**PROJECT TITLE**

**Hospitality Analysis**

**ORGANIZATION/ DEPARTMENT NAME & ADDRESS**

**Unified Mentor Pvt. Ltd.**

**SCO 17-18 STREET 31C, S Block, DLF Phase 3, Sector 24, Gurugram, Haryana 122010**

**SUBMITTED BY**

**Ms. Gauri Satish Salunke**

**M.Sc. (Applied Statistics)**

**PRN: 22060641048**

**ACADEMIC YEAR 2023 - 24**

**Under the guidance of**

**Mr. Murari Prasad**

**Designation: Head Of Data Science Department**

**Mobile: 8551804169**

# Contents

1. **Executive Summary**

2. **Study Background**

3. **Aims & Objectives**

4. **Methodology**

5. **Results**

6. **Discussion and Conclusion**

7. **Recommendation**

8. **Acknowledgement**

9. **References (including Bibliography and web references)**

10. **Annexure – (Questionnaire & other details)**

# 1. Executive Summary

## Overview:

Unified Mentor Organization (UMO) is a nonprofit organization that provides opportunities to the people by helping them to find their tone through proper guidance. Using the broad extensive network of people and community's specialists and leaders, UMO is set to help and guide individuals in their quest for a better personal and professional self

**Mission:** The following are the mission of university of management and organizational effectiveness: To provide framework mentorship programs to enhance student's ability and opportunities. These programs are launched to suit the target audiences comprising students, new working professionals and those who would be seeking a change of careers.

**Programs and Services:**

1. **Mentorship Programs:** The Office of Career Services at UMO provides specific and categorical career coaching intervention – both individual and group. These include:

   - Student Mentorship: Focuses on high school and college students, providing career advice, academic support, and life skills.

   - Professional Mentorship: Aims at early to mid-career professionals seeking guidance on career advancement, skill development, and networking.

   - Transition Mentorship: Assists individuals in career transitions, offering insights on new industry trends, resume building, and interview preparation.

2. **Workshops and Seminars:** These are regularly held to improve soft skills, develop leadership qualities, and provide industry-specific knowledge.

3. **Networking Events:** Structured to ensure that the members in the mentorship program had a common pool of professional contacts that could be used as sources of employment.

4. **Online Resources:** UMO offers its users numerous articles, tutorials, and webinars, which are grouped into different sections and topics to improve personal and professional skills.

Unified Mentor Organization holds a strategic position of coaching and empowering individuals in every aspect of their lives.

## 2. Study Background

Atliq Hospitality is a respectable and well-known brand in the hospitality industry, distinguished by its ability to offer luxurious experiences and first-rate service. They are in charge of several opulent hotels and resorts that provide guests stays they won't soon forget by fusing modern amenities with traditional charm. To keep ahead of the competition, Atliq Hospitality constantly innovates and adapts to changing demands.

**Market Challenges and the Need for Data Intelligence:** Due to competitors' calculated movements, Atliq Hospitality has recently had a difficult time retaining its market share and income, which has led to a loss of clients. The organisation is using business and data intelligence to better understand the market, streamline processes, and improve client experiences in order to address these problems.

**Competitive Pressure:** Competitors have been effectively capturing market share through aggressive marketing and innovative offerings.

1. **Customer Retention:** Losing loyal customers to other hotels with better loyalty programs and personalized experiences.

2. **Revenue Decline:** Reduced occupancy rates and declining revenues necessitate a strategic overhaul.

**Business and Data Intelligence:** Atliq Hospitality plans to integrate Business and Data Intelligence into its operations in order to address these issues. Its importance is emphasised by the following points:

1. **Market Analysis:** Using data, one may understand consumer preferences, rival strategy, and market trends.

2. **Personalized Marketing:** Customised marketing refers to using consumer data to target advertising campaigns and deliver unique visitor experiences.

3. **Operational Efficiency:** Using operational data analysis to improve service quality, cut costs, and simplify processes.

4. **Decision Support:** Offering practical information to help with strategic choices that will improve financial performance and market positioning.

**Types of Data Utilized:** Atliq Hospitality will focus on several types of data to inform its strategies:

1. Customer Data: Ratings, booking patterns.
2. Operational Data: Occupancy rates, service efficiency, and cost management.
3. Financial Data: Revenue, profit margins, and investment returns.

**Customer Data and Insights:** Atliq Hospitality wants to improve visitor experiences and loyalty by collecting and analysing consumer data. This involves:

1. **Booking Patterns:** Understanding peak times, popular room types, and booking channels.

2. **Guest Feedback:** Evaluations and remarks from guests are compiled and reviewed for continued improvement.

**Operational Efficiency:** One of the main goals is increasing operational efficiency.

1. **Occupancy Rates:** To optimise income, keep an eye on and maximise room occupancy.

2. **Service Efficiency:** Optimising service procedures to lower expenses and improve guest satisfaction.

3. **Cost Management:** Examining expenses to find places where money can be saved without sacrificing quality.

**Financial Performance:** Atliq Hospitality will leverage financial data to improve profitability. This includes:

1. **Revenue Management**: Using dynamic pricing strategies to maximise income is the practice of revenue management.

2. **Profit Margins:** Monitoring and enhancing profit margins through the application of appropriate operations management techniques.

3. **Investment Returns:** Calculating how much money can be saved by introducing new technology and enhancing current services.

