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Customer satisfaction with Restaurants Service Quality during COVID-19 outbreak: A two-stage methodology

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ABSTRACT

Online reviews have been used effectively to understand customers' satisfaction and preferences. COVID-19 crisis has significantly impacted customers' satisfaction in several sectors such as tourism and hospitality. Although several research studies have been carried out to analyze consumers' satisfaction using survey-based methodologies, consumers' satisfaction has not been well explored in the event of the COVID-19 crisis, especially using available data in social network sites. In this research, we aim to explore consumers' satisfaction and preferences of restaurants' services during the COVID-19 crisis. Furthermore, we investigate the moderating impact of COVID-19 safety precautions on restaurants' quality dimensions and satisfaction. We applied a new approach to achieve the objectives of this research. We first developed a hybrid approach using clustering, supervised learning, and text mining techniques. Learning Vector Quantization (LVQ) was used to cluster customers' preferences. To predict travelers' preferences, decision trees were applied to each segment of LVQ. We used a text mining technique; Latent Dirichlet Allocation (LDA), for textual data analysis to discover the satisfaction criteria from online customers' reviews. After analyzing the data using machine learning techniques, a theoretical model was developed to inspect the relationships between the restaurants' quality factors and customers' satisfaction. In this stage, Partial Least Squares (PLS) technique was employed. We evaluated the proposed approach using a dataset collected from the TripAdvisor platform. The outcomes of the two-stage methodology were discussed and future research directions were suggested according to the limitations of this study.

Credit author statement

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1. Introduction

The COVID-19 pandemic developed an almost overnight world distribution and brought the global economy to its knees [1–4]. The hospitality industry, in particular, faced an unprecedented challenge. The lockdowns, social distancing, and travel and mobility restrictions stripped many hospitality businesses of their customers [5]. The pandemic has hit the restaurant industry the hardest. Restaurants had to limit their operations just to take-outs [6]. With every 1% increase in new daily COVID-19 cases, restaurants lost 0.06% of their daily orders [7].

While authorities have started to ease restrictions [2,3], the hospitality industry, including the restaurant sector, is beginning to recover from the outbreak's damage. But the profound impact of the COVID-19 crisis continues to play a role in hospitality businesses [8,9]. Customers are less willing to dine in restaurants [10]. Recent studies suggest that outbreak information cues, such as the number of new cases or deaths, encourage customers to seek safety and hence avoid particular services that increase their risk [11,12]. Consequently, the operations and business environment in the hospitality industry face substantial changes. There is a need for strategies to respond to threats and open new opportunities for the sustainability of the restaurant industry [6], by which businesses have to adapt to meet customers' expectations and enhance their willingness to patronize their businesses [13].

Unlike physical products, restaurant services are evaluated by the customer in a more complex way. Restaurants offer services that are largely experiential products [14] and, in that sense, they are evaluated based on a collection of cognitive and affective attributes [15]. Such motivations can reshape individuals' decision-making processes [2,3]. The survival of many hospitality businesses, including restaurants, which heavily rely on human-to-human contact, depends on increasing the demand for their services. Such businesses have a higher breakeven point, and it is of utmost importance to figure out what will make customers return. Customers' needs and preferences have to be re-evaluated. The main question is: What are the determinants of restaurant customers' satisfaction in a time of pandemic and what are the proper means of investigating customers' behaviours and preferences?

Online customer reviews provide business owners with insights into the thoughts and feedback of customers during the outbreak and hence can be considered as good sources of information [16]. Online reviews could reveal the main concerns of customers [11], identify the factors that can lead to a customer being satisfied or dissatisfied with a service [17], and could be used to estimate customers' satisfaction levels [18].

Data analysis tools and approaches need to be upgraded constantly to meet the new requirements of data collection and analysis of online reviews. Researchers have focused on developing new approaches to capture customers' sentiments during the outbreak. Few studies showed a shift in customers' review patterns due to the outbreak [6,14,19], while others reported only slight changes in the evaluation of restaurant features [20,21]. However, only a limited number of studies are available, and there is a research gap that offers new ways to observe and interpret customers' evaluations of restaurants.

This study aims to interpret customers' evaluations of restaurants' services and satisfaction levels during the COVID-19 outbreak. A new method based on machine learning techniques was developed using social data, which is represented in the forms of textual comments and ratings. The online textual reviews and ratings were collected from TripAdvisor. The main contributions of this work to the body of knowledge are as follows:

i. Although several studies have been carried out to analyze consumers' satisfaction using survey-based methodologies, consumers' satisfaction has not been well explored during the COVID-19 outbreak, especially through the use of social data that are posted on social networking sites. In this research, we explore consumers' satisfaction and their preferences of restaurants' services during the COVID-19 crisis. The moderating effect of COVID-19 safety precautions on restaurants' quality dimensions and satisfaction is investigated as well.
ii. The first stage consisted of the analysis of social big data. The use of Latent Dirichlet Allocation (LDA) for text mining was applied to discover the satisfaction dimensions. The model has been used to analyze online textual reviews effectively in this study. During the outbreak and after loosening the confinement situation, it is of utmost importance to extract the indicators of customers' satisfaction and to improve the service quality based on customers' opinions that are reflected in online reviews. In the context of restaurants, just a few studies have explored customers' satisfaction during the pandemic, and the issue is not fully explored. More importantly, there is a need to develop new methods to investigate the reviews accordingly.
iii. We investigate big data consisting of the reviews that customers have generated using a hybrid approach of text mining, clustering, and prediction learning techniques. We used Learning Vector Quantization (LVQ), a supervised classification algorithm, to segment and groups travelers with similar preferences. Later, based on a set of performance criteria for restaurants, customers' satisfaction was predicted using Classification and Regression Trees (CART).
iv. In the second stage, based on the Stimulus-Organism-Response (SOR) model a set of hypotheses were developed to investigate the relationships between the performance criteria and satisfaction, considering the moderating effect of the COVID-19 safety measures. We used Partial Least Squares Structural Equation Modeling (PLS-SEM) and analyzed data from customers who had previous experience with the TripAdvisor platform. We also performed a subgroup analysis to examine the proposed research model based on the type of travel.
v. The results of the two-stage methodology were combined to provide a rich discussion and future guidelines to contribute to the decision-making in complex situations like the current pandemic.

The remainder of this paper is organized as follows: In Section 2 and Section 3, we present the related work and theoretical background. Section 4 discusses the analysis of online reviews using machine learning. In Section 5 and Section 6, we present the research hypotheses and PLS-SEM results. In Section 7, a discussion of the results is provided. In Section 8, we conclude our work. The list of abbreviations used in this study is presented in Table 1.

Table 1
List of acronyms used in this study.

Acronyms	Description
CART	Classification and Regression Tree
LDA	Latent Dirichlet Allocation
LVQ	Learning Vector Quantization
NLP	Natural Language Processing
PCA	Principal Component Analysis
PLS-SEM	Partial Least Squares Structural Equation Modeling
SOM	Self-Organizing Map
SVM	Support Vector Machine
CV	Convergent Validity
IC	Internal Consistency
DV	Discriminant Validity
CR	Composite Reliability
AVE	Average Variance Extracted
CA	Cronbach's Alpha
CL	Cross-Loadings
FL	Fornell-Larcker
Q^2	Stone-Geisser's Q Square
R^2	Coefficients of Determination
SOR	Stimulus-Organism-Response

2. Related works

2.1. COVID-19 and hospitality industry

The COVID-19 pandemic posed unprecedented challenges to businesses around the world, and the hospitality industry was no exception [2,3]. The industry relies heavily on customer demand to remain viable. This has created a need for intensive research efforts to help the industry adjust its operations in the time of the pandemic. The hospitality industry is recovering, albeit slowly. Hospitality businesses, due to their reliance on the physical human-to-human interaction, had to implement drastic changes to their operations to win back customers [5,13] and to ensure employees' and customers' safety [2,3]. However, studies show that customers are still reluctant to stay in hotels or dine in restaurants [10]. Google Trends data shows a noticeable decline in the trend in the use of hospitality services [22]. OpenTable has created an online data showcase that monitors the state of restaurants worldwide [23]. This ongoing study shows that the industry has not been able to reach the number of customers they had before the pandemic. Even though the decline in customer numbers has recovered from 99% in March 2020 to 40% in March 2021, data indicate a significant drop in seated customers at a global level.

