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What is the impact of service quality on customers' satisfaction during COVID-19 outbreak? New findings from online reviews analysis

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ABSTRACT

The COVID-19 pandemic has caused major global changes both in the areas of healthcare and economics. This pandemic has led, mainly due to conditions related to confinement, to major changes in consumer habits and behaviors. Although there have been several studies on the analysis of customers' satisfaction through survey-based and online customers' reviews, the impact of COVID-19 on customers' satisfaction has not been investigated so far. It is important to investigate dimensions of satisfaction from the online customers' reviews to reveal their preferences on the hotels' services during the COVID-19 outbreak. This study aims to reveal the travelers' satisfaction in Malaysian hotels during the COVID-19 outbreak through online customers' reviews. In addition, this study investigates whether service quality during COVID-19 has an impact on hotel performance criteria and consequently customers' satisfaction. Accordingly, we develop a new method through machine learning approaches. The method is developed using text mining, clustering, and prediction learning techniques. We use Latent Dirichlet Allocation (LDA) for big data analysis to identify the voice-of-the-customer, Expectation-Maximization (EM) for clustering, and ANFIS for satisfaction level prediction. In addition, we use Higher-Order Singular Value Decomposition (HOSVD) for missing value imputation. The data was collected from TripAdvisor regarding the travelers' concerns in the form of online reviews on the COVID-19 outbreak and numerical ratings on hotel services from different perspectives. The results from the analysis of online customers' reviews revealed that service quality during COVID-19 has an impact on hotel performance criteria and consequently customers' satisfaction. In addition, the

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results showed that although the customers are always seeking hotels with better performance, they are also concerned with the quality of related services in the COVID-19 outbreak.

1. Introduction

Online reviews and ratings, which are two of the most typical forms of Consumer-Generated Content (UGC), have enabled tourists to provide their preferences on the tourism services and share experiences about tourism (Amaral et al., 2014; Cox et al., 2009; Lu and Stepchenkova, 2015). Online reviews and ratings are widely used for the assessment of customers' satisfaction in tourism and hospitality contexts (Ahani et al., 2019a; Nilashi et al., 2018b). Many studies have been conducted for customers' satisfaction which largely focused on quantitative ratings provided by online users on social networking sites (Yadegaridehkordi et al., 2021).

However, it is important to use advanced techniques for linguistic analysis for extracting the dimensions of satisfaction from online reviews, which will enable researchers to gain valuable meanings from visitors comments for facilitating the decision-making process and improving the service quality (Ahani et al., 2019b). Accordingly, several machine learning techniques have been adopted to perform such data analysis in the context of tourism and hospitality (Ahani et al., 2019a; Cenni and Goethals, 2017; Chang et al., 2019; Taecharungroj and Mathayomchan, 2019). These techniques have shown that machine learning can be effectively used in discovering customers' satisfaction dimensions from large datasets. In fact, in contrast with the survey-based analysis through statistical approaches, machine learning approaches can automatically identify the customers' preferences from social big datasets in the form of online customers' reviews and ratings (Nilashi et al., 2019).

After the assessment of the alarming levels of spread and severity, the World Health Organization (WHO) declared the new coronavirus (COVID-19) outbreak as a global pandemic. Accordingly, thousands of individuals were forced to postpone trips recently. The COVID-19 pandemic has caused major global changes in the areas of healthcare and economics (Ahani and Nilashi, 2020; Nilashi et al., 2020). This pandemic has led, mainly due to conditions related to confinement, to major consumer habits and behavior changes (Sheth, 2020). The COVID-19 outbreak has affected many major tourism destinations. Travelers who have planned to travel abroad are canceling or postponing trips due to this pandemic.

The reports showed that the pandemic could lead to a loss of 305 million jobs, many in the tourism sector (ILO, 2020). The pandemic and global effort to contain it could lead to a 45%-70% decline in the international tourism economy. The domestic tourism sector has also been impacted by the control policies projected to around half of the world's population. However, domestic tourism is expected to recover more quickly than international tourism. In fact, still many hotels are providing travel services to inbound and outbound tourists by implementing several stringent protocols in accordance with the latest guidelines issued by local governments and health authorities. For example, the deployed protocols include temperature and valid health declaration checks upon arrival, high-frequency cleaning and disinfection, social distancing, contactless service options, sanitizing, and Personal Protective Equipment (PPE).

During the outbreak, it is important to discover the satisfaction dimensions from the online customers' reviews to reveal their preferences on the hotels' services. Online customers' reviews are a valuable source of information to identify the voice-of-the-customer during the outbreak. In fact, from online customers' reviews, the main concerns of the customers can be easily identified and satisfaction level can be effectively revealed. Accordingly, new data analysis tools and approaches must be developed to collect and analyze the data from online customers' reviews. In fact, traditional statistical methods through survey-based data collection approaches would not be an effective way to comprehensively evaluate the customers' satisfaction during the COVID-19 outbreak.

The aim of this study to reveal the travelers' satisfaction in Malaysian hotels during the COVID-19 outbreak through online customers' reviews. In addition, we rely on big data from UGC including textual information and numerical ratings to empirically develop and identify the dimensions of satisfaction. Accordingly, we develop a new method through machine learning approaches. The method is developed using text mining, clustering, and prediction learning techniques. We use Latent Dirichlet Allocation (LDA) for big data analysis to identify the voice-of-the-customer, Expectation-Maximization (EM) for clustering, and neuro-fuzzy for satisfaction level prediction. In addition, we adopt a dimensionality reduction technique, Higher-Order Singular Value Decomposition (HOSVD), for missing value prediction. The data was collected from TripAdvisor regarding the travelers' concerns in the forms of online reviews during the COVID-19 outbreak and numerical ratings on hotel services from different perspectives. Accordingly, this research fills a research gap in previous literature by presenting a qualitative and quantitative analysis of UGC that integrates text mining, clustering, and supervised machine learning techniques. Overall, the contributions of our work are as follows:

i. We use a text mining approach, LDA, to discover satisfaction dimensions from text-based online reviews during the COVID-19 outbreak. The LDA has shown its effectiveness in text-based reviews in e-commerce, and especially in tourism and hospitality research. During a disaster such as the COVID-19 outbreak, detecting customers' behaviors and concerns from UGC in tourism and hospitality is important to improve the service quality. In the context of tourism, several studies have investigated customers' satisfaction from customers' online reviews through developing new methods. However, this issue has been rarely explored during a disaster such as the COVID-19 outbreak.
ii. We use a clustering technique to segment social big data based on the contents that customers have generated in TripAdvisor. It has been shown that clustering techniques of big social data present better outcomes compared to conventional statistical techniques. In addition, it is difficult to process social big data without performing the clustering for preference prediction.

Hence, this research attempts to employ EM as a probabilistic, unsupervised learning and iterative algorithm to find the best segments from social big data.

iii. We use the HOSVD technique for missing value imputation. Although the use of matrix factorization techniques has proved to be effective for dimensionality reduction tasks, many phenomena are inherently multi-way and cannot be solved by these techniques. Accordingly, the tensor decomposition techniques can better solve the dimensionality reduction problem for the data which includes more than 2 dimensions. HOSVD is a multilinear generalization of SVD. This technique can effectively decompose the tensors into their main components. Therefore, similarity calculation can be effectively performed on the data with reduced dimensions. In this research, as the travelers provide the rating in several aspects of hotels, the use of HOSVD seems to be useful for missing value imputation. Accordingly, on each cluster of EM, HOSVD will be implemented and missing values will be predicted through neighborhood formation.

iv. This research adopts a neuro-fuzzy approach, ANFIS, for the prediction of customers' preferences through UGC. The quantitative data is used in ANFIS to construct the prediction models for customers' preferences prediction. For social big data in the context of tourism, it is important to discover the relationships between the input features when predicting the output, customers' satisfaction, as the relative importance of factors will be revealed for decision-making in a complex situation. In addition, relying solely on the fuzzy logic approach would not be an efficient way to predict customers' satisfaction from social big data. In fact, the method must be able to automatically generate the decision rules from the data to be used in the prediction task, in which a neuro-fuzzy system can perfectly do it.

2. Importance of online customers' reviews and ratings

The uncontrollable impact of the COVID-19 crisis forced hotel managers to redesign tourists' experiences (Bonfanti et al., 2021). It is significant for hotel managers to be aware of the immediate and post-pandemic impacts to follow suitable management policies (Ritchie and Jiang, 2019). Previous literature has explored the impacts of health pandemics on the tourism and hospitality business, entailing the influence of swine flu in the UK (Page et al., 2012) and SARS in China (Zeng et al., 2005). Various researches have also explored the impacts of the COVID-19 crisis on the tourism sector from several disciplines such as tourists' mental health (Zheng et al., 2020), travel preferences (Wen et al., 2020), and hotel management policies (Japutra and Situmorang, 2021). During this critical situation, a deep understanding of tourists' desires can aid hoteliers in presenting a better market considering strategic business advertising, development, promotion, and service enhancement.

