Agentic Guest Experience Optimizer

Proactive Hotel Satisfaction Prediction and Personalized Intervention

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https://github.com/asinisusanya/agentic-booking

Abstract: Guest satisfaction in the hospitality industry is traditionally assessed through post-stay surveys, making service improvement largely reactive. This project proposes an *Agentic Guest Experience Optimizer*, a proactive artificial intelligence framework designed to predict guest satisfaction at booking time and initiate personalized interventions before the stay occurs. The system integrates customer segmentation using unsupervised learning, supervised machine learning models for satisfaction prediction, and explainable AI techniques to identify key drivers of guest experience. Only booking-time information and historically inferred customer attributes are used, ensuring realistic deployment without data leakage. Gradient boosting models demonstrate strong predictive performance, while SHAP-based explanations provide transparent insight into feature-level contributions.

Building on these explanations, an agentic decision layer autonomously maps predicted dissatisfaction risks to tailored service interventions. These interventions are communicated through dynamically generated, personalized pre-stay emails that adapt tone and content according to guest segment and inferred intent. Experimental results show that the proposed framework is both technically effective and practically feasible, highlighting the potential of agentic and explainable AI systems to transform guest engagement in modern hotel booking platforms.

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1 Introduction

1.1 Background

Hotel booking systems have become the primary interface between guests and hospitality service providers. Modern booking platforms allow guests to select accommodation, specify stay details, and complete reservations with minimal human interaction. While these systems efficiently handle transactional aspects such as pricing, availability, and payments, they often provide limited support for understanding and managing guest expectations before the stay.

Traditionally, guest satisfaction assessment in the hospitality industry relies on post-stay feedback mechanisms, including surveys, online reviews, and rating platforms. These feedback channels are inherently reactive, as they collect guest opinions only after the stay has been completed. As a result, service providers gain insights into dissatisfaction only after the experience has already occurred, limiting their ability to take corrective action in real time.

Furthermore, post-stay surveys suffer from several limitations. Response rates are typically low, feedback may be influenced by recency bias, and negative experiences are often reported only after the guest has disengaged from the service. Consequently, hotels miss valuable opportunities to proactively address guest needs and improve satisfaction before dissatisfaction is formally expressed.

1.2 Problem Statement

Despite the availability of large volumes of historical booking and feedback data, most hotel systems lack mechanisms for early detection of potential guest dissatisfaction. Current approaches do not leverage predictive analytics to identify guests who may require additional attention before their stay.

In addition, existing booking platforms rarely support personalized interventions during the pre-stay phase. Guests receive generic confirmation emails that do not adapt to individual preferences, booking behavior, or predicted satisfaction levels. This absence of targeted communication limits the hotel's ability to manage expectations and enhance the guest experience proactively.

1.3 Objectives

The primary objective of this project is to design and evaluate an agentic artificial intelligence system capable of proactively enhancing guest satisfaction before the stay occurs. The specific objectives are as follows:

- To perform customer segmentation based on booking behavior and historical attributes in order to identify distinct guest profiles.

- To develop supervised machine learning models that predict guest satisfaction levels for upcoming bookings.
- To incorporate explainable artificial intelligence techniques to provide transparent and interpretable reasoning behind satisfaction predictions.
- To design an agentic framework that generates personalized, context-aware email interventions aimed at improving the anticipated guest experience.

1.4 Scope of the Project

The scope of this project is limited to the pre-stay phase of the guest journey. The proposed system focuses exclusively on actions that can be taken after a booking is confirmed but before the guest arrives at the hotel.

The project emphasizes email-based interventions as the primary communication channel for proactive engagement. Real-time operational changes, such as staff allocation, room reassignment, or on-site service adjustments, are not considered within the scope of this work.

Additionally, the system is evaluated in an offline setting using historical data and simulated booking scenarios. Integration with live hotel management systems and real-time guest interactions is identified as potential future work but is not addressed in this project.

2 Dataset Description

2.1 Data Sources

This project utilizes three primary datasets that represent different stages of the guest lifecycle in a hotel booking system.

- **Booking Dataset:** The booking dataset contains information collected at the time a reservation is made. It includes details such as booking date, check-in and check-out dates, number of guests, room and stay characteristics, pricing information, and booking channel metadata. This dataset represents the earliest available information and forms the core input for both customer segmentation and satisfaction prediction.

- **Feedback Dataset:** The feedback dataset consists of post-stay guest evaluations collected after the completion of a stay. It includes an overall satisfaction rating along with detailed sub-ratings related to cleanliness, service quality, comfort, and value for money. In this project, the overall rating is used as the primary target variable for supervised learning.

- **Customer Profile Dataset:** The customer profile dataset provides aggregated guest-level attributes derived from historical interactions. These include demographic information and inferred behavioral traits such as travel frequency, loyalty propensity, price sensitivity, and quality expectations. This dataset enriches booking records with longer-term behavioral context.

Table 1: Summary of Datasets and Metadata

Dataset	Key Attributes	Availability	Usage
Booking Dataset	Dates, guests, room details, pricing, booking channel	At booking time	Feature generation, clustering, prediction
Feedback Dataset	Overall rating, service quality, cleanliness, comfort	Post-stay	Target variable for supervised learning
Customer Profile Dataset	Age, travel frequency, loyalty propensity, inferred preferences	Pre-booking (historical)	Behavioral feature enrichment

2.2 Data Availability Timeline

A key design consideration in this project is the temporal availability of data, ensuring that predictions and interventions rely only on information that would realistically be known at a given point in time.

- **At Booking Time:** At the moment a booking is confirmed, only booking-related attributes and pre-existing customer profile information (if available) are accessible. These include stay duration, lead time, pricing details, number of guests, and previously inferred customer traits.
- **Post-Stay:** Guest feedback and satisfaction ratings become available only after the stay has concluded. These data are strictly used for model training, validation, and evaluation, and are not used as inputs during prediction or intervention generation.
- **Data Leakage Prevention:** To prevent data leakage, all features used for clustering and satisfaction prediction are derived exclusively from booking-time or historically available profile data. Post-stay feedback variables are excluded from feature construction and are used only as target labels.

This separation ensures that the predictive models reflect realistic deployment conditions.

Table 2: Feature-Level Metadata and Temporal Availability

Feature	**Type**	**Available At**	**Description**
Stay nights	Numeric	Booking time	Length of stay in nights
Lead time	Numeric	Booking time	Days between booking and check-in
Price per night	Numeric	Booking time	Average nightly room price
Number of guests	Numeric	Booking time	Total guests per booking
Age	Numeric	Pre-booking	Guest demographic attribute
Price sensitivity	Inferred	Pre-booking	Sensitivity to pricing changes
Quality expectations	Inferred	Pre-booking	Expected service quality level
Travel frequency	Inferred	Pre-booking	Frequency of past hotel stays
Loyalty propensity	Inferred	Pre-booking	Likelihood of repeat bookings
Overall rating	Numeric	Post-stay	Guest satisfaction score (target)

2.3 Data Characteristics

The combined dataset exhibits a mix of feature types relevant to both unsupervised and supervised learning tasks.

Dataset Size: The booking dataset contains several thousand booking records spanning multiple hotels and time periods. The feedback and customer profile datasets are joined using a common customer identifier, resulting in a unified dataset suitable for machine learning analysis.

