THE ANTECEDENTS OF CUSTOMERS' COMPLIMENTS AND COMPLAINTS TOWARDS DIFFERENT CATEGORIES OF HOTELS IN INDIA: MINING MEANING FROM BIG DATA USING LATENT DIRICHLET ALLOCATION

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DOCTOR OF PHILOSOPHY
in
MANAGEMENT

By

VINAY CH.

Under the Supervision of

Prof. B RAJA SHEKHAR

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CERTIFICATE

This is to certify that the thesis entitled **"The antecedents of customers' compliments and complaints towards different categories of hotels in India: mining meaning from big data using latent Dirichlet allocation"** submitted by **Vinay Ch**, bearing Reg. No. **16MBPH13** in partial fulfilment of the requirements for the award of Doctor of Philosophy in Management is a bonafide work carried out by him under my supervision and guidance.

The thesis has not been submitted previously in part or in full to this or any other University or Institution for the award of any degree or diploma.

Research articles related to the topic of this thesis have been:

A. Published in the following journals: -

1. Chittiprolu, V., Palani, M. V., Kumar, D. S., & Ramana, V. V. (2020). Determinants of agri-hotel customers'experience from the perspective of user-generated content: text mining analysis. Academy of Marketing Studies Journal, 24(2), 1-15.
2. Chittiprolu, V., Samala, N., Bellamkonda, R. S. (2021). Heritage Hotels & Customer Experience: A Text Mining Analysis of Online Reviews. International Journal of Culture, Tourism, and Hospitality Research. Accepted on Jan 18th, 2021.

B. Presented in the following conferences: -

1. Presented a paper titled "Hotel operating expenses, online cues, and firm performance: A moderating role of online cues" in the 12th Doctoral thesis conference organized by IBS Hyderabad, IFHE University, from Apr 18-19, 2019.
2. Presented a paper titled "Hotel operating expenses, online cues, and firm performance: A moderating role of online cues" in 10th conference on excellence in research and education (CERE 2019) held at Indian Institute of Management Indore (IIM Indore) from May 03-05, 2019.

C. Further the student has passed the following courses towards the fulfilment of coursework requirements for Ph D:

	Course Name	Credit	Results
1.	**Statistics for Business Analytics**	3	Pass
2.	**Research Methodology**	3	Pass
3.	**Academic writing**	4	Pass
4.	**Operations management**	3	Pass

Supervisor **Dean**

(Prof. B Raja Shekhar) **(Prof. P. Jyothi)**

DECLARATION

I, Vinay Ch. hereby declare that this thesis entitled **“The antecedents of customers’ compliments and complaints towards different categories of hotels in India: mining meaning from big data using latent Dirichlet allocation”** submitted by me under the guidance and supervision of Prof. B Raja Shekhar

Is a bonafide research work. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma.

Date:**27/07/2021**

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शोध प्रबांध का शीर्षक

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Regards,

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List of abbreviations

Acronym	**Full Form**
CS	Customer satisfaction
CC	Customer complaints
LDA	Latent Dirichlet allocation
LSA	Latent semantic analysis
K	Number of topics
WOM	Word of mouth
eWOM	Electronic word of mouth
FTA	Foreign tourists’ arrival
SNS	Social networking sites
STM	Structure topic modeling
DTM	Document term matrix
SEM	Structure equation modeling
OR	Online reviews
RVOL	Review volume
RVAL	Review valence
RVAR	Review variation
CL	Customer loyalty
BI	Behavior intention

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Abstract:

Technology advancements has impacted the service industry in a paramount way. It has brought many changes to the customer journey. Incredibly during the information search and evaluating the alternatives in the pre-purchase stage. With the ease of internet access, consumers can now refer to user-generated reviews (UGR) to reduce risks and uncertainty while purchasing different services and products. UGR replaces the traditional word of mouth. Consumers post their experiences and expectations in the form of UGR on third-party websites, social media, and official hotel websites. Virtual travel communities and the hotels' websites play a vital role in this process of information seeking and information sharing. Easy to use interface and options to interact with other travelers through the websites saves lot of time and effort for the tourists planning their travel and stay.

eWOM changed the business strategies, it act as a business intelligence tool. Plenty of data is available on the internet in the form of videos, images, ratings, text reviews, user browsing history, etc. Enormous data is generated on the internet, marketers mine this information to conclude consumer buying behavior. With the evolution of computer-aided technologies, researchers, managers, practitioners started using these technologies. Machine learning, deep learning, neural networks, natural language processing, and predictive modeling were advanced technologies that marketers used to get knowledgeable information from big data, which can be used for decision-making while designing products and services.

Consumers started using the internet to search about service offerings, price and feature comparison, service provider's ratings, etc. Hospitality and tourism industry is characterized by' intangibilities, inseparability, perishability, and variability. Due to the nature and risks associated with hospitality products, consumers look for some cues to build the purchase decision, such as star rating of the hotels, reviews, ratings, and WOM. Evidence proved that UGR impacts hotel sales, profits, share values, and financial performance. Moreover, positive UGR improves sales and financial performance, and negative reviews destroy the brand image and damage the hotel's reputation. Even though service failures are inevitable, service providers need to understand the reasons for the service failure. Service providers can track the positive and negative ratings and understand the determinants that drive SC and SF. Service compliments (SC) improve the team spirit among the hotel employees, while sometimes service failures (SF) or negative reviews create frustration and dilemmas among hotel employees.

Previous studies were trying to understand the reasons for SC and SF using different methodologies. Some studies used primary or survey techniques to understand the impact of SC on hotel financial performance and antecedents of SC and SF in the hotel industry. The survey data studies have some limitations: Using survey data, researchers can only build the association between variables. Second, researchers restrict themselves to pre-defined variables. Third, the respondent's bias and methodological bias may exist. These limitations can be overcome by using secondary data. The UGR is divided into quantitative ratings and qualitative ratings. Using quantitative ratings, researchers restrict the attributes. But by using text data, researchers can find hidden and new dimensions. Moreover, secondary data studies are cost-effective; researchers can collect big data from the internet and conclude the findings.

Studies on the Indian context are very negligible. The Indian hospitality market is enormous with different cultures, languages, and travel products. This study tries to understand the antecedents of SC and SF in the Indian hotel industry.

The signaling theory states that consumers look for many cues which drive the purchase behavior. Star rating creates expectations for consumers, and it gives some idea about products or service offerings. The price, brand image, and brand reputation create an expectation for customers. Consumers believe that a positive trend is associated between the star rating and service quality. The multiattribute theory states that the determinants and importance of SC and SF vary based on consumers' behavior, attitudes, and their purpose of travel. According to construal level theory, the satisfaction and overall assessment about products or services vary based on the travel type, expertise, and nationality.

This study tries to understand the SC and SF attributes towards different types of hotels and understand the importance and ranks of the attributes. To address the research question, the researcher collected data from TripAdvisor.com, a popular travel agency website. A total of 3.12 lakh reviews were used for this study. This study used text mining techniques to identify the SC and SF attributes. A latent Dirichlet allocation algorithm was applied to extract the features from the text data. The attributes importance was calculated based on the gamma value, such as the number of documents contributed to each topic.

The study findings through some essential attributes to discuss. First, the determinants of SC and SF were different for 3 hotels. Moreover, the determinants of SC and SF were distinct for 3 hotels. General or core aspects were discussed by satisfied customers, whereas dissatisfied customers discussed specific determinants.

Chapter 1

1. Introduction to tourism and hospitality sector:

According to Asia pacific chains and hotel report 2018, the number of guests rooms available in the Indian hotel industry was 2,44,000 rooms with 3551 hotels. The Indian hospitality market is proliferating, and the requirement for hotels has increased. One lakh rooms were added to the Indian hotel industry in the past decade. One hundred sixty-one hotel brands are operating (international and domestic) in India (HTL, 2018). Tourism industry contributes 10 % of the world's Gross Domestic Product (UNWTO, 2018). The service industry contribution is massive for the tourism industry, “30% of the services exports” are happening in the world to support the tourism industry(UNWTO, 2018). During 2017, the growth of the tourism industry in India is tremendous, and the performance of the Indian Tourism industry increased the overall revenue of South Asia(UNWTO, 2018). With the 7% share of foreign tourist arrivals in India in 2017, India stood top in South Asia(UNWTO, 2018). For example, foreign tourists’ arrivals (FTA) in India crossed 10 million in 2017, and 1614 million domestic tourists traveled in 2016. So, the hospitality industry in India is vast and provides employment opportunities (HTL, 2018).

1.1. Ministry of Tourism, India:

Government of India, Ministry of tourism (MoT) is the nodal agency that develops tourism policies and schedules the activities to develop and promote tourism in India and outside (Ministry of Tourism, 2019).

1.1.1. **Functions of the ministry of tourism** (source: (Ministry of Tourism, 2019))

a. Develop the policies.

b. Planning

c. Co-ordination between countries.
d. Tax regulations
e. Infrastructure development
f. Investing in research and analysis
g. International alliance
h. Develop the memorandum of understanding with other countries.
i. Overseas promotions
j. Budget development and implementations, etc.

Ministry of tourism initiated many things to improve the tourism, such as (Ministry of Tourism, 2019):

i. Adopt a heritage scheme.
ii. Visa on arrival
iii. Sustainable tourism infrastructure projects
iv. Festivals promotions
v. Make in India campaign.
vi. Rural tourism development
vii. Incentives for the tourism sector
viii. Regional connectivity
ix. Incredible India website in multiple languages and promotions across the world
x. Developing convention centers, etc.

1.1.2. Statistics:

According to the ministry of tourism (Ministry of Tourism, 2019):

i. FTA was 10.89 million in 2019 with a progress rate of 3.2%

ii. 2.93 million foreign tourists availed visa on arrival scheme

iii. Foreign exchange earnings (FEE) were 2,10,981 crores in 2019, with an expansion rate of 8.3%

1.2. Tourism products in India:

As defined by UNWTO, a Tourism Product is "a combination of tangible and intangible elements, such as natural, cultural, and man-made resources, attractions, facilities, services and activities around a specific center of interest which represents the core of the destination marketing mix and creates an overall visitor experience including emotional aspects for the potential customers. A tourism product is priced and sold through distribution channels and it has a life-cycle" (UNWTO, 2021).

India's diversity offers many tourism products. India has a rich history, majestic and young Himalaya mountains, many rivers, longest seaside line covered by three seas, different languages, traditions, festivals, cultures, and flora and fauna covered by western and eastern ghats, beautiful northeast, luxury trains, UNESCO sites, wildlife sanctuaries, many hospitals, conference halls, hotels, temples, etc. made India as preferred destinations for many International and domestic travelers (IncredibleIndia, 2020).

1.2.1. Different types of tourism products in India:

Figure 1Types of tourism products in India

Source: https://www.eoiriyadh.gov.in/page/types-of-tourism-in-india/

1.3. Popular hotel chains in India

According to Asia pacific chain report 2018, the famous international and national chains are (HTL, 2018):

Table 1 International chains in India

Chain	Number of hotels	Number of rooms
Marriott International	98	20,480
Radisson Hotel Group	87	9,931
Accor	56	9,618
Hyatt	27	6,931
Louvre Hotels Group	85	6,025
IHG	31	5,995
Wyndham	34	3,152
Hilton	16	2,533
Choice Hotels	25	1,051
Best Western	15	754

Table 2 ***Domestic chains in India***

Chain	Number of hotels	Number of rooms
Taj Hotels & Palaces	130	14,842
ITC Hotels	96	5,757
Lemon Tree Hotels	44	4,562
Oberoi Hotels & Resorts	24	3,627
Royal Orchid Hotels	44	3,089
Leela Palaces Hotels Resorts	9	2,689
CHPL Hotels & Resorts	51	2,488
Lalit Suri Hospitality Group	15	2,366
Clarks Inn Group	44	1,961
Keys Hotels	22	1,935

1.4. Popular hotel brands in India

According to Asia pacific chain report 2018, the popular international and national brands are (HTL, 2018):

Table 3 ***Domestic chain brands in India***

Domestic chain brand	Hotels	Rooms
Taj	37	5,302
Ginger	44	3,689
Vivanta	23	3,402
The Leela	9	2,689
The Gateway	26	2,449
LaLIT	12	2,200
Lemon Tree	26	2,190
Trident	10	2,167
Keys Select	15	1,553
Clarks Inn	36	1,427

Table 4 ***International chain brands in India***

International chain brand	Hotels	Rooms
Radisson Blu	34	5,201
Novotel	17	3,331
ibis	17	3,234
Luxury Collection	11	3,172
Hyatt Regency	10	3,026
Sarovar Portico	42	2,891
JW Marriott	9	2,816
Ramada	27	2,652
Crowne Plaza	11	2,596
Courtyard	14	2,285

1.5. Word of Mouth:

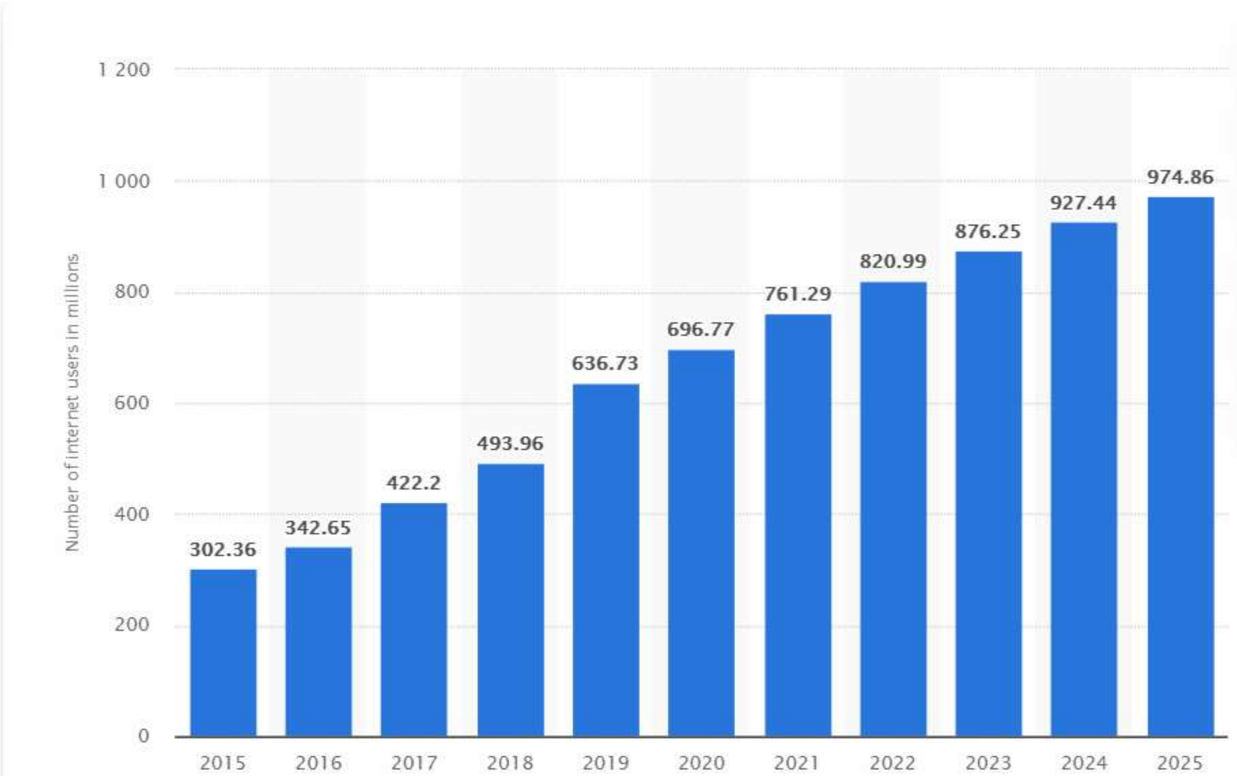
Traditionally, travelers used to get tourism-related information (for example, hotels, restaurants, travel destinations, and products), suggestions, and recommendations from friends and family members. Informal communication happens between people about products, services. In the travel industry, travelers depend on word of mouth (WOM) communication to avoid the risks. Consumers spread WOM for many reasons. Westbrook (1987) studied automobile and electronics product consumers and their pre and post-purchase behavior and identified the causes. First, to release the “inner-tension” evolved after product usage. Second, to express compliments, complaints, pleasure, and sadness. Third, share the “joy of travel” (Litvin, Goldsmith, & Pan, 2008).

1.6. Electronic word of mouth:

With the technology evolution, the travel industry adopted the latest technologies and introduced web bookings. From the past decade, internet availability and smartphones usage increased in India. For example, internet users in India increased by half a billion people in 2019 (Times, 2019). According to a Statista (consumer and market database) report, India is a second primary market for online business and predicted 974.86 million internet users by 2025. Figure 1 shows the trends of internet users in India. Moreover, 820 million people use smartphones by the end of 2022, and 14 GB of data spends monthly (India, 2021). Many travel agencies and hotels introduced mobile applications to make the reservation and business easy (Hennig-Thurau, Gwinner, & Gremler, 2002; Law, Buhalis, & Cobanoglu, 2014; Leung, Law, Van Hoof, & Buhalis, 2013; Litvin et al., 2008).

Customers use many online platforms to express their experiences, write reviews on the website, and share experiences in blogs, mobile applications, social network websites, and official web pages. The tourism industry is one of the most nuanced industries in technology adoption, innovations(HBI Staff, 2018). Enormous data in the structured and unstructured form is available for researchers, practitioners, and customers. This data can be called “big data.” J. Li, Xu, Tang, Wang, and Li (2018) reviewed the studies that used big data in the tourism industry and developed a big data framework. Generally, there are 3 data sources of big data such as user-generated, device-generated, and operational data.

Figure 2 ***Number of internet users in India***



Source: (Statista, 2020)

User-generated data plays a vital role in the hospitality industry. Users share the information in many forms, such as photos, online textual reviews, ratings, videos, etc. Online reviews(OR) are part of eWOM(X. Liu, Zhang, Law, & Zhang, 2019). With the help of technology, customers can make purchasing choices by reading the service experiences of the customers in the form of OR (Chevalier & Mayzlin, 2006). OR are influencing customers' purchase decisions(Sparks & Browning, 2011). 90% of travelers agreed that OR help them to know the destination attractions, alternatives and help them to generate new ideas before exploring the destination(Gretzel & Kyung Hyan Yoo, 2008). More than 60% of the consumers believe and trust that online reviews have up-to-date data about services and travel destinations(Gretzel & Kyung Hyan Yoo, 2008).

Ye, Law, and Gu (2009) stated that “10% improvement in reviewers’ rating can increase sales by 4.4% and a 10% increase in review variance can decrease sales by 2.8%”.

The main reasons for customers posting online reviews are to express customer satisfaction (CS) and customer complaints (CC) about any products or services. Customers express joy and discontent in the form of ratings and writing reviews on the websites. The online ratings are associated with hotel sales and profits. Extant studies proved that positive reviews increase the sales of the products or services than negative reviews. (Chevalier & Mayzlin, 2006; Floyd, Freling, Alhoqail, Cho, & Freling, 2014) If customers experience service failure, they write lengthy reviews compared with satisfied customers who may explain service failures (Zhao, Xu, & Wang, 2018). Frequent failures could lead to consumer ‘churn’, unhappy customers are willing to shift to other companies(Knox & van Oest, 2014). Retain existing customers are more profitable than gaining new customers(Knox & van Oest, 2014; Kumar, Bhagwat, & Zhang, 2015). Firms are pondering how to convert these reviews as profitable art. In the current era, the challenges for firms are customer retention and customer acquisition(Kumar et al., 2015; Kumar & Pansari, 2016). As stated by (Tax, Brown, & Chandrashekaran, 1998), customers data is used to improve the services and minimize the risk of service failures.

User-generated reviews have an economic impact on firm performance. Previous studies proved that quantitative online reviews impact hotel sales(Ye et al., 2009; Ye, Law, Gu, & Chen, 2011), Revenue per available room(Blal & Sturman, 2014; Xie, Zhang, & Zhang, 2014), short term profits(Sun & Kim, 2013), long term profits (Phillips, Barnes, Zigan, & Schegg, 2017) and share prices(Duverger, 2013). However, some studies proved that qualitative reviews also have an economic impact on firm performance. For example, Zhao, Xu, and Wang (2019) studied the effect of review attributes on customer satisfaction and proved that review attributes like polarity score, readability, word length, hotel ranking, and subjectivity significantly impact customer satisfaction. Moreover, Geetha, Singha, and Sinha (2017) studied the relationship between review sentiments on customer satisfaction and proved the relationship is significant.

So, it is necessary to understand the customer experience in detail. Online reviews help to understand the customer experience and expectations. Online reviews can be classified as quantitative reviews and qualitative reviews (Chatterjee, 2019). Extant studies used quantitative ratings for prediction purposes (Blal & Sturman, 2014; Chevalier & Mayzlin, 2006; Duan, Gu, & Whinston, 2008; Floyd, Freling, Alhoqail, Cho, & Freling, 2014; Lu, Ye, & Law, 2014; O'Neill, Hanson, & Mattila, 2008; Zhu & Zhang, 2010) and to understand the importance of service attributes on CS and CC (Geetha et al., 2017; Han, 2021; Zhao et al., 2019). In contrast, qualitative reviews such as text reviews are also used for prediction purposes (Anagnostopoulou, Buhalis, Kountouri, Manousakis, & Tsekrekos, 2020) and to understand CS and CC dimensions in detail (Lucini, Tonetto, Fogliatto, & Anzanello, 2020; Padma & Ahn, 2020; Ren, Zhang, & Ye, 2015; Sezgen, Mason, & Mayer, 2019; Xu & Li, 2016). Compared to ratings, text reviews are more illuminating, and customer write their experiences in a detailed manner. Many researchers used text reviews to understand the reasons for CS and CC, as these reviews are more informative compared to ratings. In online ratings, the service attributes are pre-classified, whereas, in-text reviews, researchers can identify the hidden and new dimensions (Xu & Li, 2016). For example, Zou (2020) used text reviews to develop the conceptual framework which relates to customer opinion on price hikes in National parks. Although extant studies identified the determinants of CS and CC in the hotel industry, studies based on Indian samples are rare. Second, according to tourism, the Indian hotel market is huge; more than 950 hotels were classified as star hotels, and 52399 rooms were available. Based on Asia pacific chains & hotel report 2018, the Indian hospitality industry is ranked 5th in terms of hotel brands. Because of the unique cultures, topology, history, etc., the Indian hospitality and tourism market attracts different kinds of tourists worldwide. Third, the cultures, food, and hotel offerings were different across the different categories of the hotels. The expectations and experiences of the consumers may change based on hotel categories (Blal & Sturman, 2014; Tanford, Raab, & Kim, 2012; Xu & Li, 2016). For example, Chittiprolu, Samala, and Bellamkonda (2021) found determinants of heritage hotels CS and CC using bi-gram analysis, and found that to be different when compared to classic hotels. As per signaling theory, consumers depend on signals for purchase decisions. Consumers used different signals to avoid uncertainty while purchasing travel-related products, such as WOM, eWOM, hotel star rating, hotel rank, etc. (BliegeBird et al., 2005; D. Verma & Gupta, 2004). Hotel star rating signals the quality of offerings. There is a positive relationship between the price and service quality in hotels. Consumers expect higher services from star hotels compared to budget hotels (Gerstner, 1985). According to expectation disconfirmation theory, consumers express their satisfaction when perceived experience is more than expected experience. Otherwise, they express their dissatisfaction (Oliver, 1980). According to multi-attribute theory, hotel attributes play an essential role in developing CS & CC. Customers perceptions and attitudes change based on perceived attributes and they prioritize them (Ajzen, 1991; Xu, 2020). For example, high-end hotel customers complain about service issues attribute, whereas low-end hotel customers complain about facility-related issues attributes (Hu, Zhang, Gao, & Bose, 2019).

