Journal of Retailing and Consumer Services 64 (2022) 102783

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Revealing travellers' satisfaction during COVID-19 outbreak: Moderating role of service quality

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A R T I C L E I N F O

Keywords:
Online customers' reviews
Customers' satisfaction
Machine learning
Service quality
Survey study

A B S T R A C T

User-Generated-Content (UGC) has gained increasing attention as an important indicator of business success in the tourism and hospitality sectors. Previous literature has analyzed travelers' satisfaction through quantitative approaches using questionnaire surveys. Another direction of research has explored the dimensions of satisfaction based on online customers' reviews using the machine learning approach. This study aims to present a new method that combines machine learning and survey-based approaches for customers' satisfaction analysis during the COVID-19 outbreak. In addition, we investigate the moderating role of service quality on the relationship between hotels' performance criteria and customers' satisfaction. To achieve this, the Latent Dirichlet Allocation (LDA) was used for textual data analysis, k-means was used for data segmentation, dimensionality reduction approach was used for the imputation of the missing values, and fuzzy rule-based was used for the prediction of satisfaction level. Following that, a survey-based approach was used to validate the research model by distributing the questionnaire and analyzing the collected data using the Structural Equation Modeling technique. The result of this research presents important contributions from the methodological and practical perspectives in the context of customers' satisfaction in tourism and hospitality during the COVID-19 outbreak. The outcomes of this research confirm the significant influence of the quality of services during the COVID-19 crisis on the relationship between hotel services and travellers' satisfaction.

1. Introduction

The huge utilization of Web 2.0 technology in several disciplines allows the generation of big data through several tools and platforms (Li et al., 2018). Big data can be generated through organizations' platforms, such as hotels, tourism agencies, and travel agencies, third-party agents such as online reviews on Booking.com, Expedia, and Skyscanner (Xiang et al., 2015), social media platforms like LinkedIn, Facebook, and Twitter (Chua et al., 2016), and specific review portals such as Yelp and TripAdvisor (Viglia et al., 2016). The analysis of big data using Artificial Intelligence (AI) approaches has brought many benefits for consumers and decision-makers (Hashem et al., 2015). Using AI approaches allows decision-makers to find hidden patterns about consumers and markets (Xie et al., 2016). Decision-makers understand that consumers refer to big data to aid their choices (Gavilan et al., 2018). AI approaches provide decision-makers with knowledge about their consumers' attitudes and behaviors (Talón-Ballestero et al., 2018). AI approaches have been used for big data analytics to enable the integration, analysis, and sharing of data (Bag et al., 2021; Zhang et al., 2021). Several studies have investigated big data analytics as a robust method to assess the

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https://doi.org/10.1016/j.jretconser.2021.102783
Received 11 April 2021; Received in revised form 4 September 2021; Accepted 21 September 2021
Available online 25 September 2021

level of consumer satisfaction and the quality of services and items (Shamim et al., 2021; Xiang et al., 2015). Online customer reviews are regarded as big data because of their high volume, diversity, and value (Ghasemaghaei and Calic, 2020).

Online comments and standardized ratings posted on online platforms are the basic forms of User-Generated-Content (UGC) (Luo et al., 2021). UGC is defined as all available electronic information, which is available for the public, generated by end-users, not by media experts (Knoll, 2016). UGC has gained increasing attention as an important indicator of business success (Gour et al., 2021). Passionate, spontaneous, and insightful reviews posted by thousands of consumers create the "wisdom of crowds" impact (Lucini et al., 2020). UGC resulted from the broad utilization of new technologies has a significant part in influencing service vendors' revenues, brand images, and service innovations (Lee et al., 2020). From the customers' perspectives, UGC has influenced consumers dramatically; allowing them to share comments or experiences with others, and accordingly, impacting their choices (Amaral et al., 2014; Cox et al., 2009; Lu and Stepchenkova, 2015; Mendes-Filho and Tan, 2009). UGC has been explored in several contexts such as electronic-food-delivery (Ray and Bala, 2021), on-demand service (Xu, 2021), hotels (Lee et al., 2020), tourism (Ahani et al., 2019a; Nilashi et al., 2018), and travel (Lucini et al., 2020; Mendes-Filho and Tan, 2009). Hence, it is significant to draw meaningful insights about consumer satisfaction from online reviews by using appropriate analytics techniques (Hu and Kim, 2018).

Customers are satisfied with the presented services when the quality dimensions of the service are fulfilled or surpassed (Chow, 2015; Lucini et al., 2020). Customer satisfaction is an important driver of customers' loyalty, which is reflected by spreading positive comments, repurchase behavior, or suggesting the item or service to other individuals (Forgas et al., 2010; Mattila, 2004; Morgan and Hunt, 1994). On the contrary, unsatisfied consumers may not return to the same vendor or service (Muturi et al., 2013), or spread negative comments among others, which might influence the business image and reputation (Muturi et al., 2013).

To assess the dimensions of travelers' satisfaction, traditional qualitative (interviews), quantitative (questionnaires), or a combination of both approaches were used by scholars (Guo et al., 2017). Still, as indicated in several studies, these methods have clear shortcomings related to time consumption and the accuracy of the outcomes (Lucini et al., 2020; Wan and Gao, 2015). The size of the sample, the inconsistency of the indicators in the factors, or random responses of the survey may add noise to the analysis and lead to biased outcomes (Chow, 2015).

As a replacement to traditional quantitative and qualitative methods, researchers from several disciplines have analyzed UGC to understand consumer preferences and needs (Chau and Xu, 2012). Consumers' reviews, which are posted online, are distinguished by their accessibility, availability, and low or free of charge cost (Guo et al., 2017). Following the direct interaction between the consumer and a particular product or service, the consumer posts his/her feedback in terms of online ratings (which might be represented in star ratings) and electronic textual comments (Flanagin and Metzger, 2013; Sparks et al., 2016). Hence, it is of great importance to use advanced approaches of text mining for deriving the dimensions of satisfaction from UGC, which will allow both researchers and decision-makers to obtain insightful outcomes from consumer feedbacks (Ahani et al., 2019b). Compared to traditional survey-based and interview-based analysis approaches, machine learning methods can indicate consumers' choices automatically from big datasets (Nilashi et al., 2019). Based on the above factors, various machine learning approaches have been utilized to conduct text mining of online reviews in many disciplines (Ahani et al., 2019a; Cenni and Goethals, 2017; Chang et al., 2019; Taecharungroj and Mathayomchan, 2019). On the other hand, focusing on the text mining method, one major challenge that faces researchers in this context is the uncertainty about the genuinity of the reviews presented on social media platforms (Moon et al., 2020).

The COVID-19 crisis is influencing market revenues, supply chain, and management strategies over the globe (Abideen et al., 2020; Azlan et al., 2020; Bakar and Ramli, 2020). Specifically, the tourism and hospitality industries are sensitive to such global crises (Cró and Martins, 2017) and should conduct suitable management strategies (Ritchie and Jiang, 2019). The tourism and hospitality industries suffer from a worldwide crash in revenues, demands, and occupancy rates (Gursoy and Chi, 2020; Rivera, 2020). Among the impacted sectors, hotels are working under serious bans and "new normal" requirements to be followed. Hotel managers are arranging how to safely present services, and, considering the continuing of the crisis, there is uncertainty concerning how these conditions may develop. Hence, decision-makers in the tourism and hospitality sectors have to be sure that they are performing the most appropriate procedures as indicated by the WHO and following local and global regulations.

During this crisis, travelers are more worried about possible health threats when they travel to a specific location. With the restrictions imposed by social distancing rules that impacted the usage of shared hotel facilities, in-room experiences and hygienic issues will be vital matters for tourists (Hu et al., 2021). A change in customers' expectations is anticipated to influence customers' perceptions of the presented services. Expectancy Confirmation Theory (ECT) indicates that customers' satisfaction with the presented services changes with changes in consumers' expectations (Oliver, 1980). Hence, based on the ECT, we hypothesize that tourists' satisfaction will be changed in the current situation based on the change in their perceptions of the quality of the provided services.

To address the increasing health risks during this crisis, the TripAdvisor portal has launched the Travel Safe initiative to enable businesses in the tourism and hospitality sectors to present their safety procedures (TripAdvisor, 2020). Many hotels in the TripAdvisor portal have presented the safety arrangements they follow to gain travelers' trust. These measures include the mandatory wearing of face masks in public areas, physical distancing measures, and providing hand sanitizer locations. On the other hand, travelers' comments indicate their understandings of Standard Operating Procedures (SOPs). Hence, it is important to investigate travelers' satisfaction during this unprecedented pandemic and to consider emerging safety requirements.

Based on the above discussion, in this study, we aim to propose a new method that integrates both machine learning and survey-based approaches to investigate and validate the factors that impact travelers' satisfaction during the COVID-19 crisis. Besides, we explore the moderating role of service quality on the relationship between hotels' performance criteria and customers' satisfaction. To simplify, we present a list of the abbreviations used in this study in Table 1. The novelty of this research falls within the following folds:

i. From the methodological aspect, this study proposes a new two-stages methodology that integrates both machine learning and survey-based approaches.
ii. From the context aspect, this study explores the quality of the presented services and travelers' satisfaction during a global health crisis such as COVID-19.
iii. From the practical aspect, we aim to present insightful outcomes for decision-makers about the important quality factors that influence travelers' satisfaction and how the quality of the services during COVID-19 influence travelers' satisfaction.

2. Online customers' reviews and ratings

Previous literature on online reviews has focused on predicting customer decisions, business revenues, and marketing policies (Anderson and Magruder, 2012; Felbermayr and Nanopoulos, 2016; Liu, 2006). In the context of the tourism and hospitality sector, online reviews have played a significant part in recent years (González-Rodríguez et al., 2021). Tourists refer to several forms of UGC, entailing microblogs,

Table 1
List of abbreviations utilized in this research.