Feature Types: The features used in this project can be categorized as follows:

- **Numeric features:** Quantitative attributes such as stay duration, lead time, price per night, number of guests, and age.
- **Inferred features:** Behavioral attributes derived from historical data, including price sensitivity, quality expectations, travel frequency, and loyalty propensity.
- **Categorical and binary features:** Indicators such as weekend stay flags and cluster assignments derived from customer segmentation.

This diverse feature composition enables the models to capture both transactional booking behavior and longer-term guest preferences, supporting accurate satisfaction prediction and meaningful segmentation.

3 Feature Engineering

3.1 Motivation for Feature Engineering

Raw booking data collected by hotel reservation systems is primarily designed for transactional and operational purposes rather than predictive analytics. Attributes such as booking dates, room prices, and guest counts, while informative, do not directly encode guest intent, expectations, or behavioral tendencies.

Machine learning models require numerical and semantically meaningful representations that capture patterns related to guest satisfaction. Feature engineering bridges this gap by transforming raw booking inputs into structured signals that reflect behavioral, temporal, and contextual aspects of a guest's stay.

In this project, feature engineering serves two main objectives:

- To enable effective customer segmentation through unsupervised learning.
- To provide informative predictors for supervised satisfaction prediction.

By translating observable booking behavior into derived features, the system gains the ability to reason about guest expectations, potential dissatisfaction risks, and appropriate pre-stay interventions.

3.2 Engineered Features

Raw booking data alone is insufficient to capture guest intent, behavioral patterns, and satisfaction drivers. Therefore, a set of meaningful features is engineered to translate booking-time information and historical customer behavior into signals usable by both unsupervised clustering and supervised satisfaction prediction models.

Table 3 summarizes the engineered features, their mathematical derivation, machine learning relevance, and business interpretation.

Table 3: Engineered Features for Customer Segmentation and Satisfaction Prediction

Feature Name	**Formula / Derivation**	**ML Relevance**	**Business Relevance**
Stay Nights	Checkout Date − Check-in Date	Captures length of stay and exposure to hotel services	Longer stays increase service interactions and dissatisfaction risk
Lead Time Days	Check-in Date − Booking Date	Indicates booking urgency and planning behavior	Late bookings often correlate with stress and higher expectations

Feature Name	Formula / Derivation	ML Relevance	Business Relevance
Price per Night	$\frac{\text{Total Price}}{\text{Stay Nights}}$	Represents perceived value and monetary commitment	Higher prices imply stronger quality expectations
Weekend Stay	Binary indicator based on check-in weekday	Encodes leisure versus business travel patterns	Weekend guests often expect premium and relaxed experiences
Number of Guests	Direct booking input	Affects service load and room requirements	Larger groups impact comfort, noise sensitivity, and amenities
Check-in Month	Month extracted from check-in date	Captures seasonal demand patterns	Peak seasons increase operational pressure and guest sensitivity
Age	Customer profile attribute	Correlates with travel preferences and expectations	Different age groups exhibit varying comfort and service needs
Price Sensitivity	Inferred from historical pricing behavior	Measures responsiveness to price changes	Highly sensitive guests are more likely to react negatively to pricing
Quality Expectations	Inferred from past ratings and interactions	Signals expected service standards	Higher expectations increase dissatisfaction risk if unmet
Travel Frequency	Derived from historical booking count	Indicates familiarity with hotel experiences	Frequent travelers benchmark services more critically
Loyalty Propensity	Inferred from repeat stays and engagement	Measures long-term customer value	Loyal guests are more forgiving but expect recognition
Cluster Assignment	Output of K-Means clustering	Provides segment-level behavioral context	Enables differentiated treatment and personalized interventions

3.3 Handling Missing and Inferred Features

Not all behavioral attributes are explicitly available at booking time, particularly for new or infrequent guests. To ensure robust model performance and realistic deployment, the system adopts principled strategies for handling missing and inferred features.

- **Cold-Start Strategy:** For new customers without historical data, inferred features such as price sensitivity, travel frequency, and loyalty propensity are initialized using population-level averages or neutral default values. This ensures that predictions remain stable while avoiding biased assumptions.

- **Defaults and Approximations:** When partial history exists, inferred features are computed using simple aggregations such as average spend, booking frequency, and historical rating trends. These approximations provide meaningful behavioral signals without requiring complex tracking infrastructure.

- **Justification:** This approach reflects real-world hotel systems where customer profiles are gradually enriched over time. As more interactions occur, inferred features become increasingly accurate, enabling progressively better segmentation, prediction, and personalized intervention.

4 Data Preparation Pipeline

This chapter describes the systematic data preparation process used to transform raw hotel booking, feedback, and customer profile data into a unified machine learning–ready dataset. The pipeline ensures data consistency, prevents leakage, and produces a clean feature matrix suitable for both customer segmentation and satisfaction prediction tasks.

4.1 Data Cleaning

Raw datasets collected from operational systems often contain inconsistencies, missing values, and heterogeneous data formats. To address these issues, several cleaning steps were applied prior to model training.

4.1.1 Date Normalization

All date-related attributes, including booking date, check-in date, and check-out date, were converted into a standardized datetime format. Invalid or malformed date entries were safely coerced to missing values. This normalization enables reliable temporal feature derivation such as stay duration and lead time.

4.1.2 Type Conversions

Numeric attributes such as price, number of guests, age, and inferred behavioral scores were explicitly converted to numerical types. This step ensures compatibility with machine learning algorithms and prevents silent type-related errors during model training.

4.1.3 Missing Value Handling

Missing values were handled according to feature semantics:

- Numeric booking-related features were imputed using median values to preserve distributional robustness.
- Behavioral and inferred attributes were retained as missing where appropriate, allowing certain models to learn from the absence of information.
- Records missing the target satisfaction rating were excluded from supervised learning to maintain label integrity.

This strategy balances robustness with realism, particularly under cold-start conditions.

4.2 Dataset Integration

After cleaning individual datasets, they were integrated into a single consolidated dataset.

4.2.1 Merging Strategy

Three datasets were merged using a common customer identifier:

- The booking dataset forms the base table.
- The feedback dataset is left-joined to attach post-stay ratings.
- The customer profile dataset is left-joined to enrich each booking with historical behavioral traits.

Left joins were used to preserve all booking records, ensuring that customers without feedback or historical profiles are still represented.

4.2.2 Leakage-Aware Integration

To prevent data leakage:

- Feedback variables are merged only for training and evaluation.
- Post-stay attributes are never used as input features during prediction.
- The overall rating is isolated as the supervised learning target.

This design reflects realistic deployment conditions where predictions are made before guest arrival.

4.3 Final Machine Learning Dataset

The output of the data preparation pipeline is a consolidated dataset stored as `feature_bookings.csv`.

4.3.1 Dataset Description

The final dataset contains one row per booking and includes:

- Engineered booking features
- Inferred customer behavioral attributes
- Cluster labels from unsupervised segmentation
- Overall satisfaction rating (target variable)

4.3.2 Feature–Label Separation

For supervised learning:

- Feature matrix (X) consists of booking-time and historical attributes only.
- Target vector (y) corresponds to the overall guest satisfaction rating.

This clear separation supports reproducible training, evaluation, and explainability while maintaining strict temporal validity.
The resulting dataset serves as the foundation for customer segmentation, satisfaction prediction, and explainable agentic intervention generation in subsequent stages of the system.