The study aims to identify the antecedents of customers' satisfaction and dissatisfaction for various hotels in India. Second, to compare the dimensions of customer satisfaction and dissatisfaction based on the importance ranking. Third, to identify and compare the dimensions of CS and CC separately for different types of hotels such as heritage hotels, Agri hotels, luxury hotels, budget hotels.

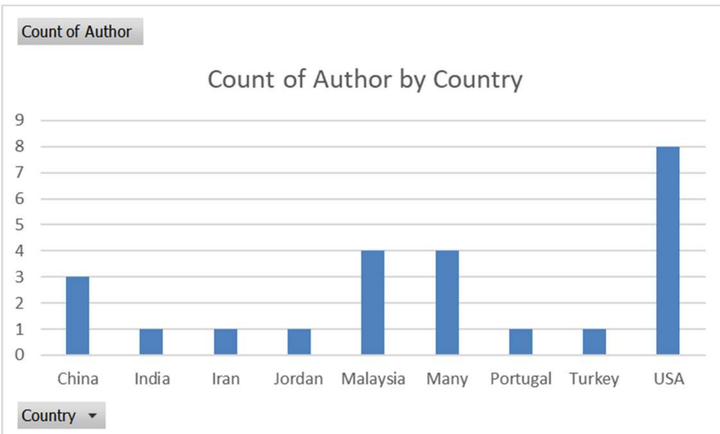
Table 5 ***Previous studies on CS and CC***

Author	Country	Sample	Methodology	Purpose
(Padma & Ahn, 2020)	Malaysia	800 reviews	CA using a critical incident technique	To find the antecedents and consequences of CS & CC in luxury hotels
(Lucini et al., 2020)	170 countries	55000 reviews, 400 airlines	Text mining, LDA	To find the dimensions of CS in the airlines industry
(Jia, 2020)	3 countries	2448 reviews	Text mining, LDA	To find the dimensions of CS and motivations in restaurants
(Alrawadieh & Law, 2019)	Istanbul, Turkey	400 reviews	Inductive deductive CA	To find the dimensions of CS in hotels
(Kuhzady & Ghasemi, 2019)	Mazandaran, Iran	10 hotels	CA	To find the dimensions of CS & CC in hotels
(Hu et al., 2019)	New York, USA	27,864 reviews	STM	To find the dimensions of CC in hotels
(Sezgen et al., 2019)	Region wise, covered all continents	5000 reviews, 50 airlines	LSA	To find the dimensions of CS in airlines
(Fernandes & Fernandes, 2018)	Oporto, Portugal	1191 guest	Chi- Square	To find the dimensions of CC and identify the complainer profiles in hotels
(Xiang, Schwartz, Gerdes Jr, & Uysal, 2015)	USA	60,648 reviews, 10537 hotels	Content analysis, regression	To find the impact of customer experience on CS
(Bilgihan, Seo, & Choi, 2018)	USA	2214 reviews	Content analysis, MANOVA	To find the dimensions of CS & CC in restaurants

(Dinçer & Alrawadieh, 2017)	Jordan	424 reviews	Content analysis	To find the dimensions of CC and identify the complainer profiles in hotels
(Guo, Barnes, & Jia, 2017)	16 countries	250,000 reviews, 26,670 hotels	LDA	To find the dimensions of CS & CC in hotels
(Xu & Li, 2016)	US	580 hotels, 3480 reviews	LSA	To find the dimensions of CS & CC in hotels in different hotels
(B. Kim, Kim, & Heo, 2016)	New York, USA	919 reviews, 100 hotels	Manual CA	To find the dimensions of CS & CC in full-service and limited-service hotels
(Berezina, Bilgihan, Cobanoglu, & Okumus, 2016)	Florida, USA	2510 reviews	CA	To find the dimensions of CS & CC in hotels
(Memarzadeh & Chang, 2015)	Kuala Lumpur, Malaysia	320 reviews	CA	To find the dimensions of CC in luxury hotels
(Ren et al., 2015)	China	300 reviews	CA using Nvivo	To find the dimensions of CS in budget hotels
(Khoo-Lattimore & Ekiz, 2014)	Kuala Lumpur, Malaysia	220 reviews	CA	To find the dimensions of CS in hotels
(Levy, Duan, & Boo, 2013)	Washington DC, USA	1946 reviews	CA	To find the dimensions of CC in hotels
(H. Li, Ye, & Law, 2013)	China	42,668 reviews	CA	To find the dimensions of CS in hotels
(Au, Buhalis, & Law, 2014)	China	822 reviews	CA	To find the dimensions of CC in hotels
(Ekiz, Khoo-Lattimore, & Memarzadeh, 2012)	Kuala Lumpur, Malaysia	320 reviews	CA	To find the dimensions of CC in luxury hotels
(Sparks & Browning, 2010)	USA	2258 reviews	CA	To find the dimensions of CC in luxury hotels

Note: CA: content analysis, LSA: latent semantic analysis, LDA: latent Dirichlet allocation, STM: structural topic modelling, MANOVA: multi variate analysis

Figure 3 ***Country wise publication details***



1.7. Research questions:

1. What were the antecedents of customer satisfaction (CS) and customer complaints (CC) towards different types of hotels?

2. What is the importance of attributes that drive customer satisfaction and customer complaints?

3. Does the attributes of customer satisfaction and customer complaints same for different types of hotels?

This study utilized the online reviews extracted from TripAdvisor.com and applied text mining analysis to extract the dimensions to determine customer satisfaction antecedents.

1.8. Research objectives:

i. To find out the antecedents of customer satisfaction (CS) and customer complaints (CC) for luxury hotels, heritage hotels, and budget hotels separately.

ii. To find out the importance ranking of the determinants of customer satisfaction and customer complaints for luxury hotels, heritage hotels, and budget hotels.

iii. To compare the determinants of customer satisfaction and customer complaints between hotels

iv. To compare the determinants of customer satisfaction and customer complaints within hotels

v. To compare the common determinants of customer satisfaction and customer complaints towards different types of hotels

vi. To identify the unique determinants of customer satisfaction and customer complaints among 3 categories of hotels

CHAPTER II

2. Literature review:

This chapter discusses the literature review, definitions of word of mouth, electronic word of mouth, customer satisfaction and customer complaints, and previous studies in customer satisfaction and customer complaints. Systematic literature review:

With the advent of the internet, tons of data is available on the internet. Many researchers and practitioners used these data to understand consumer behavior in detail. More than 1800 articles were published using these data in two decades (S. Verma & Yadav, 2021). This study did systematic literature to understand the previous studies and topics addressed using online reviews in the hospitality industry. 327 abstracts were collected from the Scopus database from 2009 to 2021. Text analysis was applied to identify the different areas. The below image shows the year-wise publications using online reviews. From 2015 onwards, studies using online reviews were increased.

Figure 4 Year wise publication details

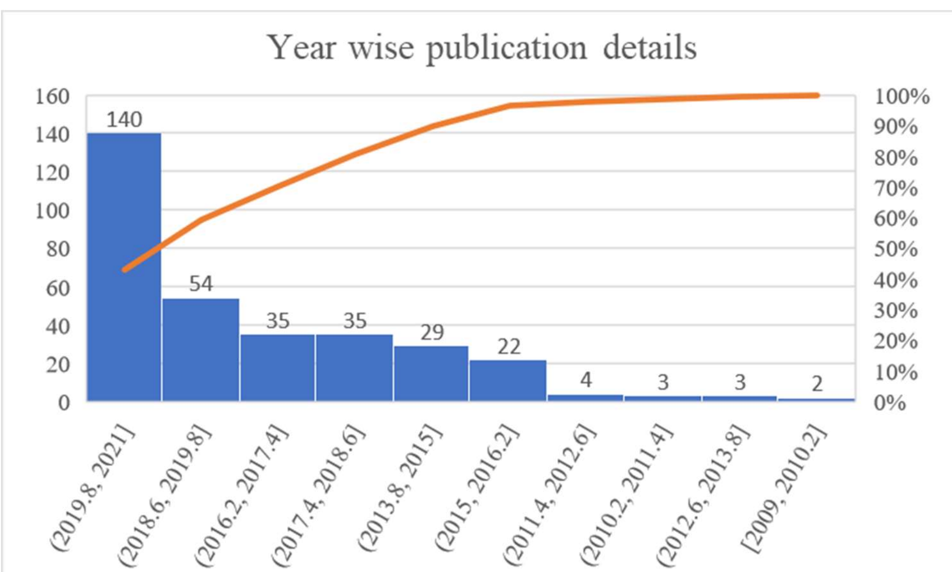
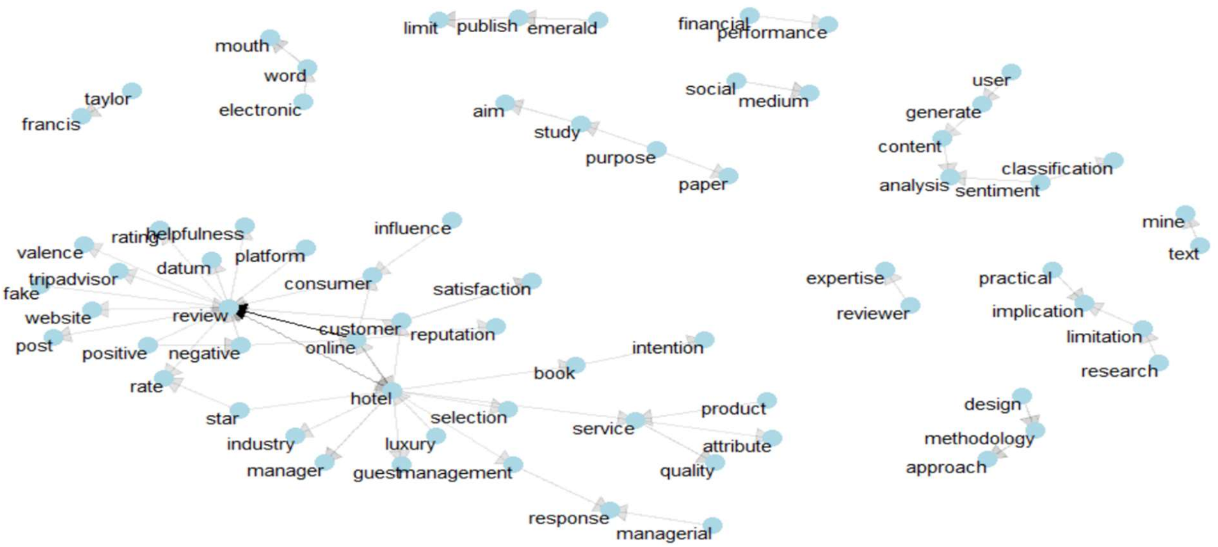


Figure 5 Word cloud

Word cloud shows the frequently repeated words. The highest frequent words appear with a bigger font size. The terms online, review, consumer, customer, service, data, analysis, satisfaction were frequently used topics in previous studies. Word cloud gives a basic idea to researchers; it is difficult to predict the topics using unigrams, because the terms meaning may change with the context (Hu et al., 2019).

Figure 6 Bigram:



In bigrams, pair of co-occurrence words appear together. Researchers can identify the topics using clusters. Four clusters were identified, which were review, customer, hotel, and service. The topics associated with reviews were negative, positive, TripAdvisor, consumer, helpfulness, fake reviews, etc. Previous studies addressed these areas. The second cluster was customer; the words associated with customers were customer satisfaction, customer reputation, customer management, etc. The next cluster was service; the terms related to service were quality, attribute, product, etc. Overall, previous studies addressed customer behavior and their experience, review credibility and service quality areas. The study applied topic modeling using LDA, and 30 topics were identified. The r square value is 0.1969. Topic-wise prevalence score and coherence score graph displayed. Twenty-eight topics were extracted and labeled, which are further grouped into five categories: Research topics, variables, data sources, sample details, and methodology.

Figure 7 Number of topics using prevalence and coherence score

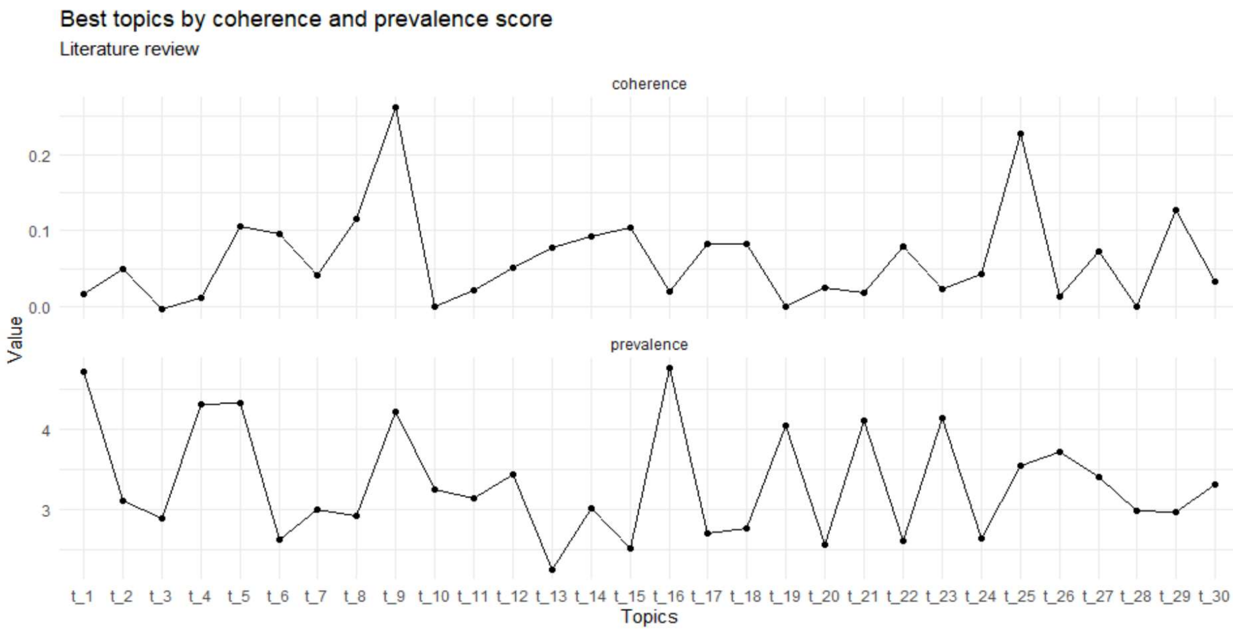
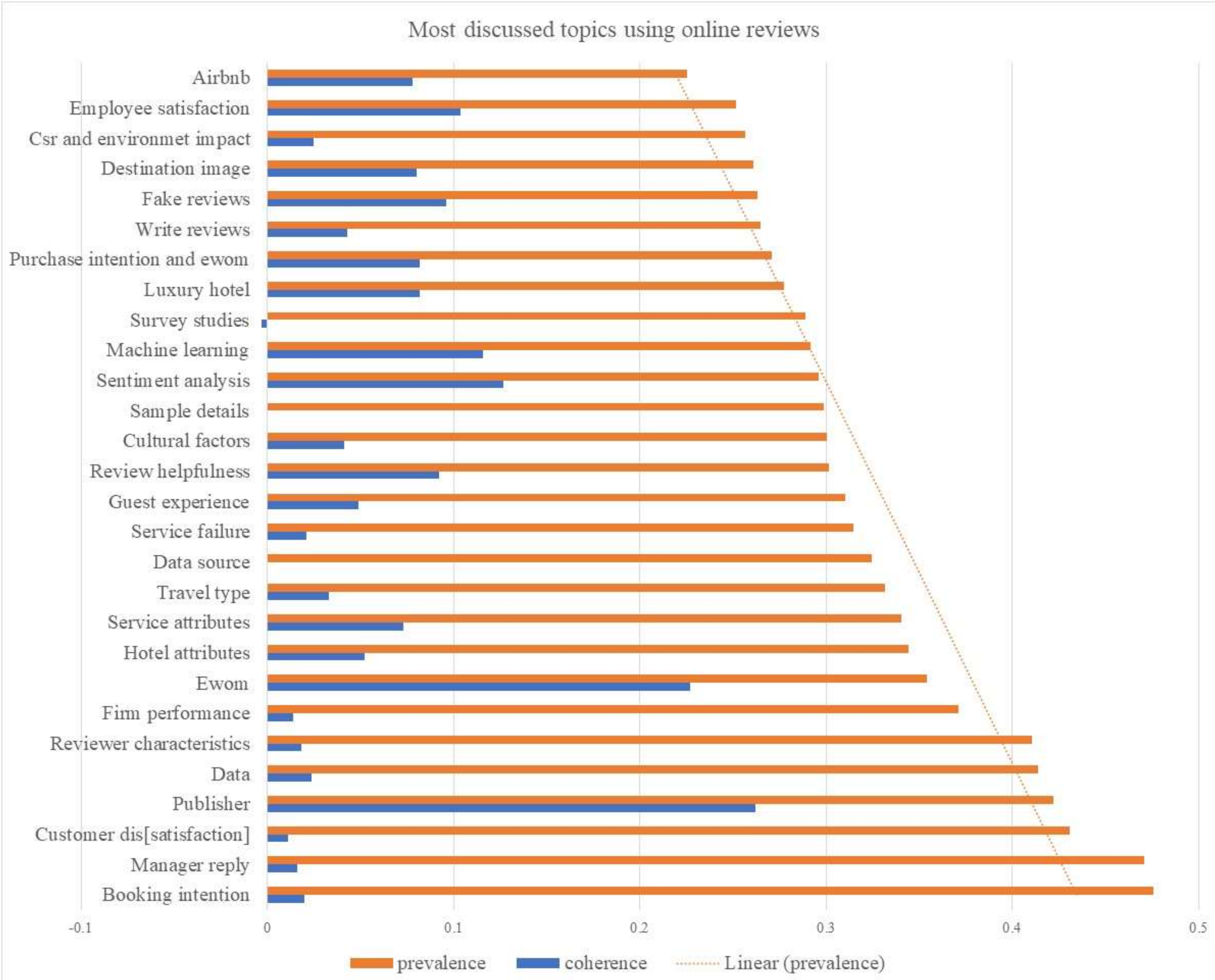


Figure 8 Topic distribution:



Note: The topic importance is correlated with prevalence score

Table 6 Feature extraction:

Topics	Dimensions
Research topics	Booking intention, customer satisfaction and dissatisfaction, firm performance, service failure, guest experience, cultural factors, service failure, helpfulness reviews, destination image, CSR (corporate social responsibilities), environmental impact, sharing economy, employee satisfaction
Variables	Reviewer attributes, review attributes, and hotel attributes
Methodology	Survey, SEM, text mining, content analysis, deep learning, machine learning, topic modelling
Data sources	TripAdvisor, AirBnB, booking.com, etc.
Sample details	Context, country, sample details

2.1. WOM:

Traditionally, consumers or customers used to take opinion on products and services from friends, family, and their social members, which impacts the purchase decision. Table 8 displays the three definitions of WOM. According to the definition, the elements are included in WOM: Sender, receiver, a message- oral, and noncommercial intention. Generally, WOM communications are private, spreads slowly between peers, and mostly it's credible information compared to eWOM (S. Verma & Yadav, 2021).

Table 7 ***Definitions of word of mouth***

Author	**Definition**
(Arndt, 1967)	"WOM can be any oral and personal communication, positive or negative, about a brand, product, service, or organization, in which the receiver of the message perceives the sender to have a noncommercial intention."
(Westbrook, 1987)	"all informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services or their sellers."
(Barreto, 2014)	"oral or written communication process, between a sender and an individual or group of receivers, regardless of whether they share the same social network, to share and acquire information, on an informal basis."

Figure 9 ***Flow of WOM:***

2.2. Electronic word of mouth (eWOM):

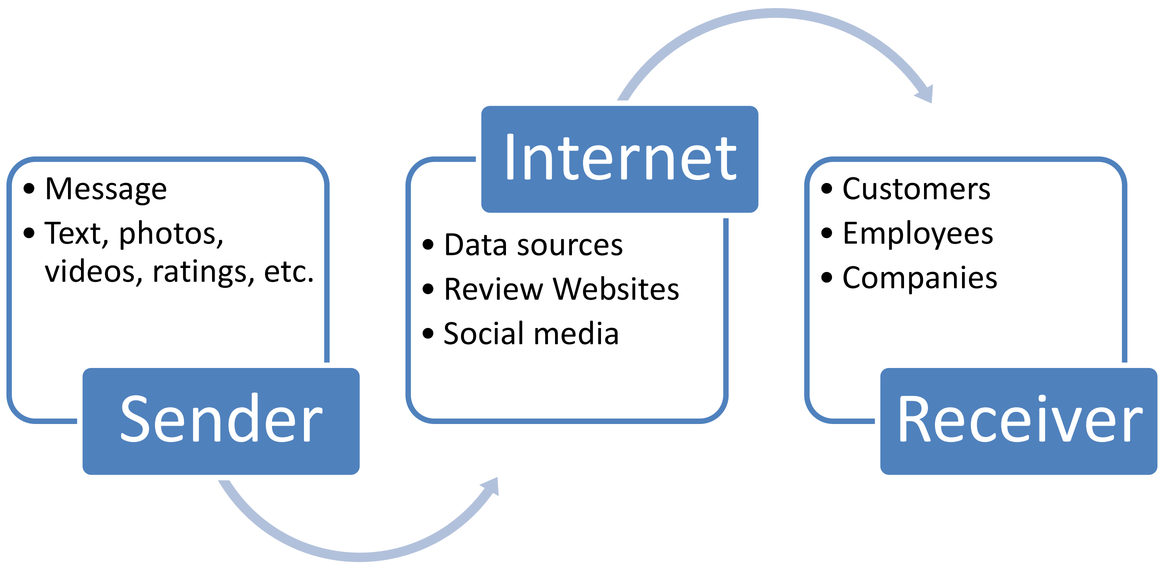
In previous studies, many authors defined eWOM with different definitions.

