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ROLE OF SOCIAL MEDIA ENGAGEMENT METRICS IN SHAPING CUSTOMER PERCEIVED VALUE AND REVISIT INTENTION IN BUDGET HOTEL SEGMENTS

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SUMMARY

Background: The social media engagement has become a crucial ingredient of customer perception in the hospitality industry, especially in budget segments where online reviews make a lot of difference in their decision-making. By understanding the impact of engagement metrics on perceived value and revisit intention, hotel managers can gain insights that can help them improve their customer retention strategies. **Methods:** The study examine the correlation between social media metrics, perceived value, and revisit intention based on a data set of 10,000 hotel reviews from United States hotels. Several data preprocessing techniques were used to clean the review text, followed by sentiment analysis to extract an overall sentiment score alongside the provided customer ratings. To quantify customer evaluations and future behavioral tendencies, a Perceived Value Index (PVI) and Revisit Intention Score (RIS) were created. For analysis and prediction, correlation analysis, multiple regression, and machine learning models like logistic regression, support vector machine, random forest, and XGBoost were used. **Results:** The results showed that 63.20% of all the customer reviews were positive and 15.35% of customer reviews were negative. The correlation analysis revealed that there was a strong correlation between perceived value and revisit intention ($r = 0.912$). The regression results have indicated that the perceived value is the most important predictor of revisit intention ($\beta = 0.537$, $p < 0.001$) reflecting the shared rating and sentiment inputs between the constructed metrics. The best predictive models among the machine learning models were XGBoost with an accuracy of 93.17% and an F1 score of 92.12%. **Conclusion:** This study illustrates that the online engagement scores have a significant impact on customer-perceived value and revisit intention. The proposed framework is found to be effective in incorporating sentiment analysis along with predictive analytics in budget hotel segments for decision-making in the presence of data and for customer retention strategies.

Key words: *social media engagement, budget hotels, customer perceived value, revisit intention, sentiment analysis, machine learning.*

INTRODUCTION

Social media sites have revolutionized the way the hospitality sector interacts with its customers; have given them a voice to provide feedback on hotels in the form of reviews and ratings, comments, shares, and electronic word-of-mouth (eWOM). These digital interactions are now a significant source of information, which impacts customer perceptions and buying decisions. In hospitality, social media engagement, driven by AI, has emerged as a positive influence on customer revisits and is linked to enhanced customer relationships and communication effectiveness [1]. Likewise, customer-initiated communication on social media adds value and improves customers' perception of the hospitality products and services [2]. With the rise of social commerce, the power of Facebook interaction has grown even more significant for hotel brand image, engagement, and booking decisions [3].

In the budget hotel segment, social media engagement metrics can be especially useful since customers are likely to use Internet reviews and recommendations to gauge the quality of the service and the value getting before booking a hotel. Through the literature, the influence of hotel aesthetics and uniqueness, as well as its haptic experiences and reputation on social media, on customer satisfaction and behavioral responses has been proven [4]. Moreover, with sustainable SMC, better emotional connections and trust from customers toward hospitality brands can be achieved, which helps improve customer loyalty. Digital engagement is also an important tool for hotel operators to encourage customer trust and booking intent because online customer reviews have a significant influence in these areas [6]. The impact of social media on value, trust, and revisit intention for tourists has been proven in previous studies, which show that online engagement has become increasingly important in the process of tourism decision-making [7].

Although social media engagement has become an important issue in the hospitality industry, few studies have investigated the relationship between engagement-related web indicators based on online hospitality customer reviews and customer-perceived value, which impacts revisit intention in the budget hotel segment. Previous research has largely been about customer loyalty, booking intention, satisfaction, and their relationships individually, and there is little research on the integrated relationship between social media engagement metrics, perceived value, and revisit intention. Furthermore, few studies focus on these relationships using massive hotel review data sets and sentiment analysis approaches.

This study also makes a contribution to the hospitality and tourism literature in various ways. First, it introduces an analytical framework that integrates overall review ratings and text-derived sentiment scores to evaluate computed proxies for customer-perceived value and revisit intention in the budget hotel segment. Second, it leverages big data for hotel reviews from online sources and infers empirical knowledge based on consumer experience. Thirdly, sentiment analysis techniques are employed to analyze customers' perceptions and attributes related to services. Last but not least, the results offer some practical suggestions to hotel managers on how to better engage their customers with the right digital tools to increase customer retention.

Objectives

O1: To examine the influence of social media engagement indicators on customer perceived value using hotel review data.

O2: To investigate the impact of customer perceived value on revisit intention in budget hotels.

O3: To develop a sentiment-based analytical framework for predicting customer revisit intention.