Atliq Hospitality uses insights from data to improve client experiences, increase operational effectiveness, and improve bottom line results. This strategy establishes the foundation for long-term success and expansion in the cutthroat hotel sector in addition to addressing present issues.

## 3. Aims and Objectives

**Aim:** To utilize business and data intelligence to regain market share and revenue for Atliq Grands.

### Objectives:

- Identify and create relevant metrics based on the provided data.

- Conduct a comprehensive analysis of the provided data to uncover key insights.

- Design and develop a dashboard according to the data and specified requirements.

## 4. Methodology

### Data Set

- ❖ **dim_date** – dates, week numbers, and day type (weekend and weekday).

- ❖ **dim_hotels** – property id, property name, category, and cities.

- ❖ **dim_rooms** – room_id and room class.

- ❖ **fact_aggregated_bookings** –property id, check-in date, room category, successful bookings, and capacity.

- ❖ **fact_bookings** – The dataset comprises various details such as booking ID, property ID, and the dates for booking, check-in, and check-out. It also includes information on the number of guests, room category, and the platform used for booking. Additional data points cover ratings, booking status, as well as the revenue generated and revenue realized from each booking.

- ❖ **Financial Stats**

  The financial statistics incorporated into this report are standard metrics exclusively utilized within the hospitality sector. Below is a list of these key financial metrics commonly employed in the industry:

1. **Revenue** – As we know is the most common metric used in every industry.

2. **RevPAR** – Revenue generated per available room is a key performance metric in the hospitality industry.

3. **ADR** – Average Daily Rate is the average daily price per room.

**Performance**

Performance statistics crucial to the analysis encompass metrics such as hotel occupancy, cancellation percentage, and room availability, all of which directly impact revenue generation. Management can influence certain factors, while others remain beyond their control.

Here is the list of Key metrics:

1. **DSRN** – which represents the available rooms that can be sold on a given day

2. **DBRN** – Daily Booked Room Nights are the number of nights booked per night.

3. **DURN** – Daily Utilized Room Nights are the nights utilized or used by the customers. This can be the checked-in nights.

4. **Cancellation %** – As the name suggests, it is the percentage of cancelled bookings.

5. **Avg Rating** – Average rating is the average rating given by a customer per booking.

6. **Day Type** – Day is the category of days in a week. Weekday and Weekend. In the hospitality industry, the weekend typically spans Friday and Saturday, differing from the traditional Saturday-Sunday weekend observed in many other sectors.

7. **Booking Platforms** – Booking platforms are the modes that are used by customers to book rooms.

8. **Week Number** – Week number is the number of weeks in a year.

9. **Property Name** – Property name is the name of individual hotels.

10. **Property ID** – Property ID is the unique ID given to the properties.

11. **WoW** – Week on Week is the metric to compare the performance change over the week.

This internship consists of three fundamental tasks, which are:

| Data Preprocessing | • Checking Outliers.<br>• Missing Values. |
| Data Exploration | • Revenue Trends over time.<br>• Revenue and average rating by city. |
| Model Building and Evaluation | • Linear , Polynomial Regression and Forecast.<br>• Threshold-Based Sentiment Analysis.<br>• Customer Lifetime Value (CLV) |

## A. Data Preprocessing

- **Outlier Detection & Removal**

Use the Interquartile Range (IQR) Method to identify and remove outliers from the dataset.

IQR = Q3 - Q1

lower_limit= Q1 - 1.5 * IQR        and        upper_limit= Q3 + 1.5 * IQR

- **Median Imputation**

Use the Median Imputation method to replace the missing values from the dataset.

## B. Graphical Representation

EDA's major objective is to provide a concise summary of the data's key features and identify any trends, abnormalities, or insights that can guide more research or decision-making. Every graph will be selected according to the type of data it contains and the particular messages it wants to provide.

## C. Model Building

**Linear Regression**

Linear Regression was chosen as it provides a straightforward approach to understanding the relationship between predictor variables and the target variable. In Linear Regression, coefficients associated with each feature provide insight into their importance in predicting the target variable.

**Polynomial Regression**

Polynomial regression is employed when the residual plot from linear regression exhibits curvature, indicating a non-linear relationship between variables. By introducing polynomial terms into the regression equation, it can better capture the observed data patterns and provide more accurate predictions, addressing the limitations of linear regression.

## D. Model Selection

When selecting a model for the analysis, it's important to evaluate the model's performance using several criteria. Here are the three key metrics and plots used for model selection:

1. R-Squared Value

2. Residual Plot

3. Actual vs. Predicted Line Plot

Based on these metrics, the Polynomial Regression model is selected.

## E. Revenue Forecasting

For businesses, forecasting is a vital tool that gives insights that support strategic planning, well-informed decision-making, and effective resource management. Through forecasting future patterns and results, companies can manage uncertainty, seize opportunities, and attain steady expansion and financial gain. Actual performance is assessed using forecasted data as a reference.

### F. Threshold-Based Sentiment Analysis

1. **Loop Through Ratings**: Iterate through each rating in the "ratings_given" column of the "fact bookings" data.

2. **Categorize Sentiment**: Check each rating against a predefined threshold (as 3). If the rating is less than or equal to the threshold, categorize it as "bad"; otherwise, categorize it as "good".

3. **Store Results**: Store the categorized sentiment (i.e., "good" or "bad") for each rating in a new column called "sentiment category" in the "fact bookings" dataset.