5 Exploratory Data Analysis (EDA)

5.1 Purpose of Exploratory Data Analysis

Exploratory Data Analysis (EDA) is conducted to gain an initial understanding of the dataset prior to applying machine learning models. In this project, EDA serves a focused and supportive role rather than an extensive exploratory exercise. The primary objectives of EDA are:

- To validate basic assumptions about the distribution of guest satisfaction ratings
- To examine simple relationships between booking-related attributes and satisfaction
- To identify any obvious anomalies or inconsistencies in the data

Since the dataset has already undergone feature engineering and structured preprocessing, EDA is intentionally kept concise and avoids post-model artifacts such as cluster assignments or explainability outputs.

5.2 Distribution of Guest Satisfaction Ratings

Figure 1 illustrates the distribution of overall guest satisfaction ratings collected from post-stay feedback.

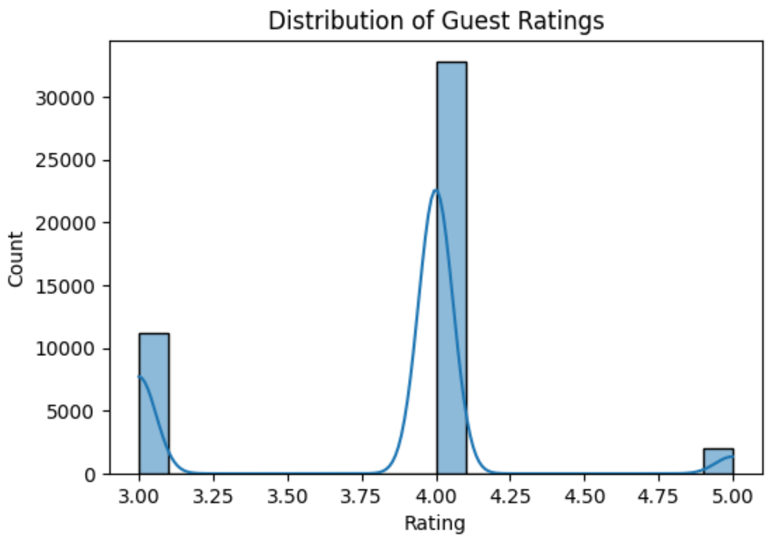


Figure 1: Distribution of Guest Satisfaction Ratings

The ratings exhibit a discrete distribution, with the majority of values concentrated around ratings of 3, 4, and 5. This reflects the common structure of hotel feedback systems, where guests typically provide integer-based satisfaction scores. The presence of sufficient variation across rating levels supports the feasibility of supervised learning approaches for satisfaction prediction.

5.3 Booking Behavior and Satisfaction

To understand how booking-related attributes may influence guest satisfaction, selected features were examined against the overall rating.

5.3.1 Lead Time vs Satisfaction

Figure 2 presents the relationship between booking lead time and guest satisfaction.

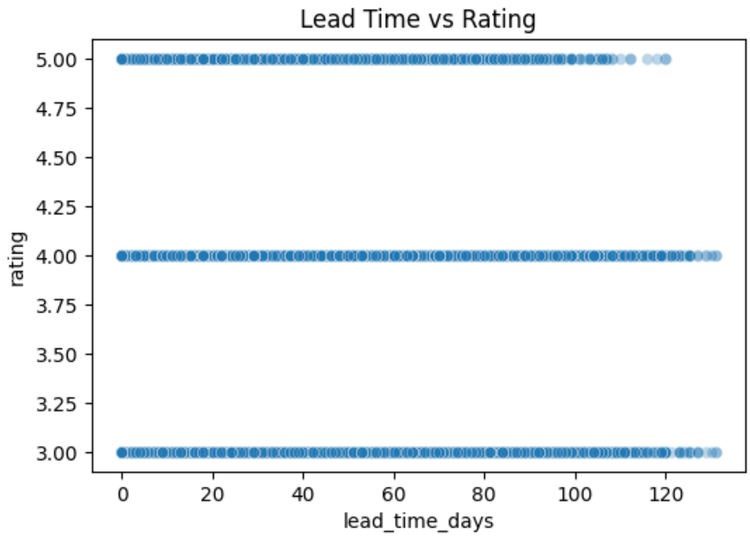


Figure 2: Lead Time vs Guest Satisfaction Rating

The visualization suggests that satisfaction ratings occur across a wide range of lead times. While no strong linear relationship is immediately apparent, shorter lead times are observed across multiple rating levels, indicating that last-minute bookings may still result in both positive and negative experiences. This supports the inclusion of lead time as a predictive feature rather than a deterministic indicator.

5.3.2 Price per Night vs Satisfaction

Figure 3 illustrates the relationship between price per night and guest satisfaction.

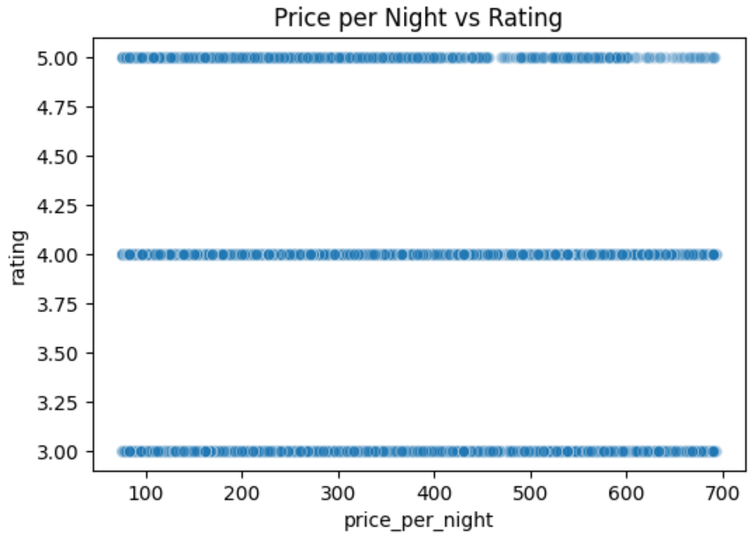


Figure 3: Price per Night vs Guest Satisfaction Rating

The plot indicates that higher prices are associated with a wide range of satisfaction outcomes. This suggests that price alone does not guarantee higher satisfaction, reinforcing the importance of contextual factors such as expectations, service quality, and guest preferences. Consequently, price-related attributes are best interpreted in combination with behavioral and inferred features.

5.4 Summary of EDA Findings

The exploratory analysis confirms that:

- Guest satisfaction ratings exhibit sufficient variability for predictive modeling
- Booking attributes such as lead time and price influence satisfaction in non-linear and context-dependent ways
- No obvious data quality issues are observed that would prevent further modeling

Based on these findings, the dataset is deemed suitable for customer segmentation and supervised satisfaction prediction, which are explored in the subsequent sections.

6 Customer Segmentation

6.1 Need for Customer Segmentation

Guests interacting with hotel booking systems exhibit diverse behavioral patterns, expectations, and sensitivity to service quality and pricing. Applying uniform engagement strategies across all guests limits the effectiveness of personalization and may fail to address early dissatisfaction risks.

Customer segmentation enables:

- Identification of distinct guest behavior profiles
- Context-aware satisfaction prediction
- Tailored pre-stay communication strategies

In this work, segmentation is used as a foundational layer that informs both satisfaction prediction and agentic email interventions.

6.2 Feature Selection for Clustering

Only features that are available **prior to guest arrival** are used for clustering to ensure deployment realism and prevent data leakage. Post-stay attributes, including ratings and feedback, are strictly excluded.