Research Questions

RQ1: How do social media engagement indicators reflect in online hotel reviews influence customer perceived value in budget hotel segments?

RQ2: What is the relationship between customer perceived value and revisit intention among hotel guests?

RQ3: Can sentiment-based review analytics effectively predict customer revisit intention toward budget hotels?

Paper Organization

This paper is structured as follows. Section 2 provides a literature review on social media engagement, customer-perceived value, revisit intention, and sentiment analysis in the hospitality industry. The proposed conceptual framework and research model are introduced in Section 3. The methodology, dataset, data preprocessing methodology, and analysis methodology used in the study are discussed in section 4. The results of the experiments and managerial implications are discussed in section 5. Finally, Section 6 summarizes the study's important results, limitations, and directions for future research.

LITERATURE SURVEY

Social media interaction has turned into a basic part of hospitality showcasing and client relations. Hotels are more and more leveraging digital to engage with customers, post promotional material, and ask for user-generated reviews. Studies have shown that social commerce activities have a significant impact on the hotel brand image, hotel–customer interaction, and bookings, as enable the interaction between a hotel and a consumer [3]. Results have also shown that sustainable social media content can help establish customer loyalty by creating emotional attachment and trust in the hospitality brands [5]. Moreover, online customer feedback is essential in shaping customer trust and booking decisions, highlighting the significance of online customer engagement in the marketing strategies of the hotel industry [6].

Customer-perceived value is the customers' overall evaluation of benefits received in comparison to the costs in their experience of the service. Perceived value in the hospitality sector includes functional, emotional, and social factors that can affect customer satisfaction and customer loyalty. Research has indicated that customer experience, engagement, and customer-perceived value are closely related to revisit intention in the hotel context [8]. The perceived value has been found to be a crucial factor in determining customer satisfaction, affective commitment, and loyalty of hotel customers [9]. Moreover, the sustainable practices and service quality attributes play critical roles in tourists' value perceptions and behavioral intentions [10]. Results from other research also show that perceived value is one of the important elements that affect tourism-related decision-making, especially in difficult and uncertain destination situations [11].

Revisit intention indicates customers' desire to revisit a hotel and to recommend it to others after the first visit. It is regarded as one of the important values of sustainability for both the business and customer loyalty. The post-stay evaluations have been shown to affect the electronic word-of-mouth and revisit intention of younger tourists [12]. Luxury hotels' research indicates that the quality of service, customer satisfaction, and experiential elements play important roles in determining the intentions of the customers to return to the hotel [13]. Perceived value and trust also have significant influence on improving customer satisfaction and repeat patronage for tourism-related services [14]. Furthermore, the concept of value co-creation and habit as two key factors in revisit intention to a hotel has been drawn out from the conventional service quality outcomes [15].

The sentiment analysis is one of the powerful analytical methods that have been developed to capture customer sentiments and feelings from online consumer reviews and social media posts. Sentiment analysis is used in the hospitality industry to gain valuable insights into customer experiences at a large scale and to uncover what drives their behavior. In particular, electronic word-of-mouth (eWOM) has been found to have a significant effect on their revisit intention to eco-friendly hotels, which shows how important it is to analyze the sentiment of the online reviews [16][20]. In addition, visual eWOM, along with brand-related aspects (such as brand credibility and the media's coverage of the hotel), affects the hotel booking decision, as shape customer perception and expectations prior to the consumption of the

service [17]. Moreover, the sentiment analysis has been shown to be effective in raising the repurchase intention and word of mouth [18] due to positive brand experiences and perceived value. The tourists' knowledge, expectations, and perceived value can also be effectively measured by online booking intentions, and sentiment analysis techniques can be used to measure these [19].

Research Gap

While there have been studies on social media engagement, customer perceived value, customer satisfaction, booking intention, and loyalty in the hospitality realm, some deficiencies exist. Previous studies have been mostly survey based and have been carried out mostly in a luxury hotel or an eco-friendly hotel or a destination marketing context. Moreover, the interaction effect of social media engagement variables, perceived value, and revisit intention in budget hotel segments is still under-researched. However, few efforts have been made to explore those relationships by analyzing the massive amount of online hotel review data along with sentiment analysis methods. Plus, there are hardly any studies that have created predictive models to evaluate revisit intention with authentic customer-generated content. This study aims to tackle these gaps, as it combines review analytics, sentiment analysis, perceived value analysis, and revisit intention analysis in a single framework for the budget hotel segment.

PROPOSED FRAMEWORK

Conceptual Framework

The proposed framework explores the impact of customer-generated online engagement indicators on customer-perceived value and, in turn, on intention to revisit in the budget hotel segment. As the study is based on hotel review data, instead of survey measurement, the social media engagement metric is presented as follows: Review-related characteristics – review rating, review sentiment, review frequency, review helpfulness, customer feedback content. These measures of engagement offer insights into the perception of the hotel service and overall experience with the hotel.