As indicated in the study by Gretzel and Yoo (2008), in the context of travel reviews, around 97% of the respondents indicated that they check other travelers' comments to plan their upcoming trip. Additionally, Prabu (2014) stated that more than 80% of travelers browse other travelers' comments before reaching the booking choice, while 53% are unwilling to choose a hotel with no reviews. TripAdvisor's hotels with positive comments and high ratings have noticed more demand, in which travelers prefer to stay for longer periods, in comparison with hotels with negative comments or low ratings (Hoisington, 2018).

Online reviews present organizations with the opportunity to perform broad consumers' behavior analysis referring to standard ratings (Nilashi et al., 2018a). Consumers basically tend to indicate their customized choices on item characteristics through electronic comments (Ahani et al., 2019c). Hence, the UGC data present a unique perspective to understand the market by considering the voice of consumers. Previous literature has indicated the impact of online reviews on both travelers and hotel managers (Ghose and Ipeirotis, 2011; Yang et al., 2009). Considering hotel managers, electronic reviews have increasingly become a basic influential factor (Yang et al., 2018). Without online reviews, hotel managers will be incapable to efficiently understand the situation of their hotels, the accurate performance, or the factors that could influence tourists' booking intentions (El-Said, 2020). It has been indicated that hotels' revenues are specifically delicate to the impact of electronic reviews (Hilbrink, 2017).

3. Previous literature of online customers' reviews and ratings

In a study by Cenni and Goethals (2017), the authors investigated negative hotel reviews through a cross-linguistic analysis. They collected 300 negative hotel reviews from TripAdvisor. In Banerjee and Chua (2016), the authors examined the rating patterns of the travelers for independent and chain hotels in America, Asia-Pacific, Europe, and Middle East-Africa. The data collection was performed from TripAdvisor. In a study by Peng et al. (2018), a cloud decision support model was proposed to select TripAdvisors hotels with probabilistic linguistic information. In (Giglio et al., 2020), consumers' perceptions of luxury hotel brands were investigated. In (Taecharungroj and Mathayomchan, 2019), 65,079 TripAdvisor's reviews of tourist attractions in Phuket, Thailand, were analyzed. LDA was used to extract dimensions of attractions. They used Naïve Bayes modeling to analyze underlying terms. In (Nilashi et al., 2018b), the authors investigated travelers' decision-making through TripAdvisor's online reviews. They used decision trees for discovering the decision rules and a fuzzy rule-based approach for travelers' preference prediction. The EM and SOM clustering approaches were used to cluster the TripAdvisor data. Borges-Tiago et al. (2021) investigated the differences between Booking.com and TripAdvisor.com in branding co-creation. They found that similar brand personality traits were presented by the users in non-commercial and commercial platforms. Pyle et al. (2021) investigated consumer trust in a complex eWOM marketspace using naïve theories through the analysis of the data from 27 interviews. In (Gerdt et al., 2019), the authors investigated the relationship between customer satisfaction and sustainability in hospitality through 52,493 online reviews of hotels. Ahani et al. (2019a) investigated market segmentation and travel choice prediction in spa hotels. They developed a model using CART, SOM, and HOSVD learning techniques. The authors used TripAdvisor's textual reviews and numerical ratings to reveal the customers' satisfaction in spa hotels. Nilashi et al. (2021) used machine learning techniques to analyze the TripAdvisor online customers' reviews for decision-making

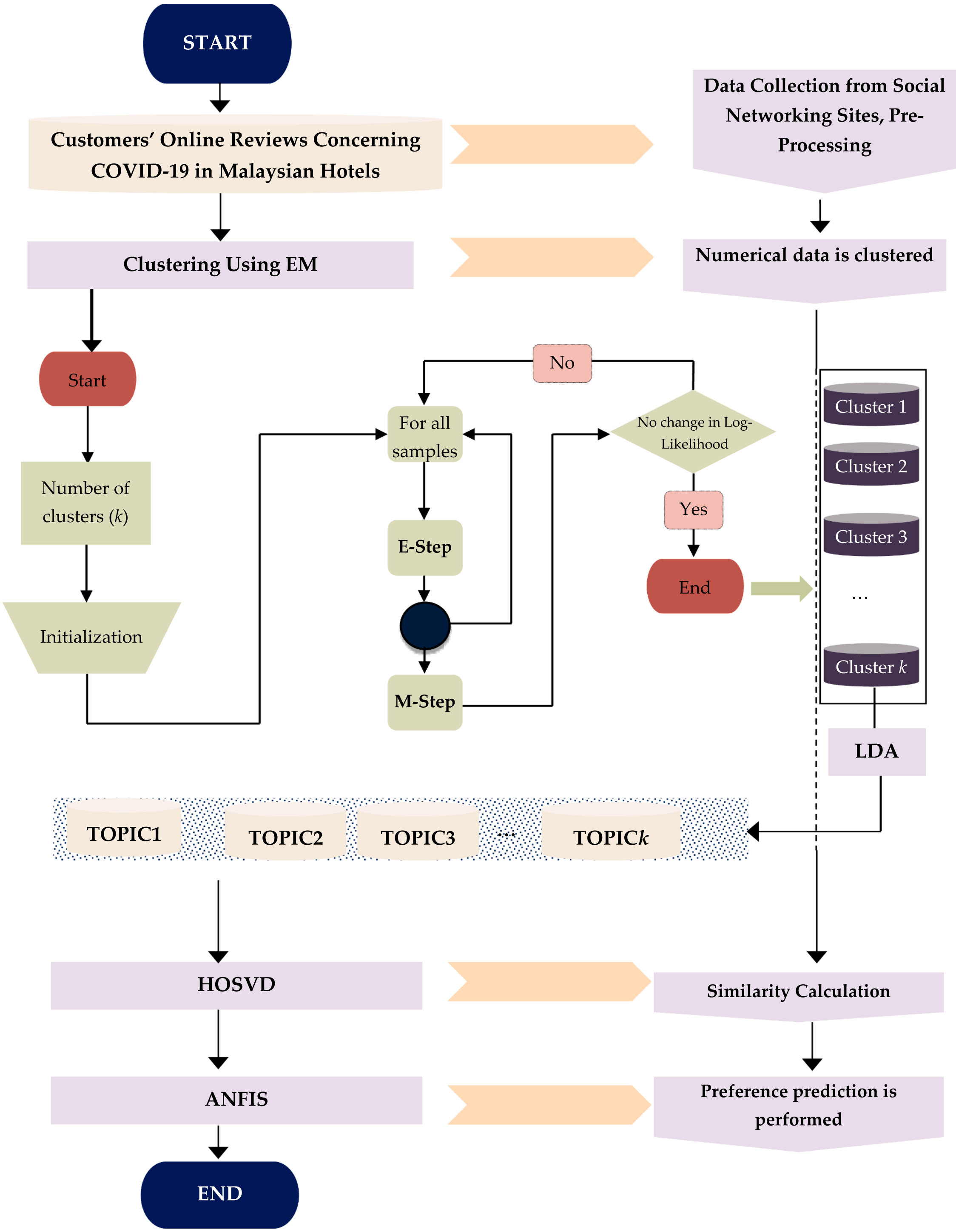

Fig. 1. Research Method.

during the COVID-19 outbreak. They used LDA for data analysis. Nilashi et al. (2019) developed a method of analysis through a machine learning technique for preference learning for eco-friendly hotels. They adopted a multi-criteria collaborative filtering approach with the aid of clustering and dimensionality reduction techniques for customers' satisfaction and decision-making. In a study by Ahani et al. (2019b), the authors presented a new method to reveal customers' preferences and satisfaction through online review analysis in Canary Islands hotels. They used clustering and Multi-Criteria Decision-Making (MCDM) approaches for ranking hotels' features.

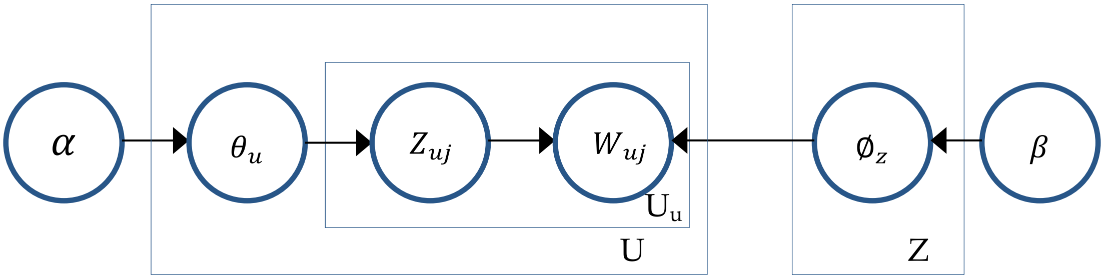

Fig. 2. The graphical representation of LDA.