Despite all the industry efforts, consumers' behaviour is still impacting the restaurant industry. The pandemic has had effects on people's decision-making, emotions, and perceptions [24]. It has shifted customers' emotions toward negativity [25], partly due to the excessive mental load that people experience to ensure the health of their families and loved ones [24] and their loss of freedom [25]. These, in conjunction with external factors, have posed a challenge to the previous findings on sentiment analysis in the field of marketing [19,26,27].

With changing consumer behaviour, scholars have responded to emerging needs. There has been a shift in the hospitality marketing and management field. Questions about what factors encourage customers to return, their sentiment about restaurants, and their perception of the 'new normal' in the industry remain unanswered. The argument on the future of hospitality industries in the pandemic is still ongoing, and research is required to pinpoint how the industry might continue to remain viable.

2.2. Online review of hospitality

Online reviews are one of the most typical forms of information-sharing concerning customers' behaviour [6,28]. There is a distinction between two types of online reviews: consumer-generated reviews and professional reviews, where the former are provided by customers and the latter are written by professional editors [29]. However, prior research has shown that consumer-generated reviews are positively associated with the online popularity of reviewed businesses. This effect is not present with editor reviews. Reviews offer a description of the customer's experiences in a textual format, and hence a qualitative style [6] and have an impact on the behaviour of other consumers [30,31]. Reviews are written from a customer's perspective [32,33], and potential clients perceive them as reliable and relevant information [34,35]. Their effect is of a real-time nature [36], which can address the changing demands of customers [37].

Hospitality research has been paying attention to customer reviews for more than a decade [29]. Previous studies have shown that tourists prefer recommendations over advertisements when they choose a restaurant [9,38]. Customers tend to share their reviews aiming to inform other customers [39]. To understand what leads customers to share their reviews, three motivations are identified; self-focused, other-focused, and company-focused reasons [40]. Konuk [39] showed that customers' tendencies to share their feedback online increase when they are satisfied with the product or service. However, when a product or service disappoints the customer, he/she tends to share even more, to taint the company's image or to inform other customers [39,41].

With the growth in the volume of the information shared by customers on the internet, thousands of consumers can discuss and evaluate products and services [42] and, as a result, online reviews have become a critical source of information [43]. Compared to surveys, the traditional sources of information about customers, online reviews are less costly and more easily collected [44,45]. Consequently, companies consider them as alternative data sources that are easier to manage [37]. On the other hand, the use of text-mining technology has enabled researchers to discover new information and analyze online reviews automatically [6].

2.3. Evaluating customer satisfaction through online reviews in the hospitality industry

Researchers have used online reviews to explain customer satisfaction or dissatisfaction [31,46] from the marketing and hospitality research field, as well as in other disciplines [6,37,47,48]. In addition, previous works have shown that the volume of reviews (the number of comments or ratings) could be used as an indicator of satisfaction [49,50].

In the hospitality context, both reviews and ratings have been used to assess the degree of satisfaction. Ratings of hotels, restaurants and the like could shed light directly on the levels of customer satisfaction and dissatisfaction, as well as their causes [51], providing restaurant quality-improvement hints [52]. There are earlier works that determine customer satisfaction that rely on ratings (e.g. Refs. [53,54]). However, the majority of research has focused on reviews or on a combination of reviews and ratings.

Previous studies on online reviews have extended the traditional approach to understanding customer satisfaction, taking into account the real opinions of travellers reflected in those reviews. Rajaguru and Hassanli [55] used online reviews coupled with ratings to investigate customer satisfaction with hotels. They confirmed that customers' perceptions of value for money are affected by hotel star ratings. Bi et al. [32] combined neural networks and an effect-based Kano model to study customer satisfaction via online reviews. Huifeng et al. [33]; using both reviews and ratings, investigated the relationship between online customer reviews and restaurant revisits and showed that the effect declines over time. Padma and Ahn [17] performed a content analysis of online reviews and ratings available on TripAdvisor to examine the satisfaction and dissatisfaction of luxury hotel customers. Studies have explored the sentiment of reviews as an indicator of customer satisfaction [56–58]. Tao and Kim [59] used online comments and ratings of cruise-ship customers to gauge their experiences of the service and predict their levels of satisfaction. A fuzzy evaluation method has been designed to calculate customer satisfaction based on online reviews [18].

Using text-mining approaches, various factors that lead to satisfaction or dissatisfaction have been identified in previous studies. Xu [60] stressed that the performance of the drivers and the cost of the order affect both the satisfaction and the volume of takeaway restaurants' reviews. Bilgihan et al. [61] detected three distinct types of customer perceptions that are reflected in their reviews: functional, mechanic, and humanistic. In another study, six emotions expressed in reviews were identified: joy, sadness, anger, fear, trust, and disgust, which could be indicators of their levels of (dis) satisfaction [62]. In another example of text-mining technology, Yan et al. [63] analyzed online reviews from a local online community in China. They found that, on the topic of restaurants, variables such as price, value, and atmosphere discussed in reviews predicted customers' revisit intentions. Their results confirmed the findings of a similar study that used sentiment analysis of Google Maps reviews [64]. Li, H. et al. [65] did not find the price to be a key indicator based on Airbnb users' experience. Other features that customers value include service, food, place, performance, excitement factors, amenities, waiting time, location, brand, and experience [14,21,63–68].

2.4. Evaluating service quality through online reviews in the hospitality industry

Service quality could be defined as the contrast between what the customer expects and what they receive [69]. Businesses assess their service quality, based on customers' perceptions, to create new opportunities [70]. The quality of services could temper customer satisfaction, loyalty [71] and company profitability [72] and hence the survival of the business [73]; this includes the hospitality industry [74]. Businesses improve their services, trying to reach higher levels of satisfaction, hoping to benefit from a larger share of the market [75].

For years, service management scholars and practitioners have been trying to improve the means of measuring service quality. The indicators of good service quality differ depending on the context [76]. The same is valid for the level of service quality, which depends on the product category [77]. In addition, many models and their subsequent results lack tangibility and do not properly shed light on customers' service experiences in reality. In order to compensate for the shortcomings of previous studies, many approaches have been developed to assess 'perceived' service quality based on information on customer experiences [78,79].

Customers' reviews could serve as valuable sources of such information [67]. To draw inferences from customers' reviews, an accurate systematic analysis, which allows the identification of relevant service quality dimensions reflected in online reviews, helps to assess the service quality in a proper manner [72]. Service quality has been framed as a multidimensional and hierarchical construct [78,80]:

i. **Interaction:** Interaction is the perception of customers of their interactions with employees when they receive a service. Yan et al. [63] conducted a content analysis on 10,136 restaurant reviews in an online life community in China and found two indicators of service quality: employee appearance and employee attitude. Clemes et al. [81] discussed that the quality of interaction could be measured via the three dimensions of interpersonal, professional and problem-solving skills. Some authors portrayed interaction quality in terms of employee characteristics, such as their reliability [15], responsiveness [82], assurances [15], inclusiveness [83], performance and empathy of service professionals and courteous attitude [15,74]. Other attributes expected of service employees include the amount of help they are willing to offer, their extent of being friendly or knowledgeable about what they do, attention to specific needs of customers, and the accuracy, reliability, and promptness of the service provided [84–86].
ii. **Physical environment:** Physical environment consists of the surrounding built environment, whether manmade, natural, or social [81], which influences the perceptions of overall quality [14,87] and might eventually influence customers' satisfaction [88]. Moreover, it plays a critical role in shaping customers' experiences [89,90], and it could provoke customers' positive emotions. Previous works assert that the arousal of positive emotion has a strong impact [91]. The physical environment has been divided into sub-dimensions, including ambient conditions, facility aesthetics, the interior, exterior and other important tangible factors [92], spatial layout, seating comfort, view, location, occasions and noise level [93], elements such as service facilities, equipment, cleanliness and transportation [94] and physical appearance [15,75,85,91,95–99].
iii. **Outcome quality:** Outcome quality is the technical quality as evaluated during service delivery [78], which determines customers' perception of service quality [100]. Service attributes determine a customer's overall experience [101] and, considering the restaurant context, have been measured via factors regarding the food and the menu [84,102]. Attributes such as service responsiveness, reliability, serviceability, cleanliness, safety, maintenance of the facility and price, together with elements such as service facilities, equipment, conformance levels and product/destination image, have also been investigated [72,82,92,93,96].