4. **Calculate Sentiment Scores**: Calculate sentiment scores using a sentiment analysis library. This could involve assigning numerical scores to each sentiment category.

## G. Customer Lifetime Value (CLV)

CLV denotes the mean income produced by every client during the course of their association with the enterprise. Given that customers are more likely to make repeat reservations or increase their spending over time, a greater CLV may be a sign of good customer loyalty and retention.

## H. Building a Business Dashboard

A business dashboard is an integrated display of vital operational data that might encompass measures, performance indicators and data set pertinent to an organization. It helps in tracking the performance, and even in evaluating and decision-making process due to the documented performance of the company.

Taking into account all the aforementioned facts, it can be concluded that a business dashboard is both a powerful and practical tool that helps companies to perform such activities that need to be based on data and make the major strategic goals more achievable.

# 5. Results

### I. Results From EDA –
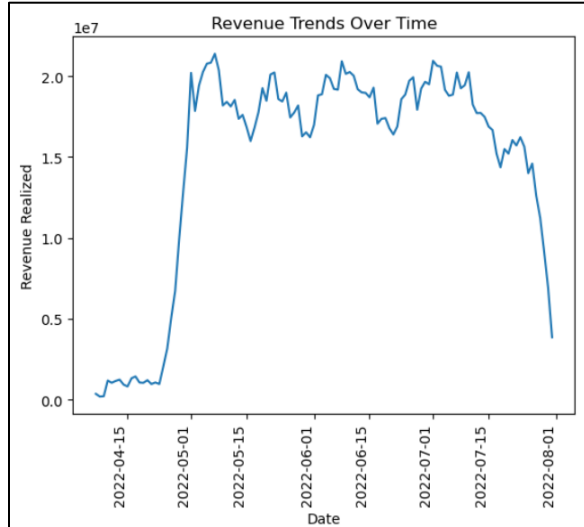


The revenue pattern displays a growing first phase, followed by oscillations, and finally a declining tendency.
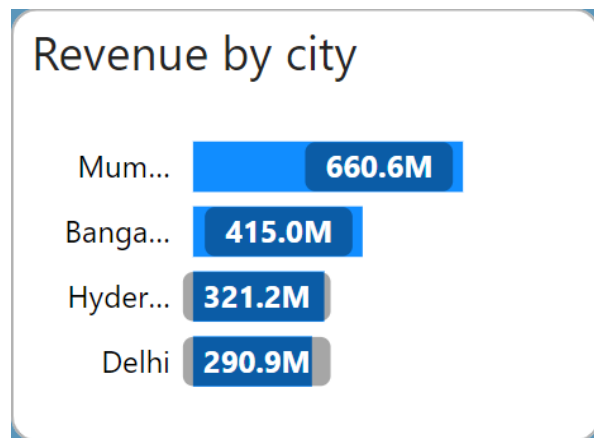


The largest revenue-generating cities are Mumbai, Bangalore, Hyderabad, and Delhi.
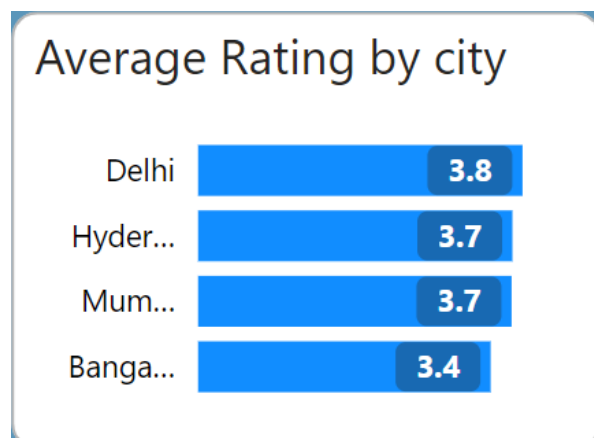


Delhi contributes the least to revenue, however it has an average grade of 3.8.

## II.    Results From Linear Regression –

```
Linear Regression:
Mean Squared Error: 9762331.262955844
R-squared: 0.7951249814993897
                          Feature    Importance
11                room_category_RT4  15250.518430
12         booking_status_Checked Out  8939.366014
13          booking_status_No Show     8919.690846
10                room_category_RT3    6940.080768
9                 room_category_RT2    3283.193781
1                        no_guests     886.494127
8          booking_platform_tripster    66.689121
3    booking_platform_direct online    47.728051
5            booking_platform_logtrip    40.292305
7            booking_platform_others    33.115412
0                      property_id     -0.661336
6      booking_platform_makeyourtrip    -5.883944
4          booking_platform_journey   -32.058723
2                    ratings_given    -88.020584
```
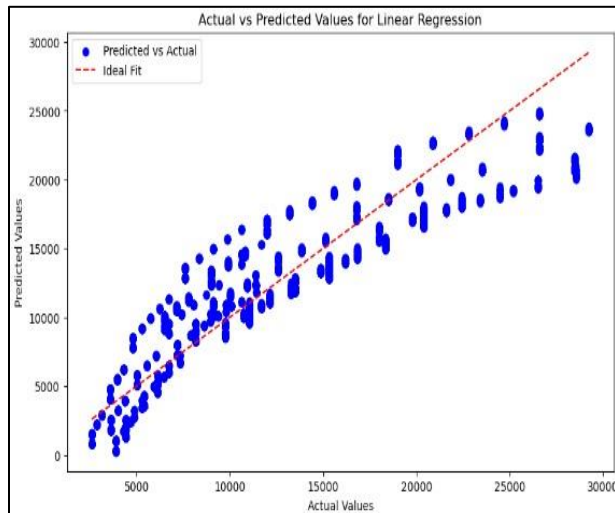
- An R-squared of 0.79 indicates our model accounts for approximately 79% of the revenue variations.
- 'Room_category_RT4' boosts revenue the most, while 'ratings_given' slightly lowers it.