4. Method

The proposed hybrid method is presented in Fig. 1. It includes several stages for online customers' reviews (textual comments and numerical ratings). In the initial stage of the method, the data is pre-prossessed. The method can analyze the qualitative and quantitative data. From the qualitative reviews, the main dimensions of satisfaction are discovered and from the quantitative ratings, the customers' satisfaction is revealed based on different hotels' features. LDA in the second stage is adopted and applied on the qualitative data to discover main topics from customers' comments during the COVID-19 outbreak. In the second stage of data analysis, we apply a clustering approach, EM, to generate several segments from the collected data. Then, we apply a feature selection approach to select the most important features in each cluster. This is performed to increase the accuracy of preference prediction through the selected features. In the last stage of our methodology, we adopted a neuro-fuzzy approach, ANFIS, to predict the customers' satisfaction through numerical ratings and input features discovered from the textual data. In the following sections, we introduce the incorporated learning techniques in the proposed method.

4.1. LDA

LDA is an unmonitored probability generative scheme that randomly produces observed documents (Blei et al., 2003). It resolves the issue of probabilistic latent semantic analysis via the treatment of topic mixture weights as k-parameters concealed random variables instead of a vast series of directly linked parameters to the relevant training set. LDA is utilized for acquiring latent subjects from a textual corpus (Guo et al., 2017). In conventional LDA schemes, the corpus consists of a series of documents, each of which is a series of words. This corpus may be considered as a matrix with each row denoting a document, each column denoting a word, and each input denoting the number of incidences of the associated word in the associated document. In the same vein, the string probability, i.e. either a document or sentence, is acquired as the possibility of the string within the domain. The LDA scheme does not hypothesize the text structure or the grammatical or syntactical traits of the language. The LDA scheme is adopted in favor of various text analysis approaches presented in previous literature because of the following reasons: (1) LDA scheme is superior in the efficient analysis of vast data at a greatly granular level and hence, (2) it provides the opportunity to discover the heterogeneity of aspects in various consumer groups. Additionally, (3) LDA aids in the derivation of practical repeatability of occurrence for every derived aspect based on its intensity concerning online reviews. As an example, travelers choose words from their personal vocabulary to represent their personal opinions on various dimensions of hotels, e.g. price, facilities, and location. Such topics, which denote the vital aspects related to tourist satisfaction, exhibit distribution over the reviews which is dependent on their repeatability of occurrence accredited to consumers' experiences from the services. The graphical description of the LDA approach is presented in Fig. 2. The LDA generative procedure is defined as follows:

***Algorithm* 1.** *LDA Procedure*

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1. *For each topic $z \in Z$*
    - *Draw a multinomial distribution$\varnothing_z$ Dir($\overrightarrow{\beta}$).*
2. *For every user $u \in U$,*
    - *Draw a multinomial distributionθ_u Dir($\overrightarrow{\alpha}$).*
    - *For every word $w \in D_u$,*

(a) *Draw a topic z Multinomial($\overrightarrow{\theta_u}$).*

(b) *(b) Draw a word w Multinomial($\overrightarrow{\varnothing_z}$).*

In LDA, multi-nominal distributions of $\overrightarrow{\theta_u}$ are assumed and $\overrightarrow{\varnothing_z}$ are depicted from conjugate previous distributions (Dirichlet distribution) through two parameters $\overrightarrow{\alpha}$ and $\overrightarrow{\beta}$. Every word w in D_u is considered as chosen by the initially depicting a topic z following the topic preference distribution $\overrightarrow{\theta_u}$ and then selecting a word w from the associated distribution $\overrightarrow{\varnothing_z}$ of the chosen topic z. Based on the LDA scheme, the possibility of a word w originated by user u is predicted as:

$$\int Dir(\theta_u; u)\left(\sum_{z=1}^{|Z|}\theta_{uz}\varnothing_{zw}\right)d\theta_u \tag{1}$$

4.2. ANFIS

This study uses Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang and Sun, 1995) to reveal the importance level of criteria of customers' satisfaction. ANFIS is based on fuzzy logic and neural network approaches. This technique is widely used in decision-making and prediction problems, especially in the tourism and hospitality context. By mapping relations between the inputs and output of the system, optimal membership functions are generated to accurately predict the output through several fuzzy rules. There are various types of Membership Functions (MF) in ANFIS such as Triangular MF, Generalized bell MF, Trapezoidal MF, and Gaussian MF. This study used Gaussian MFs for ANFIS modeling to reveal the importance level of website satisfaction criteria. ANFIS is mainly developed through five distinct layers, as shown in Fig. 3.

4.3. Expectation Maximization clustering

The Expectation-Maximization clustering approach is effective in handling big data. This clustering approach can iteratively compute the maximum likelihood from incomplete data. Expectation (E-step) and Maximization (M−step) are the two main steps of this clustering approach.

Suppose the medical tourism dataset $\mathbf{O} = \{o_1, \cdots, o_n\}$ with n tuples, EM performs the clustering in two steps to mine the parameters $\theta = \{\theta_1, \cdots, \theta_k\}$ in which $P(\mathbf{O}|\theta)$ is maximized, where $\theta_j = (\mu_j, \sigma_j)$ indicates the mean and standard deviation of the j-th Gaussian distribution. Accordingly, in E-step, we calculate the probability that o_i belongs to each distribution as:

$$P(\theta_j|o_i, \theta) = \frac{P(o_i|\theta_j)}{\sum_{l=1}^{k} P(o_i|\theta_l)}. \tag{2}$$

In M−step, $P(\mathbf{O}|\theta)$ is maximized through adjusting the parameter $\theta_j = (\mu_j, \sigma_j)$ as:

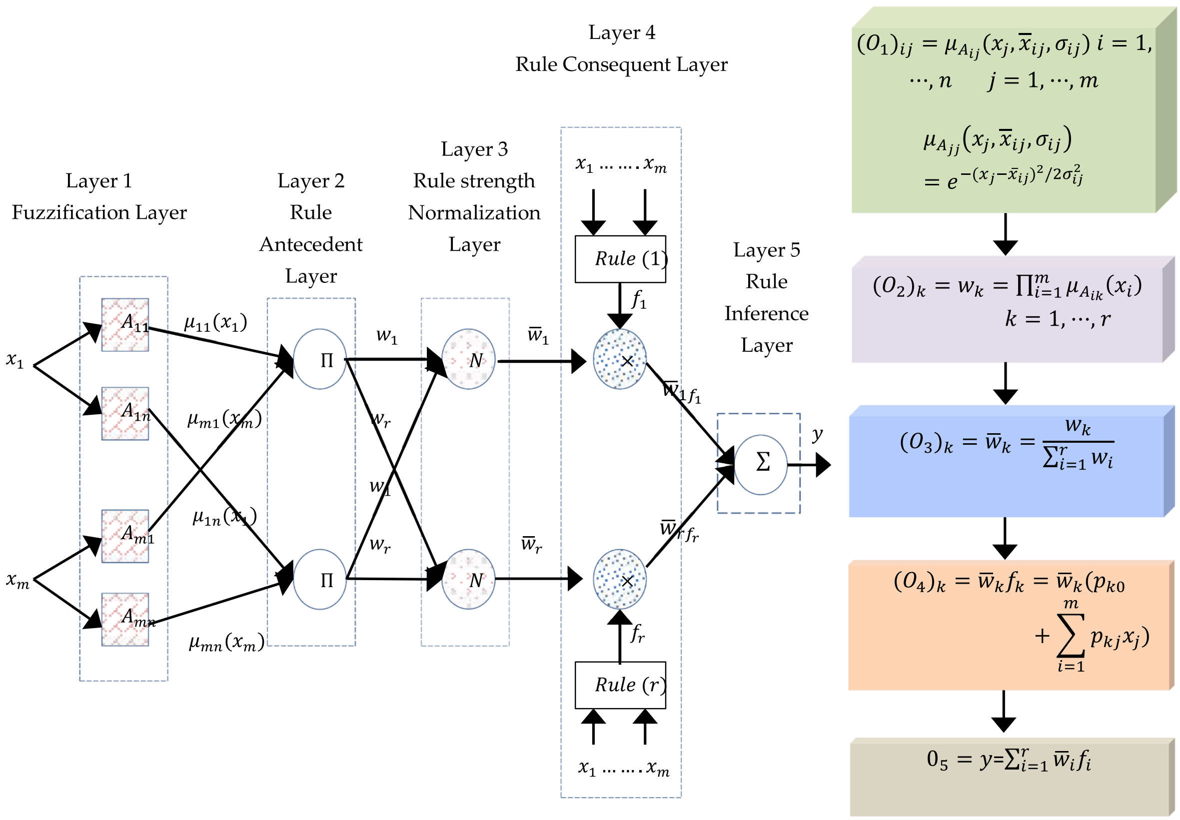


Fig. 3. ANFIS architecture with its procedure.