Abbreviation	Description
UGC	User Generated Contents
LDA	Latent Dirichlet Analysis
ECT	Expectancy Confirmation Theory
ML	Machine Learning
OBIM	Online Brand IMage
HOSVD	Higher-Order Singular Value Decomposition
PLS-SEM	Partial Least Squares Structural Equation Modeling
PLS-PM	Partial Least Squares Path Modeling
SVD	Singular Value Decomposition
SOPs	Standard Operating Procedures
WHO	World Health Organization
SSE	Sum of Squared Error value
FIS	Fuzzy Inference System
FRBS	Fuzzy Rule-Based System
WSS	Within Sum of Squares
BSS	Between Sum of Squares
TSS	Total Sum of Squares
CV	Convergent Validity
COVID-19	Coronavirus Disease 2019
IC	Internal Consistency
DV	Discriminant Validity
CR	Composite Reliability
AVE	Average Variance Extracted
CA	Cronbach's Alpha
CL	Cross-Loadings
FL	Fornell-Larcker
VIF	Variance Inflation Factor
PC	Path Coefficient
R^2	Coefficients of Determination
Q^2	Stone-Geisser's Value

picture blogs, blogs, social networks, and online communities when selecting a particular place to visit (Fan et al., 2018; Nusair et al., 2019). Hence, several studies have investigated online reviews focusing on the tourism and marketing fields and following several directions of research.

Many studies of electronic consumer reviews have concentrated basically on consumers' feedbacks about their experiences with services or items (Mitra and Jenamani, 2020; Moon et al., 2019). In a study by Mitra and Jenamani (2020), a new model of Online Brand IMage (OBIM) was presented based on unstructured customer reviews and referring to Amazon.com crawled data. The brand image was quantified based on the favourability, uniqueness, and strength of brand associations. The research presented a significant contribution from the methodological perspective by estimating brand image based on unstructured opinions. The impact of managerial responses to electronic reviews on consumer satisfaction was investigated empirically in a study by Zhao et al. (2020). The authors utilized an additional review module to enable consumers to present their complimentary comments. The result of the study indicated the vital influence of managerial responses on consumer satisfaction focusing on the e-commerce context. Still, the research outcome needs more exploration to be generalized to other contexts in other social media platforms. In a study by Mehraliyev et al. (2020), the authors attempted to evaluate the influence of previous experiences entailing the five senses on consumer ratings. Consumers' sensory experiences were acquired and investigated using text mining approaches based on the data from social media platforms. The outcomes of the research indicated the high influence of negative sensory experiences on consumer rating. Still, the generalizability of this research depends basically on the used dictionary of the classifier terms. Xu (2021) adopted a text mining approach to investigate the drivers of consumers' satisfaction based on consumers' comments in the context of restaurants. The outcomes of the research indicated the impact of the cost of the order on consumers' review behavior and expression of consumers' experiences. Within the context of restaurants, a study by Tian et al. (2021) utilized the Yalp dataset to explore the factors that influence consumers' sentiment comments. The result of the study indicated that the usage of positive comments is higher than negative comments with more focus of consumers on the provided services rather than the served food. In the context of hotels, Moon et al. (2019) concentrated on consumers' opinions about hotels based on a third-party booking portal. The authors examined the influence of the posting strategies of close-ended and open-ended reviews on establishing social media bias. Besides, a trust measure was developed to assess the authenticity of the feedback. The main contribution of their study is revealing the significant aspects that influence visitors' choices and representing hotel topics based on visual representations.

Another direction of research has concentrated on the factors that impact the adoption of UGC among travelers or the reliability of the reviews (Ayeh et al., 2013; Ukpabi and Karjaluoto, 2018). In a study by Zheng et al. (2021), the problem of the reliability of reviews was explored using a quantitative methodology by defining biased ratings based on textual reviews. The authors used deep learning techniques to explore the textual content and assessed the impact of rating prediction based on a crawled dataset from Yelp. Still, as a vital shortcoming of the study, only emotional terms in feature extraction were considered and other information and topics that might impact the sentiment were ignored.

Other studies have concentrated on investigating customers' motivations to present UGC (González-Rodríguez et al., 2021). In a study by González-Rodríguez et al. (2021), users' engagement with UGC was explored. Several influential factors were indicated as antecedents of UGC such as community, co-creation, self-concept, and empowerment focusing on the cultural differences. Another study by Christodoulides et al. (2012) indicated self-concept, co-creation, community, and empowerment, as the main drivers of UGC creation.

3. Method

The proposed methodology is presented in Fig. 1. As seen from this figure, our methodology includes two main stages, the analysis by machine learning, and the analysis by a statistical approach. In the machine learning analysis, the procedure includes data collection from social media portals, data pre-processing, text mining, clustering, and prediction. On the other hand, the survey-based stage entails data collection and data analysis using PLS-SEM. The aim of utilizing the PLS-SEM is to analyze the proposed model of satisfaction according to the factors generated from the textual reviews and performance factors. This stage follows the procedure of model assessment according to PLS-SEM which includes the development of model and hypotheses, evaluation criteria of measurement model (reflective models or formative models), and evaluation criteria of the structural model. Overall, the method of this study has two main stages as presented in Table 2.

4. Methodology

4.1. Machine learning approach

i. We used LDA for topic modeling. As a generative probabilistic modeling approach, this technique was first developed by Blei et al. (2003) to discover hidden semantic structures in a set of textual documents. The LDA approach was used effectively in previous researches in text mining in the online shopping context (Chen et al., 2018; Mou et al., 2019; Yuan et al., 2018).
ii. Following that, a clustering approach was used to cluster big data into segments based on the UGC collected from consumers' reviews. Hence, we utilized k-means as an unsupervised learning technique and an iterative algorithm for data clustering, as presented in Algorithm 2. The algorithm partitions n observations into k clusters by finding the mean distance between data points. In the Sum of Squared Error value (SSE), overall k clusters are aimed to be minimized as:

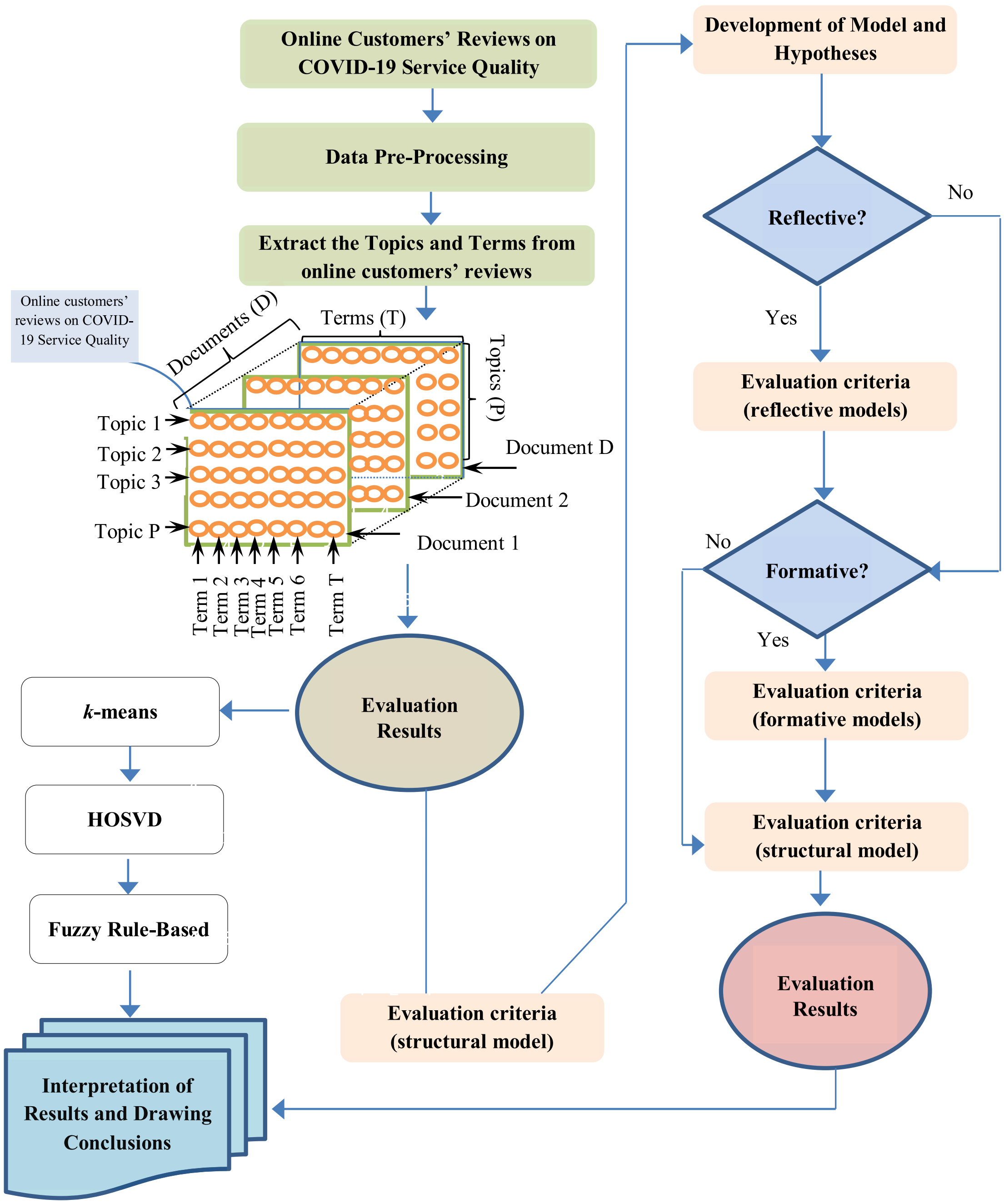

Fig. 1. Two-stage methodology for customers' satisfaction during COVID-19.

$$SSE = \sum_{p=1}^{k} \sum_{x_i \in C_p} x_i - \mu_p \tag{3}$$

Algorithm 2. K-means clustering

iii. HOSVD, which is a multilinear generalization of SVD, was used for the imputation of missing values. This approach can address the problem of dimensionality reduction for big data that entails more than 2 dimensions. This technique allows the decomposition of tensors into their basic parts, which allows the calculation of similarity on the data with minimized dimensions.

iv. The Fuzzy Rule-Based System (FRBS) was used for the prediction of customers' preferences from the crawled data. Investigating the relationship between input features is significant for the customers' satisfaction prediction. Fuzzy logic has been widely used in complex system modelling (Al-Qudah and Hassan, 2017; Selvachandran et al., 2018; Tareq et al., 2015). The FRBS which is also known as the Fuzzy Inference System (FIS) (Botta et al., 2008; Dimitriou et al., 2008; Tsakiridis et al., 2017) is based on fuzzy logic (Zadeh, 1983, 1996). This system is used to model complex systems by discovering the relationship between the input and output variables (see Fig. 2).