Table 8 ***eWOM definitions***

Author	Definitions
(Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004)	"any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet"
(Litvin et al., 2008)	"all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers"

According to the above definition, the process of eWOM include sender, internet, informal communication, and receiver. The below image shows the process of eWOM:

Figure 10 ***eWOM flow chart***



Traditionally, consumers use word of mouth to discuss products and services pros and cons within social communities informally. With the advent of technology, the internet, and web 2.0, WOM has shifted to eWOM, which is a quick and easy communication tool for consumers and marketers(S. Verma & Yadav, 2021). Due to the intangible properties of the travel products or offerings in the hotel and travel industry, consumers use different mediums to find out the information to avoid the perceived risks (Hennig-Thurau, Walsh, & Walsh, 2003). Moreover, many travel products are costly, including the "emotional risk of reference group" (Litvin et al., 2008). For example, tourists go for a holiday for different purposes, such as anniversaries, business trips, birthday celebrations, relaxation, etc. Tourists use various channels to search about destinations, attractions, rate cards from different service providers, etc. Tourists use eWOM for every phase of tourist's life cycle, which includes (Nusair, 2020):

1. Information search about destinations, products, tourists' attractions
2. To know about Visa rules
3. Compare the different rate cards and their services.
4. Choose the service providers or book their own.
5. While staying, they use it for information search, to book restaurants, etc.
6. After trip (Law et al., 2014; Leung et al., 2013; Standing, Tang-Taye, & Boyer, 2014; Wei, Ruys, Van Hoof, & Combrink, 2001)

Table 9 ***Difference between WOM and eWOM***:

Particular	**WOM**	**eWOM**
Message form	Orally	Oral, text, rating, picture, videos
Credibility	Between social group	Sometimes anonymity. Publicly information available
Privacy	Between peers	No privacy; anyone can access
Company Control	No control	No control
Diffusion speed	Very slow	Very fast
Accessibility	Less	Anyone with internet can access
Interaction type	Face to face	Virtual

Source: (Berger et al., 2020; Berger & Iyengar, 2013; Trenz & Berger, 2013)

Extant studies proved that eWOM helps tourists with purchase decisions. Consumers trust the information generated in review websites rather than information generated in official product or service websites (Gretzel & Yoo, 2008; Sparks & Browning, 2011). Extant studies proved that eWOM impacts the brand image of the product or services and impacts the purchase decision (Kala & Chaubey, 2018). A recent study by Travelport (2019) revealed that 77% of the customers refer to the online ratings, reviews, photos, and videos in social media posts when planning a trip. The information generated in eWOM is very useful for marketers to understand the consumers' expectations and experiences. More than 1800 papers were published using eWOM data (S. Verma & Yadav, 2021). Table demonstrate the different types of eWOM in tourism industry.

Table 10 ***Types of eWOM in the tourism industry:***

Types of eWOM	**Examples**	**Studies**
Consumer review websites	TripAdvisor.com, Ctrip, Bookings.com, airlinequality.com	(Chatterjee & Mandal, 2020), (Han, 2021), (Ye et al., 2009), (Anagnostopoulou et al., 2020)
Travel blogs	https://www.danflyingsolo.com/, https://abrokenbackpack.com/, https://www.lilistravelplans.com/	
Social networking sites (SNS)	YouTube, Facebook, twitter	(Mei, Bagaas, & Relling, 2019), (Aswani, Kar, Ilavarasan, & Dwivedi, 2018; Fan & Niu, 2016; Kirilenko &

		Stepchenkova, 2014),
Travel agency websites	Cox and Kings, Thomas cook, Yatra, etc.	
Brand/ company Websites	https://www.tajhotels.com/ https://www.oberoihotels.com/	
Government tourism websites	https://www.australia.com/en-us, https://www.incredibleindia.org	

Source: (Cheung & Thadani, 2012)

User-generated content (UGC) or eWOM is generated from three different sources: user-generated data, device generated data, and operations data (J. Li et al., 2018). The table displays the different data sources.

Table 11 ***Different data sources***

Category	Type	Purpose
User-generated data	Photos, videos, online ratings and reviews, blogs, social media, fan pages, etc.	Researchers used UGC data for marketing, operations, and predictive purpose
Device generated data	GPS data, Bluetooth data, roaming data, Wi-Fi data	To understand the customers' movements in destinations.
Transaction's data	Credit card data, banks data, web search data, etc.	Tourists use different websites to search about different products. Transaction data was used to know the traffic hours,

	active hours, etc.; based on these data, marketers generated the offers to increase sales.

Source: (J. Li et al., 2018; Miah, Vu, Gammack, & McGrath, 2017)

2.3. Online reviews:

Online customer reviews can be defined as peer-generated product evaluations posted on the company or third-party websites" (Mudambi and Schuff, 2010, p. 186). Online reviews (OR) are a popular form of eWOM (Bilgihan, Seo, & Choi, 2018; Chatterjee, 2020; Lucini et al., 2020; Xu, 2020). Consumers share their experiences and expectations by writing OR, sharing videos and photos in different channels like social media (Facebook, Twitter), review websites (TripAdvisor, booking.com), travel blogs, etc. Extant studies used OR to address different research questions, such as predicting sales, understanding consumer behavior, and consumers' personality and psychology. Some researchers tried to understand the quality of information available in review websites, etc.

Table 12 Previous studies on OR to predict the sales:

Author	**Purpose**
Marketing purpose: Prediction	
(Ye et al., 2009)	To test the impact of OR on hotel sales
(Chevalier & Mayzlin, 2006)	To test the effect of WOM on books sales
(Fornell, Mithas, Morgeson III,	To test the impact of CS on stock prices

& Krishnan, 2006)	
(Duan et al., 2008)	To test the impact of OR on movie sales
(Chintagunta, Gopinath, & Venkataraman, 2010)	To test the effect of OR on movie box-office collection
(Zhu & Zhang, 2010)	To test the influence of OR on video games sales
(C. K. Anderson, 2012)	To test the impact of social media on lodging performance
(Duverger, 2013)	To test the effect of UGC on hotel market share
(Sun & Kim, 2013)	To test the impact of customer satisfaction on firm performance (short term and long term)
(W. G. Kim, Li, & Brymer, 2016)	To test the impact of social media reviews on restaurant sales

Table 13 Previous studies on consumer behavior using unsupervised methods:

Author	**Purpose**
(Chittiprolu et al., 2021)	To find the antecedents and consequences of CS & CC in heritage hotels
(Padma & Ahn, 2020)	To find the antecedents and consequences of CS & CC in luxury hotels
(Lucini et al., 2020)	To find the dimensions of CS in airlines industry
(Jia, 2020)	To find the dimensions of CS and motivations in restaurants

(Alrawadieh & Law, 2019)	To find the dimensions of CS in hotels
(Kuhzady & Ghasemi, 2019)	To find the dimensions of CS & CC in hotels
(Hu et al., 2019)	To find the dimensions of CC in hotels
(Sezgen et al., 2019)	To find the dimensions of CS in airlines
(Fernandes & Fernandes, 2018)	To find the dimensions of CC and identify the complainer profiles in hotels
(Xiang, Schwartz, Gerdes Jr, & Uysal, 2015)	To find the impact of customer experience on CS
(Bilgihan, Seo, & Choi, 2018)	To find the dimensions of CS & CC in restaurants
(Dinçer & Alrawadieh, 2017)	To find the dimensions of CC and identify the complainer profiles in hotels
(Guo, Barnes, & Jia, 2017)	To find the dimensions of CS & CC in hotels
(Xu & Li, 2016)	To find the dimensions of CS & CC in hotels in different hotels
(B. Kim, Kim, & Heo, 2016)	To find the dimensions of CS & CC in full-service and limited-service hotels
(Berezina, Bilgihan, Cobanoglu, & Okumus, 2016)	To find the dimensions of CS & CC in hotels
(Memarzadeh & Chang, 2015)	To find the dimensions of CC in luxury hotels

(Ren et al., 2015)	To find the dimensions of CS in budget hotels
(Khoo-Lattimore & Ekiz, 2014)	To find the dimensions of CS in hotels
(Levy, Duan, & Boo, 2013)	To find the dimensions of CC in hotels
(H. Li, Ye, & Law, 2013)	To find the dimensions of CS in hotels
(Au, Buhalis, & Law, 2014)	To find the dimensions of CC in hotels
(Ekiz, Khoo-Lattimore, & Memarzadeh, 2012)	To find the dimensions of CC in luxury hotels
(Sparks & Browning, 2010)	To find the dimensions of CC in luxury hotels

Table 14 Previous studies on OR: other purposes

Author	**Purpose**
(Chatterjee, 2020)	To find the antecedents of review helpfulness
(Schuckert, Liu, & Law, 2016)	To find the suspicious reviews and pattern
(Zeng, Cao, Lin, & Xiao, 2020)	To find out the joint effect of online reviews and virtual reality on behavior intention
(Banerjee & Chua, 2019)	To find out the effect of review title and body sentiments on reviewer trust
(Chang, Ku, & Chen, 2020)	Visualization of managerial reply using deep learning techniques
(C. Li, Cui, & Peng, 2017)	To Study the managerial response patterns to increase the customer satisfaction
(Moro, Ramos, Esmerado, & Jalali, 2019)	To define and classify the review characteristics using gamification techniques

Table 15 Methods used:

Author	Sample	Methodology
(Chittiprolu et al., 2021)	1000 reviews	CA, bi-grams
(Padma & Ahn, 2020)	800 reviews	CA using a critical incident technique
(Lucini et al., 2020)	55000 reviews, 400 airlines	Text mining, LDA
(Jia, 2020)	2448 reviews	Text mining, LDA
(Alrawadieh & Law, 2019)	400 reviews	Inductive deductive CA
(Kuhzady & Ghasemi, 2019)	10 hotels	CA
(Hu et al., 2019)	27,864 reviews	STM
(Sezgen et al., 2019)	5000 reviews, 50 airlines	LSA
(Fernandes & Fernandes, 2018)	1191 guest	Chi- Square
(Xiang, Schwartz, Gerdes Jr, & Uysal, 2015)	60,648 reviews, 10537 hotels	Content analysis, regression
(Bilgihan, Seo, & Choi, 2018)	2214 reviews	Content analysis, MANOVA
(Dinçer & Alrawadieh, 2017)	424 reviews	Content analysis
(Guo, Barnes, & Jia, 2017)	250,000 reviews, 26,670 hotels	LDA

(Xu & Li, 2016)	580 hotels, 3480 reviews	LSA
(B. Kim, Kim, & Heo, 2016)	919 reviews, 100 hotels	Manual CA
(Berezina, Bilgihan, Cobanoglu, & Okumus, 2016)	2510 reviews	CA
(Memarzadeh & Chang, 2015)	320 reviews	CA
(Ren et al., 2015)	300 reviews	CA using Nvivo
(Khoo-Lattimore & Ekiz, 2014)	220 reviews	CA
(Levy, Duan, & Boo, 2013)	1946 reviews	CA
(H. Li, Ye, & Law, 2013)	42,668 reviews	CA
(Au, Buhalis, & Law, 2014)	822 reviews	CA
(Ekiz, Khoo-Lattimore, & Memarzadeh, 2012)	320 reviews	CA
(Sparks & Browning, 2010)	2258 reviews	CA

Note: CA: content analysis, LDA: latent Dirichlet allocation, LSA: latent semantic analysis

Extant studies used different methods to address various questions using online reviews. Some popular techniques used are:

1. Supervised method

2. Un-supervised methods
3. Mixed methodology
4. Machine learning techniques
5. Deep learning techniques
6. Data visualization
7. Experiments

2.4. **Consumer motivations to write reviews:**

Consumers write OR for different purposes. Zhao et al. (2019) did a literature review and stated four motivations that influence consumers to share eWOM: altruism and reciprocity, rewards, reputation, and psychological needs. Sotiriadis and Van Zyl (2013) stated six motivations: to express their emotions with others, to share their satisfaction, anger, and sadness factors, altruism, and share of their positive experience, and display reciprocity. The below table synthesis the motivations of customers to share their travel experience. Of the motivations, some common reasons were altruism, share the factors of satisfaction, sadness, anger, to damage the brand image by sharing negative eWOM, joy of sharing the travel information, incentives, and rewards.

Table 16 Previous studies on motivation to write eWOM

Author	Methodology	Reasons
(Hennig-Thurau et al., 2004)	Survey data, PCA & CFA	Express negative feelings, social benefits, incentives, concern about others, advice-seeking & help the organization
(Litvin et al., 2008)	Systematic literature	Inner tension, sadness, the joy of travel, satisfaction, pleasure, reciprocation, self-interest, altruism and affects
(Yoo & Gretzel, 2008)	PCA, EFA, CFA	Concern for others, venting negative feelings and collective power, enjoyment or positive self-enhancement, and help the company
(Zhao et al., 2019)	Systematic literature	Rewards, online reputation, psychosocial needs, and reciprocity and altruism
(Dixit, Badgaiyan, & Khare, 2019)	Survey data, SEM	subjective norms (SNO), ego involvement (EI), perceived behavioral control (PEBC), taking vengeance (TVE), attitude (ATT), helping the company (HRE)
(Nam, Baker, Ahmad, & Goo, 2020)	SEM	Offline expectation confirmation, Online expectation confirmation, dissatisfaction, altruism, enjoyment, attachment, and utility
(Oliveira, Araujo, & Tam, 2020)	PLS SEM	Social Influence Theory (Identification, Internalization, and Compliance), perceived

		enjoyment, Facilitators (Altruistic motivation, personal fulfillment), and Inhibitors (Environmental reasons, personal reasons, relationship reasons, and security and privacy reasons)
(Sotiriadis & Van Zyl, 2013)	Literature review	Share positive and negative experiences, the joy of sharing, concern to others, reciprocity, venting emotions, and reciprocity

Note: SEM: Structure equation modeling, PLS: Partial least squares, CFA: Confirmatory factor analysis, EFA: Exploratory factor analysis, PCA: Principal component analysis

2.5. Consumer's motivation to read reviews:

Customers do read OR for several reasons:

1. To compare the different products and services.
2. To know the pros and cons of the products.
3. To remove the ambiguity or confusion about product offerings.
4. To get the confidence to purchase the products or services.
5. To get the latest products and services offering.
6. To find similar peer groups.
7. To fulfill the anxiety or inherent enjoyment (Nam et al., 2020; Schindler & Bickart, 2005).

2.6. Customer satisfaction:

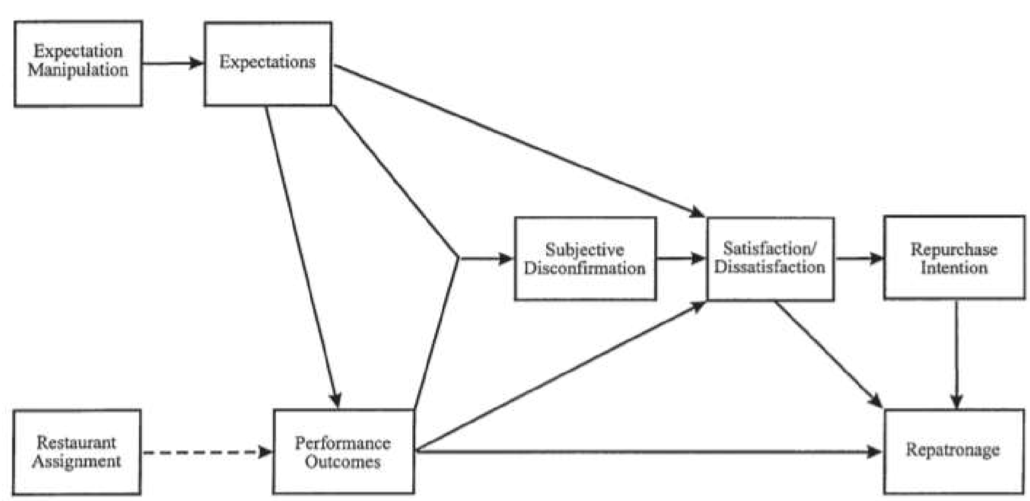
Oliver (1980) proposed the expectation-disconfirmation model, which includes four components: expectations, subjective disconfirmation (positive and negative), perceived experience, and satisfaction and dissatisfaction. Every consumer buys a product or service with some expectations in their mind, generated through WOM, advertisements, etc. When a perceived experience exceeds or does not meet, subjective disconfirmation occurs, which is positive or negative, leading to customer satisfaction and dissatisfaction (Barsky, 1992). In general, customers are satisfied, when perceived services exceed the expected services (Alegre & Garau, 2010; Xu & Li, 2016). In other words, if perceived service quality beats the desired service quality, customers express their satisfaction (Zeithaml, 2000; Zeithaml, Berry, & Parasuraman, 1996). Figure 10 shows the performance model in restaurants. Extant studies found the associations between CS and brand image, customer loyalty, repurchase intention, etc., in different contexts.

For example, Kandampully and Suhartanto (2000) studied the impact of customer satisfaction and brand image (BI) on customer loyalty (CL) in New Zealand hotels. They found that CS and BI impact the CL positively. Oh (1999) studied the relationship between service quality (SQ), customer value (CV), CS, and repurchase intention using luxury hotels and found that CV acts as a mediator between SQ and CS. CS mediate the relationship between SQ and repurchase intention (PI). PI mediates the relationship between CS and WOM behavior. In simple terms, when perceived SQ exceed the expected SQ, customers express their satisfaction, which leads to repeated purchases and WOM. Recent studies further developed the model and proved that CS impacts the firm sales (Chevalier & Mayzlin, 2006; Gomez, McLaughlin, & Wittink, 2004; Shapiro & Gómez, 2014), profits (E. W. Anderson, Fornell, & Lehmann, 1994; Liu, 2006), shares (Gruca & Rego, 2005), short term profits and long term profits (Sun & Kim, 2013), and stock prices (Fornell et al., 2006).

The below table shows the previous studies on CS and CC and their determinants. Satisfied customers are very beneficial to service providers in many ways:

1. Complaint less about services and products
2. Repeated purchases
3. Spread positive WOM.
4. Acts as an ambassador for firms
5. Improve the brand image and reputation.
6. May acts as a stockholder (Bello, Bello, & Management, 2017; H. Li, Ye, & Law, 2013; Tuncer, Unusan, & Cobanoglu, 2020; Zhou, Ye, Pearce, & Wu, 2014).

Figure 11 A model of "expectation-disconfirmation with performance model"



Source: (Oliver & Burke, 1999)

2.7. Customer dissatisfaction:

Customers are dissatisfied when the perceived experience is less than expected services (Oliver, 1980). Customer complain to service providers directly or spreads negative eWOM (Sparks &

Browning, 2010). They are different motives to complain, including seeking an explanation from service providers, expecting an apology, demanding service recovery, expressing anger and disappointment, sharing their bad experience by writing lengthy reviews, etc. (Nam et al., 2020). Dissatisfied customers may leave negative reviews on social media, keep calm, and switch to competitors (Sparks & Browning, 2010). Customers believe and trust the negative reviews, which impact their purchase decision compared to positive reviews (Filieri, Raguseo, & Vitari, 2019). Extant studies proved that negative reviews negatively impact the firm's performance by damaging the brand image, which decreases sales. For example, De Pelsmacker, Van Tilburg, and Holthof (2018) studied the effect of positive and negative reviews on Agri hotel performance and proved that negative reviews decrease sales. So, it is essential for managers, service providers to understand the reasons for the negative thoughts. Tax, Brown, and Chandrashekaran (1998) stated that consumer's reviews can be used to know the strengths and weaknesses of the hotel operations, and negative reviews reveal the failure areas. Consumers give a chance and hint to service providers about service failures in hotels. Repeated failures lead to "customer churn" (Knox & Van Oest, 2014). Evidence proved that complaining customers are beneficial to an organization in many ways:

1. Expected services are not meeting with perceived services and may not meet with brand image.
2. Most of the complaining customers are honest with service providers. They speak straight forward and explain the service issues with service providers.
3. It is a chance to service providers to understand the failure areas.
4. A successful recovery strategy gains the customers loyalty. Extant studies proved that regaining failure customers are better than gaining a new customer.

5. Handling customers complaints improves team efficiency and build the team management (Au, Buhalis, & Law, 2014; Kumar, Bhagwat, & Zhang, 2015; Morgeson III, Hult, Mithas, Keiningham, & Fornell, 2020; Sann, Lai, & Liaw, 2020; Steele, 2018).

Knox and Van Oest (2014) study customer churn behavior using 20,000 internet customers for two and half years by monitoring their profiles and revealing some interesting findings. Prior purchase and prior failure impacts the customer churn behavior. Prior successful purchase diminishes the negative effect of the subsequent service failure, whereas successive failures lead to customer churn behavior. Migacz, Zou, and Petrick (2018) studied the effects of service failures in airlines and possible service recovery actions to be taken using an experimental setting. The author found justice theory helps in the service recovery process and found that distributive justice plays a dominant role in the service recovery process. Providing higher incentives beyond consumers' expectations helps to turn dissatisfied customers into a loyal customers. Marinova, Singh, and Singh (2018) studied the impact of front-line workers' skills on service recovery in the airline industry. The researchers monitor the employee skills through video recordings and experimental settings and found that frontline workers' problem-solving skills can gain the CS and decrease the CC. Chen and Kim (2019) studied the impact of justice theory on customer emotions, overall satisfaction, and WOM behavior in the food service industry. By applying the SEM model on respondents, the study reveals that justice theory constructs positively impact positive emotions. In contrast, there is no supporting evidence on the negative emotions of the consumers. Hazée, Van Vaerenbergh, and Armirotto (2017). Umashankar, Ward, and Dahl (2017) studied the effects of service recovery on customer loyalty between strong-tied and weakly-tied customers. Initially, strong-tied customers do not complain to service providers for fear of losing relations with them. If service providers encourage and provide an authentic or open platform to complain to strong-tied customers, loyalty increases, but there is no impact on weakly-tied customers.

2.7.1. Corrective measures in the service recovery process

Service recovery is a process of initiating actions to correct the service failures and provide reasonable solutions to failure customers(C.-J. Li, Li, Fan, & Chen, 2020). Extant studies suggested multiple ways to initiate the service recovery process and to reduce service failures. According to Rawls (1971) justice theory, the service providers need to apply differential service recovery strategies based on the nature of service complaints. The theory proposed three recovery strategies: distributive justice, procedural justice, and interactional justice. Distributive justice deals with monetary compensations, and procedural justice improves process-related issues, such as software, check-in, etc. Staff behavior and attitude come under interactional justice. Evidence proved that managers need to be vigorous in social media to initiate the service recovery process, and the recency of the reply and number of managerial replies improves the CS (Xie, So, & Wang, 2017; Xie, Zhang, Zhang, Singh, & Lee, 2016). Gone those traditional ways to apologize and please the customers. Evidence suggests that the service providers need to thank the complaining customers because very few customers raise their voices with service providers (You, Yang, Wang, & Deng, 2020). Mangers and service providers need to track the OR to understand the customer experience and expectations in detail. Service providers need to apply the automated text mining techniques to extract the keywords related to service failure (Memarzadeh & Chang, 2015; Steven, 2021).

