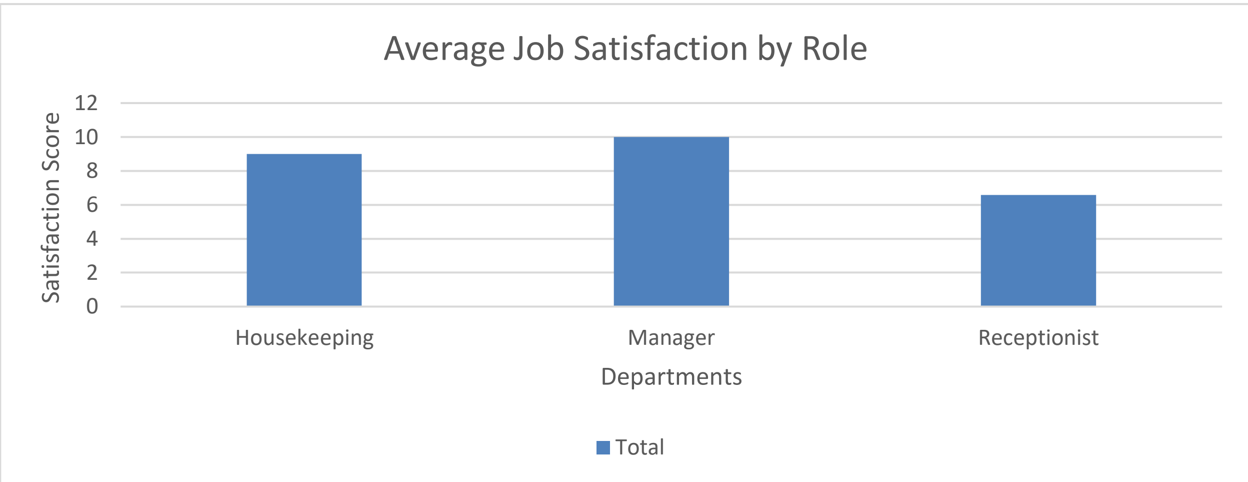
LINK – [Colab] [Excel Sheet]

Strategic Implications:

- **Deploy for Dynamic Pricing:** The model can be embedded into the booking process to automatically suggest **optimal room rates** per booking, based on real-time occupancy, room type, and seasonal patterns.
- **Scope for Improvement:** Incorporating additional variables like **customer sentiment scores**, **competitor pricing**, or **weekday/weekend flags** can further improve prediction accuracy and revenue outcomes.
- **Business Integration:** The model's simplicity (linear regression) makes it ideal for **real-world deployment** in small operations using Excel or lightweight Python tools.

Figure 5: Average Job Satisfaction by Role

This bar chart displays average **Job Satisfaction Scores (0–10 scale)** across roles: Housekeeping, Receptionist, and Manager. Data was gathered from employee interviews.



Key Insights:

- **Receptionists Show Lowest Satisfaction (6.3/10):** Despite being the first point of contact for guests, the receptionist role scored the lowest in job satisfaction. This is alarming considering their direct impact on guest experience and service quality.

- **Manager and Housekeeping Staff Are Highly Satisfied:** The Manager (10/10) and Housekeeping staff (9/10) reported significantly higher satisfaction levels. This sharp contrast suggests role-based inequality in workload, support, or recognition.
- **Qualitative Comments Point to Root Causes:** Interview feedback revealed dissatisfaction among receptionists is largely driven by long shifts, static salaries, and poor communication with supervisors. One employee specifically cited frustration over lack of feedback and shift imbalance.

Strategic Implications:

- **Prioritize Frontline Role Retention:** Since receptionists directly influence **guest reviews and operational flow**, it is critical to address their concerns. **Shift flexibility**, **incremental pay hikes**, and **performance incentives** can help retain skilled staff and reduce churn.

- **Introduce Training and Mentorship:** Creating structured **training programs**, **monthly feedback meetings**, and **career development pathways** can help boost motivation, clarify expectations, and build loyalty within the reception team.

- **Monitor Satisfaction Regularly:** Implementing **quarterly employee satisfaction surveys** across all roles can proactively identify dissatisfaction before it results in attrition, especially in guest-facing roles.