The selected features include:

- Stay nights and lead time
- Price per night
- Number of guests
- Weekend stay indicator
- Inferred behavioral traits: price sensitivity, quality expectations, travel frequency, and loyalty propensity

These features jointly capture booking intent, financial commitment, and long-term behavioral tendencies, making them suitable for guest segmentation.

6.3 Clustering Algorithm

K-Means clustering is employed due to its scalability, interpretability, and suitability for numeric feature spaces. All features are standardized prior to clustering to ensure balanced distance calculations.

The algorithm partitions guests by minimizing within-cluster variance, resulting in compact clusters with meaningful behavioral separation.

6.4 Determining the Number of Clusters

Multiple complementary methods are used to determine the optimal number of clusters K.

Elbow Method

Figure 4 illustrates the relationship between the number of clusters and inertia. A clear diminishing return is observed beyond $K = 2$, indicating that additional clusters provide limited reduction in within-cluster variance.

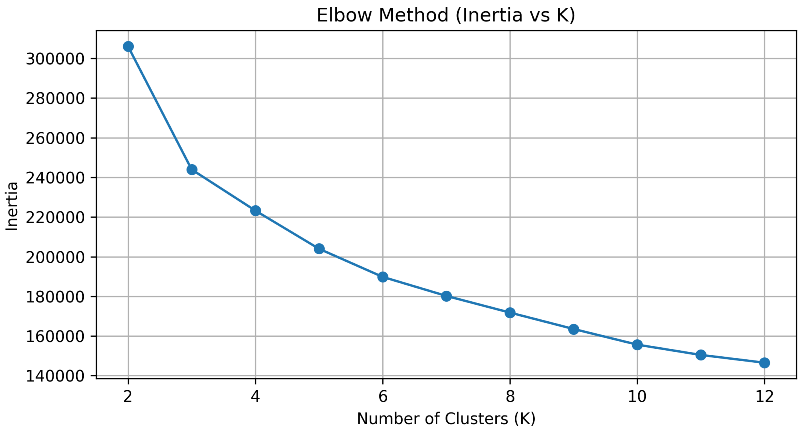


Figure 4: Elbow Method for Selecting the Number of Clusters

Silhouette Score

Figure 5 shows that the silhouette score reaches its maximum at $K = 2$, suggesting strong intra-cluster cohesion and inter-cluster separation. For higher values of K, the silhouette score consistently decreases, indicating weaker clustering quality.

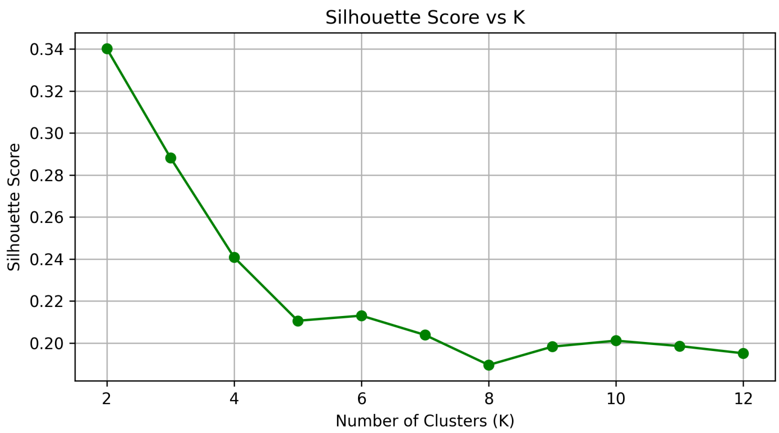


Figure 5: Silhouette Score for Different Numbers of Clusters

PCA-Based Visualization

A two-dimensional PCA projection of the clustered data is shown in Figure 6. While three visually distinct point clouds appear in the reduced space, PCA is a projection technique that preserves variance rather than true cluster boundaries.

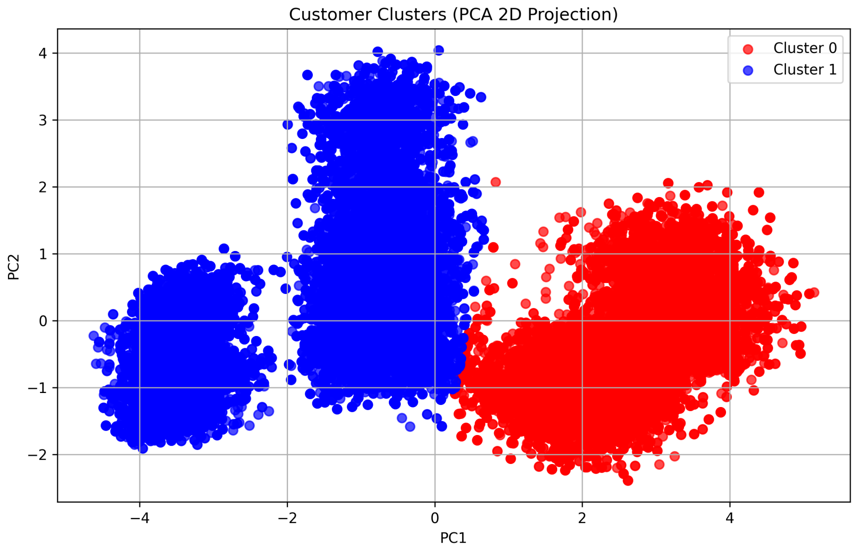


Figure 6: PCA Visualization of Guest Clusters

Importantly, the apparent third group in the PCA plot represents a variance-driven substructure rather than a stable, separable behavioral cluster. This substructure does not consistently appear when evaluated using clustering quality metrics and does not yield a meaningful business interpretation.

6.5 Final Cluster Selection Rationale

Although PCA visualization suggests three apparent regions, the final selection of $K = 2$ is based on:

- Strong statistical support from both elbow and silhouette analyses
- Stability and interpretability of resulting clusters
- Clear business-level differentiation between guest types

Increasing K beyond two results in fragmented clusters with marginal behavioral differences and reduced practical utility for intervention design.

6.6 Cluster Interpretation

The two resulting clusters are interpreted as follows:

- **Cluster 0 – Premium-Oriented Guests:** Guests in this cluster exhibit lower price sensitivity, higher quality expectations, and stronger loyalty indicators. They tend to book higher-priced rooms and expect premium services, reassurance, and personalized attention. These guests benefit from quality-focused and reassurance-driven pre-stay communication.
- **Cluster 1 – Value-Oriented Guests:** This cluster includes guests with higher price sensitivity and lower tolerance for perceived value mismatches. They prioritize discounts, convenience, and cost-effectiveness. For these guests, incentive-based messaging and clarity around value propositions are more effective.

Table 4: Behavioral Interpretation of Identified Guest Clusters

Feature Dimension	**Cluster 0: Premium-Oriented Guests**	**Cluster 1: Value-Oriented Guests**
Price Sensitivity	Low price sensitivity; willingness to pay for quality and comfort	High price sensitivity; strong focus on cost and perceived value
Quality Expectations	High expectations for service quality, amenities, and experience	Moderate expectations; satisfaction driven by value-for-money
Loyalty Propensity	Higher likelihood of repeat visits and brand loyalty	Lower loyalty; booking decisions influenced by offers and pricing
Travel Frequency	Frequent or experienced travelers	Occasional or infrequent travelers
Booking Behavior	Higher-priced bookings with longer planning horizons	Shorter lead times and budget-conscious bookings
Preferred Interventions	Reassurance, premium amenities, personalized service messaging	Discounts, offers, clear pricing, and convenience-focused messaging

6.7 Cluster Distribution

Figure 7 illustrates the distribution of guests across the two clusters, showing a balanced yet distinct segmentation suitable for downstream modeling and intervention strategies.