2.7.2. Determinants of customers complaints:

Extant studies used e-complaints or negative reviews to understand the determinants of CC in the travel industry. Zhao et al. (2019) used big data such as 127,629 reviews to predict the impact of technical features on overall customer's satisfaction in the hotel industry. They found that review length, valence, helpfulness impacts the CS, and dissatisfied customers write lengthy reviews. Au et al. (2014) try to understand Chinese and non-Chinese consumers' complaining behavior and found that the perceptions and opinions on hotels change based on their characteristics, such as age, gender, and nationality. Berezina, Bilgihan, Cobanoglu, and Okumus (2016) try to understand the determinants of CS & CC using 2510 hotel OR and found ten determinants each. They found that satisfied customers mention intangible aspects of the hotel, whereas dissatisfied customers mention tangible aspects of the hotel. Fernandes and Fernandes (2018), in a study of Oporto, Portugal hotels, identified service, cleanliness, facilities, customer care, bar, bathroom, parking, and breakfast were CC determinants. Table displays the previous studies which identified determinants of CS & CC in different contexts.

Table 17 ***Determinants of Customer satisfaction and dissatisfaction: Previous studies***

Authors	Context	CS	CC
(Chittiprolu et al., 2021)	Heritage hotels	Rooms, food, staff, physical signifiers, amenities, traditional services, services	Issues with services and reservations, room condition, pricing, stay, staff, food
(Shah, Yan, Tariq, & Ali, 2021)	Hospital patients	High-risk and low-risk patients: hospital	Staff manners, treatment experience,

		business process, parking, cafeteria service scape, and medical process, doctor related aspects	billings
(Zou, 2020)	National Park entrance fee	Place attachment, trust, fee increase	Distributive justice, public land fees
(Padma & Ahn, 2020)	Luxury Hotels	Hotel, room, staff, and travel related attributes	Hotel, room, staff, and travel related attributes
(Lucini et al., 2020)	Airlines	27 dimensions were identified	--
(Jia, 2020)	Restaurants	15 topics were identified, such as old brand, wine, snail, appetizer, etc.	
(Alrawadieh & Law, 2019)	Hotel	Rooms, service quality, hotels characteristics, food and beverages	
(Kuhzady & Ghasemi, 2019)	Hotel	Location, room, staff, and restaurant	Restaurant, Wi-Fi, room
(Hu et al., 2019)	Hotels	-	30 topics were

			identified and classified into 5 dimensions: facilities, service, location, value, general experience
(Sezgen et al., 2019)	Airlines	Staff attributes for economy class and product value for premium customers	Service attributes: seat comfort, leg room, loss of luggage, staff, and flight delay
(Fernandes & Fernandes, 2018)	Hotels	-	12 categories were identified: service, customer care, rooms, location, value, etc.
(Xiang, Schwartz, Gerdes Jr, & Uysal, 2015)	Hotels	Deals, hybrid, family friendliness, staff, core products	-
(Bilgihan, Seo, & Choi, 2018)	Restaurants	Functional: food and beverages, humanic: service and experience, and mechanical cues:	

		Facilities	
(Dinçer & Alrawadieh, 2017)	Luxury hotels	-	Service quality, hotel facilities, hygiene
(Guo, Barnes, & Jia, 2017)	Hotels	30 dimensions were identified and grouped into controlled, un-controlled, and partially controlled groups	-
(Xu & Li, 2016)	Different types of hotels: Limited, Suite hotels with food and without food, and full-service hotels	Location, room, staff	Facility, staff, Wi-Fi, noise, bathroom, parking, swimming pool, restaurants, and air condition
(B. Kim, Kim, & Heo, 2016)	Full- service and limited-service hotels	Location, staff, bed, breakfast, room size	Bathroom, noise, staff, dirtiness
(Berezina, Bilgihan, Cobanoglu, & Okumus, 2016)	Hotels	Intangible factors: Members, furniture, beach, architecture	Tangible factors: members, finance, sports, architecture

2.8. Big data:

In the tourism and hospitality industry, with the evolution of technology and the internet in business, massive data was stored by companies to understand consumer behavior, which helps for revenue maximization. Travelers or consumers generated huge data in images, text messages, videos, etc., on the internet. We call this massive data as big data. Practitioners and researchers defined big data as:

Table 18 Big data definition

Author	**Definition**
(Laney, 2001)	3V: Volume, velocity, and variety
(Gantz & Reinsel, 2011)	4V: Value, Volume, velocity, and variety
(Gartner, 2020)	"high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation. "

J. Li et al. (2018) did systematic literature and examined big data sources were: user-generated, device-generated, and operations data. By using big data, researchers extracted meaningful and detailed factors from the data. Big data helps researchers to understand the customers' phenomenon in detail. Hidden or new factors can be identified using big data. In the tourism industry, many researchers used big data to answer different research questions. Some studies were (Tirunillai & Tellis, 2014), (Xiang, Schwartz, Gerdes Jr, & Uysal, 2015), (Gandomi & Haider, 2015), (Miah et al., 2017), (Zhao et al., 2019), (Alaei, Becken, & Stantic, 2019), (Köseoglu, Mehraliyev, Altin, & Okumus, 2020), (Giglio, Pantano, Bilotta, & Melewar, 2020), (Padma & Ahn, 2020). Extant studies used different methodologies to address the diverse research questions: critical incident technique, predictive modelling, topic modelling using LDA and STM, machine learning techniques, deep learning techniques, etc.

CHAPTER III

3. Research Methodology:

This study tries to identify the antecedents and consequences of customer's satisfaction and dissatisfaction in the hotel industry. We have used secondary data to study the phenomena; extant studies used primary data to find the antecedents and consequences of customer satisfaction and loyalty in the hospitality sector. For example, Marković and Raspor Janković (2013) studied the association between service quality and customer satisfaction for Croatia hotels. The researcher used 253 observations to test the association. With the evolution of social media, huge information is available on the internet, so-called big data (Leung et al., 2013; J. Li et al., 2018; Miah et al., 2017; Standing et al., 2014). The secondary data help researchers in many ways:

i. To study the consumers' behavior in detail
ii. Large or big data is available and can be used to extract the hidden dimensions or new dimensions
iii. Can save time and money
iv. Firsthand information
v. Dynamic industry gives the latest information (Guo, Barnes, & Jia, 2017; Hu et al., 2019; Tirunillai & Tellis, 2014)

The unit of the study was India. The Ministry of Tourism, Government of India, took many initiatives to promote the Indian tourism industry domestically and globally. The ministry introduced many new policies to boost the tourism sector, such as visa on arrival, temple darshan, adopt a heritage cite, wildlife protection, etc. (Ministry of Tourism, 2020). Indian tourism offers many tourism products such as wildlife, MICE (meetings incentives, conferences, and events), luxury trains, sports tourism, medical tourism, sun- sand- sea destinations, etc. India has many cultures, languages, regions, and foods, making India a unique place to visit. India has a rich history and is one of the oldest civilization countries in the world(IncredibleIndia, 2020). Also, Indian tourism offers adventure tourism, cruise tourism to attract modern tourists. Very few studies used Indian hotel data; most of the studies used the United States, Europe, China, and far-east sample (J. Li et al., 2018). Moreover, the Indian hospitality industry is immense and contributes to the country's GDP, employment, etc.

Table 19 Studies based on Indian context in the tourism industry

Author	Context	Sample	Methodology	Purpose
(Chittiprolu et al., 2021)	Heritage Hotels	1000 reviews	Content analysis, bigrams	To identify the customer satisfaction and dissatisfaction determinants
(Geetha et al., 2017)	Hotels	20 budget and premium hotels in Goa	Multiple regression and sentiment analysis	To find the association between consumer sentiment and satisfaction
(Chakraborty, 2019)	Hotels	1400 sample, primary study	Structure equation modeling	To find the association between receiver previous knowledge and experience

				on perceived credibility
(Chakraborty & Biswal, 2020)	Hotels	1387 samples	Structure equation modeling	To find the association between online reviews, hotel booking intention, and brand image
(Sudhakar & Gunasekar, 2020)	Airlines	15404 reviews 8 airlines	Logistic regression	To find the impact of attribute ratings on customer satisfaction
(Gunasekar & Sudhakar, 2019)	Hotels	10,716 reviews 56 hotels	Logistic regression, sentiment analysis	To find the impact of attribute ratings on customer satisfaction
(Mohsin & Lockyer, 2010)	Hotels	271 samples	Importance performance analysis	To find the service quality perceptions in luxury hotels in New Delhi
This study	Hotels	3,13,000 reviews	Advance text mining	To find the antecedents of customer satisfaction and dissatisfaction in the hotel industry

The data source was TripAdvisor.com, a leading and prominent travel review website across the globe. More than 463 million travelers access TripAdvisor each month to search about the products and services. 8.6 million services were registered in TripAdvisor.com, such as hotels, restaurants, travel agents, cruises, airlines, destinations, attractions, etc.(TripAdvisor, 2021a). Moreover, TripAdvisor filters the reviews before publishing them online to consumers. It has a mechanism to detect spam, suspicious and abusive reviews (Zhao et al., 2019). Users can report suspicious reviews to TripAdvisor, and other travelers can like the reviews. Whereas TripAdvisor endorses the badge grades to reviewers (TripAdvisor, 2021b). Previous studies suggest that many reviewers can read and trust helpful reviews and expertise reviews (Chatterjee, 2019). The below table displays the previous studies which used TripAdvisor.com as a data source. Many researchers used TripAdvisor as a data source and used quantitative and qualitative data to address different research questions. For example, Giglio et al. (2020) study the customers' perceptions towards luxury hotels. The researcher used 7,395 pictures posted by consumers and identified the factors that lead to satisfaction and dissatisfaction. At the same time, some researchers used qualitative text reviews to identify customer satisfaction and dissatisfaction in different hotel settings (Bilgihan et al., 2018; Chittiprolu et al., 2021; Hu et al., 2019; Kuhzady & Ghasemi, 2019; Lucini et al., 2020; Padma & Ahn, 2020; Sezgen et al., 2019). Some researchers predict the impact of quantitative reviews on firm performance using different techniques such as multiple regression, panel data analysis, time series analysis, and econometric methods (De Pelsmacker et al., 2018; Duverger, 2013; Xie, Chen, & Wu, 2016; Xie et al., 2017; Xie et al., 2014; Xie, Zhang, et al., 2016; Ye et al., 2009; Ye et al., 2011). Some researchers extracted the technical features from text reviews and predicted the customer satisfaction and firm performance (Anagnostopoulou et al., 2020; Geetha et al., 2017; Zhao et al., 2019).

Table 20 Previous studies which used TripAdvisor as a data source:

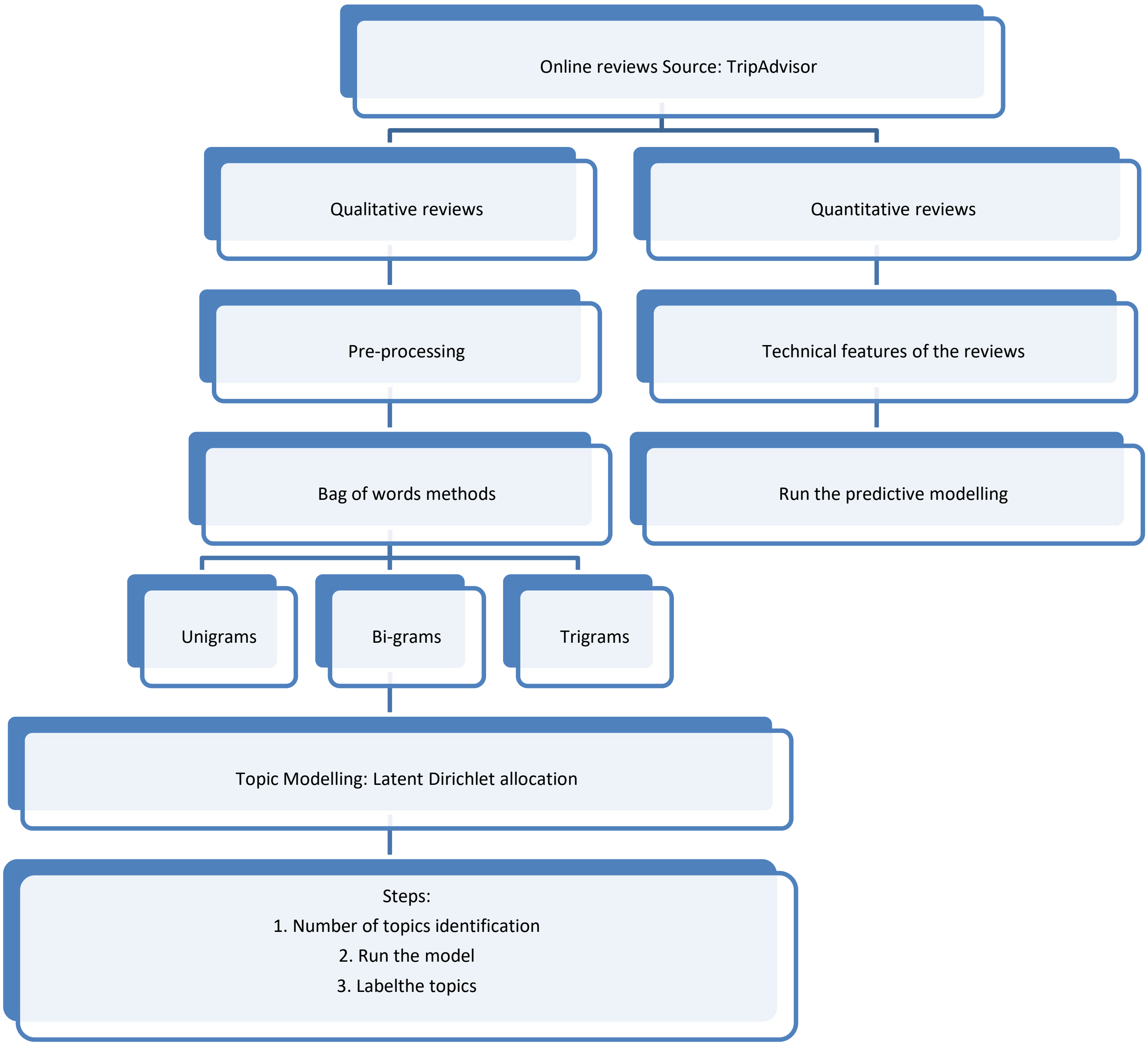
Author	Context	Sample	Methodology	Purpose
(Xie, Chen, et al., 2016)	Hotel	56,284 reviews 1000 hotels	Panel data analysis	To find the impact of online reviews on offline popularity
(Xie, Zhang, et al., 2016)	Hotel	56,284 reviews 10,793 managerial reply	Panel data analysis	To find the impact of managerial reply on hotel performance
(Torres, Singh, & Robertson-Ring, 2015)	Hotel	178 hotels reviews	Multiple regression	To find the impact of online reviews on booking value
(Zhao et al., 2019)	Hotel	127,629 reviews 155 hotels	Multiple regression	To find the impact of technical features on overall satisfaction
(W. G. Kim et al., 2016)	Restaurant	70 restaurants 16 states USA	Hierarchical multiple regression	To test the impact of review attributes on restaurant performance
(Han, 2021)	Hotel	41386 reviews 751 hotels	Seemingly unrelated regression	To examine the effect of reviewer attributes (expertise and personality) on reviewer satisfaction
Insights into	Hotels	41572 ratings	Regression	To find the suspicious

Suspicious Online Ratings: Direct Evidence from TripAdvisor		hotels Hong Kong		reviews and patterns associated with in reviews
(Chittiprolu et al., 2021)	Heritage hotels	23643 reviews	Content analysis	The researcher identified the factors that lead to customer satisfaction and dissatisfaction in heritage hotels
(Hu et al., 2019)	Different grades of hotels	27,864 reviews	STM	The researcher identified the factors that lead to customer dissatisfaction in different hotels and compared the factors hotels wise
(Sezgen et al., 2019)	Airlines	5120 reviews	LSA	The study examined the antecedents of customers' satisfaction and dissatisfaction in low-cost and full-service airlines
(Geetha et al., 2017)	Hotels	Goa hotels	Multiple regression	The authors found the impact of reviewer sentiment on customer

	satisfaction

3.1. Research methodology framework:

Figure 12 Research framework



Online reviews Source: TripAdvisor
Qualitative reviews
Quantitative reviews
Pre-processing
Technical features of the reviews
Bag of words methods
Run the predictive modelling
Unigrams
Bi-grams
Trigrams
Topic Modelling: Latent Dirichlet allocation
Steps:
1. Number of topics identification
2. Run the model
3. Labelthe topics