2.5. Customer online reviews before and during the COVID-19 outbreak

In the previous sections, we established that researchers have been studying online information sharing and customer reviews in the hospitality industry long before the COVID-19 outbreak (e.g. Refs. [9,51,103,104]). This pandemic has hit the restaurant industry hard, such that for every 1% increase in daily new COVID-19 cases, restaurants reported a 0.06% decrease in their orders [7], which harmed their revenue [6]. The outbreak has changed customers' needs and preferences. While their preferences concerning food, environment, and service remain salient and important in the long run, efforts have been made to observe and interpret new changes in restaurant customers' preferences due to the pandemic [21]. Findings suggest a shift in customers' review patterns. They have been assigning lower ratings [6] and have been evaluating the same restaurant features differently. For example, Jia [6] suggested that customers were less annoyed by queuing, a feature that raised negative feedback in normal times. The features considered important by customers have changed in some cases. Luo and Xu [21] reported more frequent use of terms such as 'delivery' and 'online ordering' in the area of takeaways and 'hygiene practices' and 'outdoor seating' regarding dine-in experiences in Yelp reviews compared to previous reviews. Yang et al.'s [14] analysis of reviews showed a more salient focus on packaging and delivery quality, in addition to hygiene, due to the COVID-19 pandemic. Another study reported an increase in the values customers placed on delivery and customer service provided by meal-kit companies after the outbreak, while the freshness and type of food served had lost some of their precedence [20]. The value placed on features such as safety, social distancing and mask policies are considered as important as previously dominant features such as service, overall experience and food quality [16]. Kutlubay et al. [105] examined the differences in comments and ratings provided by customers before and after the COVID-19 outbreak. They showed that the customer ratings had dropped during the pandemic. Their results also indicated a higher number of negative emotions in reviews in the early period of the outbreak. In contrast, Sun et al. [106] found that customers were more prone to post positive reviews and higher ratings after the COVID-19 outbreak if the service provider had implemented safety measures strictly. Another study reported a difference in customer reactions to services before and during the pandemic [107]. There have also been several reports about the changes in customer preferences for services [108–110].

3. Theoretical background

The second phase of the study is designed to investigate the role of the extracted performance and satisfaction criteria. Appraisal theory points out that customers evaluate a service's performance upon getting exposed to an environmental stimulus [111], but it is not clear how they would react to that stimulus. The stimulus can provoke positive and negative sentiments that impact customers' evaluation process. This is explained in the expectancy disconfirmation theory [112]. The theory explains that customer satisfaction is related to the prior expectation of the service. Although previous research investigated the relationship between customers' evaluation and their satisfaction, their expectations depend on several dimensions of the product or service. Customers' expectations vary as they have different perceptions of the same event [19]. Expectations depend on multiple dimensions that have been investigated focusing on various aspects in previous studies. The Stimulus-Organism-Response (SOR) model [113] has been used in the literature to study the stimuli and the behavioral responses. The model has been used to explain customers' expectations, based on their evaluation of the service and their overall satisfaction [114,115]. Additionally, the SOR model differentiates between the stimulus or environmental stimulus (a set of sensory variables) and the response, calling the former as the independent variable and the latter as the dependent variable. The stimulus influences the customers' organism, which is the internal process that intermediate the relationship between the stimulus and response. Customers' organism is reflected by the emotional reactions (in the forms of arousal and pleasure) [116,117]. These variables have been investigated in the hospitality industry literature [118], and there is a wide range of variables that directly influence customers' responses. Multiple studies have suggested various variables as moderators as well [119–121].

Hence, the SOR paradigm will be adopted in this study to explain what factors that have an impact on customer satisfaction for several reasons. First, the SOR model has been broadly applied to explain consumer behaviour [122–124]. This model has been used in the Information System literature and has been proven to be highly effective. It has been utilized in the hospitality context in explaining the relationships among the service features (stimuli), customers' emotions (organism), and eWOM (response) [125–127]. Its effectiveness has been

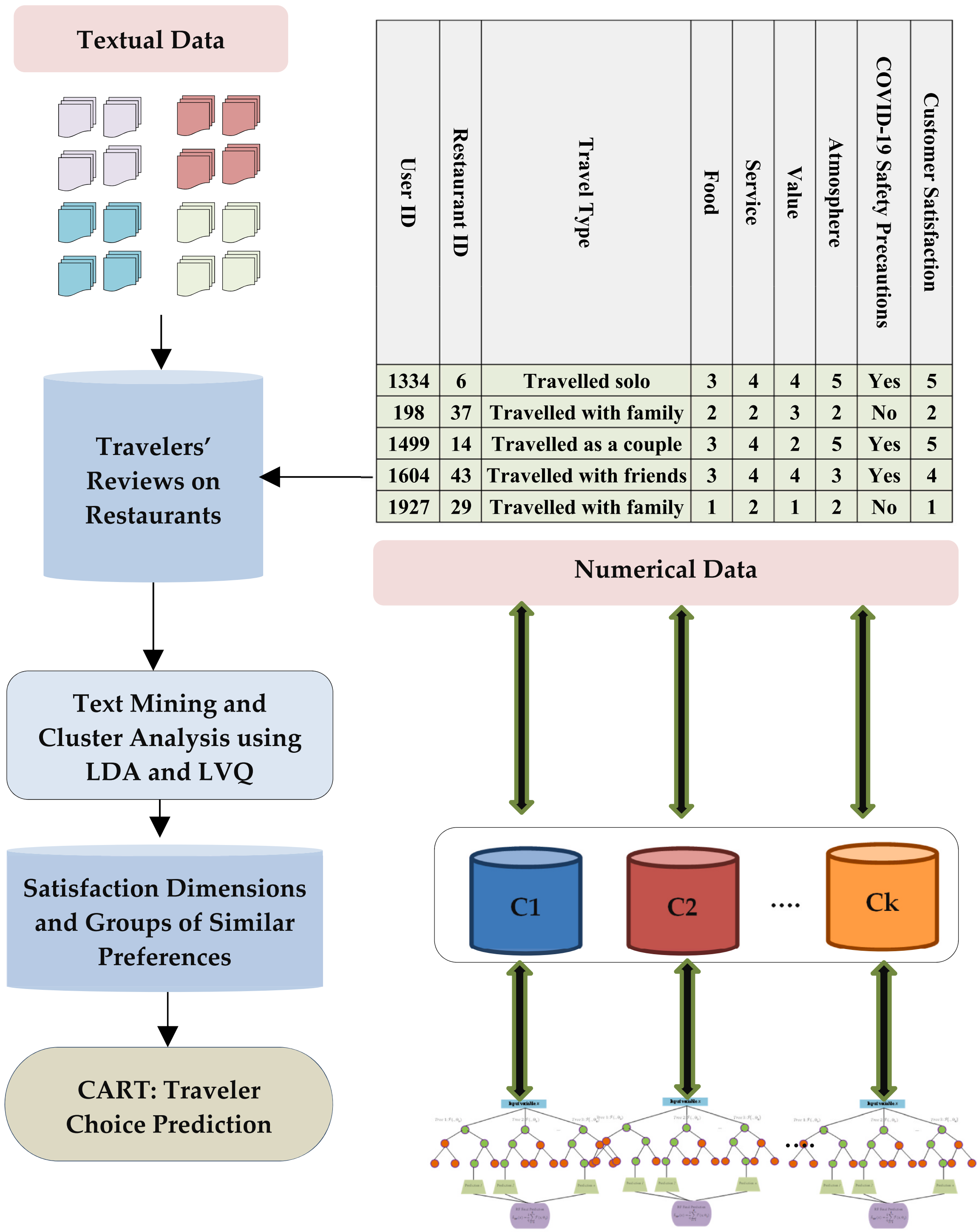

Fig. 1. The proposed method.

also proven in explaining consumers' responses during the recent pandemic [128]. For example, Liu et al. [123]) adopted the SOR model to investigate the influence of task-related signs and mood-related signs on perceived enjoyment and perceived usefulness, and accordingly the intention to purchase. Zhang et al. [129] inspected the impacts of three variables (sociability, personalization, and interactivity) on the virtual experience of customers. Second, the SOR model presents a precise and structured method to explore the influence of interpersonal interaction variables, as surroundings stimuli, on customers' overall experiences and their future intention and behaviour.