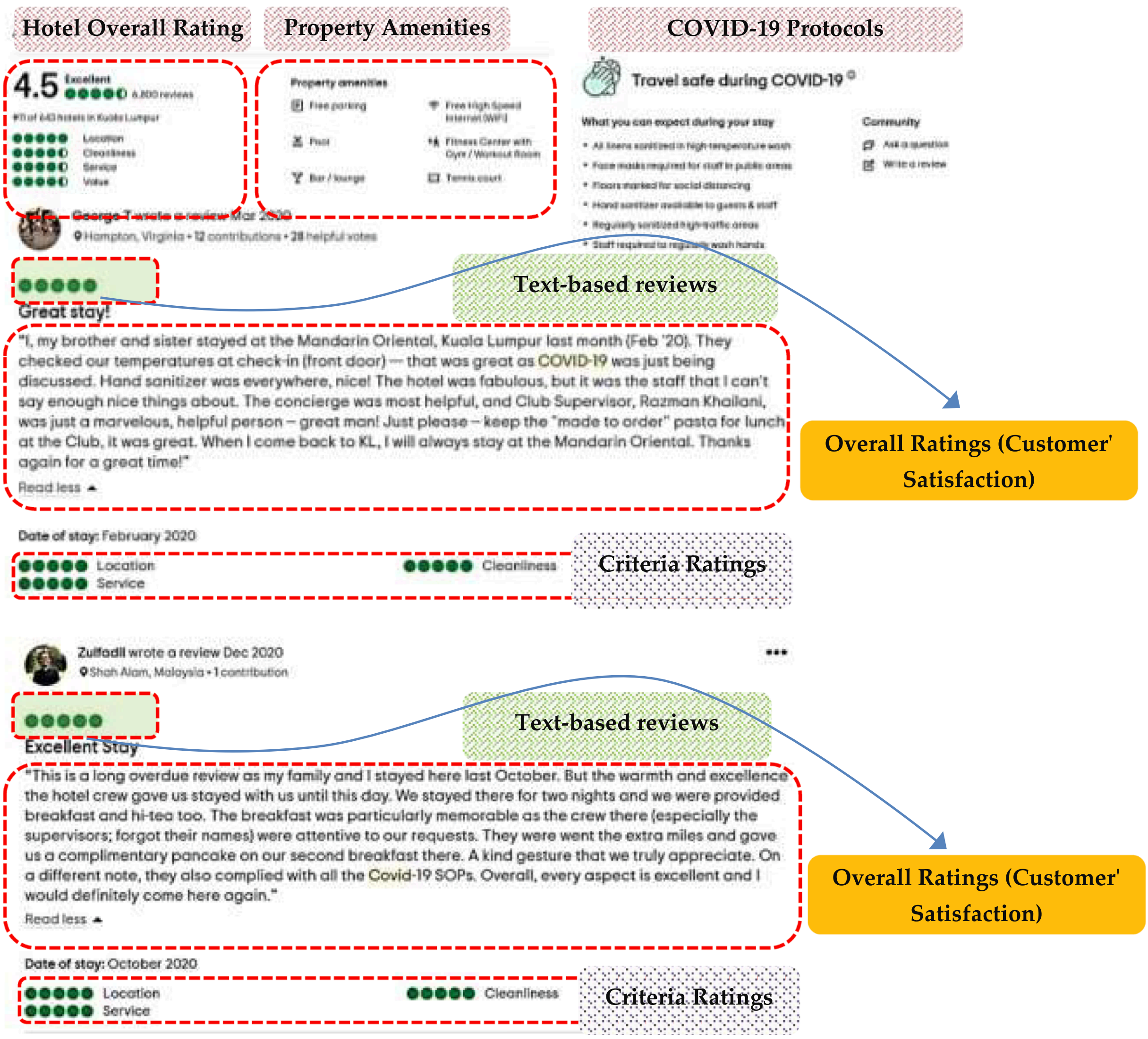


Fig. 4. The reviews provided by travelers during the COVID-19 outbreak.

$$\mu_j = \sum_{i=1}^{n} o_i \frac{P(\theta_j|o_i,\theta)}{\sum_{l=1}^{n} P(\theta_j|o_l,\theta)} = \frac{\sum_{i=1}^{n} o_i P(\theta_j|o_i,\theta)}{\sum_{i=1}^{n} P(\theta_j|o_i,\theta)}; \sigma_j = \sqrt{\frac{\sum_{i=1}^{n} o_i P(\theta_j|o_i,\theta)(o_i-\mu_j)}{\sum_{i=1}^{n} o_i P(\theta_j|o_i,\theta)}}. \tag{3}$$

In EM, E-step and M−step are iteratively conducted until converge.

4.4. HOSVD for missing value imputation

Tensor and matrix factorization techniques have played an important role in many real-world applications (Ahani et al., 2019a; Huang et al., 2008). They have contributed significantly to the development of methods to improve their efficiency. Singular Value Decomposition (SVD) is one of the matrix factorization techniques which was widely used in the literature for dimensionality reduction of the data in 2-dimensional spaces. In SVD, a real $m \times n$ matrix A can be shown as: $A = U\sum V$, $\sum$ indicates a diagonal matrix, and U and V as two $m \times k$ and $n \times k$ matrices. The diagonal elements in the matrix $\sum$ are called singular values. In SVD, by ignoring the small singular values, a good approximation of A can be obtained.

HOSVD is used for higher-order tensor decomposition. For example, a third-order tensor $\mathbf{A}$ $(I \times J \times K)(N = 3)$can be expressed as the product of its components, $\mathbf{A} = (U, V, W)\mathbf{S}$, where $U \in R^{I\times I}$, $V \in R^{J\times J}$ and $W \in R^{K\times K}$ are orthogonal. In addition, the tensor $\mathbf{S} \in R^{I\times J\times K}$ is also all-orthogonal. The matrices $U \in R^{I\times I}$ and $V \in R^{J\times J}$ are considered as two left and right-side orthogonal matrices of generated singular vectors, respectively. In term of the Frobenius norm, the truncated HOSVD ($\widetilde{A}$) is considered the optimal approximation of **A**. The Frobenius norm can be obtained by $\left\| A - \widetilde{A} \right\|_F^2$.

5. Data collection and results

TripAdvisor was used to collect data to achieve the objective of this research. The information was gathered from hotels' web pages, which are provided by TripAdvisor. Through a customized crawler, the data was collected by referring to the URL of Malaysian hotels in TripAdvisor to obtain key information such as hotel information, trip information, traveler information, and traveler ratings and reviews on the hotels. The online customers' reviews were filtered and the reviews which include COVID-19 were kept for further analysis (see Fig. 4). Totally, 1685 reviews were collected from 116 Malaysian hotels on TripAdvisor. Non-English, short, and useless reviews were removed. We have considered all reviews which provided the overall ratings along with the ratings on sleep quality, value (cost-benefit), service, location, rooms, and cleanliness. Missing values were predicted in each cluster through HOSVD by neighborhood formation in each cluster. An example of collected data from TripAdvisor is shown in Table 1.

In the first step, we applied the EM clustering technique on the users' numerical reviews for data clustering. We apply EM for different values of $k = 2, 3, 4, 5$, and 6. Then, we used the Silhouette Coefficient (SC) approach to determine the most proper number of clusters. SC is an index to measure the quality of clusters. The SC values range from $+1$ to -1, in which 1 indicates that the points are very distant from neighboring clusters. In this research, the average SC is considered for the quality of final clusters. The results for SC of different numbers of clusters are presented in Table 2. From the SC values, we found that EM with cluster number $k = 3$ (SC $=$ 0.8721) provides the highest clustering quality among other numbers of clusters. We present the clustering results in Table 3 and Table 4. In Fig. 5, the clusters are visualized on different performance criteria and overall ratings.