4.1.1. *Data collection*

In the first stage, the data is collected from TripAdvisor. In TripAdvisor, users can rate the hotels through a set of performance factors. In addition, they can share their experiences and reveal their concerns and satisfactions about the hotels' service quality through textual

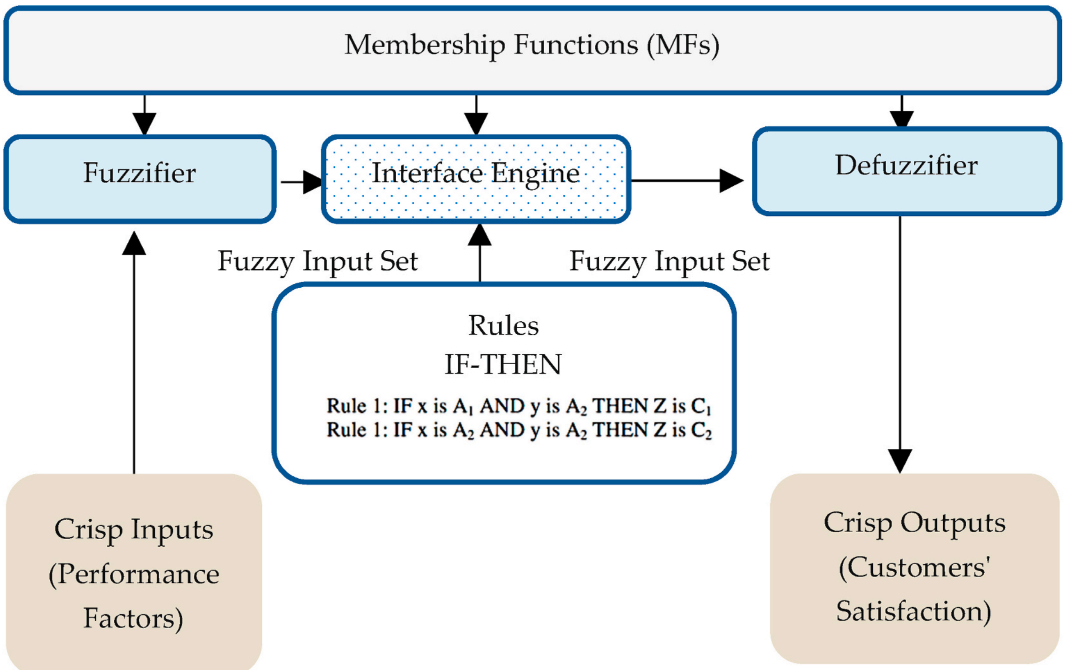

Fig. 2. A general scheme of a fuzzy rule-based system.

Table 2
The methodology of the study.

Stage	Approach
Stage 1 (Machine learning)	1- LDA was used to derive the dimensions of consumer satisfaction from a large dataset of online consumer reviews (Godnov and Redek, 2016; Loh et al., 2003). 2- K-means approach, as an unsupervised learning technique, was used for data clustering. 3- Higher-Order Singular Value Decomposition (HOSVD), which is a multilinear generalization of Singular Value Decomposition (SVD), was used for the imputation of missing values. 4- The Fuzzy Rule-Based System (FRBS) was used for the prediction of customers' satisfaction from the users' ratings.
Stage 2 (Survey-Based)	1- Based on the results, a new research model was developed, which elaborates the factors that impact consumers' satisfaction during the COVID-19 outbreak. 2- Following that, a questionnaire was developed, 3- The questionnaire was used and distributed among a group of users (as travelers), who had experience with TripAdvisor for searching hotels. 4- Using the SEM technique, the collected data was analyzed to confirm the outcomes from big data analysis. This allows the researcher to confirm the robustness of the two proposed stages.

reviews. TripAdvisor was chosen for data collection because it allows users to post their comments based on an open comment form (Moon et al., 2019). This enables the users to present much higher dimensions in comments with both positive and negative expressions rather than other portals that adopt closed comment forms. In the TripAdvisor platform, hotels with high rates and positive comments are more requested by tourists, with longer periods of stay, compared to those with insufficient or bad reviews (Hoisington, 2018). In this study, six criteria are considered as performance factors which are sleep quality, value (cost-benefit), service, location, rooms, and cleanliness. Besides, users can provide an overall rating which shows the overall satisfaction level during their stay in the hotels. These types of data have been widely used in the assessment of customers' satisfaction in the previous literature (Nieto-Garcia et al., 2019; Pacheco, 2017; Yadegaridehkordi et al., 2021). It has been shown that these factors have significant impacts on customers' satisfaction (Radojevic et al., 2018; Rhee and Yang, 2015). In Fig. 3, we present an example of users' ratings and online reviews of hotels during the COVID-19 outbreak. It is found that customers have several concerns about the hotels' service quality from different perspectives during the COVID-19 outbreak. Accordingly, we aimed to further analyze the ratings and textual reviews to find the relationships between satisfaction levels and these criteria during the COVID-19 outbreak. In this study, a total of 1538 ratings and textual reviews were collected. Many ratings on sleep quality, value (cost-benefit), service, location, rooms, and cleanliness criteria were incomplete. Accordingly, this study tried to use a method for missing values'

Algorithm 2: K-means clustering

Input k: the number of clusters, X: A dataset with n data objects
Output Set of centroids (μ_p)

k objects are arbitrarily chosen from X as the initial cluster centers
Repeat
  Assignment of each data object to its closest centroids
  Update of the cluster centers (μ_p)
Until the centroid position no change
return μ_p

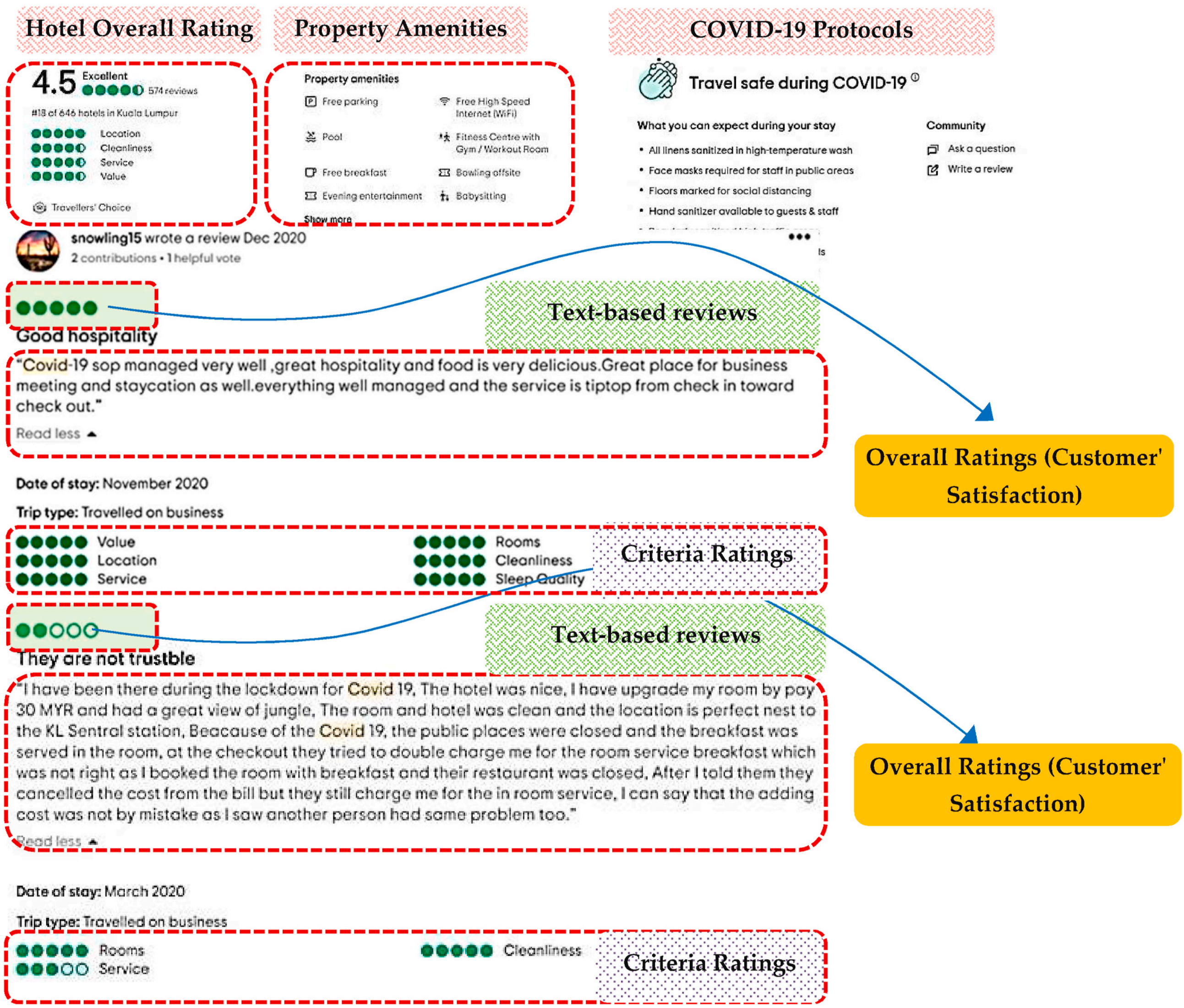

Fig. 3. The reviews provided by travelers during the COVID-19 outbreak.

imputation before they can be used in satisfaction prediction. It should be noted that we considered the data which are related to the COVID-19 outbreak in the TripAdvisor portal. An example of collected data from TripAdvisor is shown in Table 3.