4. Machine learning methodology

The proposed method, which is based on machine learning techniques, is presented in Fig. 1. The main goal of the study is to examine the available information on restaurant websites to assist travelers in making decisions. Numerical ratings of quality aspects and textual reviews of services are two important types of information that are available on restaurant websites. The numerical ratings are based on the level of quality (e.g., food, service, value, and atmosphere). We used LDA to discover satisfaction dimensions from the data that was collected from restaurants' websites on TripAdvisor. LDA is a foundational scheme in the field of topic modeling, and because of its flexibility, it allows complex analyses of textual data. LDA allows the extraction of latent topics from large amounts of unstructured review data. To determine the aspects of consumer satisfaction, we use LDA. For the numerical reviews of travelers, our method included clustering analysis. It is crucial to look for groups of travelers with similar tastes based on the data posted on restaurants' websites. Customers' reviews on services can be clustered to produce more accurate predictions of travelers' preferences for restaurants services. LVQ is the basic method that we used for clustering analysis. Finally, we used the CART technique to predict the preferences based on quality factors.

4.1. Data collection and analysis

TripAdvisor was used to obtain data for this study. The information was collected from the restaurants' websites, which are provided on the TripAdvisor platform. The data was acquired using a crawler that crawled restaurants' information through their URLs. The crawler was built to collect key data such as restaurants' information, traveler information (Travelled with family, Travelled solo, Travelled with friends, and Travelled as a couple), trip information, and users' ratings of Food, Service, Value and Atmosphere. Totally, We gathered 2158 records from 50 restaurants using the crawler. The data was preprocessed, and the database's useless records were deleted. Additionally, non-English reviews were removed from the collected data at this point. Moreover, records that do not include ratings for restaurant features (such as food, service, value, and atmosphere), or do not contain information about restaurants or travel were excluded.

We applied LDA on the textual data to generate the satisfaction dimensions. Then, the data were divided into two main groups, restaurants with COVID-19 safety precautions, and restaurants with no COVID-19 safety precautions. Then, we applied LVQ clustering to the whole dataset. The learning rate for LVQ was set to 0.05. For restaurants with COVID-19 safety precautions and restaurants with no COVID-19 safety precautions, data were clustered in 3 segments. Segment 1, Segment 2, and Segment 3 including, 828 (38.4%), 352 (16.3%) and 978 (45.3%) records, respectively. The coefficient of determination (R^2) values for clusters was 0.871, indicating that LVQ has generated high-quality segments. In Table 2, the cluster centroids are presented. In Table 3, we present LVQ segments, COVID-19 safety precautions, and level of satisfaction. In Table 1 of Appendix A, we present LVQ segments, COVID-19 safety precautions, and level of satisfaction in four groups. In Fig. 2, we present a part of the generated trees. Users can rate restaurants by giving them a rate from 1 to 5 stars on TripAdvisor with respect to four criteria, namely food, service, value, and atmosphere [130]. Previous studies have successfully used the restaurant attributes to explain the customers' decision-making process in the context of restaurants [131,132]. We also added COVID-19 safety precautions to the list in light of recent changes with the emerging COVID-19 crisis [2,3,133]. The CART technique was used to predict the level of satisfaction in 3 segments according to the aforementioned variables as the inputs.

Table 2
Cluster centroids.

Attribute	Segment 1 (LVQ1 × 1: 828)	Segment 2 (LVQ2 × 1: 352)	Segment 3 (LVQ3 × 1: 978)
Food	3.624396	4.275568	3.505112
Service	2.553140	2.579545	4.566462
Value	3.160628	4.573864	3.992843
Atmosphere	2.786232	4.477273	2.617587

5. Research model and hypotheses

Based on the literature, the current study develops a research model referring to the SOR model and analyzes the prominent emotion-inducing factors investigated in the first stage of the study to predict the potential customers' responses during the current pandemic. Therefore, the stimuli are four criteria, namely food, service, value, and atmosphere [131,132], whereas, the organism is the positive feelings toward the restaurant services which are presented in the form of satisfaction. In this study, the responses are the consumer's intention to choose a restaurant as reflected in their reviews and ratings. Based on that, the following hypotheses are provided:

H1. The quality of food has an impact on customers' satisfaction with the restaurant.

H2. The provided service has an impact on customers' satisfaction with the restaurant.

H3. The perceived value has an impact on customers' satisfaction with the restaurant.

H4. The atmosphere has an impact on customers' satisfaction with the restaurant.

We argue that the ambiguity the customers face during the COVID-19 pandemic has a moderating effect on the relationship between stimulus and organism. As the SOR framework suggests, customers might need to consider the safety precautions in their decision-making process. Previous studies have reported that consumers are sensitive to restaurants' safety measures during the pandemic [134] with more focus concerning the COVID-19 safety guidelines in restaurants [16] as well as other sectors [106,135]. The atmosphere, on the other hand, could be affected by the safety measures as well. Based on this, we present the following hypotheses:

H5. COVID-19 safety precautions have a moderating impact on the relationship between the provided service and customers' satisfaction with the restaurant.

H6. COVID-19 safety precautions have a moderating impact on the relationship between the atmosphere and customers' satisfaction with the restaurant.

We present the research hypotheses and the initial research model in Fig. 3.

6. PLS-SEM methodology

6.1. Structural equation modeling

To assess the research model, PLS-SEM was used, in which both the outer model and the inner model were examined. The survey was answered by 1358 participants who had previous experience with the

Table 3
LVQ segments, COVID-19 safety precautions and level of satisfaction.

Customer Satisfaction Level				LVQ Segments		
				Segment 1	Segment 2	Segment 3
COVID-19 Safety Precautions	No	Customer Satisfaction Level	High	0	33	47
			Low	350	39	192
			Moderate	83	102	243
	Yes	Customer Satisfaction Level	High	210	167	414
			Low	24	1	3
			Moderate	161	10	79

TripAdvisor portal. The questionnaire entailed three main parts to allow the participants to read a preface about the goal of the research, followed by simple demographic questions, and finally the main questions of the survey. To gather the data, the researchers distributed a large-scale survey for six months, starting from January 2021. Demographic data are displayed in Table 4. Survey indicators with supporting previous literature are displayed in Table 1 of Appendix B.

The outer model and the inner model should be inspected in terms of several tests to check the reliability and validity of the model of the study. SmartPLS software (www.SmartPLS.com) was used to perform the analysis tests. The factors of the model and the relationships among these factors should be examined (Hair et al., 2016). The reason for the choice of the SmartPLS is that it enables the evaluation of small and large-sized samples. As we aimed to analyze the groups of the participants based on their mode of travel, the choice of SmartPLS was suitable.

i. Assessment of the Outer Model

SmartPLS was used to inspect the outer model in terms of reliability and validity by conducting three main tests: Convergent Validity, Internal Consistency, and Discriminant Validity (we referred to them as CV, IC, and DV, respectively). CV measure inspects the items of the survey considering their outer loadings, as the least acceptable value for each indicator should be 0.7 [136], otherwise, it could be removed based on the results of Composite Reliability (CR) or Average Variance Extracted (AVE) tests. Based on this rule, and referring to the test result, all the items in the survey were kept in the research model. The second assessment of CV evaluation is the AVE test, which checks the degree of interrelation among the items of a particular factor. The result of the test should surpass 0.5 for all factors, which was met for all factors. Following that, the IC needs to be checked based on Cronbach's Alpha (CA) and Composite Reliability (CR) tests. CA result should surpass the value of 0.7 for all the factors. On the other hand, the CR test should have values above 0.7 for each factor. CA and CR tests were confirmed in this study based on the result, as presented in Table 5.