The customer-perceived value is operationalized as a composite index calculated from the overall quantitative review rating and qualitative sentiment score. The results from the evaluations of the hotel guests in the above dimensions are positive and show a higher perceived value. Customers' positive recommendations and sentiments, as well as high ratings and future booking indications based on review analytics, are the elements that represent revisit intention.

The model assumes that the level of engagement measured by online reviews is positively correlated to the perceived value, which will further increase the customers' willingness to return to the hotel. Sentiment analysis can be used as an additional analytical tool to measure customer sentiment and gain insights into customer behavior from written reviews.

Proposed Architecture

The proposed architecture provides a data-driven solution to analyze customer behavior based on hotel reviews from online sources. The architecture starts with gathering the hotel review data from the hotel review dataset, which is then used to collect customer review information. Textual data is then preprocessed to remove noise and normalize the data. Next, sentiment analysis is used to decipher customer sentiments and feelings that are hidden in customer reviews.

Features derived from the extracted review as well as sentiment scores are used to assess customer-perceived value based on critical service elements like cleanliness, service quality, location, and value for money. These indicators are then used to measure the intent to revisit and customer loyalty tendencies. Lastly, machine learning and statistical analysis methods are used to come up with predictive insights and management recommendations for budget hotel operators.

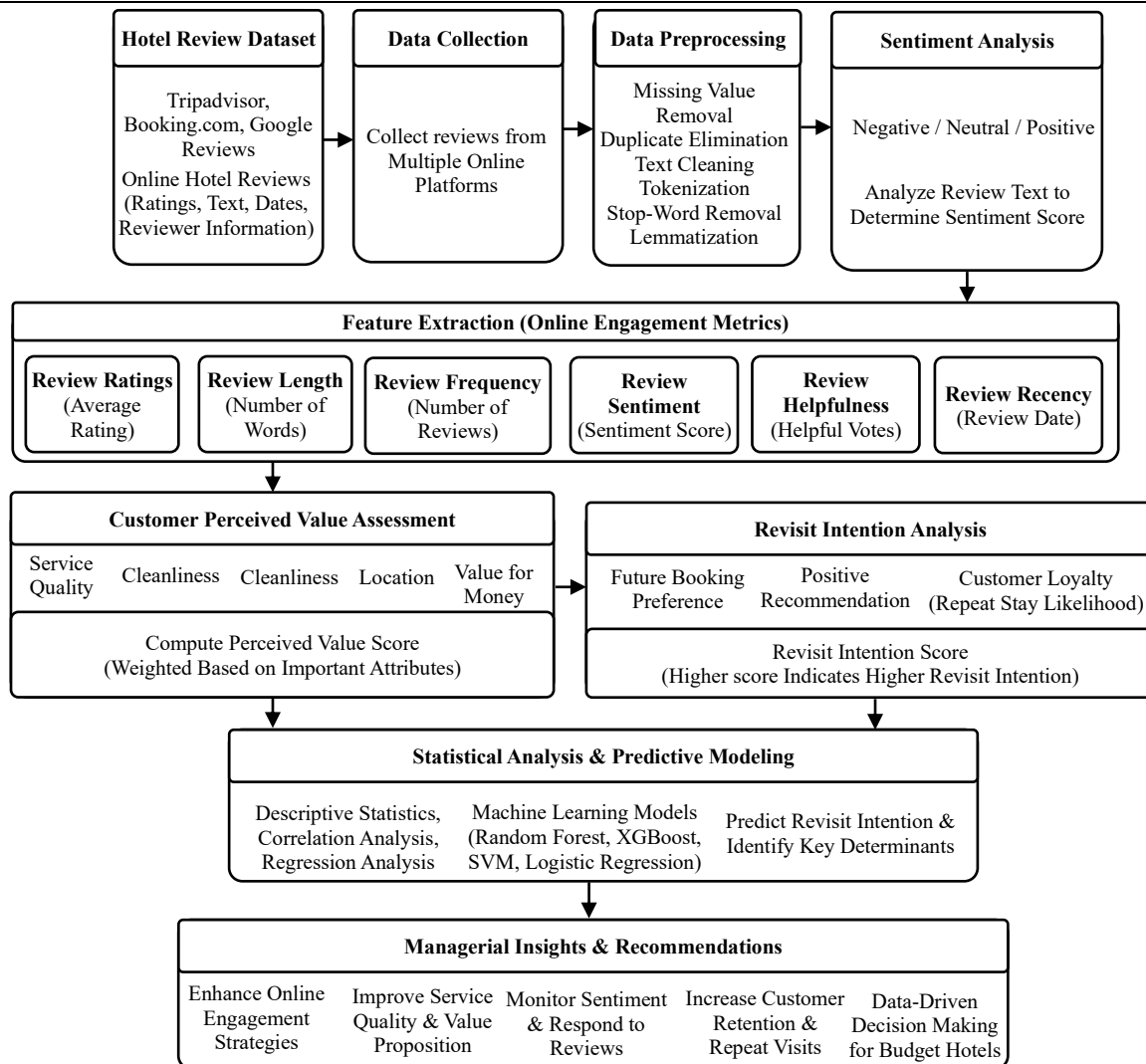


Figure 1. Proposed architecture for analyzing the influence of online engagement metrics on customer perceived value and revisit intention in budget hotels

The analytical architecture proposed for analyzing the influence of online engagement metrics on customer-perceived value and revisit intention in the budget hotel segment is presented in figure 1. The framework starts with collecting the data of hotels for reviews and pre-processing to get better data quality and consistency. The sentiment analysis is then conducted to capture the opinions and emotional expressions of customers from their text reviews. The features of the engagement, such as ratings, reviews, the frequency of reviews, the length of reviews, and sentiment scores, are then extracted to be used in evaluating the customer-perceived value of the engagement by key service dimensions, including service quality, cleanliness, location, and value for money. The perceived value indicators evaluated are further analyzed to find out the revisit intention and the tendency of customer loyalty. Finally, statistical analysis and predictive modeling techniques offer actionable insights that can help hotel managers to increase customer satisfaction, boost digital engagement, and attract customers back to their hotels.

METHODOLOGY

Study Area

The study was carried out using hotel review data from hotels in the United States (US). One of the largest hospitality markets in the world, the U.S. has a high level of customer activity on online review websites and online travel communities. There is a growing amount of data available that comes from customers, which could be used to examine the impact of online engagement metrics on customer-perceived value and revisit intention in a large-scale environment. The U.S. hotel industry