3.2. Attributes of online reviews:

Figure 13 Attributes of online reviews

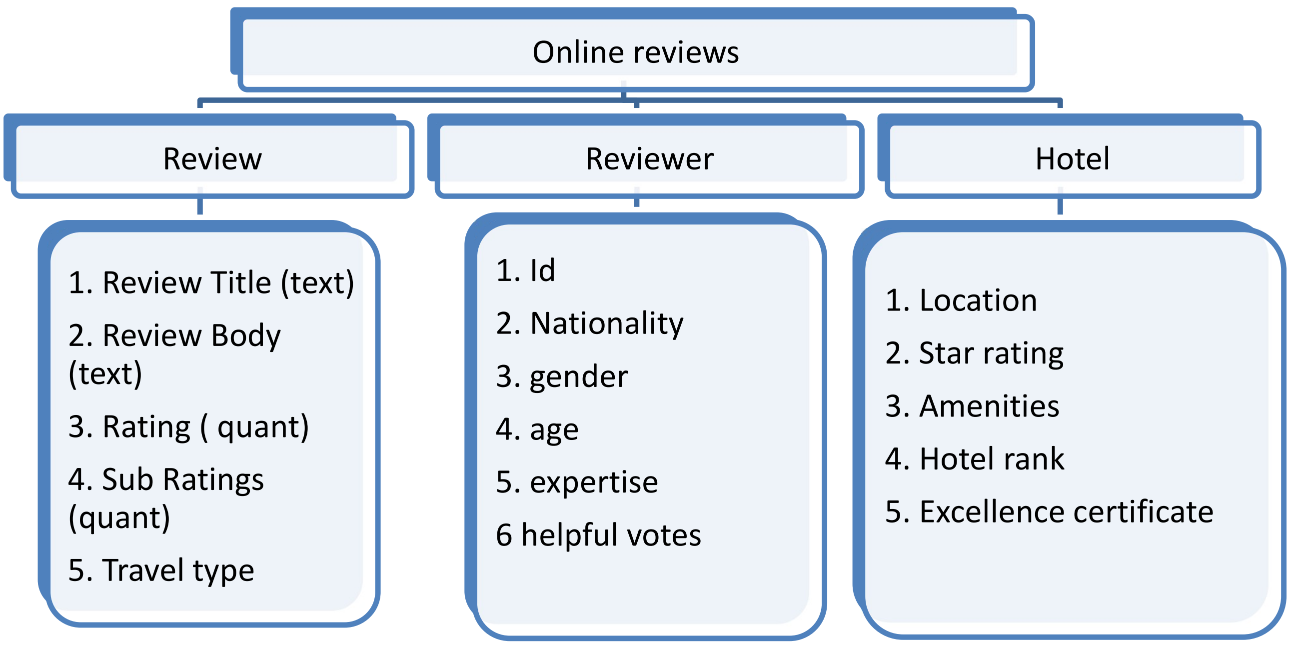


Figure 14 **Screenshot from TripAdvisor:**

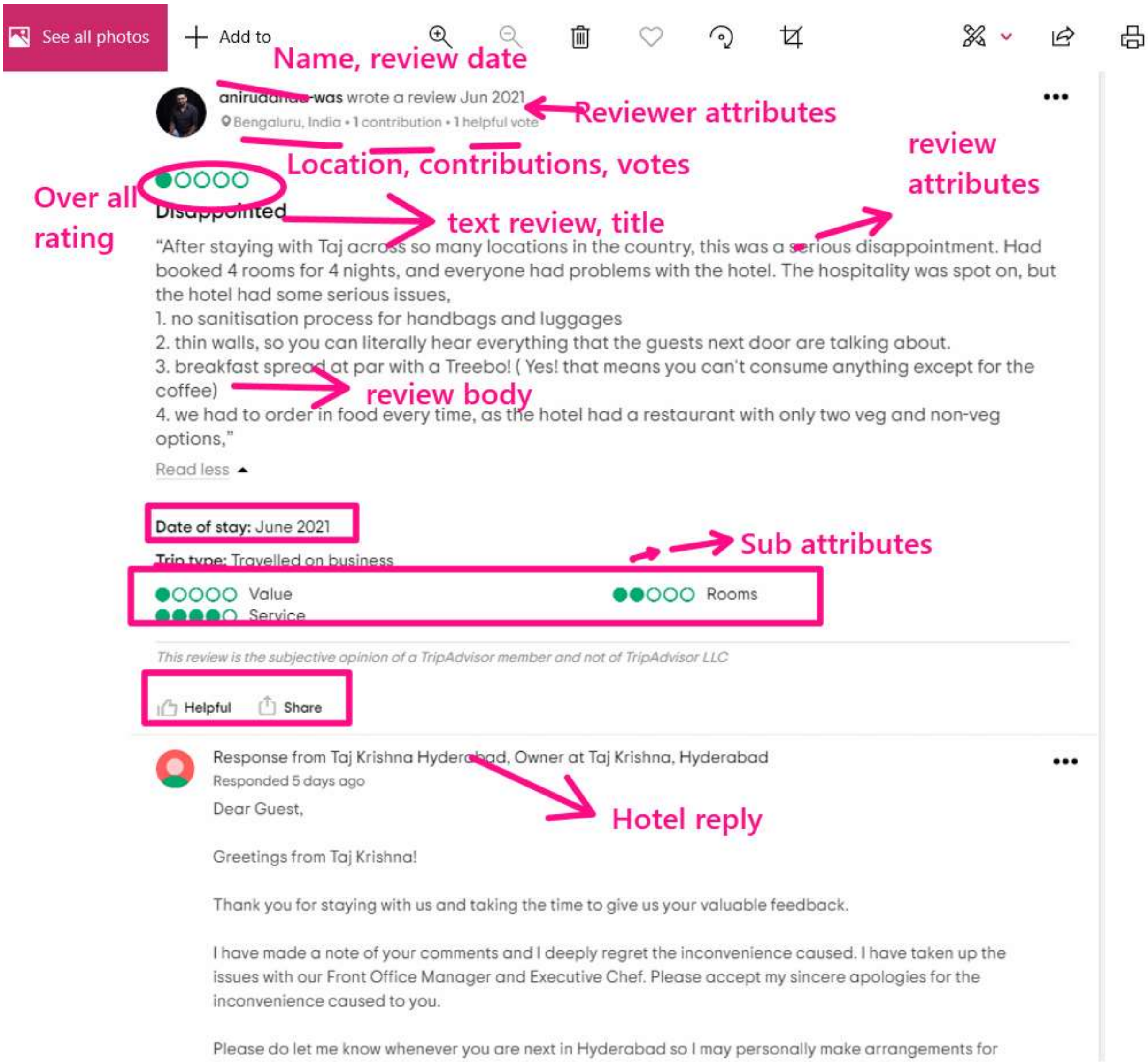


Figure 15 ***Hotel attributes screen shot***

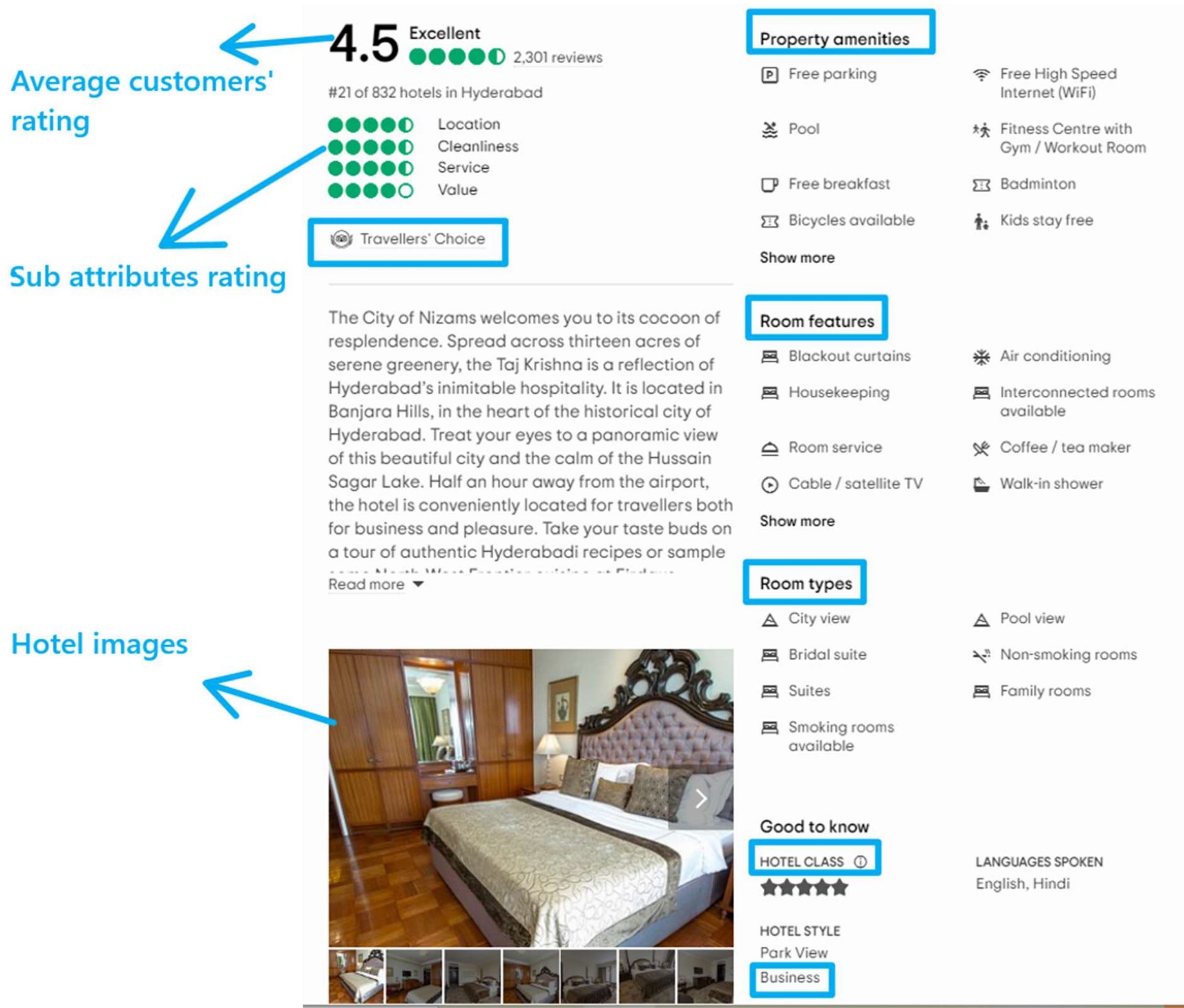


Table 21 ***Variables details:***

Type	Detail
Review attributes:	
Rating	Overall customer satisfaction on a 5-point scale (Xie et al., 2014)
Text review	It is divided into tile and body. In the title, customers write a short description of their experience. In the review body, a detailed explanation

	was written (Berezina et al., 2016)
Review recency	Difference between the date of the review written and the date of the stay (Chatterjee, 2020)
Travel type	Reviewers can mention their type of stay, such as business, leisure, friends, family, couple, etc. Extant studies divided the travel type into business and leisure (Xu, Li, & Lu, 2019).
Reviewer attributes	
Demographics	The reviewer can mention their nationality, name, gender, and age
Contribution	A total number of reviews written by the reviewer. TripAdvisor endorses the badge system to the reviewer (TripAdvisor, 2021b).
Votes	Other reviewers can upvote the review
Hotel attributes	
Star rating	With the help of the third party, TripAdvisor gives the star rating to hotels on a 5-point scale. Extant studies divide the hotels into high-end (rating 4 and 5) and low-end hotels (rating 1 and 2) based on the star rating (Hu et al., 2019; Xie et al., 2014)
Excellence certificate	Based on the overall ratings, customers feedback, amenities provided, TripAdvisor award the hotels with Excellence certificate (W. G. Kim et al., 2016)
Travelers choice award	Each year TripAdvisor allots a travelers choice award to different suppliers

3.3. Data Inclusion criteria:

Figure 16 Classified hotels in India by Ministry of Tourism

Source: https://www.nidhi.nic.in/MOT/AllindiaRpt.aspx

All India Summary Report between 01-01-2018 and 01-01-2020 **Report Date: 02-07-2021**

		Approved		Approved and Applied For ReClassification		Unclassified(Fresh Cases)	
Category	**SubCategory**	**Hotels**	**Rooms**	**Hotels**	**Rooms**	**Hotels**	**Rooms**
Bed&Breakfast/Homestay	B&B-Gold	25	130	0	0	7	44
Bed&Breakfast/Homestay	B&B-Silver	125	588	0	0	47	255
Bed&Breakfast/Homestay	Homestay-Gold	14	70	0	0	11	59
Bed&Breakfast/Homestay	Homestay-Silver	47	216	0	0	20	91
Bed&Breakfast/Homestay Total		211	1004	0	0	85	449
Heritage	Basic	30	787	0	0	3	109
Heritage	Classic With Alcohol	3	137	0	0	0	0
Heritage	Grand	3	195	0	0	2	68
Heritage Total		36	1119	0	0	5	177
Motel	Motel	0	0	0	0	1	55
Motel Total		0	0	0	0	1	55
Star Category	1 Star	4	100	0	0	4	83
Star Category	2 Star	9	296	0	0	8	235
Star Category	3 Star	305	8980	0	0	45	3197
Star Category	4 Star With Alcohol	129	6926	0	0	18	1572
Star Category	4 Star Without Alcohol	84	3319	0	0	5	181
Star Category	5 Star Deluxe	82	18825	0	0	13	2535
Star Category	5 Star With Alcohol	64	9025	0	0	18	2312
Star Category	5 Star Without Alcohol	26	2805	0	0	2	139
Star Category Total		703	50276	0	0	113	10254
Grand Total		**950**	**52399**	**0**	**0**	**204**	**10935**

Table 22 **Asia Pacific Hotel summary by Horwath HTL**

Rank	Country	Total brands	Domestic	International	Percentage	Number of Chain Hotels	Chain rooms
4	India	161	84	77	10.7	1251	133,357
3	Japan	182	136	46	12.0	2624	468,376
2	Thailand	237	144	93	15.6	1023	156579
1	Indonesia	285	197	88	18.8	1223	175659
5	Malaysia	138	`75	63	9.1	508	95831
6	Singapore	90	28	62	5.9	227	56,092

Source: HTL (2018)

Table 23 Data details:

Detail	Description
Total Number of hotels in India as on 31^{st} Dec 2017	3551 hotels
Number of keys	244,000
Listed hotel groups as per Prowess data base as on 1^{st} April 2019	161
Selected hotel groups	157
Number of hotels	787 hotels (22.16%)
Total Number of reviews	6,13,731
Selected reviews (2016 April 1^{st} to 2019 March 31^{st})	3,18,527
After purification	3,13,314
Total Sentences	14,05,000
Negative Sentences	92,536
Positive Sentences (randomly chosen)	92,536
Neutral Sentences (random)	92,536

3.4. Text Mining:

Text mining, or "discovering knowledge from the text," is a systematic method of extracting meaningful insights from unstructured data (Netzer, Feldman, Goldenberg, & Fresko, 2012).

"Text mining is the process of distilling actionable insights from text" (Kwartler, 2017)

Text reviews were data for this study. Many researchers used text data in a marketing context to derive the hidden or new dimensions from the text to understand the consumers' expectations and experiences. In today's world, the dynamics of business are changing every day. The services or product offerings were changed due to technology updates and new market offerings. Lot of text data is available to marketers, researchers, and practitioners on internet (Berger et al., 2020). This data helps marketers to segment the consumers and offer the customized services (Chatterjee & Mandal, 2020).

According to Tirunillai and Tellis (2014), the text data is unstructured, and analyzing text data is difficult. First, consumers use their own language while writing reviews. Customers use their own words and grammar. Second, the text contains many unnecessary words like stop words, city names, company names, employee names, etc. The data need to be pre-processed to use further. Third, text data can be used for the manipulation purpose. Some researchers obtained the numerical information from the text and used it for further analysis.

3.4.1. Text Pre-processing:

The text reviews are in raw form, need to be cleaned for many reasons. First, reviews contain unnecessary information like stop words, custom words. Second, to reduce the size of the document term matrix (DTM), which is an input for topic modeling. Third, to derive the bag of words and interpret topics easily (Anagnostopoulou et al., 2020; Stamolampros, Korfiatis, Chalvatzis, & Buhalis, 2019b). **Image 17** displays the text pre-processing steps. For complete analysis, we have used R programming. First, the original data will be loaded into the R program. Second, removal of special characters, punctuations, white spaces, numbers. Third, the removal of stop words and custom stop words. Fourth, lemmatization, the words converted to their root form. Next, the text data will be used for a bag of words method.

Figure 17 ***Pre-processing steps:***

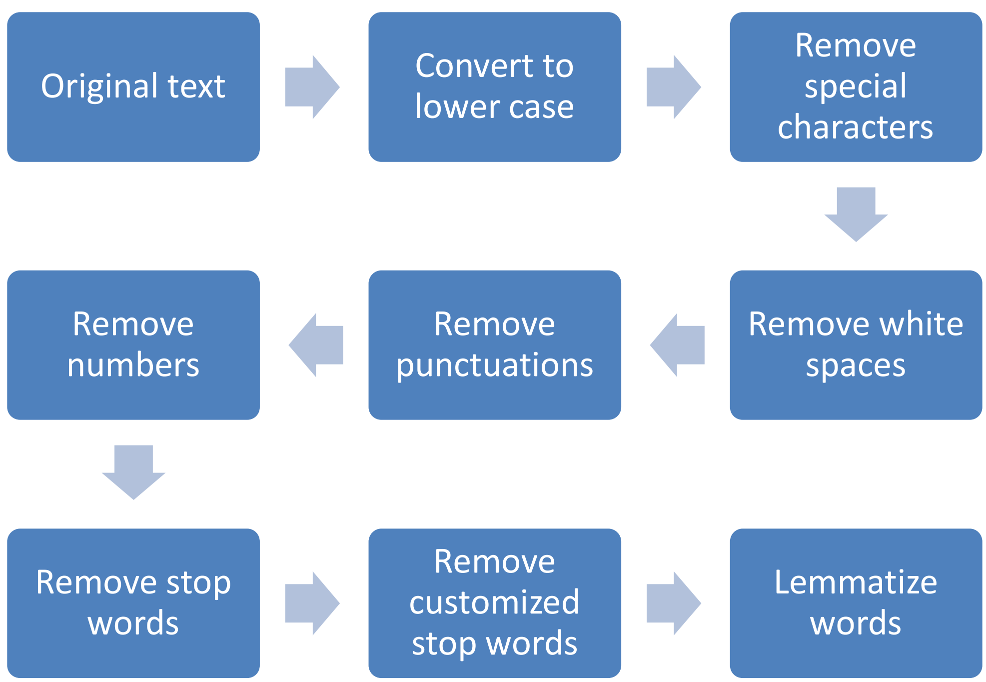


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Figure 18 ***Cleaning process example:***

Original Text"This was my 4th time staying at Taj and as always they exceeded my expectation. I got the pool view room that definitely made my stay more pleasurable. The internet was slow but the front desk was very attentive on sending the IT person to fix it. I paid premium plan for internet but it wasn't that fast either so make sure you ask them about it before paying for premium. I had free breakfast, free wifi plan and my room had bathtub was well. Overall it was a memorable stay.Highly recommend it!"

Special characters"This was my 4th time staying at Taj and as always they exceeded my expectation I got the pool view room that definitely made my stay more pleasurable The internet was slow but the front desk was very attentive on sending the IT person to fix it I paid premium plan for internet but it wasn t that fast either so make sure you ask them about it before paying for premium I had free breakfast free wifi plan and my room had bathtub was well Overall it was a memorable stay Highly recommend it "

Remove numbers"This was my th time staying at Taj and as always they exceeded my expectation I got the pool view room that definitely made my stay more pleasurable The internet was slow but the front desk was very attentive on sending the IT person to fix it I paid premium plan for internet but it wasn t that fast either so make sure you ask them about it before paying for premium I had free breakfast free wifi plan and my room had bathtub was well Overall it was a memorable stay Highly recommend it "

Lowering cases"this was my th time staying at taj and as always they exceeded my expectation i got the pool view room that definitely made my stay more pleasurable the internet was slow but the front desk was very attentive on sending the it person to fix it i paid premium plan for internet but it wasn t that fast either so make sure you ask them about it before paying for premium i had free breakfast free wifi plan and my room had bathtub was well overall it was a memorable stay highly recommend it "

Lemmatize "this be my th time stay at taj and as always they exceed my expectation i get the pool view room that definitely make my stay much pleasurable the internet be slow but the front desk be very attentive on send the it person to fix it i pay premium plan for internet but it wasnt that fast either so make sure you ask them about it before pay for premium i have free breakfast free wifi plan and my room have bathtub be good overall it be a memorable stayhighly recommend it"

Stopwords " th time stay   always exceed expectation get pool view room definitely make stay much pleasurable internet slow   front desk attentive send   person fix   pay premium plan internet   wasnt fast either make sure ask   pay premium   free breakfast free wifi plan   room bathtub good overall   memorable stayhighly recommend "

Tokenization: Removal of words (nchar<3)

Frequency of words

Term document matrix (TDM)

3.4.2. Bag of words methods:

Bag of words method summarises the repeated words and phrases. It gives the basic idea to researchers. The data visualization was done based on the bag of words method. Extant studies used unigrams, bi-grams, and trigrams to visualize the words.

Unigrams: Unigrams are a collection of frequently repeated words. Unigrams can be used to visualize the word clouds. Extant studies used unigrams to develop the dimensions, but which has some limitations. The researcher needs to read the entire document to understand the context. Second, some negated words such as not, bad change the meaning of the words(Hu et al., 2019). So, it is not suggested to use the unigrams to develop the factors or dimensions.

N-gram: In text mining, N-grams are widely used as an input for LDA and develop the dimensions. Two or more words are paired together and form N-grams. Some researchers used bigrams to develop the dimensions to understand the consumer's experience. For example, Chittiprolu et al. (2021) found the antecedents and consequences of customer satisfaction and dissatisfaction in heritage hotels using bigrams.

Document Term Matrix (DTM): DTM can be used in machine learning analysis. DTM is a matrix where each document is stored in a row and terms associated with documents are saved in the column. DTM can be used to visualize the unigrams, bigrams, and input for LDA. Sometimes the size of the DTM will be a little concern; it is advised to pre-process the data before utilizing it for LDA (Xu & Li, 2016).

3.5. Feature extraction using LDA:

Latent Dirichlet allocation is an unsupervised text mining technique to extract the latent topics from the corpus (a collection of documents) based on co-occurrence of terms. LDA is an advanced text mining method. It is a "generative probabilistic topic model", which does not assume any patterns and grammar between the documents. LDA presupposes each document is a collection of topics, and each topic is a combination of words (Zou, 2020). With the emergence of computer-aided text mining techniques, many researchers adopt LDA to identify the latent topics from the text. LDA applied in different contexts such as airlines (Korfiatis, Stamolampros, Kourouthanassis, & Sagiadinos, 2019; Lucini et al., 2020), hotels(Büschken & Allenby, 2016; Calheiros, Moro, & Rita, 2017; Guo et al., 2017; Xiang, Du, Ma, & Fan, 2017), restaurants(Jia, 2020), hospitals (Shah et al., 2021), banking (Bastani, Namavari, & Shaffer, 2019), Human resource (Jung & Suh, 2019), and marketing (Tirunillai & Tellis, 2014), etc.

Illustration 1:

"My second Taj experience, and even though the property is not as grand as Taj Krishna Hyderabad, the services and personal touch from the staff made up for it. When I checked in, I was given room no. 305 and I have been told that it's a special room and as I went in, I could see that the room has been prepared for female travellers (not so common in India, I take it?) In the bathroom there were bunch of things that are not usually in the room and in a way was a very nice touch. Talcum powder, nail clippers, nail polish remover, and other feminine products. I ran a workshop in the hotel. The meeting room was set up beautifully. Staff kept checking that we had what we needed. The level of service was beyond what I have experienced in other hotels. The 3 ladies at the front desk, Shristi and 2 others are so friendly and welcoming. I asked for a late check out because my workshop would finish way beyond mid day. No question asked.

They said, just check out whenever I need to check out! I was expecting them to charge me for checking out at 4pm, but no. The housekeeping have done a great job in keeping the room very clean. I definitely recommend this hotel to anyone travelling to Chandigarh!"

Topic1: Staff professionalism

Topic2: Customized room

Topic3: Bathroom amenities

Topic4: Conference arrangements

Topic5: Staff behavior

Topic6: Front desk response

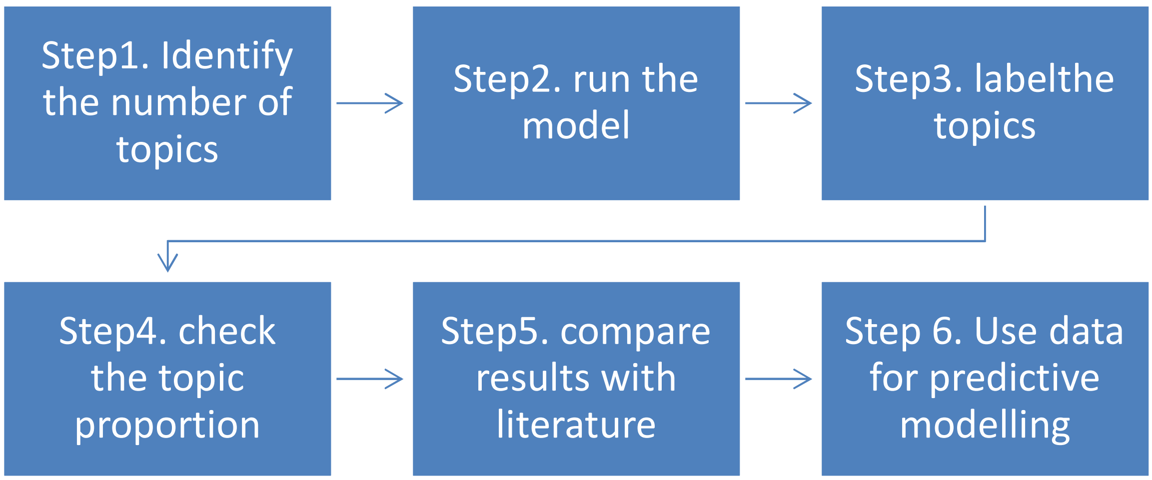
Topic 7: Service appreciation or hygiene and maintenance

Table 24 ***Terms used in LDA***

Type	**Detail**
Document (D)	Each row in DTM is a document. Generally full review or sentences can refer as a document
K	Number of topics
Perplexity score	Used to identify the number of topics. Lower the score better the model
Coherence score	Used to identify the number of topics. Higher the score better the model
Beta(β) values	The probability of word belonging to a topic
Gamma γ values	The probability of document belonging to a topic
Control parameters	Control values to run the Gibbs sampling

3.5.1. Steps in LDA:

Figure 19 LDA process



3.5.2. Step1 Identify the number of topics:

LDA does not make any assumptions on the structure of the text, grammar used in the text. The algorithm works based on Bayesian probability; it develops the topics based on words relation. Number of topics need to mention to run the LDA algorithm. Extant studies used many ways such as the trial and error method (Bastani et al., 2019), perplexity score (Taecharungroj & Mathayomchan, 2019; Xiang et al., 2017), coherence score (Fang & Partovi, 2021), and log-likelihood method (Büschken & Allenby, 2016; Korfiatis et al., 2019; Zou, 2020) to identify the number of topics (hereafter k). We have used perplexity score to predict the possible k-value. We followed two steps to calculate the number of topics as suggested by (Zou, 2020). First, we find the possible range of k value by running ten models by using k= 5, 10,15,20,25,30,35,40,45,50 topics. After identifying the possible range, next we run the model using 15 topics. The perplexity score was mapped on the y-axis and k values on the x axis. The lower the perplexity score, the better the model (Xiang et al., 2017; Zou, 2020). For a mathematical explanation of perplexity score and LDA model, refer (Blei, 2012; Grün & Hornik, 2011; Guo et al., 2017; Tirunillai & Tellis, 2014)

Table 25 ***Previous studies on identifying number of topics:***

Author	Sample	K	Method	Algorithm
(Fang & Partovi, 2021)	101,744 hotel reviews, 128,855 restaurants reviews	k=16 & 14 by using elbow plot	Coherence score	LDA
(Zou, 2020)	89,202 national park entrance fee reviews	K=19	Four methods: Log-likelihood, coherence, perplexity, and lower bond	LDA
(Jung & Suh, 2019)	204,659 reviews	K=65 reduced to 30	Perplexity score and clustering analysis	LDA
(Korfiatis et al., 2019)	557,208 reviews	K=20	Log likelihood, coherence score	STM
(Stamolampros, Korfiatis, Chalvatzis, &	289,921 reviews	K=10	Log likelihood, coherence score	STM

Buhalis, 2019a)				
(Zhang, 2019)	1,026,988 Airbnb reviews	K=15		LDA
(Taecharungroj & Mathayomchan, 2019)	25,458 beach reviews	K= 4	Perplexity method	LDA
(Bastani et al., 2019)	86,803 reviews	K=39	Trail and error	LDA
(Xiang et al., 2017)	940,000 reviews	K=5	Perplexity score	LDA
(Guo et al., 2017)	266,544 reviews	K=30	--	LDA
(Tirunillai & Tellis, 2014)	350,000	K=6	Log-likelihood	LDA

3.5.3. Step 2 Model execution:

We have used R-programming to run the model. *Topic modeling* package was used to run the model. The syntax of the LDA function is:

Mod= LDA(x=dtm, k=2, method="Gibbs", control=list (alpha=1, delta=0.1, seed=10005))

DTM (document term matrix) is the input file. After completion of text pre-processing, we built DTM.