Actual vs Predicted Values for Linear Regression

- The plot reveals a poor match between the predicted and actual values.
- This suggests that the linear regression model may not be accurately capturing all the factors influencing revenue.



Residual Plot for Linear Regression
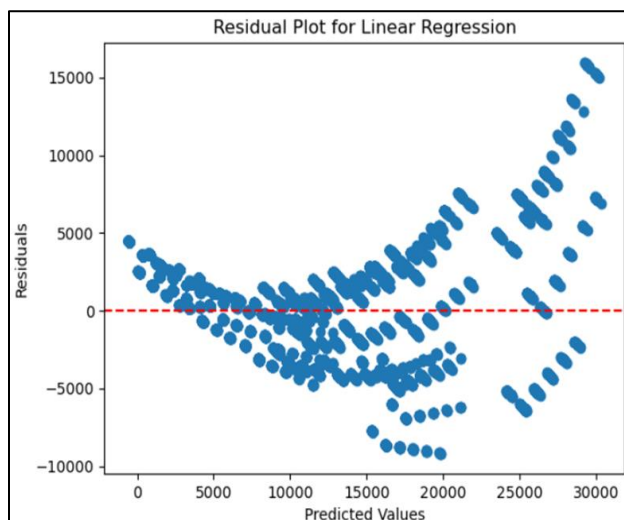
The way residuals behave suggests our model might not be perfect. It's possible that we're overlooking crucial factors that could significantly impact our analysis or decisions.

# III.    Results From Polynomial Regression –

```
Polynomial Regression:
Mean Squared Error: 4975216.487728645
R-squared: 0.8474741594286441
                                              Feature    Importance
116          room_category_RT4 booking_status_No Show   8538.339975
115      room_category_RT4 booking_status_Checked Out   8492.194318
11                                 room_category_RT3    5650.959522
110                              room_category_RT3^2    5650.959464
112      room_category_RT3 booking_status_Checked Out   4872.250171
..                                               ...           ...
98       booking_platform_others booking_status_No Show  -456.723518
74      booking_platform_journey booking_status_No Show  -470.326604
104    booking_platform_tripster booking_status_No Show  -481.421642
83      booking_platform_logtrip booking_status_No Show  -589.472917
3                                     ratings_given     -1964.653639
```
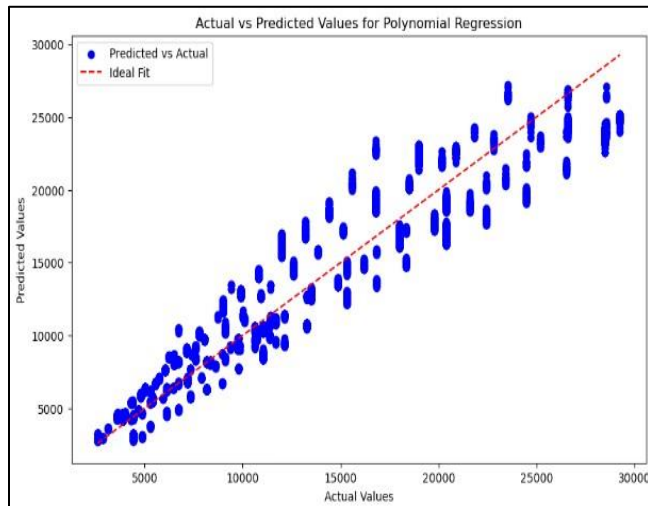
- An R-squared of 0.85 means our model explains about 85% of the revenue differences.
- 'Room_category_RT4' boosts revenue the most, while 'ratings_given' slightly lowers it.


Actual vs Predicted Values for Polynomial Regression

- The actual vs. predicted plot indicates that predicted values are closer to actual values compared to the linear regression model, demonstrating better predictive performance.
- Overall, the polynomial regression model provides a more accurate and reliable fit for the data.


Residual Plot for Polynomial Regression
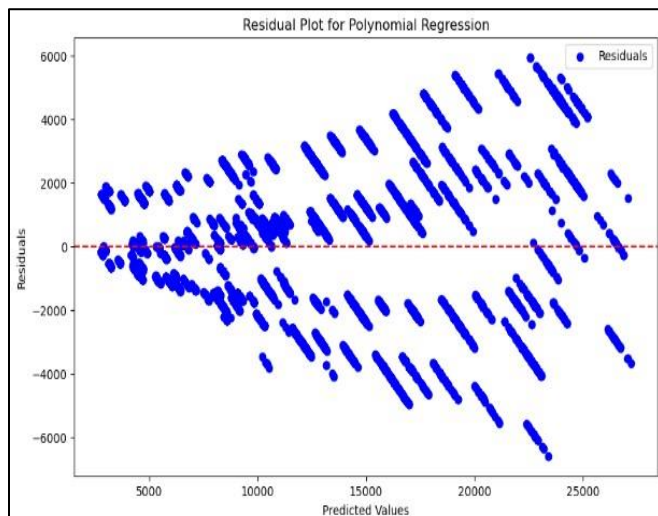
The residual plot shows a more even spread, suggesting that it captures the relationship between variables more effectively than the linear regression model.