Cross-Loadings (CL) and Fornell-Larcker (FL) measures were performed to inspect the Discriminant Validity (DV) of the research model. FL compares the level of divergence among variables with the AVE value of the individual variables. Finally, the outer loadings of all the items for a particular variable need to be higher than their cross-loadings (in the CL test). Each of the FL and CL tests achieved the required conditions, indicating the validity of the research variables. Table 6 presents the FL test, while the result of the CL test is presented in Table 1 of Appendix C.

ii. Assessment of the Inner Model

Three main measures should be inspected to examine the structural model. First, for the Path Coefficient (PC) test, bootstrapping technique was conducted using the SmartPLS tool. The significance threshold that should be met for research hypotheses is $p < 0.01$ (Hair et al., 2015). The paths between food and travelers' satisfaction, service and travelers' satisfaction, value and travelers' satisfaction, atmosphere and travelers' satisfaction were proved to be valid and significant. Additionally, the path between COVID-19 safety precautions and travelers' satisfaction was confirmed ($p < 0.01$). Path coefficient results are presented in Table 7.

Next, the Coefficients of Determination (R^2) measure is used to inspect the predictive accuracy of the model by investigating the ratio of the change of the endogenous construct through evaluating its exogenous constructs [136]. The value of R^2 should fall in the interval of 0–1, indicating more predictive accuracy with higher outcomes [136]. Based on the result, customers' satisfaction factor has R^2 value of 0.679, which is considered high. This result indicates that the model has high predictive accuracy.

Finally, the predictive relevance (Q^2 value) measure was performed. The predictive relevance has to be more than zero for the endogenous construct. The blindfolding technique was used to calculate the Q^2 measure using the SmartPLS package. Based on the test's result, customers' satisfaction achieved Q^2 values more than zero (0.445), indicating the predictive validity of the hypothesized research model. Referring to the outcome of these three measures, the final research model was given in Fig. 4.

In this research, the moderation effect of COVID-19 safety precautions on two relationships was inspected. The moderation impact indicates the external influence of a factor on a specific path in the research model, in which this link becomes stronger or weaker based on this influence [136]. The first moderating effect was significant and the results indicated that the COVID-19 safety precautions strengthened the positive relationship between service and customer satisfaction (Fig. 5a). The moderating effect of COVID-19 safety precautions on the positive relationship between the atmosphere and customers' satisfaction was also found to be significant (Fig. 5b).

In this research, we aimed to explore the research model based on the travel mode. Hence, referring to Table 4, the distribution of respondents in this research based on the mode of travel is as follows: families: 373, solo: 294, friends: 337, couples: 354. Following that, the inner model was examined for each subgroup and the research paths were inspected. As Table 8 displays, the research paths were supported in all four groups. The difference appeared in the moderating impact, as in group 1 the two moderating impacts were not supported, while in the third and fourth groups, only the second moderating impact was rejected. On the other hand, the analysis of the paths based on the second group presented the support to both moderating impacts.

7. Discussion

Online consumer reviews are playing a significant role in the image of online businesses. Consumers discuss and evaluate products and services online and their reviews provide a critical source of information for potential customers as well as business owners [42]. Customers reach their purchase decision based on these reviews [43], and business owners consider the information extracted from the reviews to make managerial decisions [45].

The use of text-mining technology enables researchers and practitioners to discover new insights about the preferences of the customers [6]. Customers' satisfaction with restaurants has been investigated via text-mining based on the online reviews in previous literature [14,137]. However, the impact of the COVID-19 outbreak has changed the

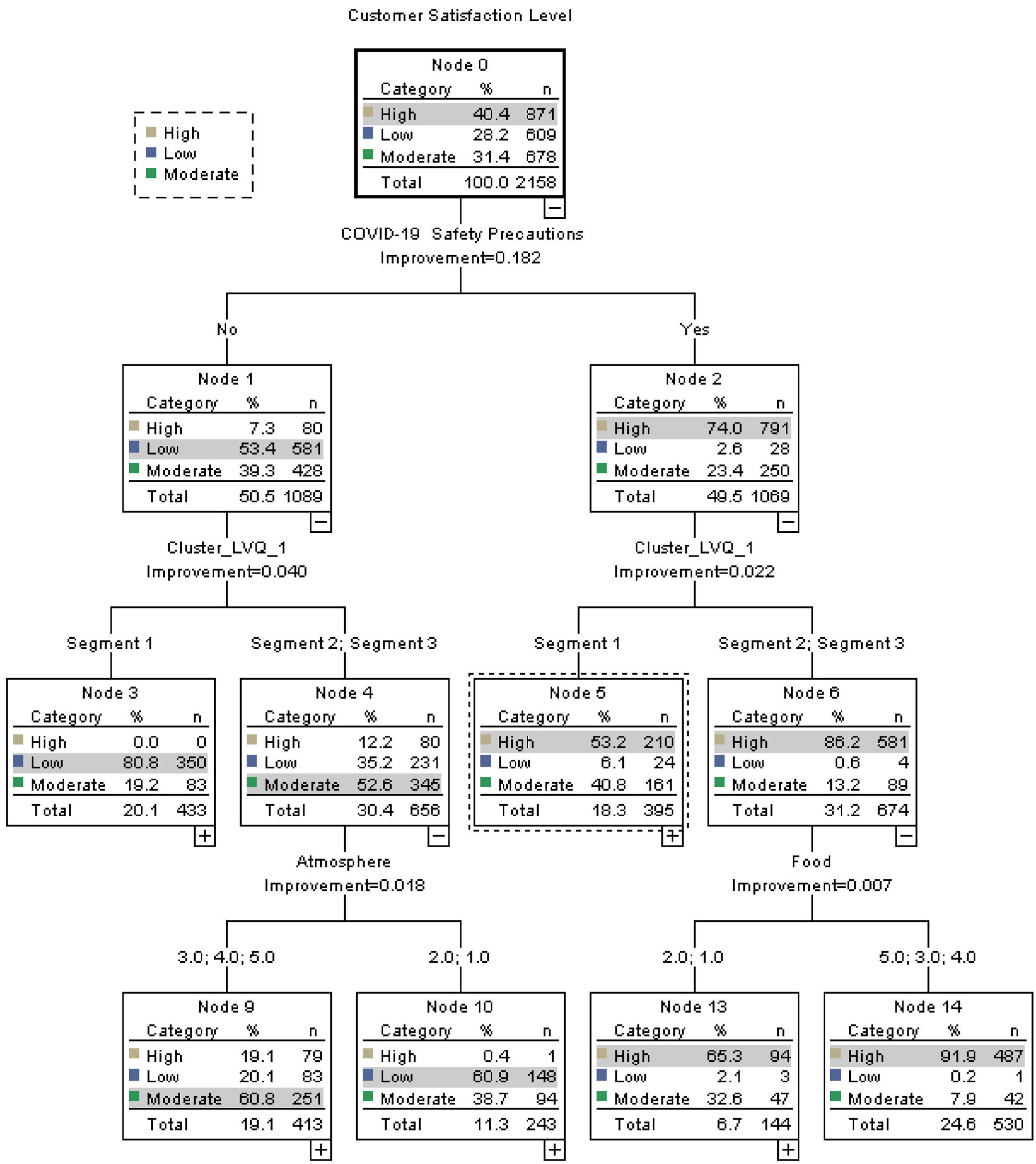

Fig. 2. CART analysis results.

business landscape, and eventually, the customer's choices and preferences have to be reinvestigated, as businesses managers need to adapt their operations and management policies. Hence, this research aims to investigate the determinants of the customers' sentiments with a restaurant within the context of the current pandemic. As the outcomes of the research presented, customers are concerned about the COVID-19 safety precautions. The results indicated that while the investigated features are important contributors to customer satisfaction, the COVID-19 safety measures observed in the restaurants could impact the link between these factors and satisfaction.