The LDA technique was applied to the online customers' reviews in each cluster of EM. The important dimensions of customers' satisfaction were generated from the textual reviews (see Fig. 6). After performing clustering and text mining, we applied HOSVD on each cluster for data dimensionality reduction. A three-order tensor $\mathbf{A} \in \mathrm{R}^{|U||I||C|}$ was considered to store the data including users, hotels, and their criteria. We aimed to decompose the tensor to exploit the latent relationships among the objects. To do so, unfolding the tensor was performed on its main modes to have 2D matrices A_1, A_2 and A_3 which are defined as follow:

$$\begin{aligned} A_1 &= U^{(1)}.S_1.V_1^T \\ A_2 &= U^{(2)}.S_2.V_2^T \\ A_3 &= U^{(3)}.S_3.V_3^T \end{aligned} \tag{4}$$

Table 1
An example of collected data from TripAdvisor.

User ID	Hotel ID	Cleanliness	Service	Value	Rooms	Location	Sleep Quality	Overall Ratings
U1	H1	3	3	4	0	3	5	4
U3	H4	3	1	0	2	3	4	5
U10	H8	5	5	0	5	0	4	4
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Ui	Hj	3	4	3	2	1	0	3
Un	Hm	5	5	5	3	3	4	5

Table 2
Silhouette Coefficient (SC) results.

Number of Clusters	SC Value
2	0.8214
3	0.8721
4	0.8539
5	0.8448
6	0.8233

Table 3
Cluster centroids.

Attribute	Segment 1 (Centroid)	Segment 2 (Centroid)	Segment 3 (Centroid)
Rooms	1.953959	2.540052	4.837086
Value	1.965009	2.514212	4.852980
Location	1.906077	2.583979	4.842384
Service	1.965009	2.633075	4.819868
Cleanliness	1.896869	2.625323	4.805298
Sleep Quality	1.893186	2.604651	4.835762
Cluster Size	**543 Ratings**	**755 Ratings**	**387 Ratings**

Table 4
1-way ANOVA for input attributes in EM clusters.

Attribute Y	Attribute X	Description				Statistical test		
Rooms	**EM Cluster**	**Values**	**Example**	**Average**	**Std-dev**	**Variance decomposition**		
		Segment 1	543	1.9540	0.6790	**Source**	**Sum of square**	**d.f.**
						BSS	2980.2139	2
		Segment 2	387	2.5401	0.7378	WSS	590.9398	1682
						TSS	3571.1537	1684
		Segment 3	755	4.8371	0.4168	**Significance level**		
						Statistics	**Value**	**Proba**
		All	1685	3.3804	1.4562	Fisher's F	4241.311928	0.000000
Value	**EM Cluster**	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	543	1.9650	0.6850	BSS	3015.3413	2
						WSS	539.6878	1682
		Segment 2	387	2.5142	0.6727	TSS	3555.0291	1684
						Significance level		
		Segment 3	755	4.8530	0.3831	**Statistics**	**Value**	**Proba**
		All	1685	3.3852	1.4529	Fisher's F	4698.831422	0.000000
Location	**EM Cluster**	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	543	1.9061	0.6345	BSS	3039.4687	2
						WSS	506.4743	1682
		Segment 2	387	2.5840	0.6598	TSS	3545.9430	1684
						Significance level		
		Segment 3	755	4.8424	0.3993	**Statistics**	**Value**	**Proba**
		All	1685	3.3774	1.4511	Fisher's F	5047.034076	0.000000
Service	**EM Cluster**	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
		Segment 1	543	1.9650	0.6659	**Source**	**Sum of square**	**d.f.**
						BSS	2867.8567	2
						WSS	575.7338	1682
						TSS	3443.5905	1684
		Segment 2	387	2.6331	0.7051	**Significance level**		
		Segment 3	755	4.8199	0.4363	**Statistics**	**Value**	**Proba**
		All	1685	3.3976	1.4300	Fisher's F	4189.205976	0.000000
Cleanliness	**EM Cluster**	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
		Segment 1	543	1.8969	0.6403	**Source**	**Sum of square**	**d.f.**
						BSS	2948.3294	2
		Segment 2	387	2.6253	0.7102	WSS	559.2753	1682
						TSS	3507.6047	1684
		Segment 3	755	4.8053	0.4345	**Significance level**		
						Statistics	**Value**	**Proba**
		All	1685	3.3674	1.4432	Fisher's F	4433.496274	0.000000
Sleep Quality	**EM Cluster**	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	543	1.8932	0.6624	BSS	3033.0023	2
		Segment 2	387	2.6047	0.6914	WSS	551.9509	1682
						TSS	3584.9531	1684
		Segment 3	755	4.8358	0.4146	**Significance level**		
						Statistics	**Value**	**Proba**
		All	1685	3.3751	1.4591	Fisher's F	4621.344252	0.000000

The core tensor was computed as follows:

$$S = A \times {}_1 U_1^{(1)^T} \times {}_2 U_2^{(2)^T} \times {}_3 U_3^{(3)^T} \tag{5}$$

This was done through the left singular vectors of the A_1, A_2 and A_3. Accordingly, the best approximation was obtained by:

$$\widetilde{A} = S \times {}_1 U_1^{(1)} \times {}_2 U_2^{(2)} \times {}_3 U_3^{(3)} \tag{6}$$

Through HOSVD decomposition, neighborhood formation of the users can be effectively performed by finding similar users in each cluster. This was done by the following formula for Cosine similarity measure:

$$Similarity_c(A,B) = \frac{X.Y}{\|X\|.\|Y\|} = \frac{\sum_{i=1}^{n} X_i \times Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2} \times \sqrt{\sum_{i=1}^{n} Y_i^2}} \tag{7}$$

where for two vectors X and Y, $\|X\|$ and $\|Y\|$ represent the Euclidean norm of vectors $X = (x_1, x_2, \cdots, x_n)$ and $Y = (y_1, y_2, \cdots, y_n)$, respectively.

In the last step of data analysis, we used ANFIS in each cluster of EM to reveal the importance level of sleep quality, value (cost-

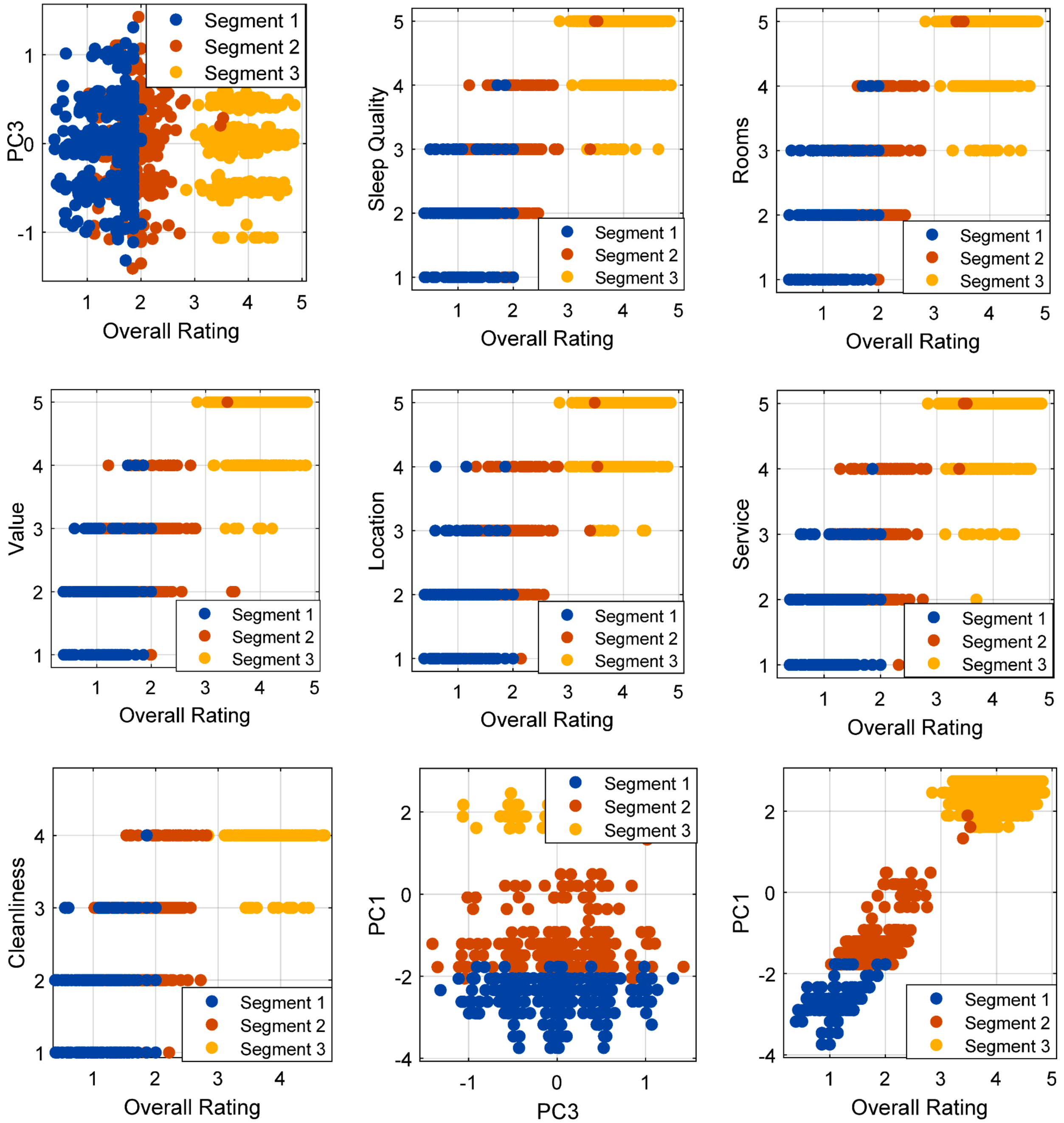


Fig. 5. EM clustering results.