4.1.2. *Data analysis*

The data was collected from TripAdvisor and the pre-processing steps were performed. LDA was applied to the textual review to generate the satisfaction dimensions. An example of the generated word cloud for the textual reviews is shown in Fig. 4. Then, the k-means clustering was applied to the clean data. Three segments ($k = 3$) were considered in the k-means. The results of clustering are shown in Table 4. The first, second and third segments' centroids are [2.322148, 1.939597, 2.119128, 2.243289, 2.006711, 2.516779], [3.665765, 3.645467, 3.552097, 3.608931, 3.657645, 3.635995], and [4.945813, 4.980296, 4.950739, 4.970443, 4.945813, 4.935961], respectively. The centroids are important when predicting new customers' satisfaction through their ratings. In addition, through these centroids, new customers are assigned to the segments according to their rating distance to the centroids. The centroids further reveal which factors are more important for the customers. For example, it is found that in Segment 1, the ratings for value criteria have been very low. In Segment 2, in which the ratings are moderate for all criteria, the location has received a lower rate than other criteria. In Segment 3, the ratings are relatively very high

Table 3
An example of collected data from TripAdvisor.

User ID	Hotel ID	Cleanliness	Service	Value	Rooms	Location	Sleep Quality	Overall Ratings
U100	H10	5	5	4	5	5	5	5
U231	H43	0	0	0	3	3	3	2
U343	H72	3	2	3	4	0	4	3
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
Ui	Hj	4	4	4	3	3	0	4
Un	Hm	2	2	2	3	3	4	3

Fig. 4. Word cloud of textual reviews.

Table 4
Cluster centroids.

Attribute	Segment 1	Segment 2	Segment 3
Rooms	2.322148	3.665765	4.932212
Value	2.539597	3.745467	4.960296
Location	2.119128	3.552097	4.950739
Service	2.643289	3.818931	4.970443
Cleanliness	2.006711	3.657645	4.945813
Sleep Quality	2.516779	3.635995	4.935961

for all criteria. It is found that customers have been highly satisfied with the value and service in Segment 3. In Table 5, k-means parameters are presented for all input variables of the dataset in each segment.

Overall, the number of records is 596, 739, and 203 respectively in Segment 1, Segment 2, and Segment 3. In this table, we also present the WSS, BSS, and TSS values of all segments. The $\frac{BSS}{TSS}$ ratio is important to be high for the clustering quality. $\frac{BSS}{TSS}$ ratio is calculated as follows:

$$\frac{BSS}{TSS} = \frac{\sum_{k=1}^{K}\sum_{j}^{p}\left(\overline{x}_{kj} - \overline{x}_{G}\right)^{2}}{\sum_{k=1}^{K}\sum_{j}^{p}\left(\overline{x}_{kj} - \overline{x}_{G}\right)^{2} + \sum_{k=1}^{K}\sum_{i\in S_k}\sum_{j=1}^{p}\left(x_{ij} - \overline{x}_{kj}\right)^{2}} \tag{4}$$

where in the k^{th} cluster, S_k is the set of instances grouped, $\overline{x}_{kj}$ is the j^{th} variable of the cluster center, and $\overline{x}_G$ indicates the grand mean of the means of each segment.

The results show that k-means has provided segments with high $\frac{BSS}{TSS}$ ratio as shown in Table 5, which demonstrates that the cluster compactness is relatively high. This will impact the result of customers' satisfaction prediction which is done in the next stage of our methodology by a fuzzy-rule-based approach.

A fuzzy rule-based approach was implemented in this study with decision rules discovered in three segments of k-means. We have considered different membership functions, Triangular and Gaussian, in our implementation. These types of membership functions are widely used in Mamdani fuzzy rule-based systems. These membership functions are shown in Fig. 5. The ranges for these membership functions are presented in Table 6. Triangular membership functions were implemented for output and Gaussian membership functions were considered for inputs. Three linguistic variables, as Low, Moderate, and High for inputs and five linguistic variables as Very Low, Low, Moderate, High, and Very High for output, were used in the Mamdani rule-based system. The generated fuzzy rules in the form of IF-THEN, in which a part of these rules discovered in 3 segments, are shown in Table 1 in Appendix A. For example, in Rule 1 of Segment 1, it is found that for [Low Level] of all performance factors, a [Very Low Level] of satisfaction is obtained for the customers. In Addition, in Rule 7 of Segment 1, when Rooms is in [Moderate Level], Value is in [Low Level], Location is in [Low level], Service is in [Low level], Cleanliness is in [Low level], and Sleep Quality is in [High level], then a [Low Level] of satisfaction can be obtained for the customers. Some fuzzy rules in the form of IF-THEN are shown in Fig. 6.

The discovered fuzzy rules were implemented in the fuzzy rule-based system for satisfaction prediction in three segments. In this system, the inputs are performance factors (sleep quality, value (cost-benefit), service, location, rooms, and cleanliness), and the outputs are the satisfaction levels. According to the segments discovered by k-means, each segment has included the most similar cases for customers' satisfaction according to the performance factors. Accordingly, we provide the results of a fuzzy rule-based system for satisfaction levels in different plots to show the customers' behavior in each segment. The results are shown in Fig. 7. From this figure, it is found that the service criterion, as a performance factor, is more important for the customers during the COVID-19 outbreak. This finding is confirmed in the 3 segments from customers' ratings of hotels.

4.2. Survey-based approach

Based on the derived factors from the first stage of the proposed approach, we designed the research model, which is presented in Fig. 8. In the proposed research model, we present the hypotheses in Table 7:

4.2.1. Data collection

To assess the proposed model, we distributed the questionnaire among travelers through social media platforms. We elaborate that we will use the collected data for research purposes only. We obtained 369 valid questionnaires, which were considered for further analysis. The data was gathered using a questionnaire that entails three main parts: (1) a preface that describes the aim of the survey, (2) the demographic

Table 5
K-means parameters.

Attribute Y	Attribute X	Description				Statistical test		
Rooms	Cluster K-Means	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	596	2.3221	1.0307	BSS	1990.1974	14
		Segment 2	739	3.6658	0.7864	WSS	333.1193	1523
		Segment 3	203	4.9322	0.2850	TSS	2323.3166	1537
		All	1538	3.3140	1.2295	**Significance level**		
						Statistics	**Value**	**Proba**
						Fisher's F	649.932491	0.000000
Value	Cluster K-Means	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	596	2.5396	0.9275	BSS	2062.4341	14
		Segment 2	739	3.7455	0.7590	WSS	612.8981	1523
		Segment 3	203	4.9603	0.1393	TSS	2675.3322	1537
		All	1538	3.1606	1.3193	**Significance level**		
						Statistics	**Value**	**Proba**
						Fisher's F	366.069582	0.000000
Location	Cluster K-Means	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	596	2.1191	1.0913	BSS	2187.3713	14
		Segment 2	739	3.5521	0.8254	WSS	459.0169	1523
		Segment 3	203	4.9507	0.3554	TSS	2646.3882	1537
		All	1538	3.1814	1.3122	**Significance level**		
						Statistics	**Value**	**Proba**
						Fisher's F	518.400829	0.000000
Service	Cluster K-Means	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	596	2.6433	0.8237	BSS	1674.6827	14
		Segment 2	739	3.8189	0.8065	WSS	514.8056	1523
		Segment 3	203	4.9704	0.1698	TSS	2189.4883	1537
		All	1538	3.2594	1.1935	**Significance level**		
						Statistics	**Value**	**Proba**
						Fisher's F	353.884209	0.000000
Cleanliness	Cluster K-Means	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	596	2.0067	1.1107	BSS	2391.4637	14
		Segment 2	739	3.6576	0.7847	WSS	441.2313	1523
		Segment 3	203	4.9458	0.3330	TSS	2832.6951	1537
		All	1538	3.1879	1.3576	**Significance level**		
						Statistics	**Value**	**Proba**
						Fisher's F	589.616057	0.000000
Sleep Quality	Cluster K-Means	**Value**	**Examples**	**Average**	**Std-dev**	**Variance decomposition**		
						Source	**Sum of square**	**d.f.**
		Segment 1	596	2.5168	1.3453	BSS	2033.9468	14
		Segment 2	739	3.6360	0.7853	WSS	508.0824	1523
		Segment 3	203	4.9360	0.3599	TSS	2542.0293	1537
		All	1538	3.3739	1.2860	**Significance level**		
						Statistics	**Value**	**Proba**
						Fisher's F	435.489118	0.000000

data of participants, and (3) the body of the survey. Data gathering was performed during a period of three months from January 2021–March 2021. The demographic data are presented in Table 8.

4.2.2. Data analysis

The reliability and the validity of the model were evaluated based on several assessments of both the inner and outer models by utilizing SmartPLS software (www.SmartPLS.com). Both variable analysis and path analysis can be conducted robustly using SEM (Structural Equation Modeling). Using SEM enables the researcher to examine the paths among endogenies and exogenous variables in the research (Hair et al., 2020). SmartPLS enables handling samples with large and small sizes, which motivated us to adopt it in this research. Analysis outcomes of each of the inner and the outer models are presented in the following sections.