## IV.     Results From Forecasting –



Forecasted Revenue Realized
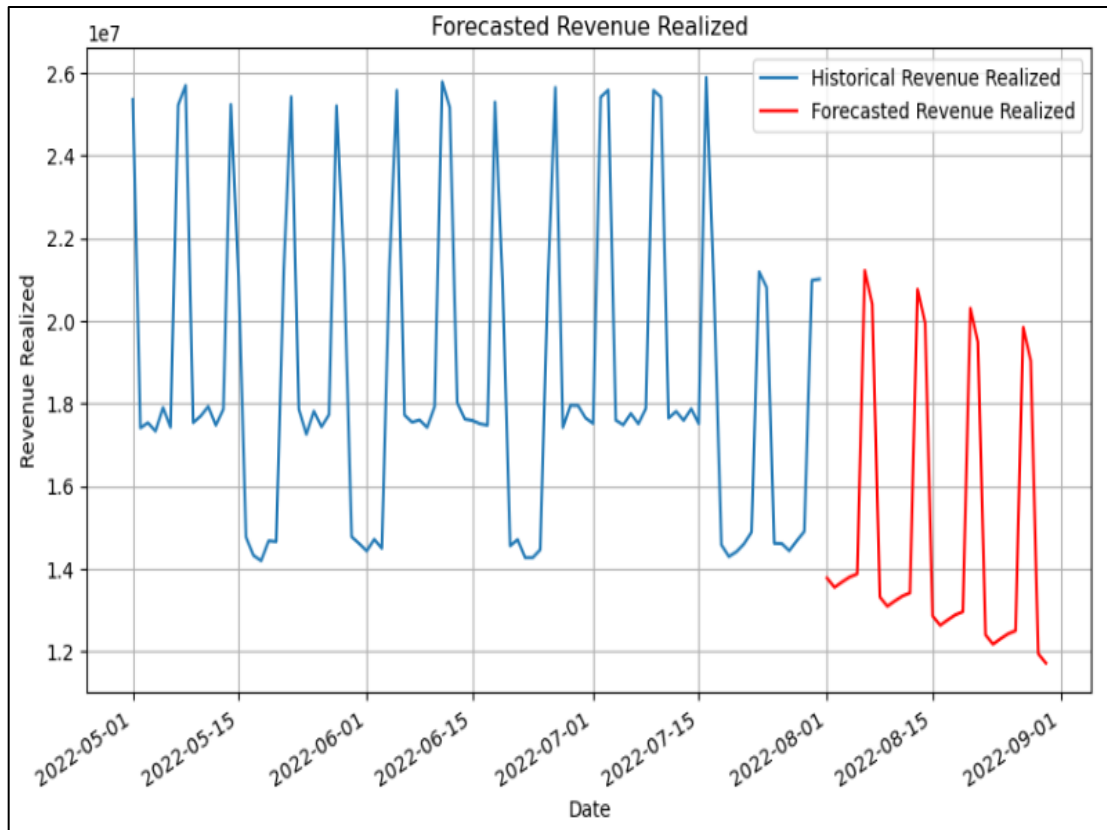
The forecast indicates a declining trend in revenue, highlighting the urgent need for strategic intervention. This decline suggests that businesses should:

- Reevaluate their marketing and sales strategies.
- Create innovative products or services to entice customers and enhance market appeal.
- Improve customer retention and satisfaction efforts.
- Optimize operational efficiencies to reduce costs.

### V. Results From Threshold-Based Sentiment Analysis –

```
Sentiment Analysis Results:
Proportion of 'Good' Sentiment: 0.80
Proportion of 'Bad' Sentiment: 0.20
```
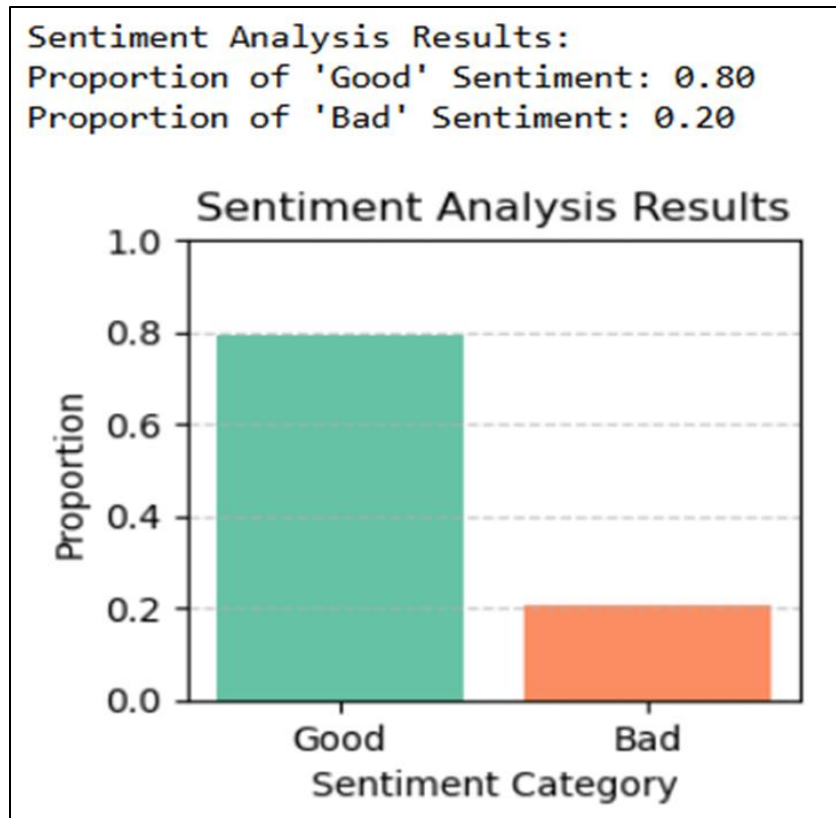