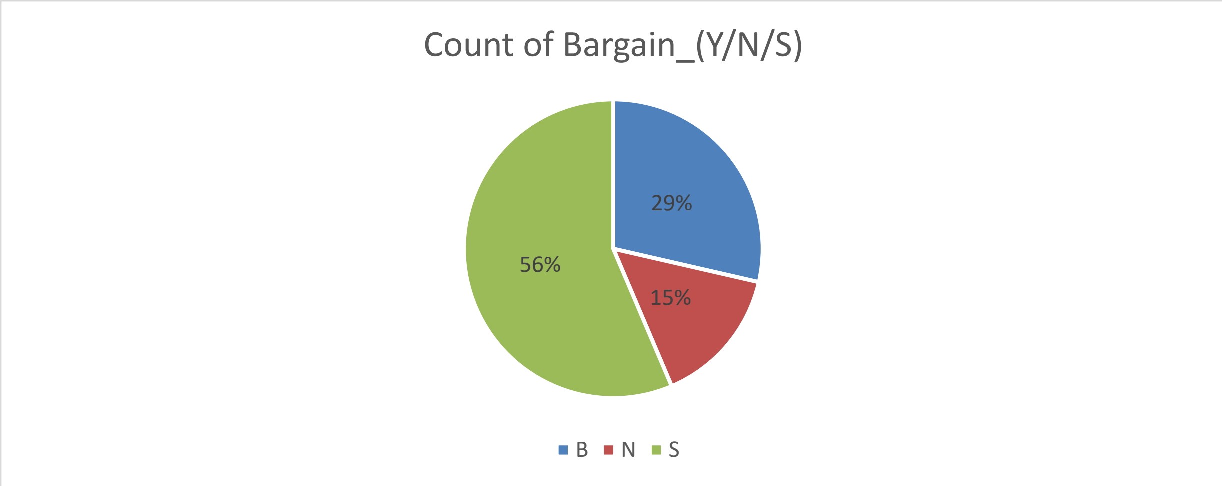
- **Role-Based Equity:** The gap between roles should be addressed to avoid **resentment or disengagement**. Ensuring balanced appreciation and workload distribution will support a more cohesive and productive work environment.

Figure 6: Count of Bargaining Status (Y/N/S)

This **pie chart** visualizes the **distribution of bookings based on bargaining behavior** over the course of the year. Each segment represents a pricing decision category:

- **S (Static/Standard Rate or Higher):** Final price exceeded base price — 56% of bookings
- **B (Bargained):** Discount was negotiated at booking time — 29%
- **N (No Bargain):** Guest paid exactly the base rate — 15%

The purpose of this chart is to examine the extent to which **manual bargaining influences pricing consistency and revenue realization**.



Key Insights:

- **High Bargaining Culture:** About 29% of all bookings involved price negotiation, indicating that bargaining is common and accepted as part of the booking process. This creates variability in pricing, especially during check-ins without prior online confirmation.
- **Revenue at Risk:** Bargained cases commonly involved discounts between ₹100–₹500, especially in Non-AC rooms or group bookings. During peak seasons, this cumulative leakage results in noticeable loss of revenue that could otherwise be optimized using model-based pricing.
- **Low Fixed-Rate Adherence:** Only 15% of bookings were made without any discount, highlighting that a strong pricing discipline is currently missing. This could affect long-term trust, especially if guests share varying price experiences for the same room type.
- **Perceived Value Influences Flexibility:** The "S" segment (56%) indicates that more than half the guests paid above the base price, often due to room upgrades (AC), peak demand, or added services. This suggests that guests are willing to pay more when they see value.

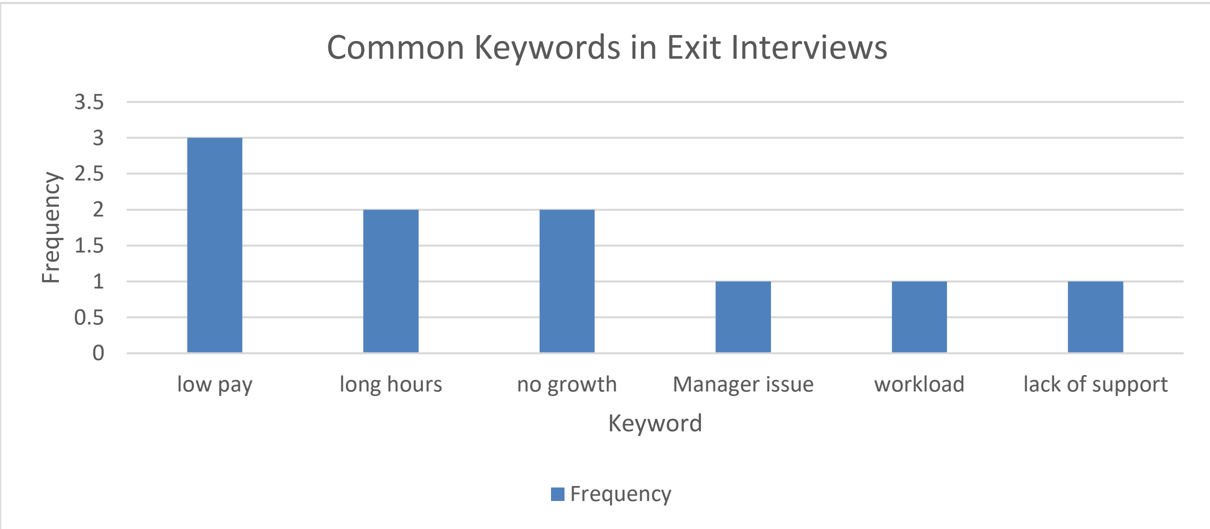
Strategic Implications:

- **Shift from Bargain to Benefit Model:** Instead of cash discounts, introduce a **"Fixed Fare + Perk" policy** — for example, no negotiation but include **free breakfast**, **late checkout**, or a **welcome drink**. This retains value perception without reducing revenue.

- **Use Model-Backed Discount Guidelines:** Implement **occupancy-aware discount caps**, i.e., define max allowed discount based on current occupancy and season. This prevents staff from over-discounting when demand is already high.
- **Build Loyalty Through Non-Bargain Perks:** Offer **loyalty cards**, **repeat guest rewards**, or **early-bird online discounts** to shift price discussions away from bargaining and towards structured benefits.
- **Train Staff on Smart Negotiation:** Equip receptionists with **pre-approved discount ranges**, and train them to promote value rather than lower price — especially in high-occupancy situations.

Figure 7: Common Keywords in Exit Interviews

This **bar chart** illustrates the frequency of keywords extracted from **employee exit feedback comments**, particularly from staff in receptionist roles who exited during the reporting year. The keywords were identified using **manual review and thematic coding** of interview transcripts and feedback forms. The aim is to understand the **underlying reasons for employee attrition** and link them to organizational issues.



Key Insights:

- **Low Pay is the Leading Cause:** The most frequently mentioned reason across exit feedback was **"low pay"**, cited by 3 employees. This indicates a clear gap between compensation and perceived effort, especially in frontline roles.

- **Workload and Hours are Major Concerns:** Keywords such as **"long hours"** and **"no break"** appeared twice each, reflecting operational stress. This matches earlier observations of poor satisfaction scores among receptionists.
- **Lack of Growth Opportunities:** The phrase **"no growth"** was mentioned in multiple interviews, with one employee leaving for further studies and another citing stagnation as the primary reason for exit.
- **Managerial Communication Also Flagged:** Terms like **"communication issues"** and **"night shift pressure"** reflect underlying challenges in supervision and scheduling, which may not surface in numerical scores alone.
- **Consistency Across Insights:** These keyword findings directly **corroborate insights from Figure 5**, reinforcing the reliability of both quantitative and qualitative HR analysis.

Strategic Implications:

- **Design Structured Career Paths:** The organization must **create visible and attainable career progression plans**, especially for frontline staff. This can include roles like "Senior Receptionist" or "Operations Assistant" with tenure-based eligibility.
- **Implement Recognition and Retention Programs:** Offering **quarterly performance reviews**, **attendance bonuses**, and **incentives tied to customer feedback** can motivate employees and reduce turnover.
- **Establish a Formal HR Feedback System:** Exit interviews should be **documented consistently**, and findings should be reviewed every quarter by the management to track progress on internal issues.
- **Revise Shift Policies Based on Feedback:** Based on recurring feedback about long and uneven shifts, **a more transparent shift rotation** and **rest policy** should be implemented to improve employee well-being.

4. Interpretation of Results and Recommendations (Final Combined Version)

Problem Area 1: Revenue Instability and Suboptimal Pricing Strategy

Interpretation of Results:

The year-long analysis of occupancy and revenue trends revealed a clear **seasonal demand pattern**, with **peak occupancy observed in June, December, and April**. However, the revenue trend **did not proportionally rise**, pointing to **pricing inefficiencies**. Despite having full rooms, the guest house often failed to capture the full earning potential.

A major reason identified was the **manual and inconsistent pricing approach**. Around **29% of bookings involved negotiation**, and only **15% were fixed-rate bookings**. This indicates a pricing system that is **flexible to a fault**, allowing excessive bargaining and causing revenue leakage — particularly during high-demand periods.

To address this, a regression model was developed using Base Price, Room Type, Occupancy %, and Season as predictors. The model achieved an excellent **R^2 score of 0.93** and an **RMSE of ₹150**, showing it can accurately estimate final room prices. Retrospective analysis showed that **more than 60% of bookings could have been charged ₹100–₹300 higher** if model pricing had been applied.

