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Predicting Key Factors Impacting Online Hotel Ratings Using Data Mining Approach: A Case Study of the Makkah City of Saudi Arabia

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Abstract

In the digital era, hotels' online reviews shape consumer behavior and satisfaction, consequently influencing hotel bookings and revenue stream. Previous research investigated the factors impacting hotels' online ratings in commercial cities; however, this study analyses the hotels' online ratings in Saudi Arabia's key religious city Makkah by data mining popular Booking.com website using classification approach. The present study employs consideration set theory as the theoretical lens and finds seven hotel attributes as the awareness set (in the priority order), viz. facilities, comfort, cleanliness, staff, location, value for money, and free WiFi. Except for value for money and free WiFi, the rest of the five hotel attributes constitute the consideration set. Hotel facilities being the most important factor, form the choice set. The study results indicate that value for money is less important in religious destinations than commercial destinations. Further, free WiFi is less critical to influence consumer ratings these days as almost all hotels provide it, and consumers have alternatives like mobile internet plans. As religious tourism is expected to drive future economic growth of nations, this study's findings would empower the hospitality and tourism industry (specifically hotels) in tourism destinations, especially Saudi Arabia, in line with its Vision 2030.

Disciplinary: Business Management and Information Systems, Hotel Management, Tourism and Hospitality.

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1 Introduction

A country's performance depends on its enterprises, which certainly includes its hospitality and tourism industry. The hotel industry is among the most critical departments of the hospitality and tourism industry. Globally, there is a rising demand for quality hotel services. In earlier times, the traditional word of mouth (WOM) played a crucial role in shaping consumer perception. With the rising use, usage, and users of the internet in the present time (Singh, 2017; Singh, 2018a; Singh, 2018b; Alshammari & Singh, 2018; Singh & Alshammari, 2020), online word of mouth (E-WOM) plays a crucial role in shaping consumer perception. As social media and online user-generated content (UGC) are becoming increasingly common, customers rely on various websites (like Booking.com, Hotels.com, Hotwire.com, Agoda.com, etc.) to review hotel ratings and make bookings. Online reviews can be defined as informal online communications directed at consumers related to the features of particular services and products or their sellers (Litvin et al., 2008).

According to the World Tourism Organization (2014), religious heritage sites would drive international tourism and economic growth in the future. So, it is sensible to expect that the hospitality and tourism industry (specifically hotels) located in religious cities would play a vital role towards this end. In this research, we take the example of Saudi Arabia, specifically the city of Makkah, and collect the online ratings given by consumers to Makkah's hotels. We believe that Makkah provides an excellent example to build our case as it is an important religious heritage site. The city of Makkah is witnessing an increasing inflow of tourists over the years. In 2015, more than 17.5 million worshippers and pilgrims visited Makkah, and the numbers are expected to rise between 25 and 30 million in 2025 (Arab News, 2016). We further believe that Saudi Arabia is an excellent example to study this case as its government policy is also actively aiming to promote the hospitality and tourism industry (of which hotels are a part). The key government policy of Saudi Arabia, Vision 2030, aims to boost non-oil revenue to $160 billion by 2020 from 43.5 billion in 2015. Specifically, for the hotel industry, Saudi Arabia plans to more than double its total number of hotel rooms as part of vision 2030 (Dickinson, 2016). Such policy initiatives by the Saudi government and the importance of Makkah's key religious heritage site make it an ideal environment to conduct this research to determine factors impacting hotels' online ratings.

Online consumer reviews are typically generated using numerical ratings, text-ratings, the number of likes and dislikes, and positive and negative reviews (Pan & Zhang 2011). In this research, we collected the numerical online reviews data of hotels located in Makkah from the popular website Booking.com. The online consumer review of Booking.com is based on cleanliness, comfort, location, facilities, value for money, free WiFi, etc. Existing research has extensively employed various techniques to analyze online review data, such as surveys (Senders et al., 2013), case studies (Munar & Jacobsen, 2013), and interviews (Ayeh et al., 2012), etc. However, data mining techniques still require further investigation, as they can present novel knowledge, patterns, and trends compared to other approaches (Dua & Du, 2016). So, we would analyze the online numerical ratings of the hotel attributes using data mining techniques.