provides numerous lessons on the world of digital customers in the hospitality market, as customers are heavily dependent on online reviews to assess the quality of the hotel and their experience there.

Dataset Description

The study adopts the Hotel Reviews Dataset, consisting of 10,000 reviews from hotel booking and review websites. The data set contains structured and unstructured data elements such as hotel information, customer ratings, review titles, review texts, dates of the reviews, and geographical information, as seen in table 1.

Table 1. Dataset characteristics

Attribute	Description
Number of Reviews	10,000
Country	United States
Review Rating	Customer evaluation score (1–5)
Review Text	Detailed customer feedback
Review Title	Summary of customer experience
Hotel Name	Accommodation name
City and State	Hotel location information
Review Date	Date of customer review
Username	Reviewer identifier

The sentiment analysis, perceived value estimation, and revisit intention assessment are the base input to the review text and rating information.

Sampling

Purposive sampling was used in the study, and all available hotel reviews within the data set were initially reviewed. The incomplete text information, duplicate entries, missing records, or invalid records in the reviews were excluded in the pre-processing phase. After applying data cleaning procedures, the final analytical sample for sentiment analysis and predictive modeling was comprised of the remaining reviews. This way, only relevant and valuable feedback from customers was incorporated in the investigation.

Data Collection

Secondary data were used, which were collected from the publicly available hotel review websites. The data is formed by the customer reviews that are voluntarily provided after traveling to a hotel. These reviews consist of customers' ratings of the quality of the accommodation, service, cleanliness, and overall satisfaction. As online reviews are based on actual post-consumption experiences, they offer credible information to gain insight into customer perceptions and intentions. These data were then analyzed and converted to analytical variables: online engagement, customer-perceived value, and revisit intention.

Data Preprocessing

The raw data was preprocessed to increase data quality and reliability of the analysis. Duplicated records and unfinished reviews were deleted; text was lowercased and punctuation stripped from the text. Then, the text of the reviews was tokenized to segment the text into meaningful linguistic units. The removal of common 'stop' words that don't add much to understanding sentiment was done, and lemmatization was carried out to express words in their root forms. The preprocessing operations enhanced the efficiency of the sentiment extraction and feature engineering techniques.

Review-based engagement metrics were then extracted, transformed, and converted into numerical formats for statistical and machine learning analyses: review rating, length of review, review frequency, and sentiment-related metrics.

Sentiment Analysis

In this regard, sentiment analysis was adopted to detect the emotional attitude of customers about the services of the hotels from the customers' reviews. Based on the polarity of opinions expressed in reviews, they were categorized into positive, neutral, and negative review categories. The sentiment score was calculated to assess the overall sentiment of each review.