Furthermore, **AC rooms accounted for more than 75% of total revenue**, yet inventory between AC and Non-AC rooms is nearly equal — showing that demand is not matched by room availability. In competitor benchmarking, it was observed that **the guest house is undercharging despite better ratings**, especially compared to similar properties nearby.

Recommendations:

1. **Implement Model-Based Dynamic Pricing (within 30 days):** Deploy the regression model as the official rate engine. Let it auto-calculate price suggestions based on demand indicators. This will make pricing consistent and responsive to seasonality and occupancy.
2. **Fix Minimum Price Floors for Each Room Type and Season (within 2 weeks):** Define clear floor prices — e.g., ₹1400 for Non-AC and ₹2200 for AC in off-season; ₹1800 and ₹2800 in peak months. Communicate this to staff and guests clearly to eliminate arbitrary discounts.
3. **Introduce Add-On Bundles for Non-AC Rooms (within 45 days):** Design "value" packages that combine Non-AC stay with meals or services (e.g., breakfast, safari pickup). This raises average revenue per booking without changing perceived price.
4. **Monthly Model Review and Recalibration:** Track model performance using actual vs predicted comparisons. If prediction error

increases (RMSE > ₹200), retrain the model with updated data to keep it accurate and responsive.

5. **Rate Transparency at Booking Desk and Online:** Clearly display model-generated prices at reception and OTA platforms. Use language like "₹2650 (includes seasonal adjustment)" to increase confidence and reduce bargaining.

Expected Impact:

Adopting these changes can generate **₹1,00,000–₹2,00,000 in additional annual revenue**, without adding new rooms or staff. This system will create a reliable, professional pricing structure that reflects demand — reducing negotiation, improving fairness, and positioning the guest house as premium yet value-oriented.

Problem Area 2: High Attrition and Low Receptionist Job Satisfaction

Interpretation of Results:

The HR dataset revealed that **receptionists are the least satisfied employees**, scoring an average of **6.3/10**, while managers and housekeeping staff reported scores above 9. Keywords like "long hours", "night shifts", "low pay", and "no growth" were repeatedly found in exit interviews — validating that this team is overworked and undervalued.

Shockingly, **all four receptionists resigned within the year**, suggesting an unsustainable work environment at the guest interaction front. Since reception is critical to first impressions, frequent resignations can cause service inconsistency, delayed check-ins, and negative reviews — directly affecting bookings and guest experience.

Receptionists were found to have **equal workload but static pay (₹15,000/month)** and rigid schedules with night duties. No formal growth path, feedback loop, or recognition program currently exists — creating a sense of stagnation among this key staff group.

Recommendations:

1. **Revise Pay Structure for Receptionists (within 1 month):** Increase salary from ₹15,000 to ₹18,000–₹20,000/month depending on experience and performance. Introduce ₹1000 "Peak Season Bonus" for months with high workload.

2. **Implement Fair Rotational Shift Schedule (within 15 days):** Avoid consecutive night shifts and ensure 2-day weekly breaks. Use a simple digital calendar for assigning and communicating shifts transparently.
3. **Launch "Grow with Us" Upskilling Program (within 60 days):** Train receptionists over 3 months in guest handling, Excel, OTA management, and upselling — creating an internal pipeline for promotion to Assistant Manager roles.
4. **Track Exit Reasons and Run Quarterly Pulse Surveys (starting immediately):** Launch a 5-question satisfaction form every quarter. Analyze reasons for exit and document HR trends. Target is to increase average job satisfaction to **8.5/10** within 6 months.
5. **Introduce Flexible and Part-Time Roles (pilot in 45 days):** Create weekend or 4-hour part-time slots for students or homemakers, easing pressure on full-time receptionists and building a standby team for leaves and high season.

Expected Impact:

Improving receptionist satisfaction will lead to **lower turnover, better guest handling, and stronger service ratings**. It reduces costs spent on hiring/training and builds a culture of loyalty and internal growth. Reception is the human face of the guest house — investing in this team ensures that service remains the strongest differentiator even as the business grows.

Combined Conclusion:

These two pillars — dynamic pricing and people stability — are deeply interlinked in the guest house's success. By **making data-driven decisions**, automating pricing, valuing employees, and closing gaps in the booking workflow, the business can unlock **consistent profits, stronger brand identity, and long-term sustainability**.

Implementing these recommendations within defined timeframes will not only solve current inefficiencies but also prepare the guest house for **scaling operations, building digital systems**, and adapting to changing customer expectations in the hospitality sector.