This study endeavors to develop a model that mines online consumer reviews of booking websites to predict key factors that impact hotels' online ratings. Following are the objectives:

1. Investigate role of leveraging online hotel reviews to enhance customers' satisfaction.
2. Generate quality datasets from filter criteria results and consumer reviews of booking website (Booking.com) for data mining.
3. Analyze generated quality datasets and determine the best algorithm for predicting key factors impacting online hotel ratings.
4. Leveraging the best algorithm and theoretical framework of the study to construct a model of factors impacting online hotel ratings.
5. Ranking the key factors impacting online hotel ratings in order of significance.
6. Suggest strategies to enhance customer satisfaction and improve hotel ratings.

2 Literature Review

The consumer choice of hotels depends on various factors. Hua et al.'s (2009) Chinese budget hotels study report that hotels' comfort, value for money, service quality, location, etc. are important in influencing customers' purchase decisions. As per Verma (2010), the hotel's location, brand name, facilities, price, quality of service, loyalty programs, etc., influence their online ratings. Bulchand-Gidumal et al. (2011) European study report that hotels' free WiFi facilities improve their online ratings by up to 8 percent. The study further recommends hotels to provide reasonably priced Information and Communication Technology (ICT) based services (like WiFi) to consumers. As per Öğüta & Cezara's (2012) Paris study, hotel location, facilities, cleanliness, comfort, staff friendliness, etc., are critical quality dimensions of online consumer ratings. Phillips et al.'s (2016) Swiss hotels study report that hotels' cleanliness, location, value for money, friendliness of the staff, etc., influence their online review ratings. As per the study of Raguseo & Vitari (2017) French study, hotels' comfort, cleanliness, facilities, value for money, etc., influence hotels' online review ratings. Chang et al. (2019) Hilton hotels study in the US reports that location, cleanliness, room service, etc., influence online ratings' consumer decisions.

The literature review demonstrates the importance of online reviews in influencing consumer decisions to book hotels and establish their significance as a mirror of consumer satisfaction. Various factors influence hotels' online ratings; the prominent among them include hotel facilities, comfort, location, staff, breakfast, cleanliness, value for money, free WiFi, etc.

3 Theoretical Background

The myriad factors impacting online ratings of hotels identified by the literature review inform the consumers about the hotel's reputation. They represent the consumers' informative component and play a key role in building hotels' online image. Marketing theorists relate this informative component to awareness of a product or brand (Keller, 1993). Online reviews build online awareness of consumers towards hotels' digital reputation and influence their decision-making (Sorensen & Rasmussen, 2004). The marketing theory that studies the importance of consumer awareness in influencing their decision making is consideration-set theory. So, this research chooses consideration set theory to build a theoretical framework for this study. Consideration set theory has been previously used in the literature to model the influence of online review ratings on consumers' choice. The research of Vermeulen & Seegers (2009) deployed this theory to study the impact of review valence (negative vs. positive reviews), hotel familiarity (lesser vs. well-known hotels), and expertise of reviewer (non-expert vs. expert reviewers) on the consumer choice of hotels. However, this research would differ from the Vermeulen & Seegers (2009) study, as we examine the impact of factors like facilities, comfort, location, staff, breakfast, cleanliness, value for money, free WiFi, etc. on the consumers' choice of hotels.

Consideration set theory describes consumer decision making as a multi-stage process. The first stage is the awareness set, i.e., the set of all possible choice options they consider under given circumstances. Consideration set is the second stage and contains narrowed down choices from the awareness set. The third stage is the choice set. In this stage, the consumers reduce their choice(s) from the consideration set to a single factor or very small choice set.

This research utilizes the consideration-set theory and produces a decision tree by data mining the online hotel ratings data collected using Booking.com from Makkah, Saudi Arabia. All the hotel attributes presented by Booking.com on which consumers give a star rating and selected via the Weka ranker search method constitute the awareness set. The intermediary nodes and the root node generated by the best performing decision tree form the consideration set. The root node of the best performing decision tree represents the choice set.