benefit), service, location, rooms, and cleanliness on the travelers' satisfaction level. In addition, we try to reveal the satisfaction level by considering the importance of COVID-19 services in each cluster. ANFIS was trained for 150 epochs with Gaussian membership functions. This type of membership function was used referring to previous literature, which indicated its high accuracy in relation to the other membership functions (see Fig. 7). In addition, a hybrid learning algorithm was used in ANFIS to construct the prediction models. In Fig. 8, the 3D plots are presented to show the relationships between the input criteria and customer overall rating (satisfaction level) for three input criteria. In Fig. 9, the predicted values against actual values for satisfaction level in three segments are presented. The R^2 values ($R^2_{Segment\ 1}$: 0.96; $R^2_{Segment\ 2}$: 0.93; $R^2_{Segment\ 3}$: 0.96) in each cluster show that ANFIS has accurately constructed the models for satisfaction prediction.

We extended our data analysis for the hotels which have negative and positive reviews on the hotels for COVID-19 service quality. We try to provide the results on the plots to show the impact of COVID-19 service quality on customers' satisfaction. Accordingly, the ANFIS is trained for two different models to show the differences between satisfaction levels versus six hotel criteria. The plots are

Fig. 6. Word cloud of textual reviews.

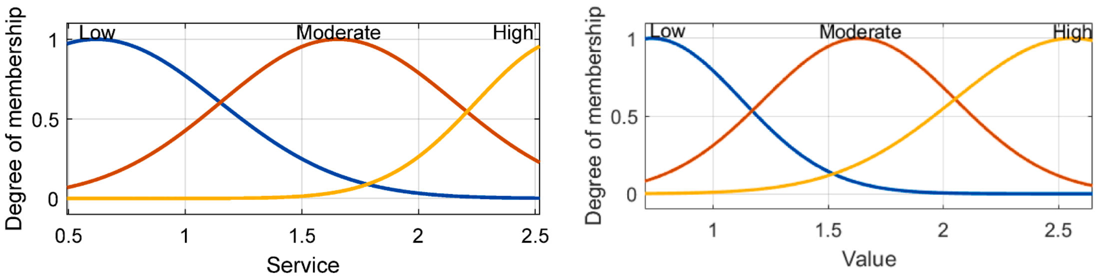


Fig. 7. Membership functions in ANFIS models.

shown in Fig. 10 for each criterion. The plots clearly indicate the importance of service quality during COVID-19 for customers' satisfaction. It is found that the hotels which provide high-quality services during COVID-19 or follow appropriate rules and protocols in accordance with the guidelines issued by local governments or health authorities can gain consumers' satisfaction. In addition, the results show that the impact of quality services during COVID-19 on the relationship between the service and satisfaction is higher than other relationships (see Fig. 10).

Furthermore, although satisfaction level in all plots is increased with the increased levels of sleep quality, value (cost-benefit), service, location, rooms, and cleanliness, however, the level of satisfaction in the hotels which provide better service quality during COVID-19 is much increased. This indicates that although the customers are always seeking hotels with better performance concerning sleep quality, value (cost-benefit), service, location, rooms, and cleanliness, they are also concerned with the quality of related services in a disaster situation. The online customers' reviews in the following examples can confirm the results of our data analysis (see Fig. 11).

6. Discussion

An increasing number of tourists rely on electronic customer reviews to evaluate the quality and the performance of hotels (Yadegaridehkordi et al., 2021). On social platforms, these reviews can impact travelers' choices dramatically (Nilashi et al., 2018b). Electronic reviews can be efficiently utilized in machine learning approaches to present insights about travelers' decision-making process and hotel choice. Although tourists' choices and preferences have been researched broadly in previous literature (Ahani et al., 2019c; Yadegaridehkordi et al., 2021), this topic is not well investigated in the context of a global outbreak such as the current crisis of COVID-19. Hence, this research aimed to explore tourists' perceptions towards hotels using electronic reviews on TripAdvisor during the COVID-19 outbreak.

The COVID-19 pandemic is impacting business revenues, operations, and management policies worldwide. Particularly, the tourism and hospitality sectors are vulnerable to such epidemics (Cró and Martins, 2017) and should follow appropriate crisis and risk management procedures (Ritchie and Jiang, 2019). As indicated by the research outcomes, travelers are more concerned about potential health risks when they visit a particular destination. Hence, hotel managers need to assure that they are following the best practices that were announced by the WHO and local authorities. In the TripAdvisor portal, several hotels indicated that they follow safety measures that entail the compulsory wearing of face masks by tourists and staff in public, following social distancing measures, and synthesizing areas regularly. Besides, travelers' reviews reflected tourists' awareness of Standard Operating Procedures (SOPs) and their concern about whether the hotel follows the SOPs or not.

As the research outcomes presented, service quality is one of the essential drivers of consumers' satisfaction. Besides, the results show that the impact of the quality of services during COVID-19 on the relationship between service and satisfaction is high. This outcome has been indicated in previous literature by many studies (Alnawas and Hemsley-Brown, 2019; Hao et al., 2015; Nunkoo et al., 2017; Ren et al., 2015). Still, service quality is a multidisciplinary factor that depends on the area under study and should be

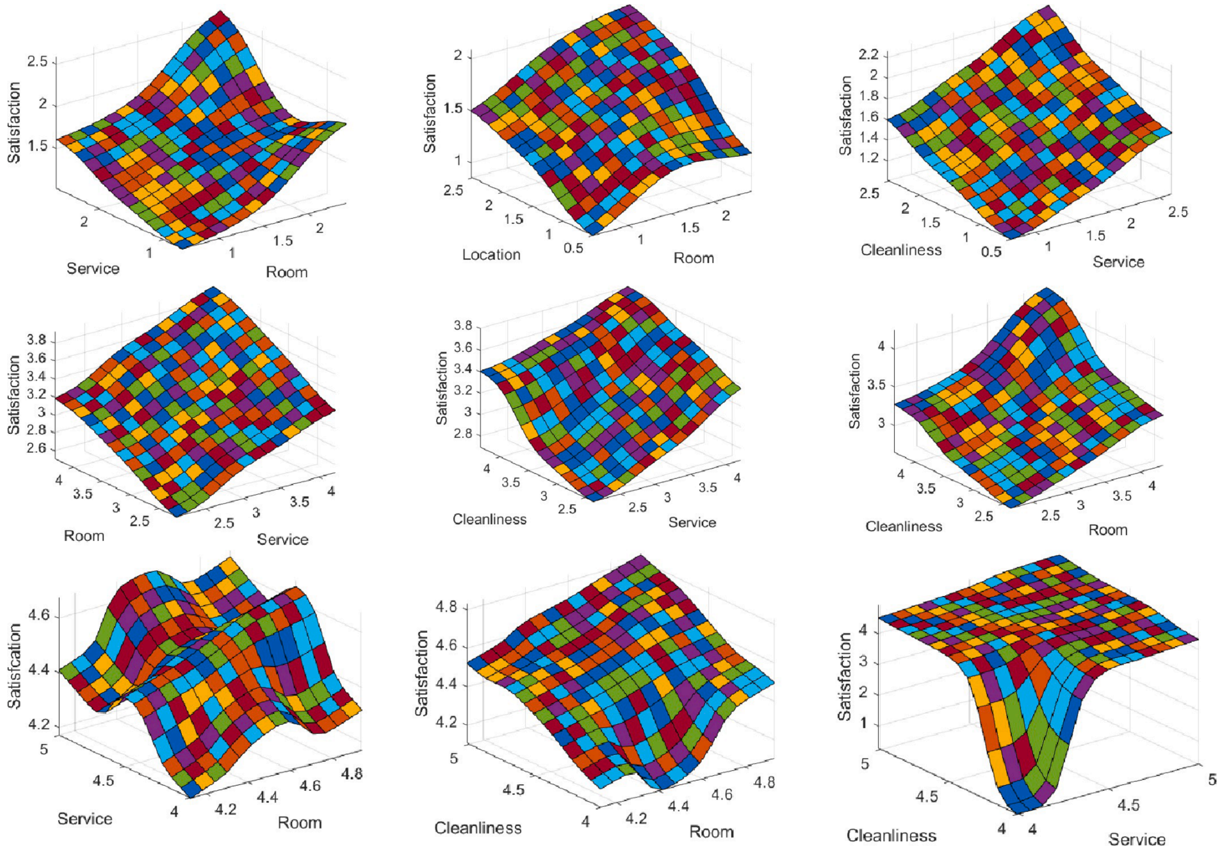


Fig. 8. The relationships between criteria and satisfaction.