Our findings showed that atmosphere is one of the essential factors to customer satisfaction during the outbreak. The results are consistent with proceeding studies (e.g. Ref. [63]). Moreover, our findings showed that the impact of the COVID-19 safety precautions on the relationship

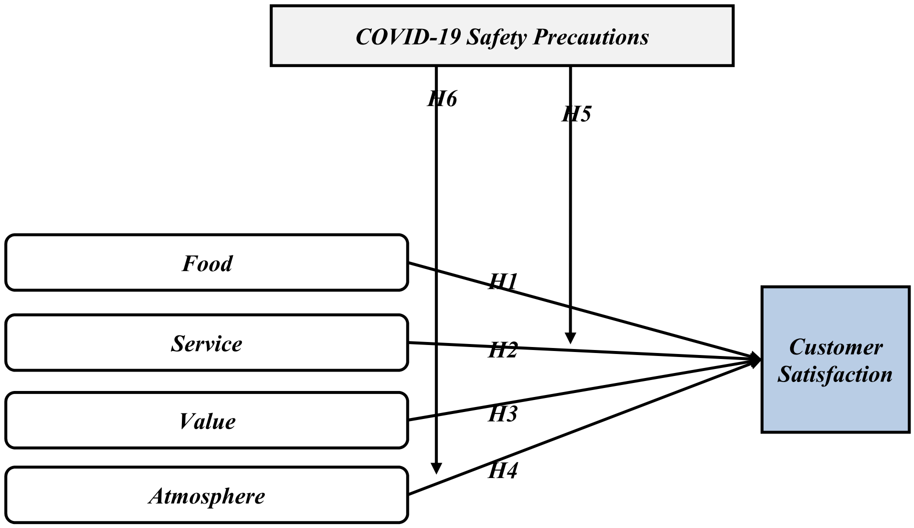

Fig. 3. Initial research model.

between atmosphere and satisfaction is significant. The effect, however, varied between the investigated subgroups. Results indicated that the effect was only present for couples. Similarly, the results showed that service is significant in determining customer satisfaction and the effect is moderated by the COVID-19 safety precautions. Although service quality is a multidimensional construct, it has been investigated both as a compound [72] and as a separate dimension [80]. Conversely, the effect was not confirmed for the solo customers of restaurants, while it was confirmed for couples, friends, and families. We also found that food and value play a significant role in the satisfaction of the customers during the outbreak, which is in line with the studies before the outbreak and provides additional support for previous studies [55,63,84,102]. Safety precautions were also indicated as an influential factor to customers' satisfaction. This implies that to adapt to the changes imposed by the current pandemic, restaurants must consider aspects related to

Table 4
Demographic results of the participants (N = 1358).

Feature	Item	Frequency	Percentage
Gender	Female	670	49.34
	Male	688	50.66
Age	18–20	148	10.89
	21–30	547	40.28
	>30	663	48.82
Marital status	Married	610	44.92
	Single	748	55.08
Occupation	Employee	525	38.66
	Employer	350	25.77
	Student	165	12.15
	Retired	208	15.31
	Others	110	8.1
Usage of TripAdvisor for Booking Restaurants in the Last Six Months	1-3 times	450	33.14
	4-6 times	375	27.61
	Over 6 times	533	39.25
Mode of Travel	Family	373	27.48
	Solo	294	21.65
	Friends	337	24.81
	Couples	354	26.07

Table 5
Constructs' reliability and validity.

Construct	CA	CR	AVE
Atmosphere	0.762	0.811	0.518
COVID-19 Safety Precautions	0.743	0.836	0.56
Customer Satisfaction	0.766	0.863	0.679
Food	0.767	0.838	0.512
Service	0.816	0.873	0.579
Value	0.868	0.902	0.648

Table 7
Path coefficient result (N = 1358).

Hypotheses	Link	β	t-value	p-value	Supported
H1	Food - > Customer Satisfaction	0.336	11.252	0	Yes
H2	Service - > Customer Satisfaction	0.224	6.979	0	Yes
H3	Value - > Customer Satisfaction	0.259	7.466	0	Yes
H4	Atmosphere - > Customer Satisfaction	0.734	31.012	0	Yes
H5	Moderating Effect 1 - > Customer Satisfaction	0.098	4.802	0	Yes
H6	Moderating Effect 2 - > Customer Satisfaction	0.092	3.893	0	Yes
Additional	COVID-19 Safety Precautions - > Customer Satisfaction	0.218	7.22	0	Yes

Table 6
Fornell-larcker criterion.

Construct	Atmosphere	COVID-19 Safety Precautions	Customer Satisfaction	Food Quality	Services	Value
Atmosphere	**0.769**					
COVID-19 Safety Precautions	0.541	**0.761**				
Customer Satisfaction	0.72	0.423	**0.824**			
Food Quality	0.595	0.68	0.618	**0.715**		
Services	0.545	0.748	0.486	0.694	**0.774**	
Value	0.618	0.633	0.437	0.648	0.767	**0.805**

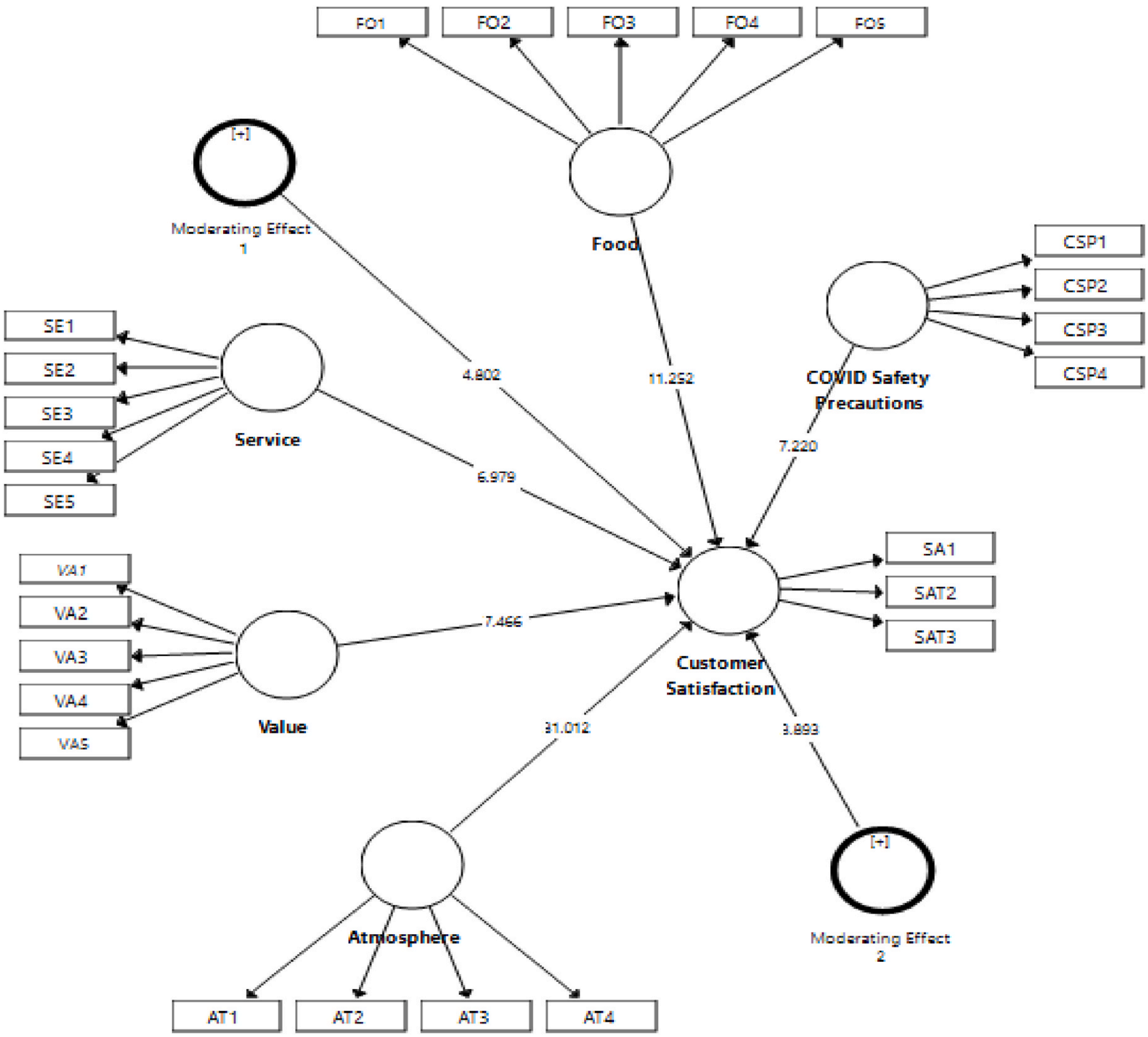

Fig. 4. Final research model.