4 Research Methodology

The study is conducted as per the following phases of the Cios et al. (2000) adapted model:

- Phase 1: Problem domain understanding –We reviewed various literature.
- Phase 2: Data understanding – In this phase, we collected aggregate numerical rating data in Microsoft Excel from Booking.com. We examined the online rating criteria employed by Booking.com. Accordingly, we considered ten non-class attributes: the hotel name (HN), hotel facilities (FA), comfort (CO), location (LO), staff (ST), breakfast (BR), cleanliness (CL), the value for money (VM), free WiFi (FW), and restaurant availability (RE). We selected the review score (RS) as the class attribute. Except for the hotel name, customers gave a numerical rating from 1 to 10 to other attributes. Data were collected in May 2019, and 172 hotels were available. The attribute relevance analysis was conducted to select relevant attributes. The attributes having large missing values were ignored as they would not enter the consideration set of consumers. Breakfast and restaurant attributes contained 119 and 104 missing values, respectively —thus ignored.
- Phase 3: Data pre-processing and preparation – In this phase, we pre-processed the data and controlled its quality. Following Larose & Larose (2014) guidelines, we checked and controlled for data incompleteness, redundancy, inconsistencies, missing values, outliers, and noise. We disregarded the attribute name of hotels as it could not affect the data mining tasks. The hotels having missing values were deleted from the dataset. Accordingly, 155 hotels were selected from a total of 172. The selected seven non-class attributes and class attribute 'review score' were

discretized as per the Booking.com criteria (Table 1). Further, we converted the data in Microsoft Excel into the Weka 3.9.4 understandable format for experimentation.

Table 1: Attribute Scores Discretization.

Attribute Score	Discretized Score	Description	Abbreviation
9.0-10.0	1	Wonderful	WO
8.0-8.9	2	Excellent	EX
7.0-7.9	3	Very Good	VG
6.0-6.9	4	Good	GD
5.0-5.9	5	Okay	OK
<5.0	6	Poor	PO

- Phase 4: Data mining –We used the classification method to construct a model for predicting the key factors impacting online ratings of hotels. We selected the algorithms that could generate decision trees to delineate the awareness, consideration, and choice sets of the consideration set theory.
- Phase 5: Evaluation of discovered knowledge –We used the best performing tree-generating algorithm to identify the awareness, consideration, and choice sets of the consideration set theory. All the data mined attributes form the awareness set. The consideration set consists of attributes in the intermediary nodes and the root node. The root node attribute is the choice set.
- Phase 6: Use of discovered knowledge – We used the identified sets of attributes to draw relevant conclusions and recommendations.

5 Modeling and Evaluation

We built the research model by entering the data into Weka 3.9.4 software. The model's dataset consists of 7 non-class attributes, 1 class attribute, and 155 instances. Before conducting the experiments, we balanced the dataset using the target attribute (Larose & Larose, 2014).

5.1 Balancing the Dataset

We applied Weka's resample filter to the class attribute 'review score' to balance the dataset. While using the resample filter, we set the BiasToUniformClass to 1.0 to ensure uniform class distribution. After resampling, the number of classes of the target attribute is 25 each. The total instances of the dataset reduce to 150 from 155.

5.2 Evaluation of Attributes

We evaluated the attributes using information gain and gain ratio evaluators of the Weka ranker search method. Both evaluators selected all seven non-class attributes (Table 2). So, we conducted the experiments using all the seven non-class attributes and 1 class attribute.

Table 2: Results of Ranker Search Method.

Attribute	Weight	Attribute	Weight
Facilities	1.938	Facilities	0.758
Comfort	1.875	Comfort	0.730
Cleanliness	1.840	Cleanliness	0.742
Staff	1.711	Staff	0.689
Location	1.450	Location	0.594
Value for Money	1.255	Value for Money	0.556
WiFi	0.920	WiFi	0.439

We applied 10-folds cross-validation to the dataset to build the classification model as it the most common and widely used method in data mining and machine-learning (Refaeilzadeh et al., 2009). We conducted the experiments on the dataset with and without pruning the decision-tree generating algorithms. We conducted experiments with and without pruning using CDT, J48, J48Consolidated, and REPTree algorithms to generate decision-trees with meaningful attributes.