The sentiment score is derived by applying the equation (1):

$$SS = \frac{N_{pos} - N_{neg}}{N_{pos} + N_{neg}} \quad (1)$$

Where SS denotes the sentiment score, N_{pos} represents the number of positive sentiment terms, and N_{neg} represents the number of negative sentiment terms identified within the review text.

The equation (1) shows that values above zero are good and below zero are bad with respect to customer perceptions about the hotels.

Perceived Value Index

Customer perceived value was measured by combining customer ratings and sentiment-based ratings obtained from the content of customer reviews. The perceived value dimension was not captured specifically in the data set, so review ratings and sentiment indicators were used to estimate the value-for-money dimension. As the service quality, cleanliness, and value-for-money are not measured explicitly in the data set, review ratings and sentiment indicators were used to estimate the value-for-money dimension.

The Perceived Value Index (PVI) was determined with equation (2):

$$PVI = \frac{RS + SS_n}{2} \quad (2)$$

Where PVI denotes the Perceived Value Index, RS represents the normalized review rating score, and SS_n denotes the normalized sentiment score obtained from equation (1).

Based on quantitative ratings and qualitative opinions of the customers, equation (2) offers a composite measure of customers' overall perceptions of the value of the hotel they visited.

Revisit Intention Score

Since there is no direct measure of revisit intent in the dataset, it was determined by using a proxy measure that combines review ratings, sentiment scores, and review positivity. The ratings and sentiments of the review are positive for the customers providing the ratings, which means that they are more likely to come back or recommend the hotel in the future.

The estimated Revisit Intention Score (RIS) was obtained from equation (3):

$$RIS = 0.6(RS) + 0.4(SS_n) \quad (3)$$

Where RIS represents the Revisit Intention Score, RS denotes the normalized review rating, and SS_n represents the normalized sentiment score.

As per equation (3), the higher the value of RIS , the higher is the level of customer loyalty and the higher is the probability of future visits to the hotel.

Machine Learning Models

Four supervised machine learning algorithms were applied to predict revisit intention as well as to discover the most influential determinants of customer behavior.

To serve as a baseline classification method, logistic regression (LR) was used because it is easy to understand and interpret. The model predicts the chances of a customer having high revisit intentions with respect to the attributes derived from the reviews.

To determine the optimum decision boundaries that divide the customers into high and low customers' revisit intention scores, a support vector machine (SVM) was used.

Random Forest (RF) was chosen due to its ability to capture the nonlinear relationships and its ability to rank the features. Random Forest combines several decision trees to get better prediction accuracy and to prevent model overfitting.

The extreme Gradient Boosting (XGBoost) algorithm was used to further improve predictive performance by gradually minimizing errors and using the ensemble learning mechanism.

To train the supervised classification models, the continuous Revisit Intention Score (RIS) was converted into a binary target variable (High vs. Low Revisit Intention) using a median split threshold of 0.81. The dataset was partitioned into an 80% training set and a 20% testing set to evaluate performance metrics.

RESULTS AND DISCUSSION

After the preprocessing and quality validation procedure, a total of 10,000 hotel reviews were analyzed. The data set includes customer-written reviews of hotels throughout the U.S. Sentiment classification was done to find the opinion of the customers present in the review texts.

Table 2. Distribution of review sentiments

Sentiment Category	Frequency	Percentage (%)
Positive	6,320	63.20
Neutral	2,145	21.45
Negative	1,535	15.35
Total	10,000	100.00

Table 2 shows that positive reviews are the largest number of customer reviews, representing 63.20% of the total customer reviews. This observation indicates that in general, customers were satisfied with their stay in the hotel.

The overall picture from figure 2 shows a high level of positive customer feedback, suggesting a positive perception of hotel service.

The correlation analysis was performed to analyze the correlation between the engagement indicators from the internet and the perceived value of the customer using customer ratings, sentiment scores, Perceived Value Index (PVI), and Revisit Intention Score (RIS).