iii. The Moderating Impact

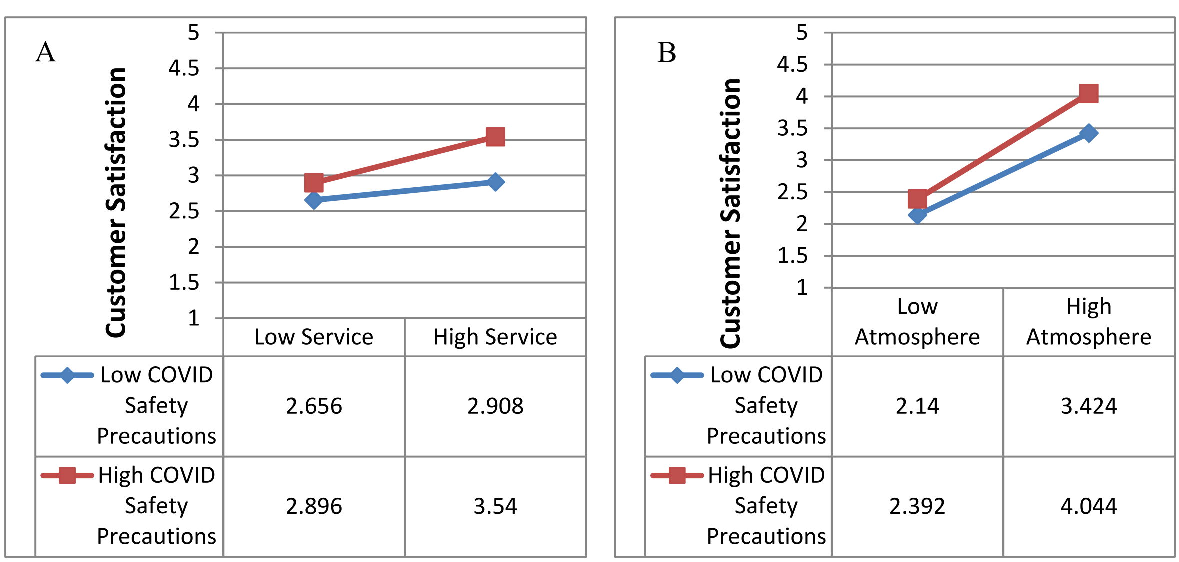

Fig. 5. The moderating impact of COVID-19 safety precautions.

iv. The Subgroups Analysis

Table 8
Path coefficient result of subgroups.

Group	Hypotheses	Link	β	t-value	p-value	Supported
Group 1 (N = 294) Solo	H1	Food - > Customer Satisfaction	0.308	4.523	0	Yes
	H2	Service - > Customer Satisfaction	0.217	2.69	0.007	Yes
	H3	Value - > Customer Satisfaction	0.276	3.675	0	Yes
	H4	Atmosphere- > Customer Satisfaction	0.757	15.621	0	Yes
	H5	Moderating Effect 1 - > Customer Satisfaction	0.101	1.906	0.057	No
	H6	Moderating Effect 2 - > Customer Satisfaction	0.076	1.304	0.193	No
	Additional	COVID-19 Safety Precautions - > Customer Satisfaction	0.198	2.834	0.005	Yes
Group 2 (N = 354) Couples	H1	Food - > Customer Satisfaction	0.33	5.635	0	Yes
	H2	Service - > Customer Satisfaction	0.201	3.03	0.003	Yes
	H3	Value - > Customer Satisfaction	0.213	2.999	0.003	Yes
	H4	Atmosphere - > Customer Satisfaction	0.706	14.401	0	Yes
	H5	Moderating Effect 1 - > Customer Satisfaction	0.109	2.578	0.01	Yes
	H6	Moderating Effect 2 - > Customer Satisfaction	0.123	2.7	0.007	Yes
	Additional	COVID-19 Safety Precautions - > Customer Satisfaction	0.208	3.482	0.001	Yes
Group 3 (N = 373) Families	H1	Food - > Customer Satisfaction	0.351	6.03	0	Yes
	H2	Service - > Customer Satisfaction	0.286	4.35	0	Yes
	H3	Value - > Customer Satisfaction	0.346	5.571	0	Yes
	H4	Atmosphere - > Customer Satisfaction	0.755	17.616	0	Yes
	H5	Moderating Effect 1 - > Customer Satisfaction	0.086	2.252	0.025	Yes
	H6	Moderating Effect 2 - > Customer Satisfaction	0.07	1.608	0.108	No
	Additional	COVID-19 Safety Precautions - > Customer Satisfaction	0.232	3.948	0	Yes
Group 4 (N = 337) Friends	H1	Food - > Customer Satisfaction	0.334	5.563	0	Yes
	H2	Service - > Customer Satisfaction	0.184	2.462	0.014	Yes
	H3	Value - > Customer Satisfaction	0.193	2.621	0.009	Yes
	H4	Atmosphere - > Customer Satisfaction	0.721	15.569	0	Yes
	H5	Moderating Effect 1 - > Customer Satisfaction	0.099	2.341	0.02	Yes
	H6	Moderating Effect 2 - > Customer Satisfaction	0.093	1.877	0.061	No
	Additional	COVID-19 Safety Precautions - > Customer Satisfaction	0.221	3.297	0.001	Yes

the COVID-19 safety precautions regarding their services.

8. Conclusion and implications

This paper examines customers' satisfaction with restaurants and the most important factors that impact customers' satisfaction during the COVID-19 pandemic. We used a two-step method based on machine learning and survey-based approaches. In the first step, the information provided on restaurant websites was examined using a newly proposed method based on machine learning techniques (text mining, clustering, and prediction learning techniques). We used both the numerical ratings of quality aspects and textual reviews of service in restaurants. The big social data was extracted from TripAdvisor consisting of 2158 records from 50 restaurants. LDA was used to discover satisfaction dimensions and the numerical reviews were analyzed using LVQ cluster analysis. Finally, the CART technique was used to predict the level of satisfaction in the generated segments. The tree showed that the lowest satisfaction was reported in restaurants that did not follow the COVID-19 safety measures. Besides, customers who rated food higher were the largest satisfied group (24.6%).

In doing so, we provided insights into the use of machine learning techniques in the field, by exploring the use of LDA for text mining to discover the satisfaction dimensions. Text mining techniques have been used actively in the management and hospitality literature. However, the use of LDA remains rare. There is also a need to develop new methods to investigate the reviews according to the latest trends in the review patterns, which could help researchers to learn and predict the context of the reviews during the COVID-19 pandemic.

In the second step, a set of hypotheses were examined using PLS-SEM methodology, by analyzing 1358 survey responses gathered in six months. The results indicated that four items of atmosphere, food, value, and service infer customer satisfaction with restaurants significantly, among which the most prominent effect was imposed by the atmosphere. We were able to confirm that the COVID-19 safety precautions observed by the restaurants amplify the effect that atmosphere and service have on customer satisfaction.

Another significant finding is the different levels of importance of the COVID-19 safety precautions in the defined market segments. We developed our hypothesis based on the SOR model and examined the moderating effect of the COVID-19 safety precautions across four subgroups namely solo, family, couple, and friends who visit the restaurants and reviewed them. Customers who were couples, with friends, or family members while visiting restaurants showed more sensitivity toward the COVID-19 safety precautions, while solo travelers did not. The magnitude of the effect of the COVID-19 safety measures on customer satisfaction was the highest for families, followed by couples, friends, and solo travelers, respectively. Whereas, the moderating effect of the COVID-19 safety measures on the relationship between each of the atmosphere and service and satisfaction was not present for solo travelers. The effect on the satisfaction was more eminent in the other three groups regarding the service, rather than the atmosphere. Solo travelers who value individual habits and seek self-satisfaction are typically less demanding than customers in groups (couple, family, friends) [138], and hence they might be aware of the COVID-19 safety precautions but complain less about them concerning service and atmosphere.