5.3 Experiments with Pruning

Table 3 depicts each tree-generating pruned algorithm's performance to indicate correctly and incorrectly classified instances. Table 3 also displays the tree's size and the number of leaves generated by the pruned decision-tree algorithms.

Table 3: Pruned Algorithms Classification Performance.

Algorithm	Correctly Classified	Size of Tree	Number of Leaves
CDT	78%	25	18
J48	84.67%	43	36
J48Consolidated	85.33%	25	21
REPTree	82.67%	25	21

We further examined each pruned algorithm's performance for accuracy, the weighted average of True Positive (TP) rate, False Positive (FP) rate, precision, recall, and F-Measure. Table 4 portrays the results of this experiment.

Table 4: Pruned Algorithms Weighted Average Performance.

Algorithm	TPRate	FPRate	Precision	Recall	F-Measure
CDT	0.780	0.044	0.770	0.780	0.766
J48	0.847	0.031	0.843	0.847	0.845
J48Consolidated	0.853	0.029	0.851	0.853	0.851
REPTree	0.827	0.035	0.826	0.827	0.820

Tables 3 and 4 demonstrate that the J48Consolidated algorithm outperforms other algorithms in classification accuracy, TPRate, precision, recall, and F-measure. Table 3 also shows that the J48Consolidated algorithm is less complicated than J48 as it has a smaller size of tree and number of leaves. Its complexity equals REPTree and is slightly more than CDT. Overall, the J48Consolidated algorithm is preferable as compared to other pruned algorithms.

5.4 Experiments without Pruning

Table 5 presents each tree-generating unpruned algorithm's performance to indicate correctly and incorrectly classified instances. Table 5 also depicts the tree's size and the number of leaves generated by the unpruned decision-tree algorithms.

Table 5: Unpruned Algorithms Classification Performance.

Algorithm	Correctly Classified	Size of Tree	Number of Leaves
CDT	83.33%	31	27
J48	87.33%	55	46
J48Consolidated	89.33%	31	26
REPTree	88%	31	26

We further examined the performance of each unpruned algorithm for accuracy and weighted average of TP rate, FP rate, precision, recall, and F-Measure. Table 6 depicts the results of this experiment.

Table 6: Unpruned Algorithms Weighted Average Performance.

Algorithm	TPRate	FPRate	Precision	Recall	F-Measure
CDT	0.833	0.033	0.834	0.833	0.832
J48	0.873	0.025	0.871	0.873	0.871
J48Consolidated	0.893	0.021	0.897	0.893	0.893
REPTree	0.880	0.024	0.878	0.880	0.878

Tables 5 and 6 demonstrate that the J48Consolidated algorithm outperforms other algorithms in classification accuracy, TPRate, precision, recall, and F-measure. Table 5 also shows that the J48Consolidated algorithm is less complicated than CDT and J48 algorithms as it has a smaller size of tree and number of leaves. Its complexity equals REPTree, but accuracy is higher. Overall, the J48Consolidated algorithm is superior to other unpruned algorithms.

5.5 Algorithm Selection

Comparison of pruned and unpruned experiments shows that J48Consolidated unpruned algorithm outperforms J48 pruned algorithm in classification accuracy, TPRate, precision, recall, and F-measure. Its complexity is a little higher as it has a greater tree size and number of leaves. Overall, the J48Consolidated unpruned algorithm is preferable to other algorithms, and therefore, it is selected for building the consideration set model. Figure 1 depicts the decision-tree generated from the J48 unpruned algorithm. We used Graphviz software version 2.38 and DOT graph description language to construct the elegant-looking decision tree.