K is the number of topics to extract.

Method= Gibb’s sampling method was used

Mod is an object; the output of LDA with sub-attributes was stored.

3.5.4. Step3: label the topics:

After running the model, LDA output produces several attributes: perplexity score, coherence score, topics and associate term, β values, and γ values. The labeling of the topics needs to do logically and manually. LDA gives the list of the topics and associated terms. Extant studies used the top 10 terms (Stamolampros et al., 2019a),30 terms (Büschken & Allenby, 2016) to infer the topic's name. This study contacted the working professionals in hotels and a group of researchers to label the topics.

3.5.5. Step4: Calculate a number of documents per topic:

LDA output gives gamma and beta values. Gamma values determine the number of documents shared by each topic. The study research question is to find the antecedents of CS & CC. This study extracted features separately to identify and compare the ranks between determinants. Gamma value helps to identify the topics which many customers discuss.

3.5.6. Step5: Compare with literature

The extracted topics will be compared with literature and develop the conceptual model based on first-order and second-order constructs.

CHAPTER IV

4. Results:

This chapter discusses the technical features of the reviews, feature extraction process, and determinants of CS & CC towards different hotels.

4.1. Technical features of the reviews:

Table 26 displays the technical features of the reviews. A total of 41,574; 134,603; and 5,849 reviews were collected for heritage, luxury, and budget hotels respectively. The mean length of negative reviews was higher for all three hotels compared to positive reviews. The mean sentiment score was low for negative rated reviews for all three hotels compared to positive reviews. The response ratio was higher for luxury hotels compared to heritage and budget hotels. The percentage of negative reviews was: 4%, 4%, and 8% for luxury, heritage, and budget hotels.

Table 26 Technical features of the reviews:

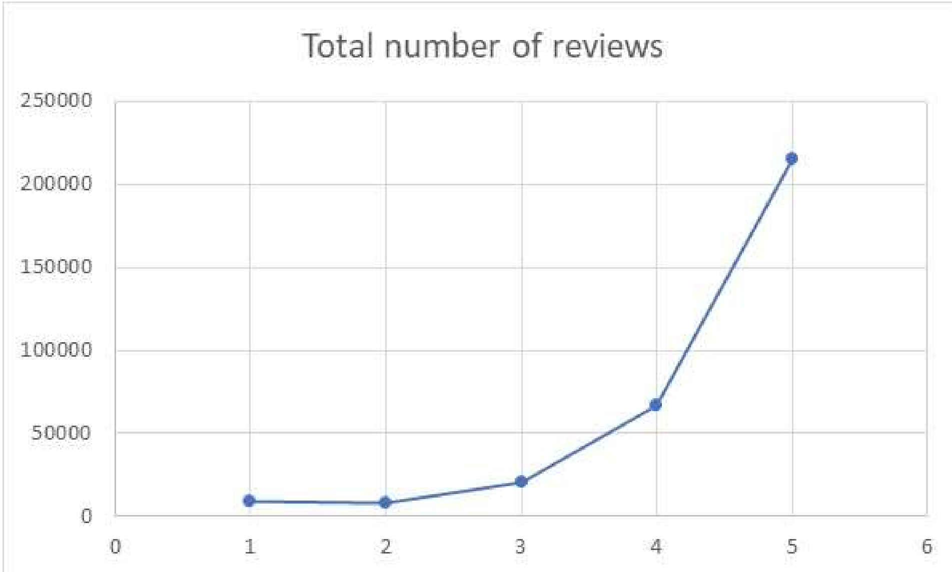
Rating	Mean review length	Mean sentiment score	Number of managers reply	Number of reviews	Percentage	Response ratio
Heritage hotels						

1	185.98	**-0.03**	417	808	1.94	0.52
2	179.06	**0.06**	472	926	2.23	0.51
3	153.9	0.25	1418	2780	6.69	0.51
4	118.88	0.54	5492	10211	24.56	0.54
5	110.86	0.65	17645	26849	64.58	0.66
Luxury Hotels						
1	160.53	**-0.08**	2502	2964	2.2	**0.84**
2	154.49	**-0.02**	2146	2469	1.83	**0.87**
3	129.92	0.12	5673	6407	4.76	**0.89**
4	96.7	0.36	20847	22956	**17.05**	**0.91**
5	87.7	0.44	92205	99807	**74.15**	**0.92**
Budget hotels						
1	178.39	**-0.07**	100	191	**3.27**	0.52
2	161.87	**-0.02**	94	198	**3.39**	0.47
3	134.37	0.16	204	530	9.06	0.38
4	113.73	0.33	701	1542	26.36	0.45
5	103.49	0.41	2544	3388	57.92	0.75

4.2. Distribution of reviews:

The below image displays the distribution of reviews. The reviews follow the J-type distribution; the number of reviews has a direct relationship with ratings.

Figure 20 Distribution of reviews



4.3. Feature extraction:

4.3.1. Step1: Identifying the number of topics

This study used the latent Dirichlet allocation algorithm to extract features of CS & CC separately. The number of topics (K) was identified by using two steps for CS & CC. First, we run the ten models using k=5,10,15,20,25,30,35,40,45,and 50. The Elbow method was used to identify the range and number of topics. Perplexity score plotted on y-axis and number of topics plotted on the x-axis. Second, after identifying the range, this study ran the 30 models and identified the ideal number of topics. The below images show the two steps which we followed for three hotels.

Figure 21 Step 1: Number of topics identifying range using perplexity score:

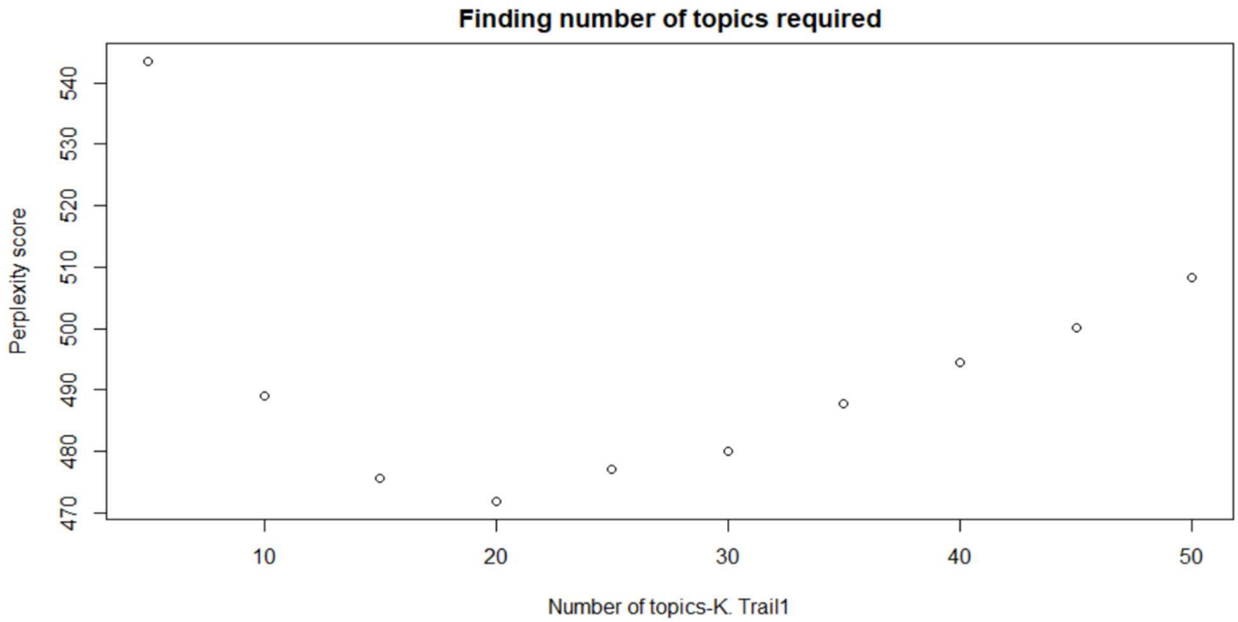
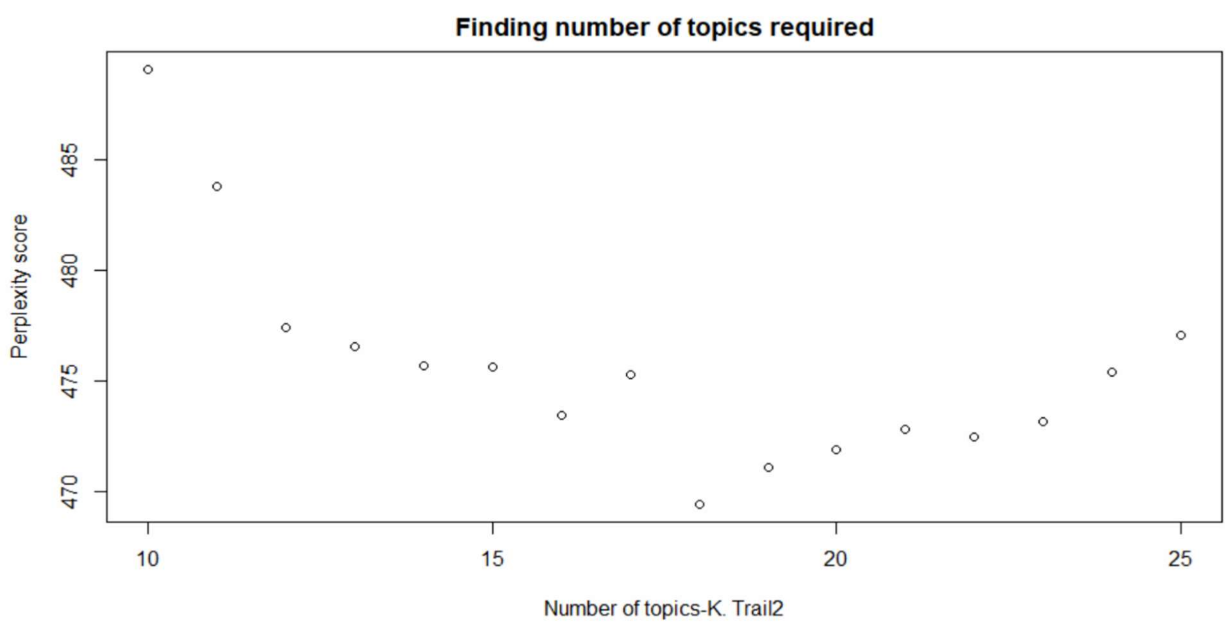


Figure 22 Step 2: Number of topics using perplexity score:



4.3.2. Step2: Running the model

This study runs the LDA models using R-programming. Many previous studies used R-programming for topic modeling (Korfiatis et al., 2019; Stamolampros et al., 2019a, 2019b). Topic modeling package was used to run the models. The output of LDA gives the topics and associated terms, which were shown in the annexure. LDA does not label the topics. This study contacted industry experts for labeling purposes. They confirmed that the factors were logical and meaningful. With their inputs, this study again contacted four research scholars who have industrial experience. The labeling was done based on their recommendations and literature support. The study aimed to identify the determinants of CS and CC and develop the conceptual model. The study categorizes the determinants into latent constructs. A thorough literature study was done to create the latent constructs. The number of latent constructs and topics for three hotels were displayed in the below table.

Table 27 Number of latent constructs and topics for 3 hotels

Type of hotels	CS: K	CS: Latent topics	CC:K	CC: Latent topics
Luxury hotels	16	9	12	9
Heritage hotels	14	8	13	7
Budget hotels	7	5	7	6

Note: K- Number of topics, CS: Customer satisfaction, CC: Customers complaints

4.4. Topic labeling

The below **tables** show the CS & CC determinants and associated factors. The ranking was done based on gamma value. The gamma value displays the number of documents or reviews shared by each topic.

4.4.1. Determinants of CS towards 3 hotels:

The common CS determinants for 3 hotels are Location, Physical surroundings, food quality & taste, restaurant services & ambiance, and staff-related attributes. The unique determinants for luxury hotels were food variety, staff response, meetings arrangements, front desk and check-in, room view, and brand image. The unique determinants for heritage hotels are royal stay, heritage tour, cultural shows, nature tour, and bathroom. Pick-up & drop was the unique determinants for budget hotels. Hotel ambiance, hotel décor & beauty, celebrations, and chef interaction were the common determinants for luxury and heritage hotels.

4.4.2. Determinants of CC towards 3 hotels:

The common CC determinants for 3 hotels are check-in, food service & quality, restaurants, bathroom& hygiene, refunds & bookings, and staff attitude. Front desk response, over price, and noise were common determinants for luxury and budget hotels. Brand image and meeting arrangements are the unique determinants for luxury hotels. Fort entrance fee and charges were the unique determinants for heritage hotels.

Table 28 CS &CC factors for heritage hotels

Determinants of customer satisfaction			
Rank	**Latent Factors**	**Frequency**	**Sub-dimensions**
1	Traditional services	1740	Royal stay (826), heritage tour (430), cultural shows (484)
2	Food related attributes	821	Food taste (576), dine-in (245)
3	Physical signifiers	804	Location & ambience (455), heritage décor and ambience (177), Nature tour (172)
4	Staff related attributes	588	Staff professionalism (60), staff helpfulness (528)
5	Room related attributes	384	Bathroom
6	Tourist attraction	148	
7	Service appreciation	240	
8	Celebrations	350	

Determinants of customer dissatisfaction			
1	Front desk	1279	Front desk response, front desk & check-inn, check-inn
2	Food related attributes	1153	Food service and quality, food price and service, restaurant, food service
3	Room related attributes	845	Bathroom and Hygiene
4	Value for money	716	Refunds and bookings, over price
5	Staff related attributes	540	Staff attitude
6	Amenities	312	
7	Noise	370	

Table 29 CS & CC for luxury hotels

Determinants of customer satisfaction			
Rank	**Latent Factors**	**Frequency**	**Sub-dimensions**
1	Service scape	9240	Location, hotel ambience, hotel décor and beauty, physical surroundings
2	Food related attributes	4050	Food variety, food quality and taste, restaurant service and ambience
3	Staff related attributes	2745	Staff professionalism, staff response
4	Meetings arrangement	2655	
5	Front desk and check inn	1392	
6	Room related attributes	1170	Room view
7	Celebrations and chef interaction	213	
8	Recommend or positive word of mouth	476	
9	Brand image	684	
Determinants of customer dissatisfaction			
1	Value for money	4656	Billings & refund, overcharge
2	Room related attributes	3549	Bathroom
3	Food related attributes	2974	Food service and hygiene, restaurant
4	Brand image	2316	
5	Staff related attributes	1200	Staff attitude
6	Front desk response	704	
7	Checkin and pick up and drop	1770	
8	Noise	1892	

9	Events	308

Table 30 CS & CC for budget hotels

Determinants of customer satisfaction			
Rank	**Latent Factors**	**Frequency**	**Sub-dimensions**
1	Staff related attributes	376	Friendly staff
2	Food related attributes	358	Food quality and taste, dine in
3	Pick up and drop	280	
4	Positive WOM		
5	Location	175	Location and physical attraction, physical attractions
Determinants of customer dissatisfaction			
1	Food related attributes	367	Food taste and price, dine-in
2	Check in and bookings	336	Bookings
3	Value for money	243	Billings
4	Pick up and drop	200	
5	Room related attributes	141	Bathroom
6	Staff related attributes	41	Staff attitude

Table 31 Comparison of satisfaction determinants

Factors	Luxury	Heritage	Budget
Location	Yes	Yes	Yes
Hotel ambience	Yes	Yes	
Hotel décor and beauty	Yes	Yes	
Physical surroundings	Yes	Yes	Yes
Food variety,	Yes		
Food quality and taste,	Yes	Yes	Yes
Restaurant service and ambience	Yes	Yes	Yes
Staff professionalism	Yes	Yes	Yes
Staff response	Yes		
Meeting's arrangement	Yes		
Front desk and check inn	Yes		
Room view	Yes		
Celebrations and chef interaction	Yes	Yes	
Recommend or positive	Yes		Yes

word of mouth			
Brand image	Yes		
Royal stay		Yes	
heritage tour		Yes	
cultural shows		Yes	
Nature tour		Yes	
Bathroom		Yes	
Pick-up & drop			Yes

Table 32 Comparison of dissatisfaction determinants

Factors	Luxury	Heritage	Budget
Front desk response	Yes	Yes	
Check-in	Yes	Yes	Yes
Food service & quality	Yes	Yes	Yes
Food price & Restaurants		Yes	Yes
Restaurants	Yes	Yes	Yes
Bathroom & Hygiene	Yes	Yes	Yes
Refunds & bookings	Yes	Yes	Yes
Overprice	Yes	Yes	
Staff attitude	Yes	Yes	Yes
Amenities		Yes	
Noise	Yes	Yes	
Brand image	Yes		
Meeting’s arrangements	Yes		
Pick up & drop			Yes

CHAPTER V

Discussion:

With the progression of technology and the internet in the tourism industry, social media usage increased by tourists. Social media played an essential role in tourists' life cycle, such as information search, products or services comparison, price comparison, reservations, and post-purchase experience. Consumers share a lot of information on social media by writing OR, sharing photos, videos, etc. This information is crucial for marketers to understand the perceptions and expectations of tourists regarding travel services. From the past decade, studies on OR got tremendous attention from researchers. Researchers addressed different questions using OR in the hospitality and tourism industry: impact of OR on product sales (Chevalier & Mayzlin, 2006; Duan et al., 2008; Floyd et al., 2014; Zhu & Zhang, 2010), on hotel sales (Blal & Sturman, 2014; Ye et al., 2009), on hotel occupancy (C. K. Anderson, 2012; W. G. Kim, Lim, & Brymer, 2015), hotel long term performance (Duverger, 2013; Sun & Kim, 2013), and restaurant sales (S. Kim, Koh, Cha, & Lee, 2015; W. G. Kim et al., 2016). Extant studies applied unsupervised techniques to identify and understand the antecedents of CS and CC (Anagnostopoulou et al., 2020; Guo et al., 2017; Jia, 2020; H. Li et al., 2013; Lucini et al., 2020; Padma & Ahn, 2020; Piramanayagam, Sud, & Seal, 2020; Sezgen et al., 2019; Shah et al., 2021).

It is understood that OR plays a dominant role in the tourism and hospitality industry. Customers refer to OR, which drives their purchase decision and removes ambiguity about products and services (Litvin, 2019; Litvin et al., 2008). They trust the information available in review websites rather than information generated on official websites (Gretzel & Yoo, 2008). So, OR gives clarity about the tourism products. Customers share positive and negative information in the form of OR. The OR can be quantitative and qualitative. Customers share and write OR. Extant studies divided online ratings into three levels: Review valence: customers rate their overall satisfaction about products or services. It is a hedonic tone of the consumers. Consumers express their satisfaction by rating positively. Review volume: the total number of reviews. Review variation: the variance between review ratings (Xie, Chen, et al., 2016; Xie et al., 2014). Extant studies followed ratings to identify positive and negative ratings. TripAdvisor follows the five-point rating system. Rating 1 and 2 are classified as negative reviews, and ratings 4 and 5 were classified as positive reviews (Kuhzady & Ghasemi, 2019; Xu & Li, 2016; Xu et al., 2019). Positive reviews increase product or service sales. Negative reviews damage the brand image and reputation.

Moreover, consumers trust the negative information generated in social media (Chevalier & Mayzlin, 2006). Chevalier and Mayzlin (2006) studied the impact of online reviews on book sales using data from two online retailers. They found that with the improvement of overall ratings, the sales of the books also increase, and the one-star rating impact was more on sales. Consumers do not depend on ratings blindly, and they read the text reviews before making the purchase decision. Viglia, Minazzi, and Buhalis (2016) studied the impact of online ratings on hotel occupancy rates of 346 hotels. They found that with a one-point increase in ratings, the occupancy rate will increase by 7.5 %. To improve the hotel's financial performance, brand image, and brand reputation, hotel operators need to understand the expectations and experiences of the customers. Customers write their experience on social media by writing textual reviews. Text reviews are unstructured and customers express their feelings and emotions by writing these reviews. Text mining helps to identify the hidden or new dimensions in detail. So, service providers need to understand the reasons of CS and CC. Previous studies used text reviews to identify the antecedents of CS and CC.

The study's objective is to understand the antecedents of CS and CC towards different types of hotels. This study used big data to understand consumer behavior in detail. The data was collected from TripAdvisor.com using a web crawler developed in Python, and data was stored in an excel file. R-programming was used to identify the dimensions, and the LDA algorithm was used to determine the dimensions.

5.1. Technical features of the reviews:

Table 26 summarizes the technical features and descriptive statistics of the reviews. The results gave exciting findings. The word length of the reviews was higher for negative reviews compared to positively rated reviews. Extant studies stated that dissatisfied customers write lengthy reviews compared to satisfied customers (Zhao et al., 2019). The study results were in line with (Chevalier & Mayzlin, 2006) and (Zhao et al., 2019) study. According to Prospect theory, consumers are more sensitive to losses rather than winnings. Dissatisfied consumers explain and express their negative feelings in detail. The mean sentiment score was negative for negative rated reviews. There was a positive correlation between sentiment score and online ratings. The number of reviews follows the J-type distribution, which was proportion with ratings. Some authors tested the credibility and self-selection bias while giving ratings and proved that online travel agencies follow the quality criteria before displaying on websites (Aral, 2014; Smironva, Kiatkawsin, Lee, Kim, & Lee, 2020). The response ratio from the managers was higher for luxury hotels compared to heritage and budget hotels. This phenomenon explains that luxury hotel customers pay premium prices, and they generate higher revenue. The number of rooms in luxury hotels was higher compared with heritage and budget hotels. So, hotels spend a considerable amount to engage the luxury hotels' customers in social media by responding promptly. Previous studies proved that managerial reply positively impacts hotel revenue (Xie et al., 2017; Xie et al., 2014; Xie, Zhang, et al., 2016). Moreover, response time and message content create a positive brand image for consumers (Sparks, So, & Bradley, 2016).