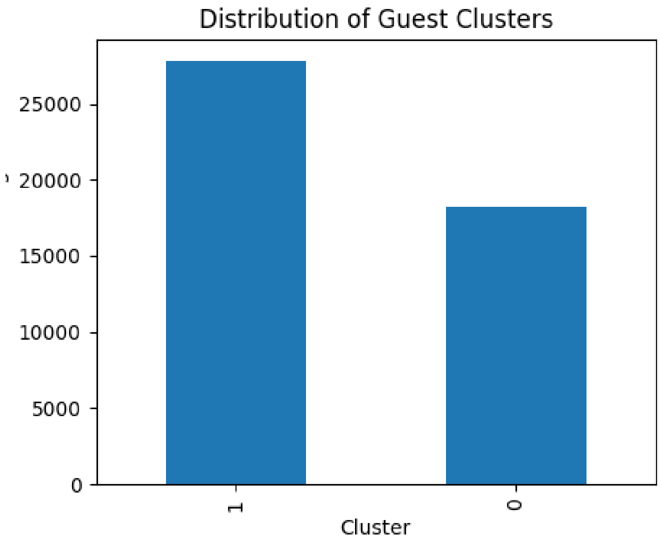


Figure 7: Distribution of Guests Across Clusters

This segmentation provides a robust behavioral context for satisfaction prediction and agentic email generation in subsequent stages of the system.

7 Satisfaction Prediction (Supervised Learning)

7.1 Problem Formulation

The objective of this stage is to predict a guest's overall satisfaction score *before* the stay takes place. Since the output variable is continuous and ordered, the problem is formulated as a **regression task**.

Given a set of booking-time and historically inferred guest features, the model learns a mapping:

$$f(\mathbf{X}) \rightarrow \hat{y}$$

where $\mathbf{X}$ represents the booking feature vector and $\hat{y}$ denotes the predicted overall guest satisfaction rating.

This prediction enables proactive interventions before the guest experience occurs, rather than relying on post-stay feedback alone.

7.2 Input Features and Target Variable

The supervised learning model is trained using features that are either available at booking time or inferred from historical customer profiles.

Input Features (X):

- Stay nights
- Lead time (days)
- Price per night
- Weekend stay indicator
- Number of guests
- Check-in month
- Guest age
- Price sensitivity (inferred)
- Quality expectations (inferred)
- Travel frequency (inferred)
- Loyalty propensity (inferred)
- Customer cluster label

Target Variable (y):
The target variable is the *overall guest satisfaction rating*, collected post-stay from the feedback dataset. This value is used exclusively for model training and evaluation and is not available during real-time prediction.
To avoid data leakage, all post-stay information is strictly excluded from the input feature set.

7.3 Model Selection Strategy

To ensure robust evaluation, two complementary modeling pipelines were designed.
Pipeline B – Traditional Regression Models:

- Linear Regression
- Lasso Regression
- Ridge Regression
- Random Forest Regressor
- Extra Trees Regressor
- Gradient Boosting Regressor
- Multi-layer Perceptron (MLP)

Pipeline A – Gradient Boosting Models:

- XGBoost
- LightGBM
- CatBoost

Traditional models provide interpretable baselines, while gradient boosting models are included due to their ability to model non-linear interactions and heterogeneous guest behavior patterns.

7.4 Model Training and Evaluation

The dataset was split into training and validation subsets using an 80:20 ratio. Models were trained on the training set and evaluated on the validation set.
Two error-based metrics were used for evaluation:

- **Root Mean Squared Error (RMSE)**
- **Mean Absolute Error (MAE)**

RMSE penalizes larger prediction errors more strongly, while MAE provides an interpretable measure of average prediction deviation.

7.5 Results and Best Model Selection

Table 5 summarizes the performance of all evaluated models.

Table 5: Performance Comparison of Supervised Learning Models

Pipeline	**Model**	**RMSE**	**MAE**
A	LightGBM	**0.4678**	**0.3645**
A	XGBoost	0.4703	0.3665
A	CatBoost	0.4771	0.3724
B	Gradient Boosting	0.4810	0.3761
B	Ridge Regression	0.4874	0.3797
B	Linear Regression	0.4874	0.3797
B	MLP Regressor	0.4911	0.3899
B	Lasso Regression	0.4946	0.3835
B	Random Forest	0.5396	0.3986
B	Extra Trees	0.5735	0.4069

LightGBM achieved the lowest RMSE and MAE among all evaluated models, indicating superior predictive accuracy. Its gradient boosting framework effectively captures non-linear relationships between booking behavior, inferred preferences, and satisfaction outcomes. Additionally, LightGBM offers fast inference and seamless integration with SHAP-based explainability, making it well-suited for deployment in an agentic guest engagement system. Accordingly, LightGBM was selected as the final satisfaction prediction model.

8 Explainable AI (SHAP Analysis)

8.1 Need for Explainability

While accurate satisfaction prediction is essential, predictive performance alone is insufficient for a proactive and agentic guest experience system. Hotel operators require not only a prediction, but also a clear understanding of *why* a particular guest is expected to be satisfied or dissatisfied.

Explainability is critical for three key reasons:

- **Trust:** Black-box predictions without justification are difficult to trust in operational decision-making. Transparent explanations increase confidence in automated interventions.
- **Interpretability:** Hotel staff and business stakeholders must understand which guest attributes drive predicted satisfaction in order to reason about model behavior.
- **Actionability:** Personalized pre-stay interventions (e.g., emails, offers, reassurance messages) require knowing which factors negatively or positively influence a specific guest's predicted experience.

To address these requirements, this project integrates SHAP (SHapley Additive exPlanations) to explain both global model behavior and individual booking-level predictions.

8.2 SHAP Methodology

SHAP is a game-theoretic explanation framework that attributes a model's prediction to individual feature contributions. Each feature is assigned a SHAP value that represents its marginal contribution to the prediction relative to a baseline.

Formally, the predicted satisfaction score can be expressed as:

$$\text{Predicted Rating} = \text{Base Value} + \sum_{i=1}^{n} \phi_i \tag{1}$$

where:

- **Base Value** represents the average model prediction across the training dataset.
- ϕ_i is the SHAP value of feature i, indicating how much that feature increases or decreases the predicted rating.

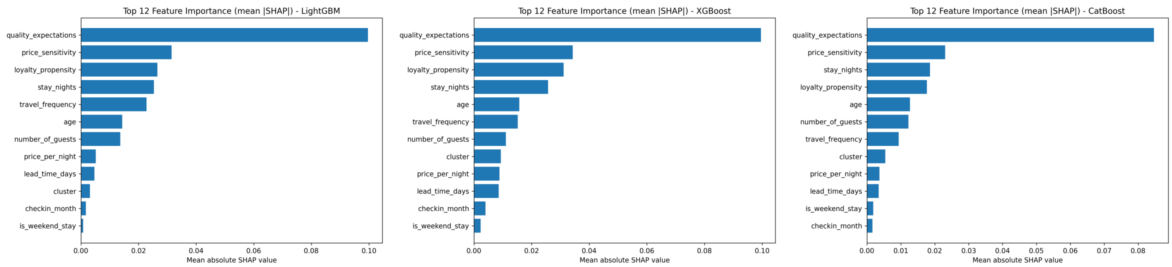
This additive structure ensures consistency, local accuracy, and interpretability, making SHAP particularly suitable for explaining tree-based ensemble models such as LightGBM, XGBoost, and CatBoost.