4.2.2.1. Assessment of the outer model. Researchers must inspect two categorizations of indicators namely reflective and formative measurement models when deploying variables (Nilashi et al., 2016). Variables adopted in IS areas might have a reflective or formative origin (Hair et al., 2013). Deploying a questionnaire in the research and assessing the survey correlates to the method of deploying the measurement model. Thus, when deploying the outer model, the researcher needs to examine two different types of measurement specifications, which entail reflective and formative measurement research models. Both measurement specifications need to be assessed when examining outer models as each

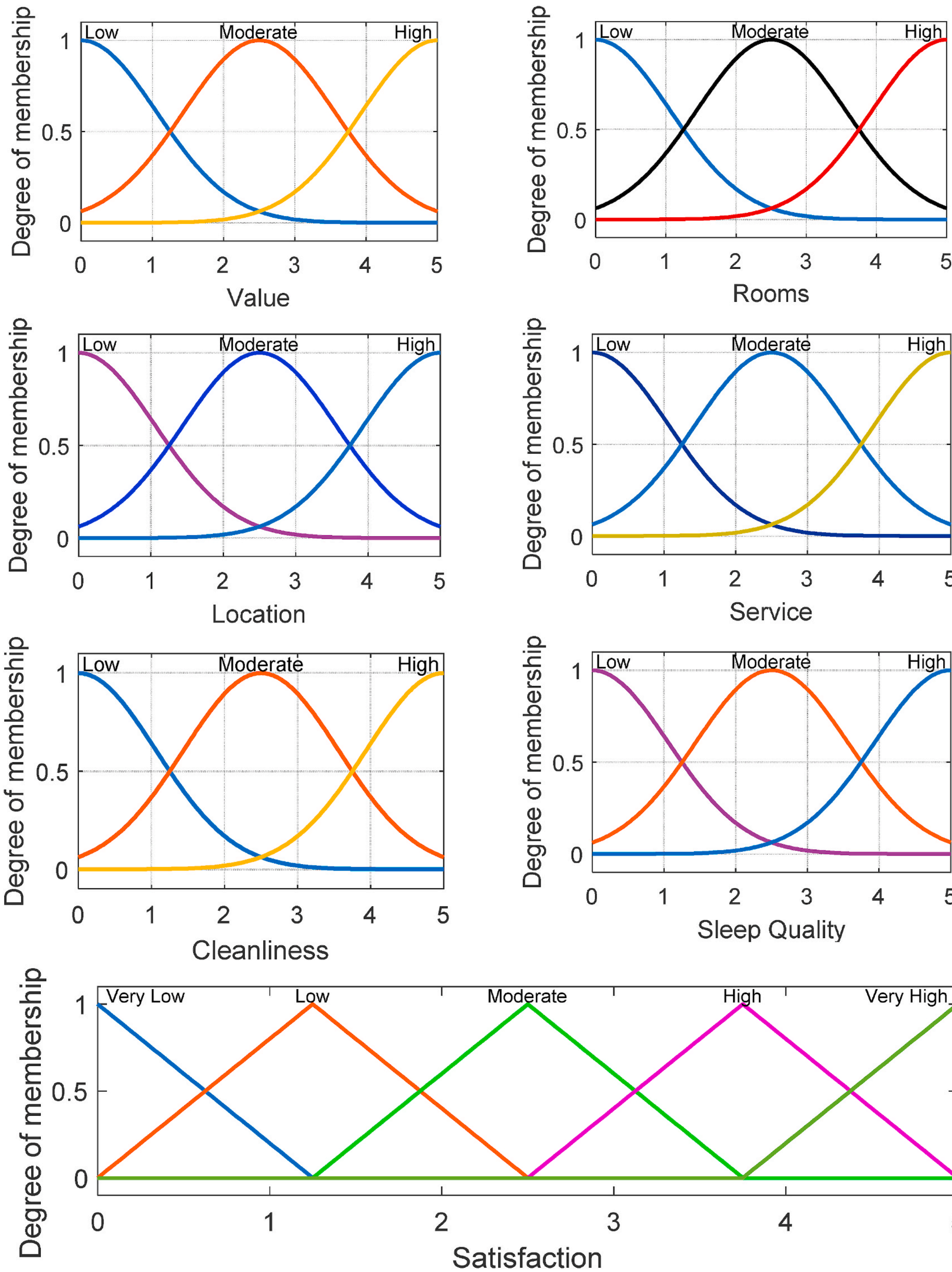

Fig. 5. Membership functions for Mamdani rule-based system.

type is operated according to a specific concept and provides different evaluative results (Hair et al., 2013). Hence, a specific and suitable outer model analysis was indicated in this research to proceed to the empirical analysis. Still, there is no obvious rule to aid the researcher to decide which variable specification (reflective or formative) is better to assess the variable in a specific study. Particularly, the choice to determine which outer model is suitable to adopt is one of the methodological problems that face researchers in many areas. The operational definition of study variables can be inferred and determined by referring to the previous literature (Hair et al., 2013). Referring to previous literature, the "Value" and the "Room" variables were considered as formative variables. The references of the survey items are presented in Table 2 in Appendix A.

4.2.2.1.1. Assessment of reflective variables. In this study, the reflective outer model was assessed using SmartPLS based on three basic evaluations which are: Convergent Validity (CV), Internal Consistency (IC), and discriminant validity (DV) (Hair et al., 2020). In the CV evaluation, all items of the questionnaire were checked in terms of their outer loadings, in which each item should have outer loading above 0.7, as indicated by Hair et al.'s (2013) rule. Items with outer loadings between 0.4 and 0.7 should be deleted only if this can enhance the outcomes of Composite Reliability (CR) or Average Variance Extracted

Table 6
Membership functions for inputs and output variables in Mamdani fuzzy rule-based system.

Variable Type	Variable Name	Type of MF	Linguistic values and ranges of membership functions				
Input	Rooms	Gaussian	Low [1.062–2.776e-17]	Moderate [1.062 2.5]		High [1.062 5]	
	Value	Gaussian	Low [1.062–2.776e-17]	Moderate [1.062 2.5]		High [1.062 5]	
	Location	Gaussian	Low [1.062–2.776e-17]	Moderate [1.062 2.5]		High [1.062 5]	
	Service	Gaussian	Low [1.062–2.776e-17]	Moderate [1.062 2.5]		High [1.062 5]	
	Cleanliness	Gaussian	Low [1.062–2.776e-17]	Moderate [1.062 2.5]		High [1.062 5]	
	Sleep Quality	Gaussian	Low [1.062–2.776e-17]	Moderate [1.062 2.5]		High [1.062 5]	
Output	Satisfaction	Triangular	Very Low [-1.25 -1.388e-17 1.25]	Low [0 1.25 2.5]	Moderate [1.25 2.5 3.75]	High [2.5 3.75 5]	Very High [3.75 5 6.25]

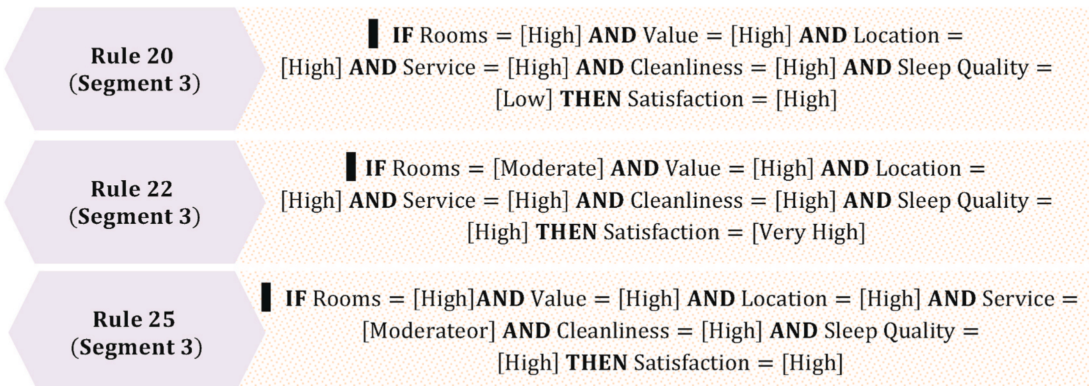

Fig. 6. Fuzzy rules in the form of IF-THEN.

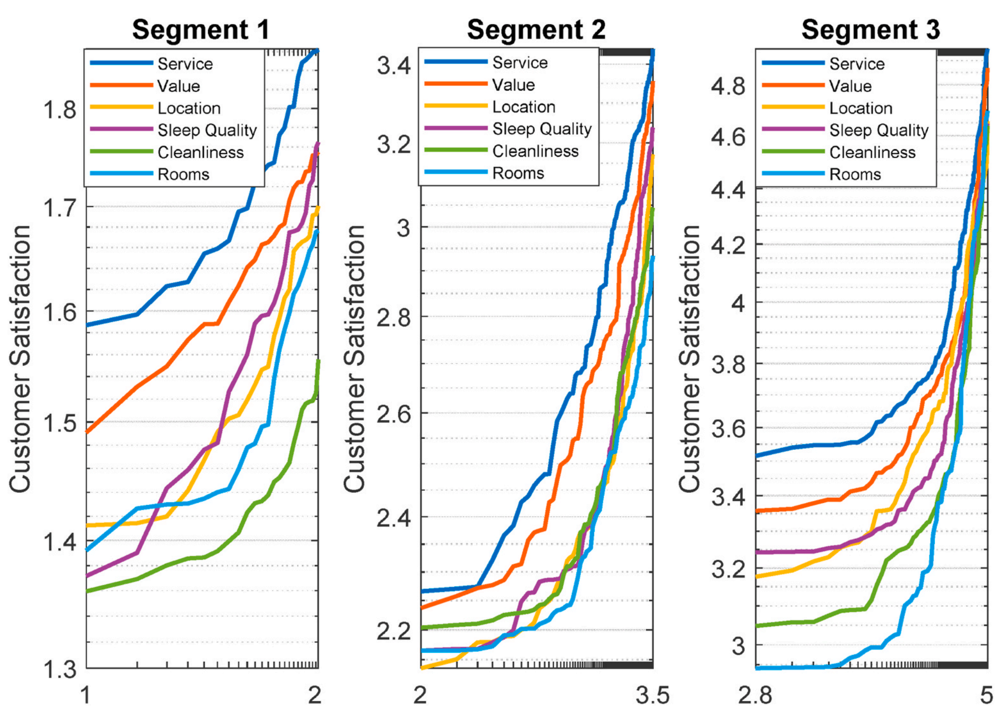

Fig. 7. Impact of performance factors on customers' satisfaction during COVID-19 outbreak.

(AVE) tests. As all the questions met this condition, we decided to keep the questions for further analysis. In the second measure of the CV assessment, the AVE test was evaluated. AVE inspects the level of correlation among questions of the same variable, which must be above the value of 0.5. All variables met the minimum value of the AVE test. The IC of the model can be inspected based on two main measures: Cronbach's Alpha (CA) and CR tests. Each presented variable should have values above 0.7 for each evaluation, which was proved as presented in Table 9.