5.2. Common and different factors of CS and CC:

The findings show that CC and CS dimensions differ depending on hotel type or class. Furthermore, the importance and ranks also vary between CS and CC attributes. The common factors of CS, which include Location, physical surroundings, food quality & taste, staff helpfulness & professionalism, and restaurant services & ambiance, were core offerings of the hotels. The common factors of CC, including check-in, food service & quality, dine-in, bathroom & hygiene, staff attitude, and refunds & bookings, were more specific. Hotel ambiance, décor& beauty, celebrations, chef interaction were common CS factors between luxury and heritage hotels. Front desk response, overprice, and noise were common CC factors between luxury and heritage hotels.

5.3. Determinants of CS and CC: Luxury hotels

This section discusses the determinants and their importance which drive CS and CC in luxury hotels. 17 CS and 12 CC determinants were identified and grouped into nine categories. The common CS and CC determinants in luxury hotels are food, staff, meetings arrangement, room, front desk, and star reference. Servicescape was the most influential determinant of CS, including hotel décor & beauty, location, ambiance, and physical surroundings (Durna, Dedeoglu, & Balikçioglu, 2015). Extant studies proved that servicescape dimensions have a positive association with brand image and re-purchase of the hotels. Hotels spend an enormous amount on décor and ambiance to improve the customer mood and emotions. This study results in line with Barreda and Bilgihan (2013), Cetin and Walls (2016) studies. The next influence dimension was food-related attributes (f&b) which includes food variety, quality & taste, restaurant services & ambiance. The f&b services have a positive association with operating performance, such as occupancy and hotel profits in luxury hotels. F&b services generate higher income after rooms revenue, an essential department for luxury hotels (Mun, Woo, & Seo, 2020). The results are in line with Padma and Ahn (2020) study. The next determinant was staff-related attributes, which includes staff professionalism, helpfulness, attitude, and response. According to service profit chain theory, satisfied customers work with positive motivation, leading to customer satisfaction (Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994). Evidence proved a positive association between employee satisfaction (ES) and CS, ES & hotel performance (Kuo, 2007; Solnet, 2006; Torres & Kline, 2013). The results are in line with (Berezina et al., 2016), (Xu & Li, 2016), (B. Kim, Kim, & Heo, 2016). The next determinant was meeting arrangements. Banquets generate a considerable amount in star hotels, and many business travelers use hotel banquets to conduct the meetings (LaFleur & Hyten, 1995; McCleary, Weaver, & Hutchinson, 1993). The results are in line with Guo et al. (2017) study. Front desk and check-in was the fourth important determinant in CS. Luxury hotels invest in the latest technology for a smooth check-in process, such as mobile check-in, smart keys, updated CRM software, etc. The next determinant was room-related attributes, including room amenities, room size, room view, hygiene & cleanliness in rooms. Room-related attributes were the core attributes of any hotel. Luxury hotel customers pay premium prices and expect nice rooms with customized amenities, views, and sizes. Giglio et al. (2020) analyzed 7395 consumer pictures posted in TripAdvisor about luxury hotels in the UK and found that consumers prioritize room features rather than amenities. This study results are in line with Padma and Ahn (2020), Khoo-Lattimore and Ekiz (2014) studies. The next determinant was brand image. Luxury hotels position their brand name in market. According to signaling theory, consumers believe that branded hotels provide the best service quality rather than budget hotels. H.-b. Kim and Kim (2005) studied the impact of brand equity on financial performance in luxury hotels and proved that brand image plays the significant impact on financial performance. Satisfied customers spread the positive word of mouth and recommend the brand to others. Chef interaction plays a vital role for CS. Some customers want to learn the food recipe and appreciate the chef about food quality and taste. Some hotels display the kitchen transparently to their customers to show the safety standards and hygiene procedures followed while cooking. According to Pine, Pine, and Gilmore (1999) experiential economy model, the education attribute engages the customers and creates customer satisfaction.

As discussed earlier, CC determinants were more specific. Many CC are related to service issues, and they are intangible. Value for money attribute, including over-price and bookings & check-in, was the most criticized attribute by luxury customers. Many business travelers stay in luxury hotels, and their billings & reservations are made from the company side (Xu & Li, 2016). So, front desk staff needs to communicate with the reservation department for a smooth check-in process. Bathroom was the second most discussed CC attribute. Luxury hotel consumers expect hygiene, clean, and branded bathroom amenities. Extant studies proved a positive relationship between bathroom amenities and customers attitude. Jeong and Kubickova (2020) studied the impact of brand packaging on customer behavior in luxury and budget hotels. They proved that providing bathroom amenities in a bottle leads to a better brand image, which impacts the customer's re-visit intention. Our results are in line with many studies: (Xu & Li, 2016), (Hu et al., 2019), (Guo et al., 2017), (Dinçer & Alrawadieh, 2017). Star reference was the CC factor; in luxury hotels, consumers refer to the star category and expect higher service quality. Failure to meet the expectations leads to CC. Sleep quality was the next influential determinant leads to CC. The noise was a part of sleep quality. Quality sleep is a vital attribute for consumers; many hotels started sleep programs for a better sleep quality (Sanand, 2021). Our results are in line with Xu and Li (2016) study.

5.4. Determinants of CS and CC: Heritage hotels

This section discusses the determinants and their importance which drives CS and CC in heritage hotels. 11 CS and 11 CC determinants were identified and grouped into 8 and 7 categories. The common CS and CC determinants in heritage hotels are food, staff, and room-related attributes. These attributes were the core offerings of the hotels. The unique CS determinants were traditional services, royal services, physical signifiers, tourist attractions, and celebrations. The unique CC factors were a front desk, value for money, amenities, and noise. The CC attributes are service issues which are intangible, whereas CS attributes are tangible. The results are in line with (Berezina et al., 2016) study. The unique attributes for heritage hotels were traditional services, which are royal stay, heritage tours, and cultural shows. Many heritage tourists visit and stay in heritage hotels to experience the past or authentic experiences: royal stay, authentic food, knowing the local cultures, history of the place, etc. These dimensions create an authentic experience for guests. The results are in line with Henderson (2013) study. The next CS dimension was the physical signifier, including décor, style, location, physical beauty, and ambiance. Heritage hotels do not damage and alter the style of the hotel to provide an original and authentic experience to tourists. The results are in line with See and Goh (2019), Wong, Yen-Nee Ng, Valerian, Battistotti, and Society (2014), Hussein and Hapsari (2020) studies.

The attributes of CC were issues with the front desk, food, staff, room, value for money, amenities, and noise. Of the dimensions, four dimensions were unique to CC: front desk issues, value for money, amenities, and noise. Of the seven CC attributes, four dimensions were related to intangible service problems.

5.5. Determinants of CS and CC: Budget hotels

This section discusses the determinants and their importance which drive CS and CC in budget hotels. 7 CS and 7 CC determinants were identified and grouped into 5 and 6 categories. The common CS and CC determinants in budget hotels are pick-up & drop, food, staff, and room-related attributes. These attributes were the core offerings of the hotels. The unique CS determinants were positive WOM and location. The unique CC factors were check-in & bookings, and value for money. The CC attributes are service issues and intangible, whereas CS attributes are tangible.

5.6. Managerial implication

The findings of the study have some important implications for hotel service providers. First, the determinants were different towards different categories of the hotels. Second, the importance ranking was dissimilar for CS and CC. The factors which cause CS and CC were distinct for different types of hotels. Third, the CS factors were more general, but CC factors were more specific. 95 percentage of the reviews were positive; managers need to motivate employees by sharing these compliments. The employees should receive appreciation from managers, which leads to employee loyalty. Managers should use these compliments for marketing and promotion purposes. Although the percentage of negative reviews was less (< 5%), they may damage the brand image and reputation of the hotels. Dissatisfied customers spread negative word of mouth, which may damage the brand image. On average unhappy customers circulate their negativity to at least 16 persons (Steele, 2018). Moreover, the managers can identify the weak spots and service failure areas.

The sentiment score of the positive reviews was positive, whereas negative reviews had a negative sentiment score. Managers can apply automated text analysis to identify the causes of service failures and CS. The manager's reply for luxury hotels was 80 percent, but it was low for heritage and budget hotels. Extant studies proved that managers' replies impact hotel occupancy and create trust in fellow consumers (Xie et al., 2017; Xie et al., 2014; Xie, Zhang, et al., 2016). The manager replies should not follow the general message; they openly discuss their efforts, increasing the CC and CS (Proserpio & Zervas, 2017). They need to thank the customers for their attempt in writing messages rather than apologizing to create confidence in purchase decisions (You et al., 2020). The recency and message content are also important. The majority of consumers read the text messages before purchasing any products (Xie, Zhang, et al., 2016).

This study used text reviews and identified CS & CC factors in three hotels. Customers express their positive and negative feelings on the web. Managers do not control this information, which is wealthy compared to survey data (Guo et al., 2017). Managers can use this information, appreciate their employees for positive reviews, and develop a strategy plan to improve weak spots (Tax et al., 1998). The attributes and importance ranks were different for the three hotels. Each hotel has unique CS and CC factors. Managers need to segment the hotels and plan the service offerings. Many CS factors were general, such as décor, location, physical surroundings, rooms, food, restaurants, staff, etc. The CC factors were specific, such as staff behavior, noise, food service & quality, refunds, hygiene, bathroom, noise, etc. According to Herzberg two factor theory, motivation, and hygiene factors lead to CS and CC (Chitiris & Journal, 1988; Herzberg, 2017). Customers praised hotel décor, ambiance, physical surroundings, and core services for luxury hotels and heritage hotels.

Many compliments attribute are about hygiene attributes: food, staff, room-related attributes. Failure to provide these attributes leads to dissatisfaction. Décor, physical surroundings, location, hotel ambiance & beauty were motivational factors. Failure to provide these factors does not lead to dissatisfaction; customers are delighted if appropriately delivered. Customers complained about mechanic, operational, and humanic clues. The mechanic clues were noise, music, cleanliness, hygiene, maintenance, etc. the humanic clues were front desk response, staff behavior, staff rudeness, staff responsiveness, etc. The Check-in process, refunds, reservations, billing, etc., are operational cues. Managers need to train the employees to deliver exceptional services. Need to teach professional skills, a positive mindset, some etiquette, and manners. Hotels need to invest in software for smooth operations. According to Hofstede's national culture index score, the power distance score is 77, individualism:48 (https://www.hofstede-insights.com/country-comparison/india/). The front desk staff may not have the power to make decisions; hotel managers need to train the employees to handle the complaints by providing some case studies.

Hotel managers should be active in third-party review websites. They should track the reviews to get the expectations and experiences of the consumers. Managers can understand the expectations and experiences of the customers to provide customized services.

5.7. Theoretical implication

Previous studies used online reviews to address various research questions, such as consumer behavior, prediction on hotel financial performance, trust, reasons to write and read reviews, and psychological perspectives. Extant studies used many methodologies to address the research question: sentiment analysis, topic modeling, frequency analysis, critical incident techniques, manual analysis, etc. This study tries to understand the antecedents of CS and CC. According to customer disconfirmation theory, customers express their satisfaction when perceived experience is higher than expected experience. This study contributes to previous studies about CS and CC in the hospitality and tourism industry. This study used big data and applied LDA to identify CS and CC factors. Results reveal that CS attributes are more general, whereas CC determinants were more specific. According to prospect theory, consumers are susceptible to failures compared to gains (Koc, 2019). Dissatisfied customers damage the brand image and reputations by writing lengthy reviews compared to satisfied customers. The determinants and importance ranking of CS and CC were different for different categories of the hotels. According to multi-attribute theory, customers prioritize the perceived attributes based on reviewer and hotel characteristics: purpose of travel, nationality, hotel type, and expertise. Consumers build some expectations based on prior experience, advertisements, eWOM, etc. Luxury hotel customers complained about star reference and value for money attributes. According to signaling theory, consumers look for some cues before booking the hotel stay: eWOM, WOM, star rating, etc. Luxury and heritage hotel customers pay premium pay compared to budget hotels. So, they expect premium services. Failure to meet these services leads to dissatisfaction. The attributes of CS & CC were different between hotels. The unique CS for heritage hotels were: heritage quality aspects, including royal stay, authentic stay, heritage tours, and authentic services. The exclusive

CS determinants for luxury hotels were: events arrangements, room view & size, and star reference. According to Herzberg two factor theory, the motivational factors do not lead to dissatisfaction when not provided. Customers express their displeasure when hygiene factors are not supplied. So, the service providers need to examine the CS & CC factors to offer delightful experiences (Chan & Baum, 2007). While the percentage of negative reviews was minimal, service providers need to apply recovery strategies to mitigate the brand reputation damage and brand image. According to Rawl's justice theory, service providers need to use differential recovery strategies to minimize service failures. Distributive justice, procedural justice, and interactional justice are part of the justice theory (Rawls, 1971). The purpose of attributes is that distributive justice can apply when a customer mentions financial loss; procedural justice can improve operational efficiency, and interactional justice can improve staff performance. For example, if a customer mentions about staff attitude and professionalism, the service operator can apologize to the customers and train the employees.

5.8. Limitations & future research

Although this study used big data and applied advanced text mining techniques to extract the CS & CC dimensions, it is vital to emphasize some shortcomings. First, the data was collected from one data source TripAdvisor, and future studies can collect data from different data sources. Second, this study does not consider the reviewer profiles, such as nationality, expertise, travel types, and gender. According to Hofstede's national cultural dimensions, the reviewer or travel cultural dimensions impact the service evaluation process. Their expectations and experiences may differ based on reviewer characteristics. Third, this study divided the reviews into positive and negative reviews based on online ratings. Still, some satisfied customers may share the negative information, and dissatisfied customers may share the positive information (B. Kim et al., 2016). Fourth, while TripAdvisor has a robust scrutiny system to screen the biased or fraud reviews, we did not consider the bandwagon or social influence bias on subsequent reviews. Fifth, this study did not consider the hotel's geographic location, such as metro and non-metro cities. Sixth, this study used the LDA algorithm to extract the dimensions, the labeling of topics done manually with the help of four research scholars to eliminate the subjective bias. Seventh, this study does not consider the chain affiliation, brand reputation. Future studies can divide the hotels into a chain and non-chain hotels and identify the determinants separately. Eight, manager replies to reviews impact the customer impression on hotels and create the trust towards service quality. Future studies can examine the manager's efforts on the service failure-recovery process.

5.9. Conclusion

The study identified the determinants of CS and CC towards different types of hotels, such as luxury hotels, heritage hotels, and budget hotels. This study used text reviews retrieved from TripAdvisor.com to extract the hidden dimensions. The topic modeling technique was applied using a latent Dirichlet allocation algorithm and extracted CS & CC dimensions. Results demonstrate that the determinants of CS and CC were different towards three types of hotels (luxury, heritage, and budget hotels). The importance ranking of attributes was different based on the type of hotel. The study findings provide clear theoretical and managerial implications. This study used big data to infer the dimensions of CS & CC and used advanced text mining techniques. Earlier studies used survey data to test the association between service quality attributes on CS and behavior intentions. Unlike survey data, online reviews provide the latest and reliable information. The determinants can be used to develop a conceptual model.

Furthermore, CC factors need to receive more consideration because these reviews may damage the brand image and reputation of the hotels.

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Annexure:

Table A 1 Customer satisfaction Dimensions: All hotels

Factor	Terms	Gamma
Bathroom	clean,spacious,comfortable,neat,bathroom,modern,amenity,maintain,size,appoint,tidy,equip,comfy,cozy,shower,bath,water	77184
friendly staff	staff,friendly,helpful,courteous,extremely,attentive,professional,hospitable,polite,efficient	67540
stafff professionalism	staff,helpful,friendly,courteous,polite,cooperative,extremely,supportive,humble,professional	58565
food ambience	food,quality,service,awesome,ambience,excellent,taste,ambiance,superb,improve,cleanliness	53020
positive eWOM	stay,comfortable,pleasant,recommend,night,highly,enjoy,enjoyable,memorable,strongly	52800
hospitality	excellent,service,food,hospitality,ambience,facility,people,dine,town,round,resturant,hygiene,	48144
food taste	food,restaurant,delicious,tasty,serve,meal,yummy,variety,dish,prepare,taste,local,fresh,authentic	47113
service excellence	service,excellent,provide,outstanding,exceptional,prompt,customer,house,level,impeccable,impress,extraordinary	47082
celebrations	feel,warm,birthday,home,smile,greet,happy,upgrade,lounge,surprise,celebrate	45611
Lobby Ambience	visit,enjoy,family,time,love,friend,spend,vacation,awesome,happy,live,recommend,music	42182
amenities	nice,pool,swim,restaurant,facility,clean,activity,people,roof,cozy,lobby,ambience	40404
Value for money	star,luxury,money,facility,worth,price,decent,pretty,class,comfort,offer,standard,amenity,bite	37860
food variety	breakfast,buffet,dinner,spread,variety,option,lunch,include,morning,menu,complimentary,dine	37068
ambience and décor	property,beautiful,maintain,nicely,luxurious,lovely,charm,lobby,grand,huge,modern,interior,design	36666
Location	location,locate,airport,convenient,close,easy,shop,free,main,heart,road,walk	34232
events	staff,guest,team,care,hospitality,meet,banquet,support,event,management	23360

staff service appreciation	staff,check,front,helpful,reception,desk,quick,fast,office,smile,efficient,warm,smooth,ready,security	21980
travel type	stay,business,trip,perfect,visit,travel,week,bangalore,night,short,leisure,review	15540
Tourism attractions	view,beautiful,lovely,beach,relax,property,peaceful,garden,location,calm,perfect,lake,quiet,nature,environment	13000

Table A 2 Customer dissatisfaction Dimensions: All hotels

Factor	**Terms**	**Gamma**
Bathroom	Bathroom,dirty,clean,water,shower,toilet,light,break,towel,door,properly,bath,wall,carpet	68068
Food variety	Food,breakfast,restaurant,buffet,limit,option,serve,dinner,lunch,taste,menu,spread,dine,variety	53253
Smell and hygiene	Smell,floor,noise,noisy,enter,smoke,sleep,inside,hear,loud,change	46660
Overall experince	Experience,stay,terrible,horrible,recommend,start,visit,avoid,pathetic,time	46260
Value for money	Disappoint,time,stay,expect,didn,standard,disappointment,expectation,visit,wasn,brand,property	45518
Service issues	Service,poor,pathetic,slow,food,customer,quality,restaurant,maintenance,extremely,level,	42744
Amenities	Pool,nice,view,beach,swim,property,beautiful,location,lovely,	37457
Traffic and location	Location,airport,road,close,locate,walk,traffic,main,difficult,drive,crowd,busy,pick,taxi	36276
Staff professionaliosm	Staff,reception,rude,friendly,trouble,guest,helpful,train,unprofessional,extremely,management	30900
Check in and arrival	Check,time,late,hour,arrive,wait,morning,flight,reach,delay,leave	24132
Internet	Wifi,provide,expensive,offer,lack,charge,drink,cold,facility,basic,free,internet	19992
Billing and front desk	Book,front,desk,call,office,wrong,reception,travel,reservation,request,bill,card,mistake,cancel,	13544
Over charge	Property,star,price,money,worth,maintain,rate,average,overpriced,compare,poorly,facility,manage,standard,expensive	8078

Table A 3 Determinants of customer satisfaction-Heritage

Factor	Terms	Gamma
Staff professionalism	staff,amaze,care,visit,stay,book,star,helpful,trip,experience,short,leave,clean	60
staff helpfulness	staff,recommend,helpful,highly,excellent,extremely,friendly,stay,fabulous,meal,polite,courteous	528
tourist attraction	nice,excellent,food,service,stay,time,quality,outstanding,location,provide,surround,enjoy,ambiance	148
service aprreciation	wonderful,stay,check,memorable,home,front,facility,staff,moment,arrive,fantastic	240
celebrations	night,suite,spacious,detail,beautiful,luxury,attention,extra,amaze,cake,wife,meet,anniversary	350
bathroom	lovely,walk,restaurant,bathroom,dine,absolutely,minute,fantastic,include,shower,shop,staff,close,	384
food taste	food,staff,stay,friendly,comfortable,clean,delicious,relax,enjoy,spacious,pleasant,restaurant	576
dine-in	restaurant,breakfast,price,pool,stay,drink,menu,dinner,serve,bite,couple,floor,style	245
Location & ambience	pool,beautiful,garden,view,fort,location,swim,table,love,charm,balcony	455
heritage décor and ambience	property,heritage,maintain,breakfast,buffet,feel,restaurant,house,stay,locate,food,beautiful	177
Nature tour	spend,night,lake,beach,view,relax,book,amaze,bird,private,villa,boat	172
royal stay	special,feel,experience,hospitality,team,care,family,smile,ensure,treat,warm,entire,request,guest	826
heritage tour	tour,offer,return,history,hour,beautifully,local,time,ground,build,perfect,amenity	430
cultural shows	dinner,experience,beautiful,live,peacock,morning,restaurant,traditional,music,dance,rajasthani,rambagh	484

Table A 4 Determinants of customer dissatisfaction- Heritage

Factor	Terms	Gamma
food service and	food,service,poor,quality,heritage,standard,star,restaurant	140

quality		
food price and service	visit,lunch,fort,money,recommend,experience,worth,waste,buffet,food,charge	213
restaurant	restaurant,serve,dinner,table,drink,menu,meal,buffet,food,dine,waiter,dish,time,coffee,wait	320
amenities	pool,view,nice,price,restaurant,recommend,lake,swim,breakfast,tire,clean,enjoy,front	312
refunds and bookings	book,time,call,card,check,website,reservation,receive,email,credit	308
food service	water,staff,breakfast,cold,clean,bottle,wifi,bathroom,leave,heat,shower,poor	480
front desk response	stay,reception,hour,didnt,service,leave,arrive,half,late,time,call,couldnt,staff,wait,expensive	477
noise	night,stay,staff,noise,complain,sleep,move,loud,morning,music,hear,noisy	370
front desk & check-inn	time,provide,request,front,desk,experience,guest,person,family	396
over price	charge,price,check,bill,rate,cost,rupee,money,issue,people,amount,feel,expensive,checkout	408
bathroom and Hygiene	bathroom,floor,window,dirty,door,garden,light,shower,wall,mosquito,toilet	845
check-inn	stay,book,night,suite,travel,change,house,offer,friend,couple,double,date,refuse,heritage	406
staff attitude	staff,management,experience,hospitality,people,rude,attitude,call,guest,owner,terrible	540

Table A 5 Determinants of customer satisfaction: Luxury hotels

Factor	**Terms**	**Gamma**
Restaurant service and ambience	Service, excellent, food, provide, quality, customer, experience, cafe, staff, facility, outstanding,	975
Food quality and taste	Nice,food,stay,staff,enjoy,family,awesome,recommend,clean,visit,friend,friendly,helpful,tasty	1491
Food variety	Food,restaurant,buffet,dinner,breakfast,chef,serve,taste,dish,variety,enjoy	1584