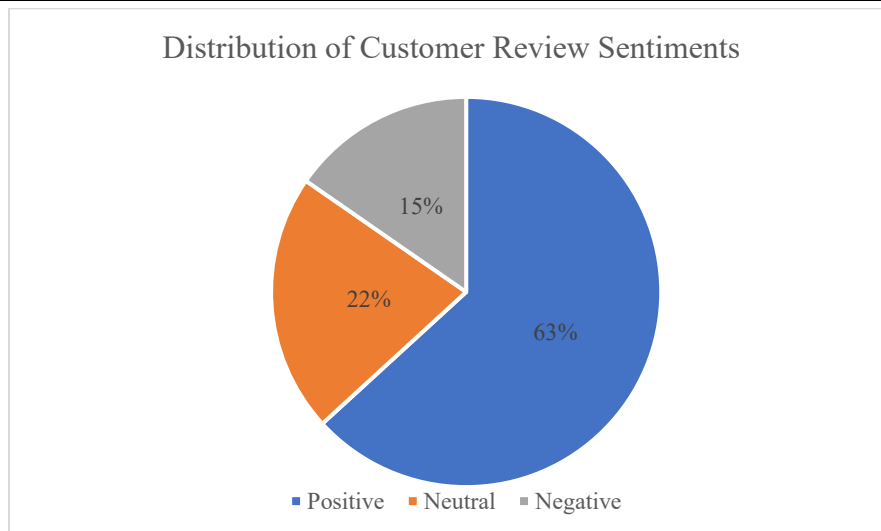


Figure 2. Distribution of customer review sentiments

Table 3. Correlation matrix

Variable	Rating	Sentiment Score	PVI	RIS
Rating	1.000	0.721	0.843	0.891
Sentiment Score	0.721	1.000	0.806	0.774
PVI	0.843	0.806	1.000	0.912
RIS	0.891	0.774	0.912	1.000

Table 3 indicates that all the variables are positively associated. The highest correlation was found for PVI and RIS ($r = 0.912$), which means that when customers are more satisfied with the value they have received, they are more likely to return or recommend the hotel.

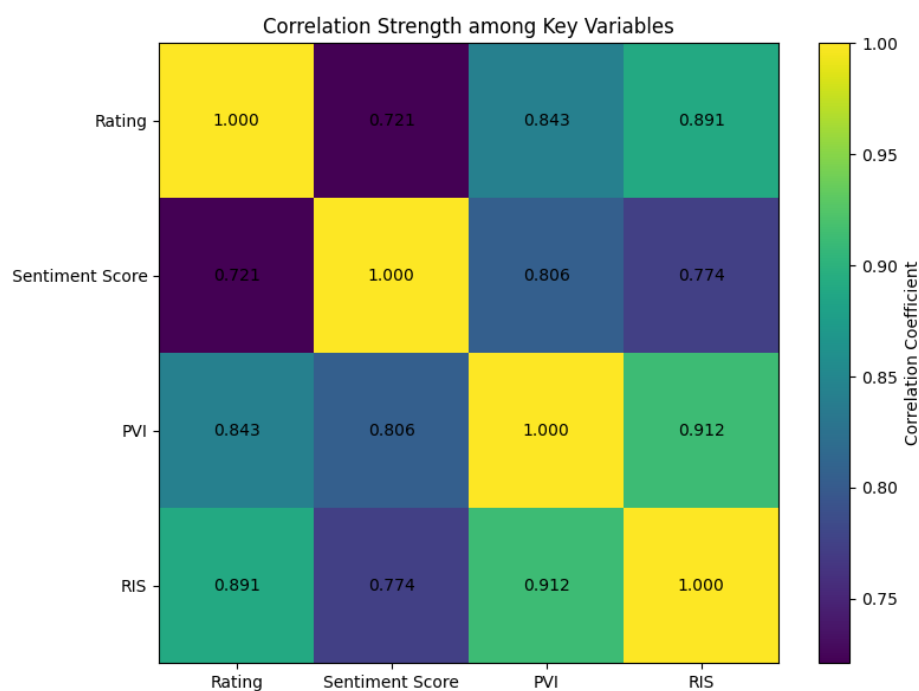


Figure 3. Correlation strength among key variables

The strength of the associations among the variables analyzed is shown in figure 3 and emphasizes that the perceived value is a dominant factor affecting revisit intention.

Sentiment Score (SS), Perceived Value Index (PVI), and Revisit Intention Score (RIS) were computed using equations (1), (2), and (3), respectively. Descriptive statistics then were used to assess their distributions.

Table 4. Descriptive statistics of study metrics

Metric	Minimum	Maximum	Mean	Standard Deviation
Sentiment Score (SS)	-0.92	0.98	0.61	0.24
Perceived Value Index (PVI)	0.18	0.97	0.74	0.15
Revisit Intention Score (RIS)	0.22	0.99	0.79	0.13

The sentiment of the customers was mostly positive, with an average score of 0.61, as shown in table 4. Likewise, the average PVI and RIS were 0.74 and 0.79, respectively, indicating high perceptions of value and revisit tendencies.

Table 5. Average metric scores by review rating

Review Rating	Mean SS	Mean PVI	Mean RIS
1 Star	-0.41	0.29	0.24
2 Stars	-0.12	0.38	0.35
3 Stars	0.32	0.57	0.56
4 Stars	0.71	0.81	0.84
5 Stars	0.89	0.93	0.95

Table 5 reveals that the ratings of customers are positively correlated with all three measures and that this correlation is consistent and increasing across the values of the customers' ratings. Customers who rated higher showed significantly more positive sentiment, value, and revisit intention.