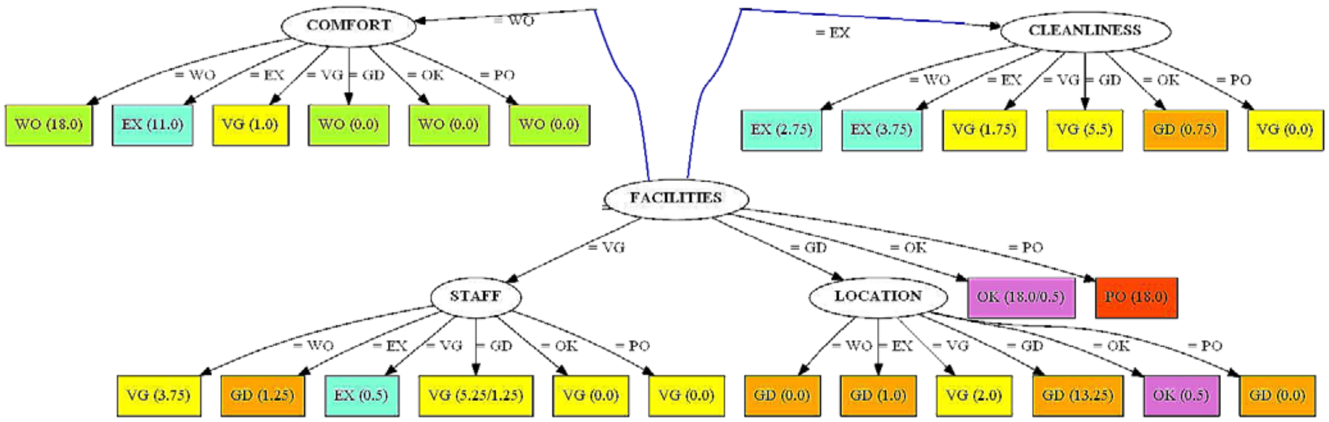

Figure 1: J48Consolidated Unpruned Decision Tree.

5.6 Consideration Set Model

As per the consideration set theory presented in section 4, all the attributes on which consumers give a star rating on Booking.com and selected via the Weka ranker search method constitute the awareness set. In the present study, the information gain and gain ratio evaluators of the Weka ranker search method selected all seven non-class attributes (Table 2). So, attributes like hotel facilities, comfort, cleanliness, staff, location, value for money, and free WiFi form the awareness set.

All the attributes available in the root and intermediary nodes of the J48Consolidated unpruned decision tree form the consideration set. So, attributes like hotel facilities, comfort, cleanliness, staff, and location form the awareness set.

The root node of the J48Consolidated unpruned decision tree represents the choice set. So, hotel facilities constitute the choice set.

Figure 2 presents the consideration set model generated from this study.

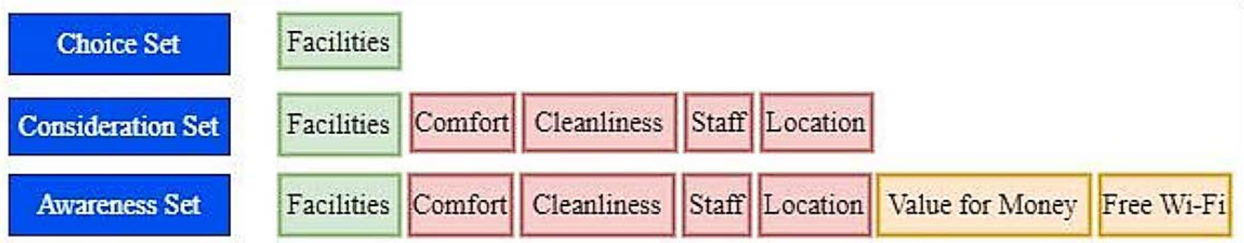

Figure 2: Consideration Set Model of Factors Impacting Hotels' Online Ratings.

6 Discussion

The consideration set model presented in Figure 2 depicts the key factors impacting hotels' online ratings. The research suggests seven key factors in priority order that influence hotels' online review ratings, such as facilities, comfort, cleanliness, staff, location, value for money, and free WiFi. Hotels can focus on the factors identified by this research. This will increase stakeholders' confidence and trust (Singh & Agarwal, 2011; Singh & Grover, 2011; Singh et al, 2011; Singh, 2018c) and improve consumer satisfaction (Singh et al., 2015).

All these identified seven factors constitute the awareness set of the consideration set theory. Except for value for money and free WiFi, the remaining five factors form the consideration set. This suggests that customers pay less attention to the value of money spent while visiting a religious destination like Makkah. In this aspect, this research differs from Hua et al. (2009), Phillips et al. (2016), and Raguseo & Vitari (2017). The could be because these researches were conducted in commercial cities, whereas the present study takes a religious destination.