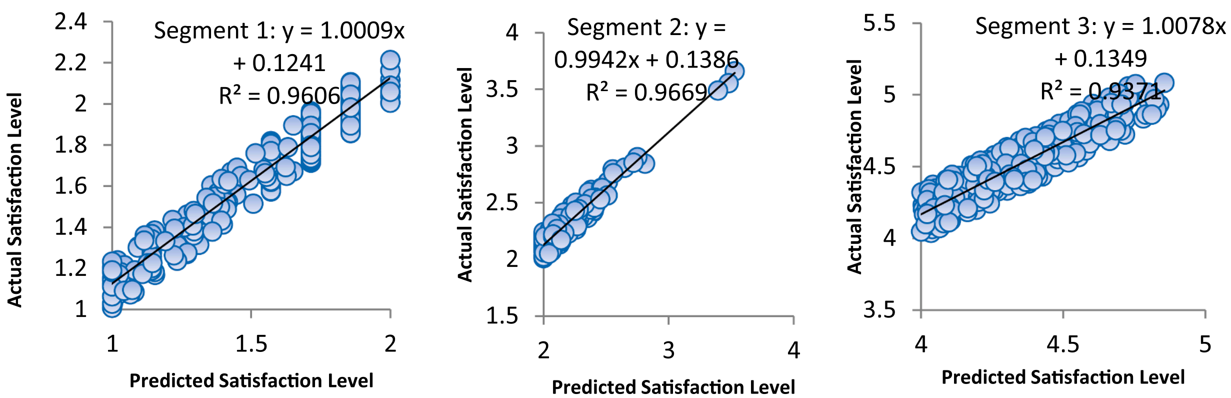


Fig. 9. Predicted values vs. actual values for satisfaction level in 3 clusters.

explored using several methods (Ameen et al., 2020). Tourists' reviews of the service quality depend on the way the classification of ratings of hotels is presented (Huang et al., 2018; Nunkoo et al., 2020; Rauch et al., 2015; Román and Martín, 2016). Following the COVID-19 crisis, food and beverage aspects are not the only variables to concentrate on anymore, several aspects related to COVID-19 preventive measures gained tourists' concerns. Particularly, during the COVID-19 crisis, tourists are putting new services related to hygiene, safety, and social distancing measures at the top of their priorities.

7. Conclusion

The outcome of this research is important to understand tourists' satisfaction and destination choices, which enables decision-makers to enhance their advertising policies, presented services, and decision-making process. Thus, this study aimed to explore

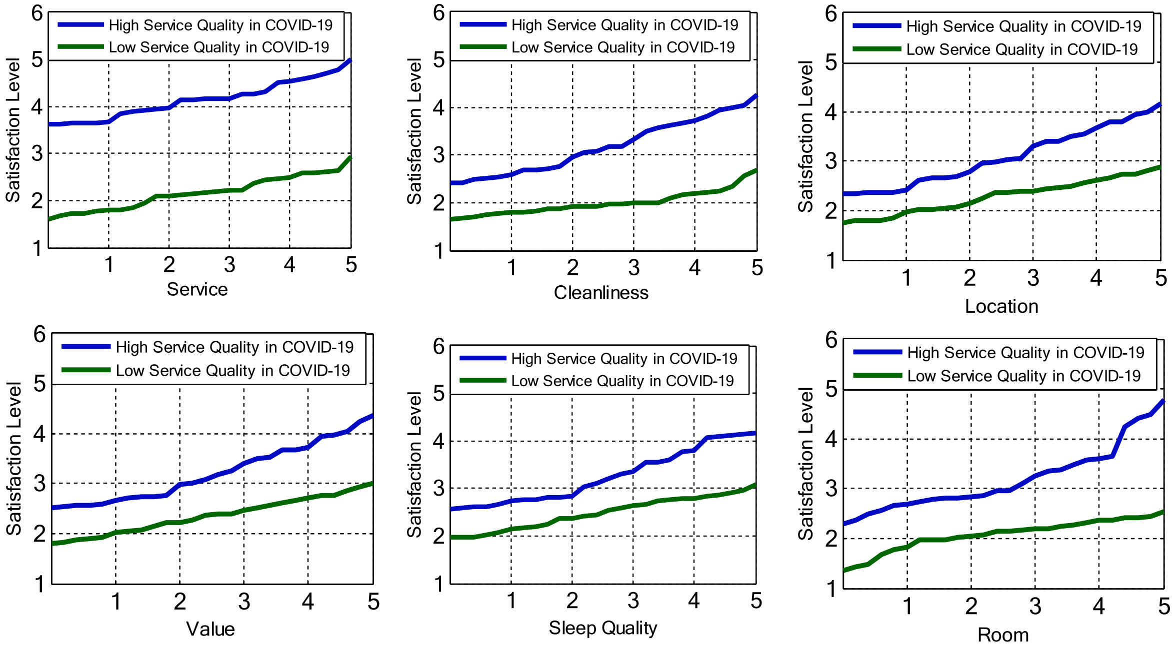


Fig. 10. The impact of service quality during COVID-19 outbreak on customers' satisfaction.

tourists' online reviews during the COVID-19 outbreak. Besides, the influence of service quality during COVID-19 on hotel performance and customers' satisfaction was elaborated. To achieve the research goal, a new approach, which utilized machine learning techniques, was proposed. The approach is based on text mining, clustering, and prediction learning techniques. Latent Dirichlet Allocation was deployed for big data analysis to capture tourists' perceptions from the voice-of-customer, Expectation-Maximization was used for clustering the data, ANFIS was utilized for satisfaction level prediction, and Higher-Order Singular Value Decomposition was used for missing value imputation. The data was collected from TripAdvisor regarding tourists' concerns in two main forms of online reviews and numerical ratings of hotels' services from different aspects. The outcomes from the analysis of online customers' reviews revealed that service quality during COVID-19 has influenced tourists' perceptions of hotels' performance and accordingly tourists'' satisfaction. The research output indicated the importance of the quality of services, particularly during the COVID-19 crisis.

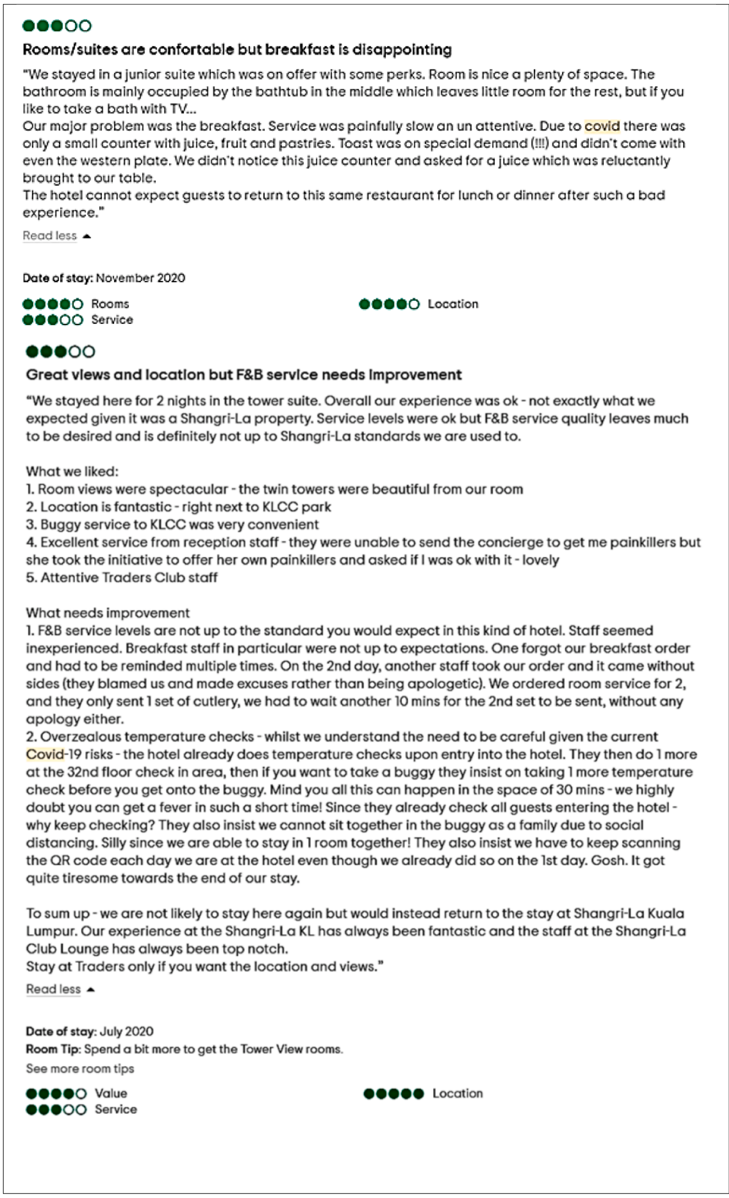
Several hotel groups have publicly announced their dedication to hotel hygiene aiming to confront tourists' concerns. Positive and negative perceptions are essential to decision-makers to understand consumers' overall experiences. With the penetration of the internet in the individuals' lives in all aspects, customers are hooked online, whereby they share experiences and perceptions in several online portals through customer reviews (Park et al., 2014). Customers' perceptions can be captured in a standardized rating approach, textual reviews approach; or both approaches incoherence (Siering et al., 2018).