8.3 Global Feature Importance

Global SHAP analysis explains which features are most influential across all bookings. This helps validate whether the model relies on intuitive and business-relevant signals.

Figure 8 presents the mean absolute SHAP values for the top features across three boosting models. Across all models, inferred behavioral attributes such as *quality expectations*, *price sensitivity*, and *loyalty propensity* consistently emerge as the most influential predictors.

This confirms that guest satisfaction is driven not only by transactional booking details, but also by latent behavioral characteristics derived from historical data.



(a) LightGBM (b) XGBoost (c) CatBoost

Figure 8: Global feature importance based on mean absolute SHAP values

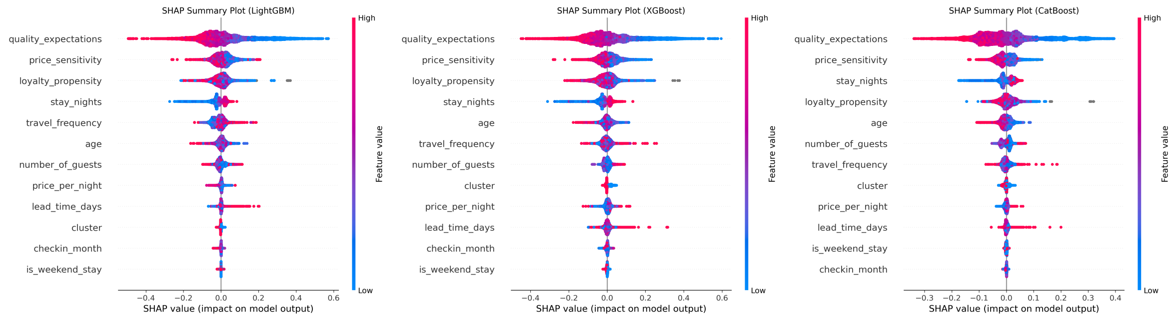
8.4 SHAP Summary Plots

SHAP summary plots provide deeper insight by showing both feature importance and the direction of influence. Each point represents a booking, colored by feature value (low to high).

Figure 9 shows that:

- Higher *quality expectations* strongly increase predicted satisfaction when matched appropriately, but also contribute to dissatisfaction when unmet.
- Higher *price sensitivity* tends to reduce predicted satisfaction unless value-aligned interventions are applied.
- Longer stays increase exposure to service quality, amplifying both positive and negative effects.

These patterns align with real-world hospitality dynamics and further validate the model's behavioral reasoning.



(a) LightGBM (b) XGBoost (c) CatBoost

Figure 9: SHAP summary plots showing feature impact and value distribution

8.5 Local Explanation Example

Beyond global insights, SHAP enables per-booking explanations, which are essential for personalized interventions.

For a given booking, the model output is decomposed into individual feature contributions. For example, a predicted satisfaction score may be influenced positively by high loyalty propensity and quality expectations, while being negatively impacted by short lead time or high price sensitivity.

This localized explanation allows the agentic system to:

- Identify dissatisfaction risks before the stay
- Select appropriate messaging strategies (reassurance, discounts, value clarification)
- Generate context-aware and explainable pre-stay emails

Thus, SHAP serves as the critical bridge between predictive modeling and autonomous, explainable decision-making within the proposed agentic framework.

9 Agentic Email Generation System

9.1 Motivation for an Agentic Approach

Traditional hotel communication systems rely on static email templates that are triggered by predefined rules. Such systems lack adaptability, personalization depth, and contextual awareness of individual guest needs.

In contrast, an *agentic* approach enables autonomous decision-making based on real-time predictions and explanations. Rather than sending generic confirmations, the proposed system dynamically reasons about guest behavior, satisfaction risk, and intent, and then generates tailored pre-stay interventions.

The key motivations for adopting an agentic architecture are:

- **Beyond static templates:** Messages are generated dynamically based on predicted satisfaction drivers rather than fixed rules.
- **Autonomous decision-making:** The system independently selects tone, content, and interventions without manual configuration.

9.2 End-to-End Agentic Pipeline

The agentic email system follows a sequential decision pipeline that transforms raw booking information into personalized communication. The pipeline is illustrated conceptually as:

Booking Data → *Satisfaction Prediction* → *SHAP Explanation* → *Intent Inference* →
Intervention Selection → *Email Rendering*

Each stage refines the system's understanding of the guest and contributes to the final email content. This layered design ensures traceability and explainability at every step.

9.3 Intent Inference

Intent inference translates SHAP explanations into high-level guest needs. Rather than reacting to raw feature values, the system interprets the *direction and magnitude* of SHAP contributions. For example:

- High positive SHAP contribution from *quality expectations* indicates a need for reassurance and premium service communication.
- Negative contribution from *lead time days* suggests urgency and potential arrival-related stress.
- Strong influence from *price sensitivity* signals a value-seeking intent.

These signals are mapped to interpretable intents such as *reassurance*, *value optimization*, or *convenience prioritization*. This step converts model explanations into actionable reasoning.

9.4 Intervention Selection

Once guest intents are inferred, the system selects appropriate interventions. Interventions represent concrete service actions or messaging strategies aligned with hotel operations.
Examples include:

- Reassurance-focused interventions (room preferences, quiet floors, concierge access)
- Value-based incentives (discounts, complimentary services)
- Convenience-oriented actions (express check-in, short-stay optimization)

This mapping ensures that interventions are not arbitrary but directly justified by model-driven insights.

9.5 Personalized Email Rendering

The final email is generated using a structured renderer that adapts:

- **Tone** based on the detected customer cluster
- **Content blocks** based on selected interventions
- **Language style** to match guest expectations

Cluster-based tone adaptation plays a critical role:

- **Cluster 0 (Premium-Oriented Guests):** Formal tone, reassurance, exclusivity, and personalized service emphasis.
- **Cluster 1 (Value-Oriented Guests):** Friendly tone, efficiency, clarity, and incentive-driven messaging.

Content is grouped into logical sections such as *Smooth Arrival*, *Personalized Suggestions*, and *Thoughtful Courtesy*, ensuring readability and coherence.

9.6 Sample Email Outputs

Two representative examples illustrate the effectiveness of the agentic system.

9.6.1 Cluster 0 – Premium-Oriented Guest Example

The generated email emphasizes reassurance, exclusivity, and personalized attention, aligning with high quality expectations and loyalty propensity. Suggested interventions include spa access, curated dining experiences, and personalized room arrangements.

```python
# ------------------------------------------------------------
#                     LOCAL TESTING
# ------------------------------------------------------------
if __name__ == "__main__":
    sample_booking = {
        "booking_id": "test123",
        "lead_time_days": 45,
        "stay_nights": 4,
        "price_sensitivity": 0.15,
        "quality_expectations": 0.85,
        "travel_frequency": 12,
        "price_per_night": 420,
        "loyalty_propensity": 0.8,
        "age": 42,
        "number_of_guests": 2,
    }

    hotel_context = {
        "offers": [
            "Complimentary␣welcome␣drink",
            "Late␣checkout␣upon␣availability",
            "Exclusive␣spa␣access"
        ],
        "local_events": [
            "Jazz␣Night␣at␣Sky␣Lounge",
            "Chefs␣Table␣Experience"
        ]
    }

    result = generate_email_for_booking(
        sample_booking,
        hotel_context,
        guest_name="Alex",
        hotel_name="Cinnamon␣Grand"
    )
```

Generated Email (Cluster 0)

Dear Alex,

We are delighted to welcome you to Cinnamon Grand. To ensure a seamless and comfortable arrival, our team has prepared a few thoughtful arrangements for your stay.