**Positive Sentiment: Approximately:** 80% of the sentiments expressed are positive or classified as "good."

**Negative Sentiment**: Around 20% of the sentiments conveyed are negative or categorized as "bad." This indicates that the majority of sentiments are positive, while a smaller portion expresses negative opinions or feedback.

### VI. Results From Customer Lifetime Value –

The CLV is calculated to be 14,916.01, reflecting the average revenue generated per customer over their lifetime with the company. A higher CLV may indicate strong customer loyalty and retention, as customers are likely to make repeat bookings or spend more over time.

## VII. Results From Business Dashboard –



**Atliq Hospitality Dashboard**

| City | Room Class | B. Status | B. Platform | Month | Property | Category | Week No. |
|------|-----------|-----------|-------------|-------|----------|----------|----------|
| All | All | All | All | All | All | All | All |

| | Revenue | RevPar | DSRN |
|---|---------|--------|------|
| | **1.69bn** | **7.34K** | **2.53K** |
| | ↑ 0.2% | ↑ 0.2% | ↑ 0.2% |
| | Occupancy % | ADR | Realisation % |
| | **57.79%** | **12.70K** | **70.14%** |
| | ↑ 0.2% | ↑ 0.2% | ↑ 0.2% |

| day type | RevPAR | Occupancy % | ADR | Realisation % |
|----------|--------|-------------|-----|---------------|
| Weekday | 7.1K | 55.8% | 12.7K | 69.9% |
| Weekend | 8.0K | 62.6% | 12.7K | 70.6% |

**Revenue by room_class**

| Room Class | Revenue |
|------------|---------|
| Elite | 0.55bn |
| Premium | 0.46bn |
| Presidential | 0.37bn |
| Standard | 0.31bn |

**Occupancy % by city** — Delhi 60.4%, Hydera... 58.0%, Mumbai 57.8%, Bangal... 55.7%

**Total Bookings by city** — Mumbai 23.9K, Hydera..., Bangal..., Delhi (31.6K, 42.9K, 34.5K)

**Occupancy % by city**

| City | Occupancy % |
|------|-------------|
| Delhi | 60.4% |
| Hyder... | 58.0% |
| Mum... | 57.8% |
| Banga... | 55.7% |

**Revenue by city**

| City | Revenue |
|------|---------|
| Mum... | 660.6M |
| Banga... | 415.0M |
| Hyder... | 321.2M |
| Delhi | 290.9M |

**Average Rating by city**

| City | Rating |
|------|--------|
| Delhi | 3.8 |
| Hyder... | 3.7 |
| Mum... | 3.7 |
| Banga... | 3.4 |

**Realisation % and ADR by booking_platform**

Realisation %: 70.6%, 70.5%, 70.3%, 70.2%, 70.1%, 69.9%, 69.8%
Platforms: logtrip, journey, direct o..., direct of..., others, makeyo..., tripster
(ADR scale 12.6K – 12.8K)

| Property Name | City | Revenue | T. Bookings | ADR | DSRN | DBRN | DURN | Realisation | Cancellation | Avg. Rating |
|---------------|------|---------|-------------|-----|------|------|------|-------------|--------------|-------------|
| Atliq Bay | Bangalore | 81M | 5736 | 14.2K | 96 | 63 | 44 | 70.5% | 24.3% | 4.3 |
| Atliq Bay | Delhi | 56M | 4762 | 11.7K | 98 | 52 | 36 | 69.3% | 25.2% | 3.1 |
| Atliq Bay | Hyderabad | 68M | 7246 | 9.4K | 121 | 80 | 56 | 70.2% | 24.7% | 4.3 |
| Atliq Bay | Mumbai | 51M | 3388 | 15.2K | 83 | 37 | 26 | 69.6% | 25.4% | 2.4 |
| Atliq Blu | Bangalore | 72M | 5669 | 12.7K | 117 | 62 | 43 | 69.8% | 24.6% | 3.1 |
| **Total** | | **1688M** | **132939** | **12.7K** | **2,528** | **1,461** | **1,025** | **70.1%** | **24.8%** | **3.6** |

**Trend by Key Matrix** — RevPAR, ADR, Occupancy %

**RevPAR** - Revenue per available room | **DSRN** - Daily sellable room nights | **ADR** - Average Daily Rate | **DBRN** - Daily Booked Room Nights | **DURN** - Daily Utilized Room Nights

- Total revenue reached $1.69 billion, marking a slight increase of 0.2%.

- Occupancy Rates: Overall occupancy at 57.79%, with weekends seeing higher rates.

- Room Class Revenue: Elite class generates the highest revenue.

- Customer sentiment shows Delhi receiving the highest average rating.