This is in line with the theory expectation disconfirmation theory, which explains the differences in customers' satisfaction by their expectations. Customers from different groups naturally have different expectations of the services and therefore, the same stimulus could provoke different sentiments. According to the construal level theory [139], people interpret the same event differently. Customers' preferences might vary according to their goals of visiting. For example, family and couple travelers tend to be more willing to pay in their travel experience, depicting a lower construal level, while solo travelers present a higher construal level which makes them more likely to be satisfied. [140], explaining their attitude toward the safety precautions. This effect has been observed in drivers of ratings and satisfaction in studies of other sectors [141].

The study contributes to the existing knowledge by proposing a new approach for predicting satisfaction based on online reviews, in the forms of text and ratings, and travelers' behavioral preferences during the pandemic. It adds to the previous studies that have used a broad range of methods to identify indicators of customers' satisfaction [6,9,48]. The findings explored the role of factors with a more extensive description. Moreover, the presented insights about the market segmentation could address the research gap by identifying the shared views and key factors during the pandemic for four different groups of customers. In doing so, this study broadens the scope of the analysis of online reviews during the pandemic by improving our understanding of customer preferences in the post-COVID-19 period.

In terms of managerial implications, the findings can help restaurant managers in their decision-making process during and after the COVID-19 crisis. This research highlights the important aspects of business that are significant to the customers during the pandemic. The restaurants could provide differentiated service for each group of customers according to the variations in the impacts of the driving factors, of each group, on the level of satisfaction. The findings could help managers to optimally allocate resources to prioritize the needs and expectations of each group focusing on the provided services. Utilizing the outcomes of the study, the business owners in this sector might be able to mitigate easier the changes imposed by the COVID-19 crisis. The ability to differentiate service quality according to the preferences of each subgroup of restaurant customers enables managers to adjust their services promptly, leading to higher levels of satisfaction which is a key driver of revenue growth [2,3].

The pandemic has influenced the consumer's perceived level of importance of the features, hence, it is of essential value for restaurants to comprehend the changes and adapt accordingly, especially because it is more likely that the effects might persist a long time after the pandemic is over. That, of course, requires the presence of the restaurants in the platforms that enable customers to express their views and make their feedback heard. Restaurants and dining businesses have played an important role in the development of the tourism field, which accordingly has an important impact on the growth of the community [142,143]. Hence, it is vital to investigate customers' perceptions using new approaches that integrate up-to-date analysis methods. The novel method of this study that integrates two approaches to capture customers' assessment of restaurants can help to meet this goal.

Our work, however, had limitations that should be addressed. We did not investigate any causal relationship. Our findings were based on predictive outcomes. Further experiential studies are required to confirm the causal relationships. We relied only on reviews posted during the pandemic, which limits the number of reviews in this study. Future study could be conducted focusing on differences between the reviews and the ratings in three time periods; before the COVID-19 outbreak, the early months of the pandemic, and the subsequent pandemic period to examine how the state of the pandemic have changed customers' preferences and levels of satisfaction over the time. In addition, our findings should be carefully generalized to other business sectors in the hospitality industry. Moreover, we did not take into account the context or different cultural features in our study. This limits our findings from being generalized to other cultures, specifically in the countries where English is not used by native people. A multi-language analysis can be conducted to address this limitation. Future studies are encouraged to enrich the data with more predictors and more variables that could impact customers' satisfaction.

Acknowledgments

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Appendix A

Table 1
LVQ segments, COVID-19 safety precautions and level of satisfaction in four groups

Customer Satisfaction Level				Travel Type											
				Travelled as a couple			Travelled solo			Travelled with family			Travelled with friends		
				LVQ Segments											
				Segment 1	Segment 2	Segment 3	Segment 1	Segment 2	Segment 3	Segment 1	Segment 2	Segment 3	Segment 1	Segment 2	Segment 3
COVID-19 Safety Precautions	No	Customer Satisfaction Level	High	0	5	9	0	7	6	0	1	9	0	20	23
			Low	62	6	41	65	8	26	47	5	26	176	20	99
			Moderate	12	11	48	12	18	29	17	16	44	42	57	122
	Yes	Customer Satisfaction Level	High	0	0	0	140	117	305	40	34	71	30	16	38
			Low	0	0	0	18	0	1	5	1	1	1	0	1
			Moderate	0	0	0	121	8	60	28	2	9	12	0	10

Appendix B

Table 1
Survey items

Construct	Indicators	Research Items	References
Atmosphere	AT1	The appearance of the employees is neat.	[144]
	AT2	The interior design of the restaurant is attractive.	
	AT3	The temperature of the restaurant is acceptable.	
	AT4	The layout allows easy movement around.	

(continued on next page)

Table 1 (*continued*)

Construct	Indicators	Research Items	References
Food Quality	FO1	The restaurant served good quality food.	[145]
	FO2	The restaurant served food that meets the hygiene measures.	
	FO3	The restaurant served food based on social distancing measures.	
	FO4	The restaurant served tasty food.	
	FO5	Dining at this restaurant looks safe to me.	
COVID-19 Safety Precautions	CSP1	Only immunized people are allowed to enter the restaurant.	From the Online Reviews
	CSP2	Workers wear masks all the time.	
	CSP3	Workers sanitize surfaces frequently.	
	CSP4	Hand sanitizers are available.	
Satisfaction	SAT1	I am satisfied with this restaurant.	[146]
	SAT2	My satisfaction with this restaurant is high.	
	SAT3	I am glad that I selected this restaurant.	
Service	SE1	The restaurant presents comfortable utilities.	[147]
	SE2	Service is provided at an acceptable time.	
	SE3	The services are presented quickly.	
	SE4	The provided services met my expectations	
	SE5	The presented services are of high quality.	
Value	VA1	The price meets the provided services.	[148]
	VA2	The food deserves the price I paid.	
	VA3	The restaurant provides a worthy value of money.	
	VA4	Overall, the restaurant deserves the price I paid.	
	VA5	The served food worth's the presented prices	

Appendix C

Table 1
Cross-loadings Test

	Atmosphere	COVID-19 Safety Precautions	Customer Satisfaction	Food Quality	Services	Value
AT1	0.674	0.445	0.289	0.437	0.43	0.513
AT2	0.682	0.479	0.316	0.404	0.455	0.578
AT3	0.71	0.571	0.332	0.462	0.496	0.587
AT4	0.857	0.296	0.806	0.452	0.346	0.35
CSP1	0.3	0.761	0.267	0.474	0.632	0.381
CSP2	0.258	0.791	0.265	0.481	0.602	0.374
CSP3	0.322	0.724	0.293	0.546	0.488	0.44
CSP4	0.626	0.715	0.396	0.512	0.585	0.618
FO1	0.471	0.568	0.383	0.727	0.699	0.65
FO2	0.389	0.585	0.351	0.723	0.493	0.393
FO3	0.428	0.476	0.458	0.797	0.463	0.431
FO4	0.281	0.467	0.265	0.606	0.372	0.341
FO5	0.504	0.426	0.621	0.781	0.482	0.447
SAT1	0.806	0.296	0.857	0.452	0.346	0.35
SAT2	0.555	0.376	0.854	0.527	0.444	0.376
SAT3	0.483	0.4	0.758	0.578	0.436	0.364
SE1	0.44	0.5	0.346	0.546	0.784	0.694
SE2	0.485	0.556	0.355	0.55	0.815	0.741
SE3	0.347	0.672	0.374	0.51	0.728	0.381
SE4	0.309	0.664	0.373	0.486	0.688	0.367
SE5	0.489	0.516	0.39	0.541	0.805	0.735
VA1	0.545	0.54	0.447	0.617	0.739	0.863
VA2	0.456	0.524	0.261	0.469	0.509	0.764
VA3	0.443	0.473	0.307	0.49	0.513	0.783
VA4	0.5	0.503	0.259	0.436	0.49	0.749
VA5	0.534	0.522	0.416	0.554	0.742	0.858

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