Smooth Arrival Our team is ready to handle any special requests you have — tell us what matters most. We will be happy to assist with anything else you may need upon arrival.

Personalized Suggestions We recommend our signature spa and chef's tasting menu for an elevated stay. Complimentary fruit basket on arrival (subject to availability). We'll prioritize a quiet, high-floor room with thoughtful amenities. Would you like a room upgrade or spa package? We can reserve it now.

A Thoughtful Courtesy As a valued guest, enjoy a special courtesy on us. We can apply your loyalty benefits and ensure your preferences are remembered.

Warm regards, The Cinnamon Grand Team

Cluster detected: 0 Predicted Satisfaction: 3.70

The generated email reflects a premium-oriented intervention strategy derived directly from the booking inputs. A long lead time of 45 days and a multi-night stay indicate a planned, non-urgent reservation, reducing the need for logistical urgency. The high nightly rate (420) combined with very low price sensitivity (0.15) signals that cost is not the primary concern for this guest.

Furthermore, the high quality expectations (0.85), frequent travel history (12 trips), and strong loyalty propensity (0.8) suggest an experienced guest who values service consistency and personalized attention. As a result, the agent avoids discount-driven messaging and instead emphasizes reassurance, premium amenities, and exclusive experiences such as spa access and curated dining.

The formal tone and absence of promotional language align with the guest's demographic profile and inferred expectations. Overall, the intervention prioritizes perceived service excellence, which the model identifies as the dominant driver of satisfaction for this booking.

9.6.2 Cluster 1 – Value-Oriented Guest Example

The email adopts a friendly, concise tone and highlights discounts, complimentary services, and convenience-focused offerings. This aligns with higher price sensitivity and short-stay behavior.

In both cases, the content differs substantially despite similar hotel context, demonstrating genuine personalization.

```
# ------------------------------------------------------------
#                          LOCAL TESTING
```

```
# ---------------------------------------------------------
if __name__ == "__main__":
    sample_booking = {
        "booking_id": "text123",
        "lead_time_days": 2,
        "stay_nights": 1,
        "price_per_night": 95,
        "number_of_guests": 1,
        "price_sensitivity": 0.85,
        "quality_expectations": 0.35,
        "travel_frequency": 1,
        "loyalty_propensity": 0.15,
        "age": 24,
    }

    hotel_context = {
        "offers": [
            "10%␣off␣dinner␣buffet",
            "Complimentary␣Wi-Fi",
            "Free␣welcome␣drink"
        ],
        "local_events": [
            "Night␣Market",
            "Street␣Food␣Festival"
        ]
    }

    result = generate_email_for_booking(
        sample_booking,
        hotel_context,
        guest_name="Alex",
        hotel_name="Cinnamon␣Grand"
    )
```

Generated Email (Cluster 1)

Hi Alex,

Thanks for choosing Cinnamon Grand! We're excited to welcome you and have prepared a few thoughtful details to make your arrival and stay as easy and enjoyable as possible.

Smooth Arrival Priority express check-in to save your time. Clear directions and parking info to make arrival smooth. A quick arrival guide and express services for short stays are prepared.

Personalized Suggestions Free Wi-Fi and complimentary shuttle service to nearby attractions. Local events include the Night Market and Street Food Festival.

A Thoughtful Courtesy Complimentary welcome drink upon arrival and 10% off the dinner buffet for this stay.

Warm regards, The Cinnamon Grand Team

Cluster detected: 1 Predicted Satisfaction: 3.89

This email is generated for a value-oriented guest whose booking inputs indicate a short, price-sensitive stay. A very short lead time of 2 days and a single-night reservation suggest urgency and limited planning. The low price per night (95) combined with high price sensitivity (0.85) indicates that perceived value and cost-effectiveness are critical satisfaction factors.

Lower quality expectations (0.35), minimal travel frequency (1), and weak loyalty propensity (0.15) further imply that this guest is unlikely to respond to premium positioning. Consequently, the agent prioritizes efficiency-focused messaging such as express check-in and clear arrival guidance, reducing friction during the stay.

Incentive-based interventions, including complimentary services and dining discounts, are emphasized to directly address the risk of dissatisfaction driven by value mismatch. The friendly tone and selective use of emojis align with the guest's demographic profile and casual travel intent. This example illustrates how the system adapts its intervention strategy to maximize satisfaction under strong price constraints.

9.7 Deriving Model Inputs from Real User Data

Although the examples use hard-coded inputs for demonstration, all required features can be realistically derived from standard hotel booking systems and CRM data.

- **Direct booking inputs:** Features such as stay nights, lead time, price per night, number of guests, and check-in date are directly collected during the booking process.
- **Derived transactional features:** Weekend stay flags and check-in month are computed from booking dates. Price per night is derived by dividing total booking price by stay duration.

- **CRM-based behavioral features:** Attributes such as travel frequency and loyalty propensity are calculated from historical booking counts and loyalty program participation.
- **Inferred behavioral traits:** Price sensitivity and quality expectations are estimated using historical booking patterns, spending behavior, and prior feedback distributions. For new customers (cold-start cases), population-level defaults or cluster-based averages are used.
- **Cluster assignment:** Customer clusters are predicted using the trained segmentation model based solely on pre-stay features.

This ensures that the agentic system can operate in real-world deployment without relying on post-stay or unavailable information.

9.8 Summary

By integrating prediction, explanation, and autonomous decision-making, the proposed agentic email generation system transforms passive booking confirmations into proactive experience optimization. The system not only predicts satisfaction but also explains it, reasons about guest intent, and takes justified, personalized action before the stay occurs.

10 Evaluation and Discussion

This section evaluates the proposed Agentic Guest Experience Optimizer from both technical and business perspectives. The discussion focuses on predictive performance, explainability effectiveness, and practical feasibility within real-world hotel booking systems.

10.1 Technical Evaluation

10.1.1 Prediction Accuracy

The supervised learning component was evaluated using standard regression metrics, namely Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Multiple models were trained and compared across two pipelines: traditional machine learning models and gradient boosting-based models.

Among all evaluated models, LightGBM achieved the lowest RMSE and MAE, indicating superior predictive accuracy. This performance can be attributed to LightGBM's ability to capture non-linear interactions between booking characteristics, inferred behavioral traits, and customer segments. The results demonstrate that satisfaction levels can be reasonably predicted using only pre-stay information, supporting the feasibility of proactive interventions.

10.1.2 Explainability Effectiveness

Explainable AI was incorporated using SHAP to ensure transparency in model predictions. SHAP analysis provided both global and local explanations, identifying how individual features contributed to predicted satisfaction scores.

Globally, features such as quality expectations, loyalty propensity, price sensitivity, and lead time emerged as dominant drivers. Locally, per-booking explanations enabled the system to understand the specific reasons behind a predicted satisfaction level. This explainability layer plays a critical role in bridging predictive outputs with actionable decisions, ensuring that the agentic system does not operate as a black box.