DV test is performed to inspect the discriminant degree of each variable from other variables using two main measures of cross-loadings (CL) and Fornell-Larcker criterion (FL). In the FL test, the correlation between each variable and other variables is assessed to assure that it is below the square root of the AVE of that variable, which is supported as presented in Table 10. In the CL test, the outer loadings of variables'

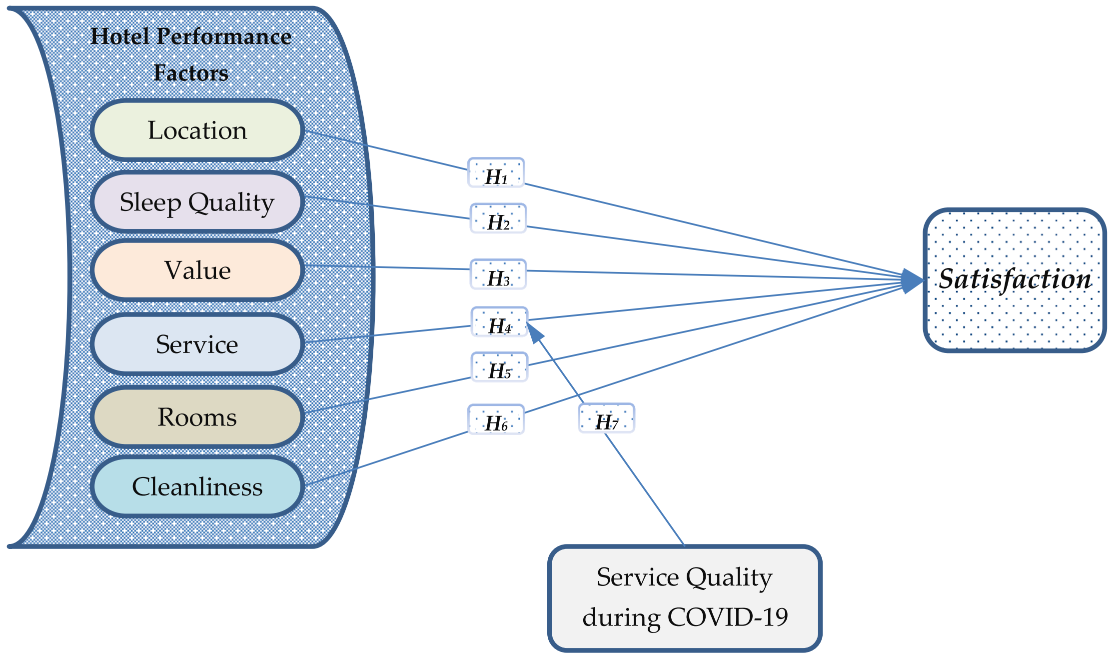

Fig. 8. Proposed model for customers' satisfaction during COVID-19.

Table 7
Presented hypotheses.

No.	Hypothesis	References
H1	The location of the hotel has a direct influence on travelers' satisfaction.	Yang et al. (2018)
H2	Sleep quality has a direct influence on travelers' satisfaction	Zhi et al. (2016)
H3	The perceived value has a direct influence on travelers' satisfaction	(Chen and Tsai, 2008; Tung, 2013)
H4	The presented services have a direct influence on travelers' satisfaction	Solimun and Fernandes (2018)
H5	The room of the hotel has a direct influence on travelers' satisfaction	(Li et al., 2020; Padlee et al., 2019)
H6	The cleanliness of the hotel has a direct influence on travelers' satisfaction	(Bhatnagar and Dheeraj, 2019; Li et al., 2020)
H7	The quality of the services during COVID-19 has a moderating influence on the relationship between presented services and travelers' satisfaction	Based on the outcomes from the ML approach

Table 8
Demographic results of the participants (N = 369).

Feature	Item	Frequency	Percentage
Age	18–20	309	83.7
	21–30	50	13.6
	>30	10	2.7
Marital status	Married	155	42
	Single	214	58
Occupation	Employee	115	31
	Employer	50	13.5
	Student	55	15
	Retired	140	40
	Other	9	0.5
Usage of TripAdvisor	Once	50	13.6
	2-3 Times	200	54.2
	More than 3 times	119	32.2
Mode of Travel	Family	111	30
	Solo	50	14
	Friends	208	56

Table 9
Constructs' reliability and validity.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Cleanliness	0.753	0.857	0.666
Location	0.830	0.921	0.854
Satisfaction	0.772	0.867	0.685
Service	0.810	0.840	0.513
Service Quality during COVID-19	0.745	0.838	0.565
Sleep Quality	0.813	0.915	0.843

indicators must be above its cross-loadings, which is confirmed in Table 11.

4.2.2.1.2. Assessment of formative variables. On the contrary to reflective measure, a formative measure holds the variance in construct's indicators. As the reflective measure assumes that there is a correlation between indicators, a formative measure assumes that there is a difference between construct indicators. "Value" and "Room" variables are the formative variables in the research model. Hence, to assess the validity and reliability of the formative model, two main tests were carried out which are: collinearity statistics and the bootstrapping algorithm of the factors. Variance Inflation Factor (VIF) was used to assess the collinearity of formative indicators (Hair et al., 2020). In the formative indicators' test, it is important to make sure that there is no high correlation between the underlying indicators. If the VIF of the indicator is equal to or higher than 5, there is a collinearity issue. As presented in Table 12, each of the indicators has VIF less than 5, which indicates that there is no collinearity issue within the data.

To assess the significance of the factors, a bootstrapping algorithm is applied. The outer weights obtained by the bootstrapping procedure should be different from zero and surpass a minimum threshold of 1.96 for the t-value. As Table 13 presents, all outer weights are different from zero and all indicators meet the minimum threshold of the t-value, except RO2 and RO4. In such cases, as suggested by Hair et al. (2013a), the outer loadings should be checked for these specific indicators to see if they pass a minimum threshold of 0.50. If the outer loading of any of the examined indicators passes the minimum threshold, this indicator should be retained for further analysis. As presented in Table 13, all

Table 10
Fornell-Larcker criterion.

	Cleanliness	Location	Satisfaction	Service	Service Quality (COVID-19)	Sleep Quality
Cleanliness	0.816					
Location	0.461	0.924				
Satisfaction	0.479	0.601	0.828			
Service	0.489	0.573	0.733	0.717		
Service Quality during COVID-19	0.629	0.506	0.439	0.583	0.752	
Sleep Quality	0.369	0.514	0.513	0.598	0.553	0.918

Table 11
Cross-loadings Test's Results.

	Cleanliness	**Location**	**Satisfaction**	**Service**	**Service Quality (COVID-19)**	**Sleep Quality**
CL1	0.755	0.321	0.301	0.327	0.485	0.249
CL2	0.876	0.407	0.476	0.443	0.487	0.321
CL3	0.813	0.392	0.367	0.414	0.586	0.326
LOC1	0.430	0.923	0.552	0.490	0.464	0.467
LOC2	0.422	0.925	0.559	0.568	0.472	0.484
SA1	0.370	0.486	0.857	0.759	0.314	0.408
SA2	0.413	0.546	0.863	0.545	0.390	0.430
SA3	0.421	0.466	0.760	0.471	0.407	0.448
SC1	0.441	0.368	0.290	0.337	0.772	0.366
SC2	0.473	0.348	0.290	0.307	0.801	0.341
SC3	0.606	0.366	0.324	0.362	0.738	0.360
SC4	0.372	0.417	0.387	0.665	0.692	0.544
SER1	0.370	0.486	0.857	0.759	0.314	0.408
SER2	0.337	0.437	0.288	0.668	0.513	0.493
SER3	0.373	0.314	0.288	0.696	0.442	0.412
SER4	0.306	0.359	0.321	0.725	0.477	0.437
SER5	0.372	0.367	0.325	0.731	0.570	0.476
SQ1	0.311	0.477	0.476	0.559	0.519	0.920
SQ2	0.366	0.467	0.466	0.538	0.495	0.916

Table 12
Variance inflation factor results.

Construct	Variable	VIF
Value	VA1	1.465
	VA2	1.944
	VA3	1.785
Room	RO1	1.425
	RO2	2.231
	RO3	2.175
	RO4	‘2.053

Table 13
Variance inflation factor results.

Variable	Items	Outer Weights	Outer Loadings	T Statistics (|O/STDEV|)	P Values
Room	RO1	0.713	0.911	5.875	0
	RO2	0.09	0.667	0.581	0.561
	RO3	0.43	0.768	2.865	0.004
	RO4	0.062	0.63	0.37	0.712
Value	VA1	0.521	0.86	5.033	0
	VA2	0.296	0.82	2.316	0.021
	VA3	0.379	0.817	3.192	0.002

indicators have outer loadings that pass the minimum threshold, so the researcher retained all the items in the model for further analysis.

4.2.2.2. Assessment of the inner model. After the assessment of the outer model, the links among research variables were inspected. Hence, evaluating the proposed links using the path coefficient (PC) measure is a very significant procedure. We performed other assessments of the inner model, which are: coefficients of determination and Stone-Geisser's Q^2 value. In the following, we will elaborate on the outcomes of various metrics regarding the inner model. The final inner model is given in Fig. 9.

4.2.2.2.1. Path coefficient (hypotheses testing). To assess the model paths, a bootstrapping procedure was conducted using SmartPLS 3 to inspect the significance of the links among variables in the study (Hair et al., 2020). Hypotheses testing results are presented in Table 14. The outcomes affirm the significance of all research links in the presented model. The outcomes of the inner model analysis revealed that the effect of service quality on consumers' satisfaction is the highest effect among research links (0.639), followed by the influence of service quality during COVID-19 on users' satisfaction (0.321). The influences of each of the "Value", Sleep Quality", "Rooms", "Location", and "Cleanliness" on travelers' satisfaction, are significant, with β values of 0.283, 0.189, 0.194, 0.218, and 0.113, respectively.