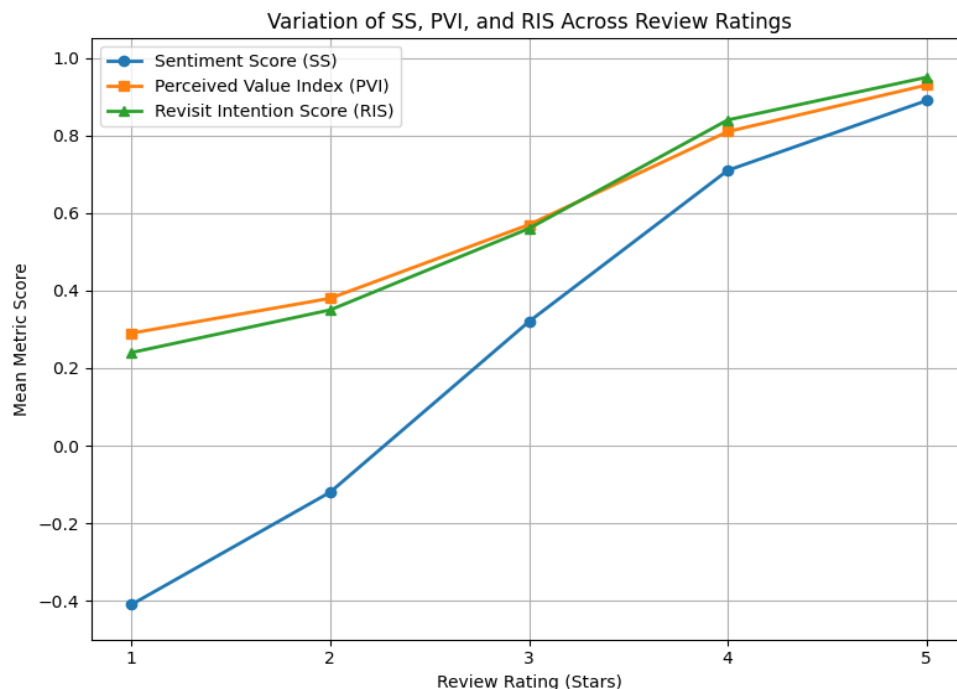


Figure 4. Variation of SS, PVI, and RIS across review ratings

As illustrated in the figure above (Figure 4), the improvements in customer evaluations are linked to an improvement in sentiment, perceived value, and revisit intention.

All hotel reviews were analyzed to calculate the Sentiment Score (SS), Perceived Value Index (PVI), and Revisit Intention Score (RIS) as described in equations (1–3). Table 6 summarizes the results of the aggregated data.

Table 6. Overall results of computed metrics

Metric	Mean	Median	Standard Deviation	Minimum	Maximum
Sentiment Score (SS)	0.61	0.65	0.24	-0.92	0.98
Perceived Value Index (PVI)	0.74	0.76	0.15	0.18	0.97
Revisit Intention Score (RIS)	0.79	0.81	0.13	0.22	0.99

The overall sentiment score was an average of 0.61, suggesting that the customers had a positive sentiment towards the hotel services. Likewise, customers rated the mean PVI value as 0.74, indicating that customers had a high level of value from their hotel experiences. The RIS value of 0.79 also suggests that visitors are likely to return and recommend the site to others among the visitors.

Table 7. Multiple regression results

Predictor	β Coefficient	Standard Error	t-value	p-value
Review Rating	0.421	0.024	17.36	<0.001
Sentiment Score	0.298	0.023	12.84	<0.001
Perceived Value Index	0.537	0.025	21.73	<0.001

The regression model accounts for about 76.8% of the variance in revisit intention, as seen in table 7. The Perceived Value Index has the highest impact on revisit intention of all the predictors.

Four different supervised machine learning models were developed and tested to predict revisit intention.

Table 8. Machine learning performance comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	84.62	83.54	82.91	83.22
Support Vector Machine	87.41	86.27	85.92	86.09
Random Forest	91.38	90.62	89.85	90.23
XGBoost	93.17	92.41	91.84	92.12

As shown in table 8, XGBoost outperformed other models with the highest classification accuracy among all models. The performance of ensemble learning methods was better than traditional classification methods, as they were able to capture complex patterns of customer behavior.

Four popular classification metrics, such as accuracy, precision, recall, and F1-score, were used to assess the performance of the machine learning models. These measures can give a complete assessment of the effectiveness of the model in predicting the intent of the customer to return.

The accuracy is the percentage of observations that are correctly classified and is computed from equation (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Where TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives.