This study presents a methodological contribution by adopting a new approach that integrates Latent Dirichlet Allocation, EM, and ANFIS approaches. The integration of these techniques enables investigating tourists' opinions and ratings effectively. Several quantitative, qualitative, or mixed approaches (such as surveys, interviews, and focus groups) have been used in previous literature to assess customers' satisfaction as an essential indicator of customers' overall experience (Guo et al., 2017; Lucini et al., 2020). Still, these approaches are time-consuming and may present inaccurate outcomes (Wan and Gao, 2015). This can be justified by the limited size of the sample or the inconsistency in the measurement indicators (Chow, 2015). Respondents of the questionnaire may answer the questions randomly which will add noise to the outcomes (Wan and Gao, 2015). Besides, the indicators of the survey are usually adopted from previous literature and may not be able to capture emerging consumer preferences (Lucini et al., 2020).

Considering the practical contribution of this research, tourists' perceptions are essential for decision-makers in the tourism and hospitality sectors. The research outcomes present indications for hotel managers during the COVID-19 crisis about the significance of each aspect of service quality, in which they can utilize these outcomes to enhance tourists' satisfaction. COVID-19 has influenced consumers' services forever. The operation of the tourism and hospitality businesses has been changed to form long-term plans that can confront the current crisis. It is significant for decision-makers to understand that travelers focus on browsing electronic reviews before they persuade to the booking decision. Hotels need to be present and verified in popular portals among tourists such as TripAdvisor. Hotel managers should handle negative comments conveniently. By presenting an appropriate response to constructive criticism, travelers will feel that their worries are being appropriately managed. Additionally, motivating tourists to share their experiences through eWOM can aid other tourists who have doubts regarding travel and destination choice.

8. Limitations of research and future work

This research has few limitations that should be investigated for future research directions. First, by investigating and comparing



Rooms/suites are confortable but breakfast is disappointing

"We stayed in a junior suite which was on offer with some perks. Room is nice a plenty of space. The bathroom is mainly occupied by the bathtub in the middle which leaves little room for the rest, but if you like to take a bath with TV...
Our major problem was the breakfast. Service was painfully slow an un attentive. Due to covid there was only a small counter with juice, fruit and pastries. Toast was on special demand (!!!) and didn't come with even the western plate. We didn't notice this juice counter and asked for a juice which was reluctantly brought to our table.
The hotel cannot expect guests to return to this same restaurant for lunch or dinner after such a bad experience."

Read less

Date of stay: November 2020

Rooms Location
Service

Great views and location but F&B service needs improvement

"We stayed here for 2 nights in the tower suite. Overall our experience was ok - not exactly what we expected given it was a Shangri-La property. Service levels were ok but F&B service quality leaves much to be desired and is definitely not up to Shangri-La standards we are used to.

What we liked:
1. Room views were spectacular - the twin towers were beautiful from our room
2. Location is fantastic - right next to KLCC park
3. Buggy service to KLCC was very convenient
4. Excellent service from reception staff - they were unable to send the concierge to get me painkillers but she took the initiative to offer her own painkillers and asked if I was ok with it - lovely
5. Attentive Traders Club staff

What needs improvement
1. F&B service levels are not up to the standard you would expect in this kind of hotel. Staff seemed inexperienced. Breakfast staff in particular were not up to expectations. One forgot our breakfast order and had to be reminded multiple times. On the 2nd day, another staff took our order and it came without sides (they blamed us and made excuses rather than being apologetic). We ordered room service for 2, and they only sent 1 set of cutlery, we had to wait another 10 mins for the 2nd set to be sent, without any apology either.
2. Overzealous temperature checks - whilst we understand the need to be careful given the current Covid-19 risks - the hotel already does temperature checks upon entry into the hotel. They then do 1 more at the 32nd floor check in area, then if you want to take a buggy they insist on taking 1 more temperature check before you get onto the buggy. Mind you all this can happen in the space of 30 mins - we highly doubt you can get a fever in such a short time! Since they already check all guests entering the hotel - why keep checking? They also insist we cannot sit together in the buggy as a family due to social distancing. Silly since we are able to stay in 1 room together! They also insist we have to keep scanning the QR code each day we are at the hotel even though we already did so on the 1st day. Gosh. It got quite tiresome towards the end of our stay.

To sum up - we are not likely to stay here again but would instead return to the stay at Shangri-La Kuala Lumpur. Our experience at the Shangri-La KL has always been fantastic and the staff at the Shangri-La Club Lounge has always been top notch.
Stay at Traders only if you want the location and views."

Read less

Date of stay: July 2020
Room Tip: Spend a bit more to get the Tower View rooms.
See more room tips

Value Location
Service

Online customers' reviews: *Stay was almost perfect with the promo price and service offered. Staff very friendly and helpful. Satay is the best in the world.* ***However my request for HDMI cable not fulfil and access to pavilion mall is uncomfortable due to COVID-19 SOP.***

Online customers' reviews: ***Due to covid-19 restrictions, only one dedicated lift to the lobby, do a quick temperature scan and changing lifts to the reception.*** *I was allowed early check in at 1pm, so grateful as we can settle down in the room with the kids before heading out for lunch. Check in was quick and straightforward. Your keycard is needed to head to your floor so good additional security there.*

Online customers' reviews: ***Kudos to hotel for following covid-19 SOP in accordance to government requirements.*** *Will definitely return and spread the words to my friends. Keep up the good work team.*

Online customers' reviews: *Nice place. best experiences too. Their customer service friendly. Tq Mr SYAMIM for many helping.* ***The staff also really helpful and comply with covid SOP.*** *Good environment good facilities good location. It was a wonderful stay with affordable price.*

Online customers' reviews: ***Overzealous temperature checks - whilst we understand the need to be careful given the current Covid-19 risks - the hotel already does temperature checks upon entry into the hotel.*** *They then do 1 more at the 32nd floor check in area, then if you want to take a buggy they insist on taking 1 more temperature check before you get onto the buggy. Mind you all this can happen in the space of 30 mins - we highly doubt you can get a fever in such a short time! Since they already check all guests entering the hotel - why keep checking? They also insist we cannot sit together in the buggy as a family due to social distancing. Silly since we are able to stay in 1 room together! They also insist we have to keep scanning the QR code each day we are at the hotel even though we already did so on the 1st day. Gosh. It got (Nilashi et al., 2018b) quite tiresome towards the end of our stay.*

Fig. 11. The impact of service quality on service criteria and customers' satisfaction during COVID-19 outbreak.

online ratings and textual opinions of travelers which are presented in various languages, different locations, and within different contexts, future research routes can be followed. Second, another study can compare online ratings and textual opinions of travelers, before and after the COVID-19 pandemic, for the same hotels, which will provide useful outcomes for hotel managers in order to contrast what areas have been impacted the most during this outbreak concerning tourist satisfaction. Third, the study concentrated on the gathered data from one tourism platform. Another study can utilize the data from other portals, which will present more generalizable outcomes. Fourth, electronic comments and ratings are changing over time. Hence, to address the changeable consumers' needs, future research can consider methods to investigate the electronic opinions and ratings in an incremental manner. Fifth, the study concentrated on the tourism and hospitality area. Thus, applying the findings of this study to other areas needs more investigation, particularly within the COVID-19 context, as the factors that can impact customers' satisfaction rely on the kind of rated product or services.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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