4.2.2.2.2. Coefficients of determination (R^2 value). The predictive accuracy of the model was assessed using the R^2 value. R^2 inspects the ratio of the variance of the endogenous variable, which is represented using its exogenous variables (Hair et al., 2020). R^2 falls within the interval 0 to 1, with higher predictive accuracy linked to higher values. The R^2 value for the "Satisfaction" is 0.661, which is a high value. As this study is classified under a consumer-based fold that targets to predict customers' satisfaction, the value of R^2 is considered high. The result indicates that research variables can anticipate 66.1% of the change of

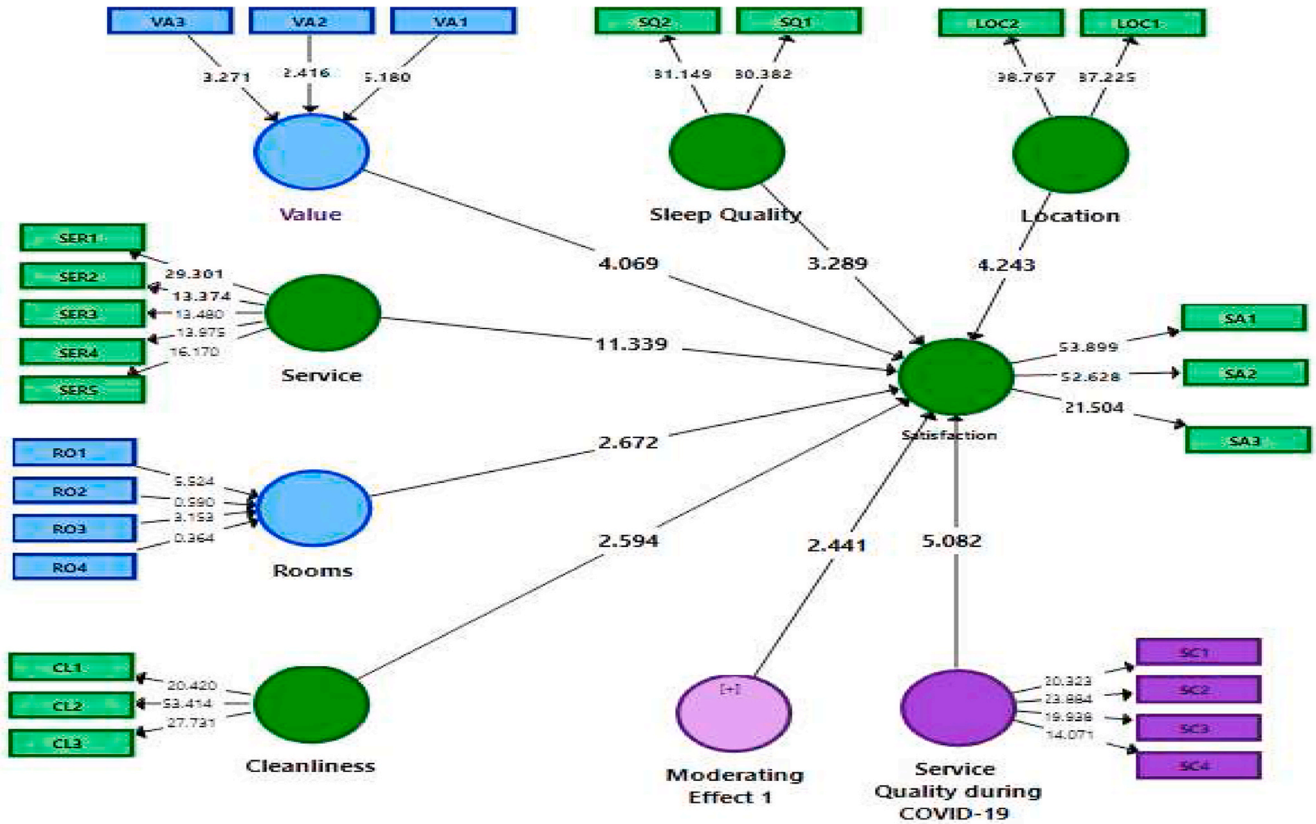

Fig. 9. The Final Research model.

Table 14
Path coefficient result.

	Original Sample	Standard Deviation	T Statistics	P Values
Cleanliness - > Satisfaction	0.113	0.044	2.585	0.010
Location - > Satisfaction	0.218	0.050	4.402	0.000
Moderating Effect 1 - > Satisfaction	0.070	0.030	2.288	0.023
Rooms - > Satisfaction	0.194	0.081	2.411	0.016
Service - > Satisfaction	0.639	0.058	10.976	0.000
Service Quality (COVID-19) - > Satisfaction	0.321	0.059	5.396	0.000
Sleep Quality - > Satisfaction	0.189	0.063	3.003	0.003
Value - > Satisfaction	0.283	0.064	4.393	0.000

consumers' satisfaction.

4.2.2.2.3. Stone-Geisser's (Q^2 value). The last measure that was performed to inspect the inner model is the predictive relevance (Q^2 value). The predictive relevance of the model was calculated through Q^2 test outcomes, which should be more than zero for its endogenous reflective variables. Hence, to calculate Q^2, we performed a blindfolding procedure using the SmartPLS software. The outcome of Q^2 is 0.429 for the "Satisfaction" variable, which met the required threshold.

4.2.2.2.4. The moderating effect. The moderation influence indicates that the link among two variables is strengthened or weakened by the influence of another variable (Hair et al., 2020). In this study, we concentrate on the interpretation of the influence of the quality of the service during COVID-19 on the relationship between the service and consumers' satisfaction. Hence, our target is to decide whether the moderator variable has a vital influence on the path or not. To achieve this we used the two-stage method to operationalize the interaction term using SmartPLS (Hair et al., 2020). Analysis results indicated that the quality of the services during COVID-19 has a moderating influence on the relation between the service and consumers' satisfaction, with a higher quality of the service during COVID-19 leading to a higher positive relationship between the service and satisfaction ($\beta = 0.070$). Fig. 10 shows how the quality of the services during COVID-19 moderates the relation between the service and consumers' satisfaction.

5. Discussion

Electronic reviews present a reliable source of information for the majority of travelers to assess the quality of the presented services and the performance of hotels (Yadegaridehkordi et al., 2021). With the advent of social media, electronic reviews have influenced travelers' choices considerably (Nilashi et al., 2018). Travelers' opinions and ratings of the service quality rely on the display and the categorization of aspects to be reviewed and rated (Huang et al., 2018; Nunkoo et al., 2020; Rauch et al., 2015; Román and Martín, 2016). Electronic reviews can be processed using machine learning techniques to provide inferences about travelers' destinations and hotel choices. Although this topic has been investigated in proceeding studies (Yadegaridehkordi et al., 2021), it is not well-explored in the context of a worldwide epidemic like COVID-19, which is directly linked to travelers and hospitality sectors. Hence, this study focuses on exploring travelers' impressions towards hotels using the posted opinions and ratings on TripAdvisor through the COVID-19 pandemic. Thus, we investigated travelers' online opinions and ratings during this crisis using a text-mining approach. Besides, the influence of service quality during COVID-19 on hotel performance and customers' satisfaction was elaborated. The textual reviews show that the service quality during the outbreak is important for the customers and it has impacted their satisfaction level during the COVID-19 outbreak. This finding is confirmed in the 3 clusters derived from customers' ratings of hotels.

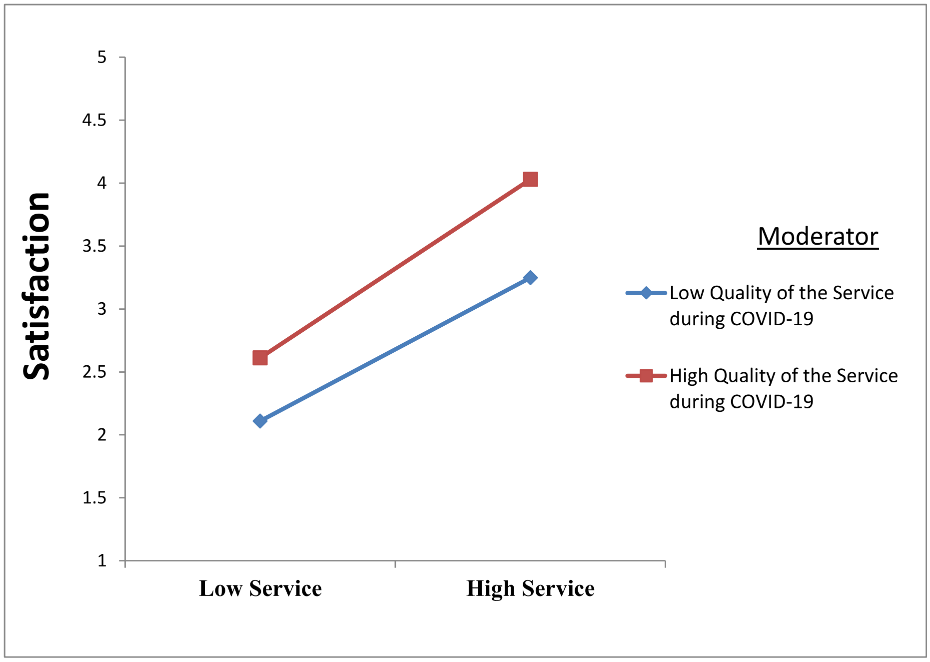

Fig. 10. Structural model (variance-based technique).

To support the outcomes from the first stage of the proposed methodology, the most influential variables were used to develop a research model of travelers' satisfaction. Following that, a questionnaire was designed and distributed among travelers and the data was analyzed using the SmartPLS program. In the research model, we hypothesize that each of "Location", "Sleep Quality, "Value", "Service", "Rooms", and "Cleanliness" has a positive influence on travelers' satisfaction. Additionally, we hypothesize that the quality of the services during COVID-19 has a moderating influence on the relationship between the service and travelers' satisfaction. The outcomes of the structural model analysis highlighted the significant role of the quality of the services presented by the hotels on consumers' satisfaction. Particularly, the findings of the study indicate the significant influence of the quality of services during this crisis on the relationship between service and satisfaction. This finding has been hypothesized and proved in proceeding studies (Alnawas and Hemsley-Brown, 2019; Hao et al., 2015; Nunkoo et al., 2017; Ren et al., 2015). Service quality has been investigated in previous literature in several contexts and focusing on various dimensions. This variable needs to be explored using several approaches trying to capture the various dimensions of quality. During COVID-19, service quality is not only restricted to food and accommodation aspects and there are several quality variables linked to COVID-19 preventive procedures which gained travelers' attention. Through this pandemic, travelers are placing new quality measures related to social distancing, hygiene, and safety at the top of their focus.