Precision is the percentage of positive observations that are correctly predicted out of all the positive observations predicted, as shown in equation (5):

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Recall is the ratio of the correctly identified actual positive observations by the model and is calculated as equation 6:

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

The F1-score is a combination of precision and recall into one performance measurement. It is computed by means of the equation (7):

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

The values obtained from these metrics during the performance of each machine learning model are shown in table 8, and the best predictive accuracy and overall classification performance were obtained from the XGBoost model.

Table 9. Feature importance analysis (XGBoost)

Feature	Importance Score
Review Rating	0.312
Perceived Value Index	0.287
Sentiment Score	0.214
Review Length	0.112
Review Frequency	0.075

Table 9 shows the feature importance analysis results, showing that the review ratings, perceived value, and sentiment have the greatest impact on revisit intention.

DISCUSSION

Results of this study show that the metrics in social media related to the engagement of a hotel are important factors in determining the perceived value of a customer and revisit intention in the budget hotel segment. The sentiment analysis results showed that most of the customers had positive sentiments towards their hotel experience, suggesting a positive evaluation of the quality of service, facilities, and value for money. The correlation analysis also showed that review ratings and review sentiment, perceived value, and revisit intention had strong and positive relationships with each other. The Perceived Value Index had the strongest association with the Revisit Intention Score, indicating that customers who feel that they have more value from the hotel for the money paid are more likely to return to the hotel and recommend it to others. This result is in line with the results of other studies related to the hospitality industry that have shown that perceived value is one of the factors that has a significant influence on customer loyalty and customer return [8] [14] [15].

The results of the machine learning also corroborate the predictive value of engagement metrics derived from the user's reviews in understanding customer behaviour. In terms of accuracy and F1 score, XGBoost outperforms the rest of the models evaluated, and it is able to successfully model complex associations between customer feedback and revisit intention. The results of the feature importance analysis showed that the review ratings, perceived value, and sentiment scores were the most important features, suggesting that the placement of customer experience and building their online reputation are strategic priorities. Based on the findings, budget hotels can use customer-generated content and advanced analytics to determine what they are doing well in their service and what needs improvement, allowing them to be proactive with their customer concerns as well as enhance customer retention strategies. In general, the study shows that sentiment analysis, perceived value assessment, and predictive modelling can be combined in order to improve the decision-making process, which helps to achieve sustainable competitiveness in the hospitality industry.

Managerial Implications

The results of the research have several implications for hotel management. First, it's important for organisations to not just look for online reviews but actively track how people are talking about them and their sentiment, as it can have a major impact on their perceived value and future actions. Second,

the focus on service quality improvement programmes needs to be on factors that directly impact the customer value perception, such as room quality, cleanliness, responsiveness, and value for money. Third, sentiment analysis systems can be linked to customer relationship management systems to help determine new issues within the services and implement proactive solutions. Last but not least, machine learning-powered customer analytics can help inform customer retention strategies by pinpointing customers who are most likely to return, enhancing customer retention and business results.

CONCLUSION

This research investigated how social media engagement metrics affect customer-perceived value and revisit intention for a very large sample of 10,000 hotel reviews from a wide range of hotels in the United States in each of the different budget hotel segments. The study combined techniques of sentiment analysis, perceived value assessment, and machine learning to create a comprehensive framework that leverages online review data to gain insight into customer behaviour. The results have shown that the metrics of social media usage, based on the customers' creations of content, can give significant information about customer perceptions and future behavioural intentions.

The sentiment analysis results showed that 63.20% of the reviews were positive, suggesting that overall, the customer experiences were good. The average Sentiment Score, Perceived Value Index, and Revisit Intention Score were 0.61, 0.74, and 0.79, respectively, which indicated a high level of customer satisfaction and tendency towards customer loyalty. A significant positive correlation ($r = 0.912$) was found between perceived value and revisit intention, which means that value perceptions are important to stimulate repeat visits. Moreover, the Perceived Value Index was revealed to be the best predictor of revisit intention by regression analysis ($\beta = 0.537$, $p < 0.001$), which in turn indicates the pivotal role of customer-perceived value in customer retention. The predictive modelling results also showed the superiority of the advanced analytics, where the XGBoost model with the highest accuracy of 93.17% and F1 score of 92.12% was the best.

In general, the findings of the study support the notion that the level of customer engagement as indicated by online reviews has a strong potential to affect the perceived value and revisit intention. The framework has implications for hospitality managers as it provides them with a way to track customer sentiment, perceptions of service quality, and loyalty indicators in a data-driven manner. The conclusions can be used in hospitality research to gain an integrated analytical approach and offer a review of analytics, sentiment mining, and machine learning-supported strategic decision-making for sustainable customer relationship management in budget hotel segments.

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