- Key Metrics: RevPAR $7.34K, ADR $12.7K, Realisation % at 70.14%.

- Booking Platforms: Realisation % ranges from 69.9% to 70.6%, with consistent ADR around $12.7K.

- Property Insights: Atliq Bay in Bangalore stands out with $81 million in revenue.

# 6. Discussion and Conclusion

The analysis highlights a declining revenue trend, indicating a need for strategic interventions. Polynomial regression shows a better fit than linear regression, suggesting a complex relationship between variables. With 80% positive sentiment, customer satisfaction is generally high, though there's room for improvement. Despite lower revenue contribution, Delhi maintains a solid average rating of 3.8. Weekday occupancy rates are moderate, while weekend rates are strong, pointing to a need to enhance weekday performance.

The hotel's revenue increased slightly to $1.69 billion, driven by high weekend occupancy and positive sentiment in elite rooms, particularly in Delhi. Atliq Bay in Bangalore stands out with $81 million in revenue.

The results emphasise how critical it is to deal with the problems that have been found and build on the advantages that the information has shown. A more stable and long-term growth trajectory can be ensured by the company by concentrating on these areas and better aligning its strategies with operational capabilities and market demands.

## 7. Recommendations

- **Reevaluate Marketing and Sales Strategies:** Develop targeted marketing campaigns based on customer segmentation and preferences to more effectively reach potential customers.

- **Innovate New Products or Services:** To improve client convenience and experience, use cutting-edge technology like smartphone check-ins, smart room features, and personalized messaging.

- **Improve Customer Retention and Satisfaction:** Creating novel and inventive goods and services can draw in new clients and open up new sources of income.

- **Optimize Operational Efficiencies**: To cut down on human labour, minimise errors, and boost operational efficiency, use technology to automate repetitive and routine processes.

- **Enhance Data-Driven Decision Making**: Utilize advanced data analytics to gain deeper insights into customer behavior, market trends, and operational performance.

# 8. Acknowledgement

My deepest appreciation goes out to Mr. Paras for giving me the chance to work on this project at Unified Mentor Organisation. My professional development during this endeavour has been greatly influenced by his mentorship, advice, and confidence in my abilities.

I'm deeply appreciative of the director's contributions and support, Dr. Sharvari Shukla, for her encouragement, and insightful advice throughout this journey.

To everyone who has helped my winter internship project succeed, straight or indirect, I also want to express my sincere gratitude. I sincerely appreciate your help, since your knowledge, motivation, and skill have all tremendously enhanced my educational journey.

I would want to express my appreciation to the whole staff at Unified Mentor Private Limited for creating a learning and development-friendly atmosphere. My winter internship assignment has been enriched and made to remember thanks to your combined efforts.

Finally, but just as importantly, I want to express my gratitude to my family and friends for their unwavering love, support, and comprehension during this journey. Their unwavering inspiration and support have been my pillar of strength, motivating me to conquer challenges and strive for excellence in whatever I do.

I express my gratitude once more for providing me with this chance and for playing a crucial role in my career advancement.

# 9. References

## ➕ Bibliography

1. Lee, M., Yoo, S.-E., & Yoo, C. W. (2016). Predictive Modeling of Hotel Customer Satisfaction Using Data Mining Techniques.

2. Martínez-Torres, M. P., & Toral, S. (2020). Sentiment Analysis in Hospitality and Tourism: A Systematic Literature Review.

3. Zhang, Z., Zhang, X., & Law, R. (2018). Forecasting Hotel Room Demand with Machine Learning Models.

4. Woodside, A. G., & Decrop, A. (2017). The Impact of Customer Reviews and Ratings on Hotel Revenue.

5. Mattila, A., & Baker, J. (2015). A Review of Customer Lifetime Value Models in the Travel and Tourism Industry.

## ➕ Web References

1. Predictive Modeling of Hotel Customer Satisfaction Using Data Mining Techniques. (n.d.). Retrieved from https://www.sciencedirect.com/science/article/pii/S0278431915300794

2. Predictive Modeling of Hotel Customer Satisfaction Using Data Mining Techniques. (n.d.). Retrieved from https://www.sciencedirect.com/science/article/pii/S0278431915300794

3. Predictive Modeling of Hotel Customer Satisfaction Using Data Mining Techniques. (n.d.). Retrieved from https://www.sciencedirect.com/science/article/pii/S0278431915300794

4. Predictive Modeling of Hotel Customer Satisfaction Using Data Mining Techniques. (n.d.). Retrieved from https://www.sciencedirect.com/science/article/pii/S0278431915300794

5. Predictive Modeling of Hotel Customer Satisfaction Using Data Mining Techniques. (n.d.). Retrieved from https://www.sciencedirect.com/science/article/pii/S0278431915300794

## 10. Annexure

**Learnings from this Project:**

- **Star Schema data model.**

**Star Schema Model**

- **Description**: Learned the principles and implementation of the Star Schema data model, which is crucial for efficient querying and data warehousing.
- **Application**: Applied this model to structure the data in a way that enhances query performance and simplifies reporting.