6. Conclusion

This study presented significant outcomes to the research community by presenting a new approach to understand travellers' experiences and choices. This approach allows managers to present a better performance in terms of their advertising strategies, the quality of the services in general and during COVID-19 particularly, and the management of hotels. To meet the aim of the study, a new methodology, which adopted machine learning procedures and a survey-based approach, was presented. The methodology integrates text mining, segmentation, and prediction learning approaches with SEM techniques in a novel two stages approach. In the first stage, LDA was used for topic modeling, k-means as an unsupervised learning technique was used for clustering the data, Higher-Order Singular Value Decomposition was used for missing value imputation, and Fuzzy Rule-Based System was used for the prediction of customers' preferences from the users' ratings. The data was gathered from TripAdvisor focusing on the travellers' perception based on online opinions and numerical ratings of hotels considering several elements. The findings of analyzing online comments and ratings indicated that the quality of the presented services during this crisis has impacted travelers' experiences which influence travelers' satisfaction. The finding also pointed out the vital role of the quality of services, especially through this crisis. Following that, in the second stage, the extracted variables, which influence consumers' satisfaction, were used to develop a research model. Besides, a questionnaire was designed and distributed among travelers and the data was collected. Using the SEM technique, the collected data was analyzed to confirm the outcomes from big data analysis.

6.1. Theoretical contribution

Previous literature has adopted various quantitative and qualitative approaches to assess consumers' experiences. Still, exploring consumers' satisfaction has followed one of the two main directions: (1) inspecting consumers' online reviews through text mining approaches, or (2) developing a research model based on previous literature and investigating the research model based on a deployed instrument. Although several studies have explored customers' satisfaction as an indicator of business performance using a survey-based approach (Guo et al., 2017; Lucini et al., 2020), this approach has several shortcomings related to the data collection and the accuracy of the findings (Wan and Gao, 2015). This can be referred to several aspects such as the sample size or the inconsistency in the indicators of the deployed instrument (Chow, 2015). The participant of the survey may respond to the questions on a random-base which will present noise to the findings (Wan and Gao, 2015). Additionally, the items of the questionnaire are usually designed referring to proceeding researches and may not locate emerging preferences of consumers accurately (Lucini et al., 2020). This study has a novel contribution related to the adopted methodology, which integrates text mining and survey-based approaches. In this study, we adopted a sequential mixed approach in which we seek to elaborate on or extend the outcomes of one approach with another approach (Cresswell, 2009). The integration of these approaches allows investigating travelers' experiences efficiently and overcoming the shortcomings of these approaches.

6.2. Practical contribution

The implications of this crisis on hotels and the hospitality sector have forced hotel groups to adopt new policies regarding hotel hygiene trying to address the increasing health threats. Both positive and negative feedbacks are important to managers to understand travelers' overall experiences. Online portals allow customers who are hooked to the internet to post their feedback about their experiences in several aspects (Park et al., 2014). Customers' feedbacks can be located in a standardized rating form, textual comments, or by integrating both methods simultaneously (Siering et al., 2018). Hotels are consumer-centric businesses that need to understand consumer choices and needs. Hence, it is important to consider the possible amendments to tourists' experiences resulted from the influence of this crisis (Chan et al., 2021).

The practical contribution of this study falls within several folds. First of all, understanding travelers' experiences is of great importance for service vendors in the tourism sector. Hence, the adopted two-stages methodology enables the investigation of travelers' perceptions from different perspectives. By integrating the text-mining approach with a survey-based approach, we were able to consider online reviews that were posted on the TripAdvisor portal based on travelers' actual experiences and travelers' perceptions based on a survey-based questionnaire. The particular context of this study imposes that referring to a survey-based approach alone to capture travelers' perceptions, which is usually designed referring to the previous literature may not capture the emerging needs of travelers.

Second, during COVID-19, the tourism and hospitality market has been influenced the most among other sectors. The uncertainty in this sector has led decision-makers to try to design long-term schemes that can survive during the current crisis. Travelers' experiences reflected by online opinions and ratings are vital for both decision-makers to enhance their services and for other travelers to reach the right choice. By utilizing popular online portals like TripAdvisor, managers can address negative opinions and answer travelers' concerns, which will influence travelers' trust and help them reach an appropriate decision (Nilashi et al., 2021).

Third, research findings can present directions for hotel managers during the COVID-19 epidemic. Particularly, the importance of maintaining the level of quality of the provided services was indicated as an important driver of traveler's satisfaction in this study. As presented in Fig. 4, it is found in the online reviews that consumers' reviews are focused now on new dimensions of "services", indicating that tourists expect to get more services related to the crisis. Besides, tourists are more worried about the preventive protocols of the hotel during the pandemic, like monitoring the number of visitors, taking guests' temperatures, and maintaining hygiene measures. This is referred to the fact that tourists are more worried about their health and safety, which present significant insights for hotel managers. It is expected that even after the crisis ends, safety and hygiene measures will still be essential dimensions of the quality of the services, in which hotel managers will be more flexible to unexpected conditions.

6.3. Limitations of research and future work

Although this research has several theoretical and practical contributions, the research has few limitations that should be addressed and allows future research directions to be followed. First, considering the machine learning stage applied in this research, future work may explore how electronic reviews and ratings can be bound together to explore consumer satisfaction more accurately. Investigating and comparing the electronic ratings and textual comments which are written in different languages and within different locations can be utilized as a future research direction. Second, the study focused on the data from one travel platform. Hence, the generalizability of the outcomes needs caution. Future work should gather data from various travel portals to confirm whether tourists' perceptions of services change among various portals. Third, electronic reviews and ratings are not static and subject to variations over time. Hence, it is recommended that future research considers approaches to explore the electronic comments and ratings incrementally. Fourth, the research concentrated on the tourism and hospitality field. Therefore, applying the outcomes of this study to other fields needs more caution, because the variables may differ based on the type of presented services. On the other hand, considering the survey-based stage, the empirical exploration of this stage falls within a wide field of user experience studies, with emerging research opportunities that should be considered to further explore other variables considering customer satisfaction. The integration of machine learning and survey-based approaches allows future research directions that might be followed. Hence, the research outcomes can be further investigated with a qualitative approach in data gathering through in-depth interviews, open discussions, and observations. Such wealth in research of this developing phenomenon would present more details, which will support the outcomes from the integrated methodology presented in this research. Finally, a considerable piece of PLS-PM researchers has concentrated on the utilization of PLS-PM in predictive applications (Evermann and Tate, 2016). Compared to PLS-SEM, PLS-PM can estimate complex path models with many variables and items (Sharma et al., 2019; Shmueli et al., 2016). This methodology can be utilized as future work to facilitate the assessment of the predictive performance.

Appendix A

Table 1
A part of fuzzy rules discovered from users' ratings

Rule #	Rooms	Value	Location	Service	Cleanliness	Sleep Quality	Satisfaction	Segment
1	Low	Low	Low	Low	Low	Low	Very Low	Segment 1
2	Low	Low	Low	Low	Moderate	Low	Very Low	Segment 1
3	Low	Low	Moderate	Low	Low	Moderate	Very Low	Segment 1
4	Moderate	Low	Low	Low	Moderate	Low	Very Low	Segment 1
5	High	Low	Low	Low	High	High	Low	Segment 1
6	Low	Low	Low	High	Low	Low	Low	Segment 1
7	Moderate	Low	Low	Low	Low	High	Low	Segment 1
8	Low	Low	Low	High	Low	High	Moderate	Segment 1
9	Low	Low	High	Low	Low	High	Low	Segment 1
10	Low	High	Low	Low	Low	High	Low	Segment 1
11	Low	Low	Moderate	Moderate	Moderate	Low	Moderate	Segment 1

(continued on next page)

Table 1 (*continued*)

Rule #	Rooms	Value	Location	Service	Cleanliness	Sleep Quality	Satisfaction	Segment
12	Moderate	Moderate	High	Moderate	High	High	Moderate	Segment 2
13	Moderate	High	High	Moderate	Moderate	Moderate	Moderate	Segment 2
14	High	High	Moderate	Low	Moderate	High	Moderate	Segment 2
15	Moderate	Moderate	Moderate	High	High	High	High	Segment 2
16	High	High	Moderate	High	Moderate	High	High	Segment 2
17	High	Moderate	Low	Moderate	Low	High	Moderate	Segment 2
18	High	High	High	High	Low	High	Very High	Segment 3
19	High	High	Low	High	High	High	Very High	Segment 3
20	High	High	High	High	High	Low	Very High	Segment 3
21	High	High	High	High	High	High	Very High	Segment 3
22	Moderate	High	High	High	High	High	Very High	Segment 3
23	High	High	Moderate	High	High	High	Very High	Segment 3
24	High	High	High	High	High	Moderate	Very High	Segment 3
25	High	High	High	Moderate	High	High	High	Segment 3

Table 2
Survey Items

NO.	Factor	Items	Survey Questions	References
1	Location	LOC1	The hotel is close to transportation.	Dong et al. (2014)
		LOC2	The hotel is near attractions.	
2	Sleep Quality	SQ1	The surrounding environment helps me to sleep.	Zhang et al. (2018)
		SQ2	The surrounding atmosphere helps me to sleep.	
3	Value	VA1	I consider the price of services provided by the hotel to be reasonable.	Suhartanto et al. (2013)
		VA2	The service I received from the hotel was excellent compared to what I had given up.	
		VA3	The hotel offers good value for money.	
4	Service	SER1	The hotel presents a comfortable and tidy service.	Zhang et al. (2019)
		SER2	Service could be finished within the time promised.	
		SER3	Service is fast and efficient.	
		SER4	Provide various services to meet the needs of customers.	
		SER5	Staffs respect customers' personal needs.	
5	Cleanliness	CL1	Hotel rooms are always clean.	Bhatnagar and Dheeraj (2019)
		CL2	I choose the hotel which has spotlessly clean rooms.	
		CL3	The hotel has hygienic surroundings.	
6	Rooms	RO1	The hotel's room has god furniture.	Padlee et al. (2019)
		RO2	The hotel's room is peaceful.	
		RO3	The facilities work adequately in the room.	
		RO4	The room is very cozy.	
7	Satisfaction	SA1	I am satisfied with my choice of this hotel.	Khuong and Ha (2014)
		SA2	I think I did the right thing to choose this hotel.	
		SA3	My overall satisfaction with the hotel is high.	
8	Service Quality with COVID-19	SC1	COVID-19 SOP was managed very well.	Based on the online reviews
		SC2	The hotel is taking safety measures.	
		SC3	Staff members are following safety protocols.	
		SC4	All measures are followed to forbid the spread of COVID-19.	

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