Also, the study's finding suggests that customers place less importance on free WiFi to select hotels. So, we differ from Bulchand-Gidumal et al.'s (2011) study as free WiFi does not enter the customers' consideration set. This could be because free WiFi is provided by almost all hotels these days. Customers have internet plans on their mobile, and their dependence on hotels' free WiFi is limited.

From the five factors in the consideration set, the hotels' facilities are the choice set. This indicates that customers visiting a religious destination like Makkah place a high consideration for facilities. This could be because they are looking for a spiritual experience, so they expect hotels to provide the necessary facilities to enrich that experience. Table 2 also places facilities as the most desirable attribute.

Table 2 further shows that comfort is the second most crucial factor. This depicts that customers place high consideration on religious experience, so they require better comfort. The third most important factor is cleanliness (Table 2). The fourth factor is the staff and their attitude (Table 2). A good staff attitude can also play a vital role in enriching customers' religious and general tourism experience. The fifth factor in order of importance is the location of hotels (Table 2). This could be a helpful factor for hotels choice in a religious destination like Makkah, where customers may prefer a location closer to Ka'bah. The sixth important factor is value for money, and the last factor in order of priority is free WiFi (Table 2).

7 Conclusion

In the digital era, E-WOM plays a key role in influencing customers' travel and booking decisions. This research leverages the data mining approach and establishes the importance of online review ratings in influencing the consumers' hotels' choice. Specifically, the study identifies and cross-validates seven specific factors impacting hotels' online ratings, such as facilities, comfort, cleanliness, staff, location, value for money, and free WiFi. While the previous research identified these factors in commercial destinations, this research-validated these factors in the context of Saudi Arabia's Makkah's religious destination. Identifying factors impacting hotels' online review ratings in the context of religious destinations would provide a unique edge to world tourism as religious destinations would drive international tourism and economic growth in future.

This study examines the factors impacting online review ratings using the consideration set theory as it explores the impact of consumer awareness on their decision making. Adapting the Cios et al. (2000) data mining model, the study generated pruned and unpruned CDT, J48, J48Consolidated, and REPTree algorithms. The unpruned J48Consolidated algorithm depicted the best model performance; it was used to construct the J48Consolidated decision tree and subsequently generate the consideration set model.

According to the consideration set model, all seven factors form the awareness set viz. facilities, comfort, cleanliness, staff, location, value for money, and free WiFi. These factors were also selected in the Weka ranker search method. Expect value for money and free WiFi; the remaining five factors constitute the consideration set. Since the value for money is not a part of the consideration set, it is less important for customers in religious destinations. Also, free WiFi is less important to customers as almost all hotels provide it, and customers have sufficient alternatives like mobile internet plans. The hotel facilities constitute the choice set.

Further, this study ranked the factors impacting hotels' online ratings in priority order using information gain and gain ratio evaluators of the Weka ranker search method. After facilities, customers consider hotels' comfort level, followed by cleanliness, staff, location, value for money, and free WiFi.

Overall, this research produces significant knowledge for promoting the hotel and tourism sector. The hotels can improve the critical factors to improve their online ratings, consequently, bookings and profits. This would also allow them to improve their customers' satisfaction and play their part in contributing to the national economic growth and development. Specifically, for Saudi

Arabia, the research is a step forward in creating useful knowledge for the hotel industry, which would help them attract consumers and play their part in achieving Saudi vision 2030.

8 Availability of Data and Materials

The data and materials used in this study can be made available on a request by contacting the corresponding author.

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10 Contribution and Workload

Both authors equally contributed to this study. The acknowledgment of the authors' contribution stands as follows:

Ibrahim Abdullah Alhamad: Conceptualization, funding acquisition, project administration, resources, supervision, substantiation, writing - review & editing.

Harman Preet Singh: Data curation, formal analysis, investigation, methodology, software, experimentation, validation, visualization, roles/writing - original draft.

11 Availability of Data And Material

Data can be made available by contacting the corresponding author.

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