- **Understanding problem statement & given data properly before proceeding to conclusions.**

**DAX FORMULA**

| | |
|---|---|
| **Revenue** | **Revenue = SUM(fact_bookings[revenue_realized])** |
| **Total Bookings** | **Total Bookings = COUNT(fact_bookings[booking_id])** |
| **Total Capacity** | **Total Capacity = SUM(fact_aggregated_bookings[capacity])** |
| **Total Succesful Bookings** | **Total Succesful Bookings = SUM(fact_aggregated_bookings[successful_bookings])** |
| **Occupancy %** | **Occupancy % = DIVIDE([Total Succesful Bookings],[Total Capacity],0)** |
| **Average Rating** | **Average Rating = AVERAGE(fact_bookings[ratings_given])** |
| **No of days** | **No of days = DATEDIFF(MIN(dim_date[date]),MAX(dim_date[date]),DAY) +1** |
| **Total cancelled bookings** | **Total cancelled bookings = CALCULATE([Total Bookings],fact_bookings[booking_status]="Cancelled")** |

| | |
|---|---|
| **Total Checked Out** | **Total Checked Out = CALCULATE([Total Bookings],fact_bookings[booking_status]="Checked Out")** |
| **Total no show bookings** | **Total no show bookings = CALCULATE([Total Bookings],fact_bookings[booking_status]="No Show")** |
| **No Show rate %** | **No Show rate % = DIVIDE([Total no show bookings],[Total Bookings])** |
| **Booking % by Platform** | **Booking % by Platform = DIVIDE([Total Bookings],<br> CALCULATE([Total Bookings],<br> ALL(fact_bookings[booking_platform])<br> ))*100"** |
| **Booking % by Room class** | **"Booking % by Room class = DIVIDE([Total Bookings],<br> CALCULATE([Total Bookings],<br> ALL(dim_rooms[room_class])<br> ))*100"** |
| **ADR** | **ADR = DIVIDE( [Revenue], [Total Bookings],0)** |
| **Realisation %** | **Realisation % = 1- ([Cancellation %]+[No Show rate %])** |
| **RevPAR** | **RevPAR = DIVIDE([Revenue],[Total Capacity])** |
| **DBRN** | **DBRN = DIVIDE([Total Bookings], [No of days])** |
| **DSRN** | **DSRN = DIVIDE([Total Capacity], [No of days])** |
| **DURN** | **DURN = DIVIDE([Total Checked Out],[No of days])** |

| | |
|---|---|
| **Revenue WoW change %** | **"Revenue WoW change % =**<br>**Var selv =**<br>**IF(HASONEFILTER(dim_date[wn]),SELECTEDVALUE(dim_date[wn]),MAX(dim_date[wn]))**<br>**var revcw = CALCULATE([Revenue],dim_date[wn]= selv)**<br>**var revpw =**<br>**CALCULATE([Revenue],FILTER(ALL(dim_date),dim_date[wn]= selv-1))**<br>**return**<br>**DIVIDE(revcw,revpw,0)-1"** |
| **Occupancy WoW change %** | **"Occupancy WoW change % =**<br>**Var selv =**<br>**IF(HASONEFILTER(dim_date[wn]),SELECTEDVALUE(dim_date[wn]),MAX(dim_date[wn]))**<br>**var revcw = CALCULATE([Occupancy %],dim_date[wn]= selv)**<br>**var revpw =  CALCULATE([Occupancy %],FILTER(ALL(dim_date),dim_date[wn]= selv-1))**<br>**return**<br>**DIVIDE(revcw,revpw,0)-1"** |
| **ADR WoW change %** | **"ADR WoW change % =**<br>**Var selv =**<br>**IF(HASONEFILTER(dim_date[wn]),SELECTEDVALUE(dim_date[wn]),MAX(dim_date[wn]))**<br>**var revcw = CALCULATE([ADR],dim_date[wn]= selv)**<br>**var revpw =**<br>**CALCULATE([ADR],FILTER(ALL(dim_date),dim_date[wn]= selv-1))**<br>**return**<br>**DIVIDE(revcw,revpw,0)-1"** |

| | |
|---|---|
| **Revpar WoW change %** | **"Revpar WoW change % =**<br>**Var selv =**<br>**IF(HASONEFILTER(dim_date[wn]),SELECTEDVALUE(dim_date[wn]),MAX(dim_date[wn]))**<br>**var revcw = CALCULATE([RevPAR],dim_date[wn]= selv)**<br>**var revpw =**<br>**CALCULATE([RevPAR],FILTER(ALL(dim_date),dim_date[wn]= selv-1))**<br>**return**<br>**DIVIDE(revcw,revpw,0)-1"** |
| **Realisation WoW change %** | **"Realisation WoW change % =**<br>**Var selv =**<br>**IF(HASONEFILTER(dim_date[wn]),SELECTEDVALUE(dim_date[wn]),MAX(dim_date[wn]))**<br>**var revcw = CALCULATE([Realisation %],dim_date[wn]= selv)**<br>**var revpw = CALCULATE([Realisation %],FILTER(ALL(dim_date),dim_date[wn]= selv-1))**<br>**return**<br>**DIVIDE(revcw,revpw,0)-1"** |
| **DSRN WoW change %** | **"DSRN WoW change % =**<br>**Varselv =**<br>**IF(HASONEFILTER(dim_date[wn]),SELECTEDVALUE(dim_date[wn]),MAX(dim_date[wn]))**<br>**var revcw = CALCULATE([DSRN],dim_date[wn]= selv)**<br>**var revpw = CALCULATE([DSRN],FILTER(ALL(dim_date),dim_date[wn]= selv-1))**<br>**return**<br>**DIVIDE(revcw,revpw,0)-1"** |