10.2 Business Impact Analysis

10.2.1 Proactive Satisfaction Improvement

Traditional hotel feedback systems rely on post-stay surveys, which are inherently reactive. In contrast, the proposed system enables satisfaction risks to be identified before the guest arrives. By predicting dissatisfaction early and triggering targeted interventions, hotels can proactively influence guest perception during the stay rather than reacting after negative feedback has already been recorded.

The generated personalized emails demonstrate how minor interventions—such as reassurance, service prioritization, or value-based incentives—can be aligned with individual guest expectations. Such proactive engagement has the potential to improve overall ratings, increase repeat bookings, and strengthen brand perception.

10.2.2 Reduction of Negative Feedback Risk

High price sensitivity and short lead times were observed to correlate with increased dissatisfaction risk. The system explicitly addresses these risk factors by recommending cost-effective offers and efficiency-oriented services. By intervening early for high-risk bookings, the likelihood of negative reviews and service complaints can be reduced, contributing to more stable long-term satisfaction metrics.

10.3 Practical Feasibility

10.3.1 Integration with Booking Systems

The proposed framework is designed to integrate seamlessly with existing hotel booking platforms. All predictive inputs are derived from data available at booking time or from pre-existing customer profiles. The agentic pipeline can be triggered immediately after booking confirmation, allowing personalized emails to be sent automatically without manual intervention.
Importantly, the system does not require changes to hotel operations in real time. Instead, it leverages communication-based interventions, making deployment feasible with minimal disruption to existing workflows.

10.3.2 Scalability Considerations

From a scalability perspective, the system is well-suited for large-scale deployment. Clustering and model training are performed offline, while real-time inference involves lightweight operations such as feature transformation, model prediction, and template-based email rendering. The use of gradient boosting models and precomputed explainability artifacts further supports efficient scaling across thousands of bookings per day.
Overall, the evaluation demonstrates that the proposed agentic system is not only technically sound but also practically viable and business-relevant for modern hospitality environments.

11 Limitations and Future Work

While the proposed Agentic Guest Experience Optimizer demonstrates strong potential for proactive satisfaction management, several limitations remain. These limitations also highlight opportunities for future enhancement and research.

11.1 Current Limitations

11.1.1 Cold-Start Inference

A key limitation of the system is its reliance on inferred behavioral features such as price sensitivity, quality expectations, travel frequency, and loyalty propensity. For first-time guests or customers with limited historical data, these attributes must be approximated using default values or weak signals derived from booking characteristics. Although this strategy enables model inference in cold-start scenarios, it may reduce prediction accuracy for entirely new guests.

11.1.2 Offline Email Simulation

In the current implementation, personalized email generation is evaluated in an offline environment. Emails are generated and displayed as simulated outputs rather than being delivered through an actual email service. As a result, the system does not capture real guest engagement metrics such as email open rates, click-through behavior, or response actions.

11.1.3 Absence of a Real-Time Feedback Loop

The system operates in a one-directional manner, where predictions and interventions are generated without incorporating live feedback from guest interactions. There is no mechanism to adapt future interventions based on guest responses or changing preferences during the stay. This limits the system's ability to continuously learn and improve from real-time outcomes.

11.2 Future Enhancements

11.2.1 Integration of Live Contextual Data

Future versions of the system could integrate real-time external data sources, such as weather forecasts, local event APIs, and seasonal demand indicators. Incorporating such contextual signals would enable more dynamic and situationally aware interventions, further improving the relevance of recommendations.

11.2.2 Real Email Delivery and Engagement Tracking

A natural extension of this work is the deployment of the agentic system with real email delivery infrastructure. Tracking guest interactions with emails would provide valuable feedback signals that could be used to evaluate intervention effectiveness and refine personalization strategies.

11.2.3 Reinforcement Learning for Intervention Optimization

Beyond supervised learning, reinforcement learning approaches could be explored to optimize intervention policies. By treating guest satisfaction outcomes as rewards, the system could learn which interventions maximize long-term satisfaction across different guest segments. This would transform the agentic system from a rule-guided decision engine into a continuously learning optimization framework.

Overall, these future directions offer a pathway toward a fully autonomous, adaptive, and context-aware guest experience optimization system.

12 Conclusion

This project presented the design and implementation of an *Agentic Guest Experience Optimizer*, a proactive artificial intelligence framework for enhancing hotel guest satisfaction before the stay occurs. By combining customer segmentation, supervised satisfaction prediction, explainable AI, and autonomous intervention generation, the system moves beyond traditional reactive feedback mechanisms commonly used in hospitality.

A key contribution of this work is the demonstration that guest satisfaction can be reasonably predicted using only booking-time information and historically inferred customer attributes. Clustering enabled the identification of distinct guest segments with differing expectations and sensitivities, while gradient boosting models provided accurate satisfaction predictions. The integration of SHAP-based explainability ensured transparency and allowed predictive outputs to be translated into meaningful, personalized actions.

The agentic email generation component illustrated how explainable model insights can be operationalized into targeted interventions. Rather than relying on static templates, the system dynamically adapts tone, content, and recommendations based on predicted satisfaction drivers and customer segment characteristics. This approach highlights the potential of agentic AI systems to autonomously reason, decide, and act in real-world service environments.

Overall, the findings suggest that proactive, explainable, and agent-driven personalization can play a significant role in improving guest experience and reducing dissatisfaction risk. The proposed framework offers a scalable and practically feasible foundation for intelligent guest engagement in modern hospitality systems, while also opening avenues for future research in adaptive and reinforcement-based personalization strategies.

References

Cinnamon Hotels Data. Kaggle Dataset. Available at: `https://www.kaggle.com/datasets/asinisusanya/cinnamon-hotels-data`

Appendix A: Sample Feature Tables

Table 6 presents a representative subset of the engineered features used for clustering and satisfaction prediction. Only booking-time and historically inferred attributes are included to reflect realistic deployment conditions.

Feature Name	**Description**	**Type**	**Availability**
stay_nights	Number of nights between check-in and check-out	Numeric	Booking-time
lead_time_days	Days between booking date and check-in date	Numeric	Booking-time
price_per_night	Average room cost per night	Numeric	Booking-time
number_of_guests	Total number of guests in booking	Numeric	Booking-time
is_weekend_stay	Indicator for weekend arrival	Binary	Booking-time
price_sensitivity	Inferred sensitivity to price changes	Inferred	Historical / Derived
quality_expectations	Inferred expectation of service quality	Inferred	Historical / Derived
travel_frequency	Estimated annual travel frequency	Inferred	Historical / Derived
loyalty_propensity	Likelihood of repeat bookings	Inferred	Historical / Derived
cluster	Assigned customer segment label	Categorical	Model-derived
rating	Post-stay overall satisfaction score	Numeric	Post-stay (Label)

Table 6: Representative engineered features used in the final ML dataset

Appendix B: Pseudocode of Core Components

B.1 Feature Engineering Pipeline

```
FOR each booking record:
    Convert date fields to datetime
    Compute stay_nights
    Compute lead_time_days
    Compute price_per_night
    Derive weekend indicator
    Fill missing numeric values with median
RETURN engineered feature set
```

B.2 Customer Segmentation (K-Means)

```
SELECT pre-stay features
STANDARDIZE feature values
FOR k in candidate cluster sizes:
    Train K-Means model
    Compute inertia and silhouette score
SELECT k with best trade-off
ASSIGN cluster labels
```

B.3 Agentic Email Generation Pipeline

```
INPUT booking features
PREDICT satisfaction score
EXPLAIN prediction using SHAP
MAP SHAP signals to guest intents
SELECT interventions based on intents
RENDER personalized email
```