Staff professionalism	Stay,staff,clean,excellent,helpful,comfortable,friendly,extremely,reception,pleasant,courteous	831
Staff response	Service,staff,feel,home,lounge,stay,club,star,restaurant,warm,attention,exceptional,special,friendly	1914
Location	Location,breakfast,airport,locate,business,restaurant,facility,close,trip,shop,comfortable,clean	2270
Hotel ambience	Visit,amaze,food,hospitality,love,experience,staff,awesome,ambience,time,super,serve,delicious,friend,ambiance	2088
Hotel décor and beauty	Experience,feel,beautiful,moment,treat,world,luxury,suite,lake,guest,magnificent,step,real,ground,life	2054
Physical surroundings	Property,amaze,relax,enjoy,family,activity,beautiful,nature,perfect,food,maintain	2828
Meetings arrangement	Team,front,guest,desk,meet,housekeeping,event,people,office,smile,hospitality,care,chef,banquet,conference	2655
Front desk and check inn	Check,night,book,leave,time,wait,breakfast,late,arrival,hour	1392
Room view	Pool,view,lovely,swim,huge,garden,include,luxury,restaurant,bathroom	1170
Celebrations and chef interaction	Special,experience,chef,memorable,team,care,mention,family,birthday,cake,stay,wonderful,surprise	213
Recommend or positive word of mouth	Stay,staff,recommend,highly,night,wonderful,amaze,beautiful,lovely,fantastic,helpful,attentive,absolutely	476
Brand image	Stay,time,mumbai,wonderful,perfect,travel,business,people,care,world,service,class,sofitel,touch	684

Table A 6 Determinants of customers dissatisfaction: Luxury hotels

Factor	**Terms**	**Gamma**

Bathroom	Dirty,bathroom,star,shower,smell,floor,clean,change,smoke,water,light,toilet	3549
Billings & refund	Book,charge,card,bill,reservation,money,stay,travel,email,amount,credit,refund,cancel,issue	3090
Overcharge	Stay,night,book,breakfast,charge,price,offer,extra,trip,free	1566
Brand image	Property,star,stay,experience,money,staff,novotel,pathetic,waste,brand,worth	2316
Front desk response	Call,front,desk,check,time,phone,speak,office,duty,didn,person,answer,talk,wait,numb	704
Staff attitude	Staff,rude,experience,horrible,hospitality,visit,attitude,unprofessional,recommend,reception	1200
Food service and hygiene	Water,service,coffee,breakfast,staff,stay,clean,time,housekeeping,cold,glass,bottl	1140
Restaurant	Food,restaurant,serve,table,dinner,buffet,lunch,menu,taste,breakfast,drink,waiter	1834
Checkin and pick up and drop	Check,hour,time,reception,wait,minute,ready,arrive,leave,didn,airport,late	1770
Noise	Stay,night,sleep,experience,complain,party,morning,noise,door,floor,management,music,loud,hear,terrible	1892
Events	Guest,event,people,meet,business,management,security,enter,team	308
Overall experience	Service,poor,food,customer,terrible,quality,experience,horrible,pathetic,location,recommend,standard,disappoint	300
Bad experience	Time,request,call,check,change,experience,visit,family,book,disappoint,pathetic,friend,inform	1192
Tourist attractions & location	Pool,stay,staff,review,nice,view,feel,close,restaurant,walk,swim,trip,food,beach,write,beautiful,friendly	2170

Table A 7 Determinants of customer satisfaction: budget hotels

Factor	**Terms**	**Gamma**

food quality and taste	food,service,excellent,restaurant,visit,awesome,quality,chef,special,delicious,table,ambience,dine,friend	106
dine in	breakfast,restaurant,buffet,offer,modern,amenity,bathroom,locate,beautiful,luxury,excellent	252
friendly staff	nice,helpful,staff,friendly,comfortable,heritage,beautiful,panjim,clean,charm,feel,lovely	376
pick up and drop	airport,night,close,stay,clean,flight,comfortable,hour,morning,dinner,arrange	280
positive WOM	staff,recommend,highly,check,front,stay,desk,travel,beautiful,price,excellent,wife,trip	222
location and physical attraction	property,location,pool,enjoy,visit,view,maintain,beach,staff,relax,serve,spacious,swim	144
physical attractions	boat,trip,river,location,ganges,people,food,perfect,restaurant,live	31

Table A 8 Determinants of customer dissatisfaction: budget hotels

Factor	**Terms**	**Gamma**
check in and bookings	staff,front,service,call,check,desk,guest,property,lounge,request,phone,person,airport,reservation	336
food taste and price	food,price,service,poor,star,quality,location,average,visit,breakfast,beach,walk,restaurant	108
dine in	food,property,experience,staff,service,serve,buffet,restaurant,dinner,option,beautiful,meal,stay,comfortable	259
billings	charge,check,time,provide,bill,card,family,leave,money,extra,rate,include,credit,standard,rupee	243

pick up and drop	airport,breakfast,trip,floor,review,taxi,staff,close,noise,choose,recommend,clean,road,late,driver	200
bookings	book,stay,experience,travel,pool,heritage,spend,cost,didn,suite,website,reception,change,manage	190
bathroom	bathroom,water,clean,dirty,shower,toilet,towel,avoid,reception,sheet,stain,maintain,terrible,door	141
staff attitude	staff,guest,time,call,service,money,people,rude,expect,disappoint,poor,start,customer,care,recommend,attitude	41

Table A 9 Descriptive statistics by rating wise: All hotels

Rating	Mean review length	Mean Sentiment	Total number of reviews	Percentage	Number of replies	Response Ratio	Number of reviews from mobile phones	Percentage
1	184.76	-0.09	8553	2.69	6808	0.8	4739	0.55
2	174.6	-0.02	7556	2.37	6327	0.84	3285	0.43
3	168.49	0.14	20370	6.4	17402	0.85	7853	0.39
4	127.23	0.38	67151	21.08	59538	0.89	25085	0.37
5	126.76	0.46	214897	67.47	198673	0.92	113428	0.53
Total	123.07	0.39	318527	100	288748	0.91	154390	0.48

Bag of words method:

Figure A 1 Customer satisfaction Word cloud- All hotels

Figure A 2 Customer dissatisfaction Unigram All hotels

however
breakfast
much
service
need
work
make
small
check
great
give
just
book
come
good
pool
poor
business
night
visit
nice
first
place
area
issue
time
also
never
feel
reception
room
restaurant
trip
bite
staff
location
stay
star
thing
take
disappoint
look
really
even
like
little
experience
food
property
bathroom

Figure A 3 Bigrams Customer satisfaction: All hotels

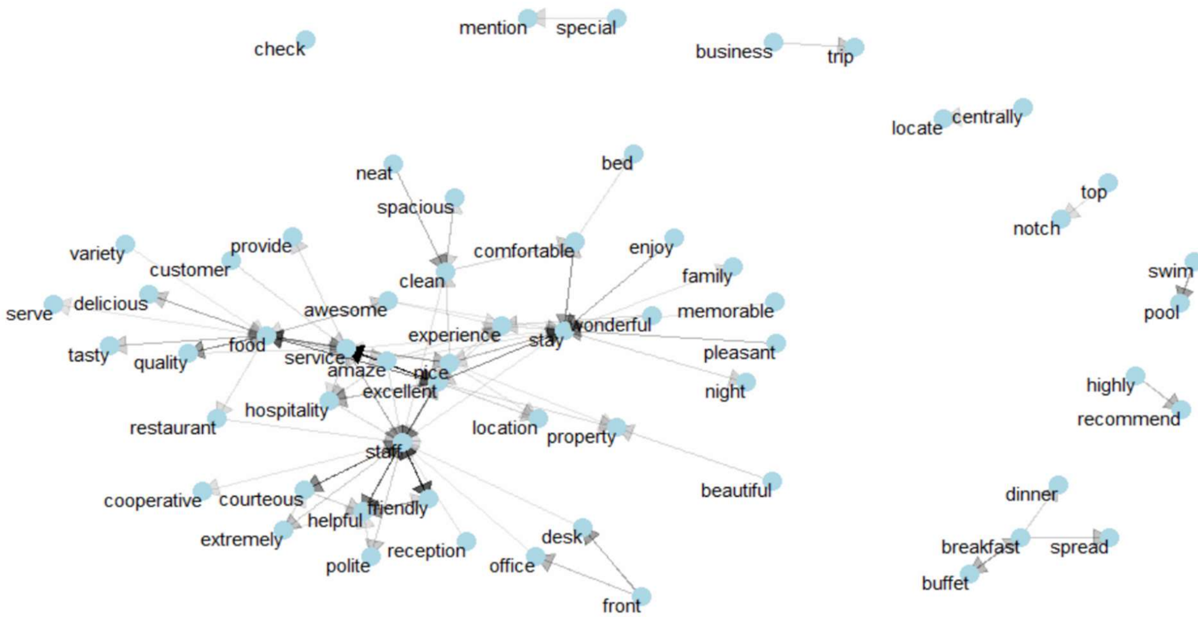


Figure A 4 Image Bigrams Customer Dissatisfaction: All hotels

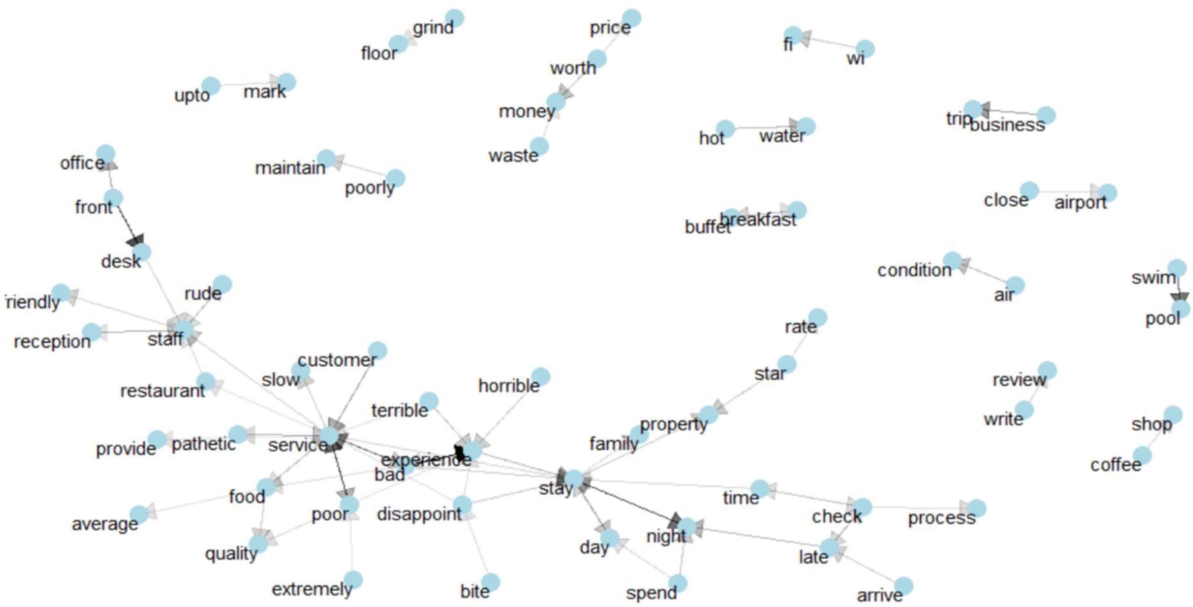


Figure A 5 Trigram Customer satisfaction: All hotels

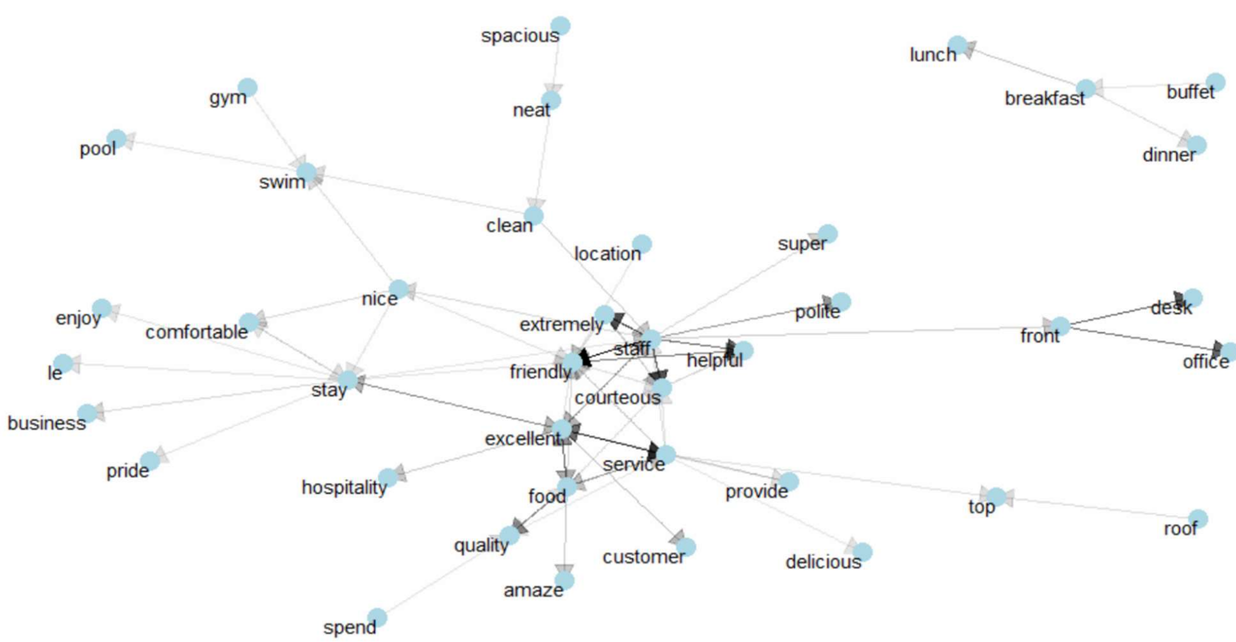
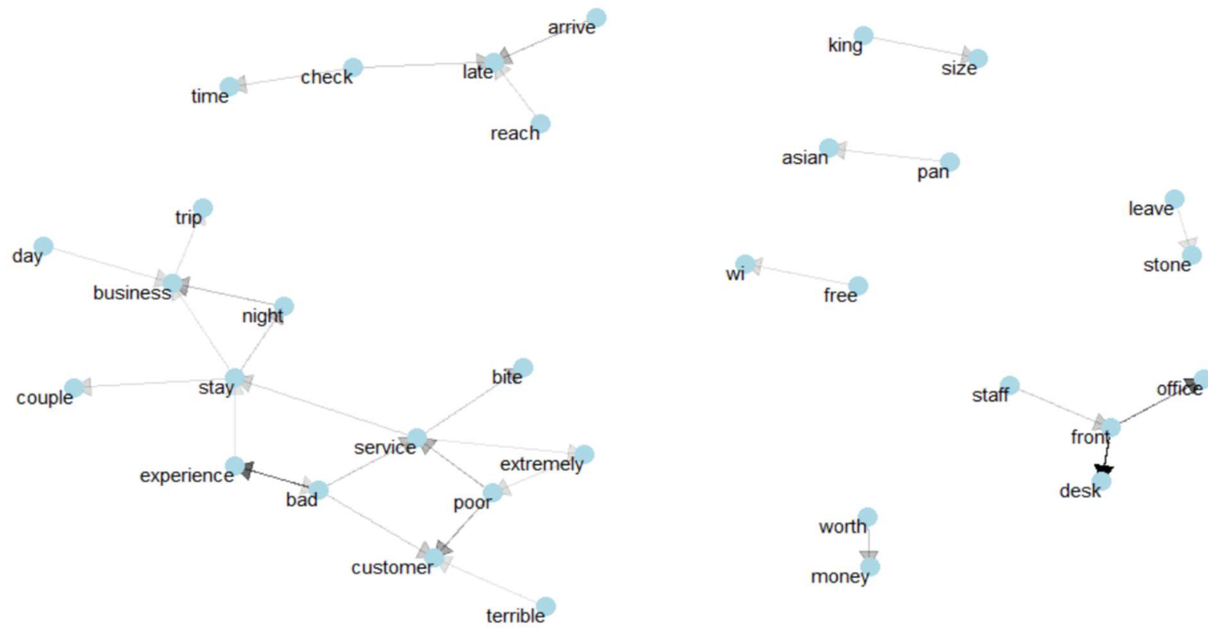


Figure A 6 Trigrams Customer dissatisfaction: All hotels



Feature extraction:

Table A 10 CS& CC factors for all hotels:

Rank	Latent factor	Number of documents	Sub dimensions
	Customer satisfaction factors		
1	Staff attitude and professionalism	148085	Friendly staff (67540), professional staff (58565), staff responsiveness (21980)
2	Overall experience and recommendation	148026	Positive eWOM, service excellence, service appreciation
3	Food related attributes	137201	Food ambience (53020), food taste and quality (47113), food variety (37068)
4	Room related attributes	77184	Bathroom
5	Location	47232	Location (34232), tourists' attractions (13000)
6	Celebrations	45611	
7	Lobby ambience	42182	
8	Amenities	40404	

9	Value for money	37860	
10	Ambience and décor	36666	
11	Events	23360	
	Customer dissatisfaction factors		
1	Overall Negative experience & eWOM	89004	Overall experience, service issues
2	Room related attributes	68068	Bathroom
3	Value for money	67140	Brand image or expectations (45518), billing and front desk (13544), over charge (8078)
4	Amenities	57449	Amenities(37457), internet(19992)
5	Food related attributes	53253	Food variety
6	Smell and hygiene	46660	
7	Location	36276	Traffic and location
8	Staff related attributes	30900	Staff professionalism
9	Check in and arrival	24132	

Number of topics using perplexity score:

Figure A 7 Trail 1: Customer satisfaction

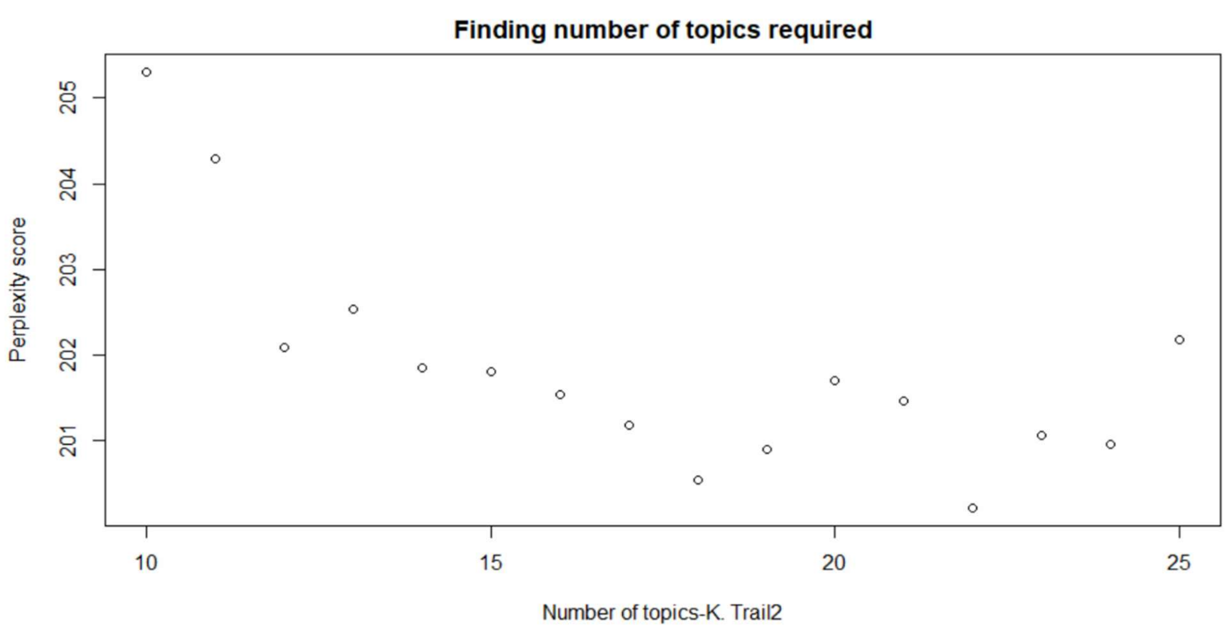
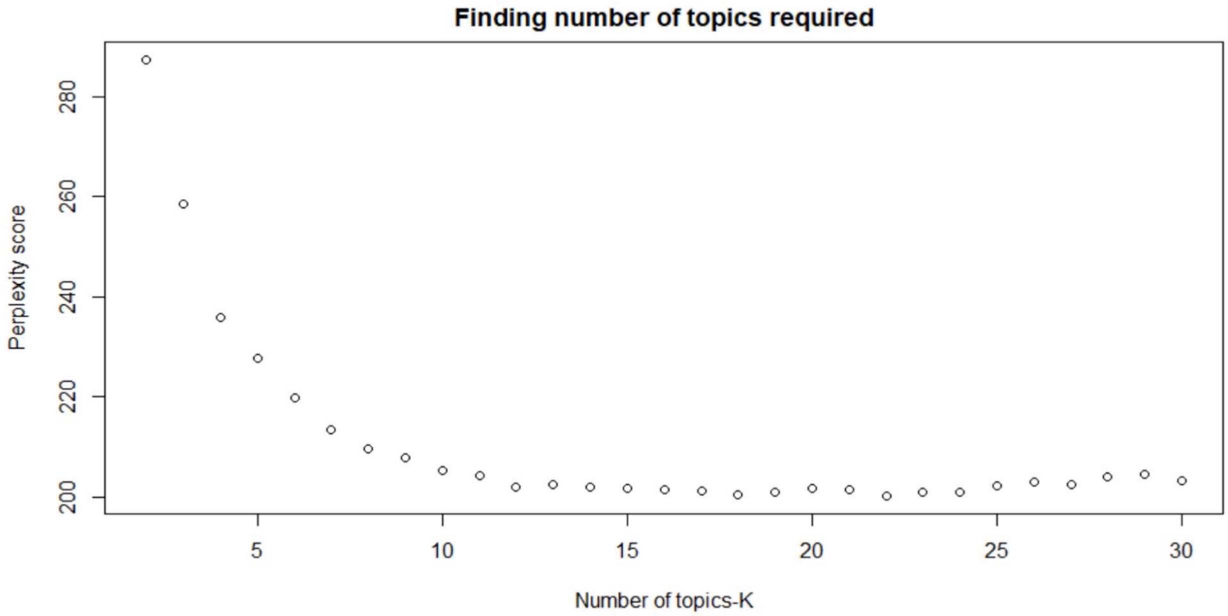


Figure A 8 Trail 2: Customer satisfaction



Heritage hotels:

__Figure A 9 Positive word cloud: Heritage hotels__

Figure A 10 Positive bigrams: Heritage hotels

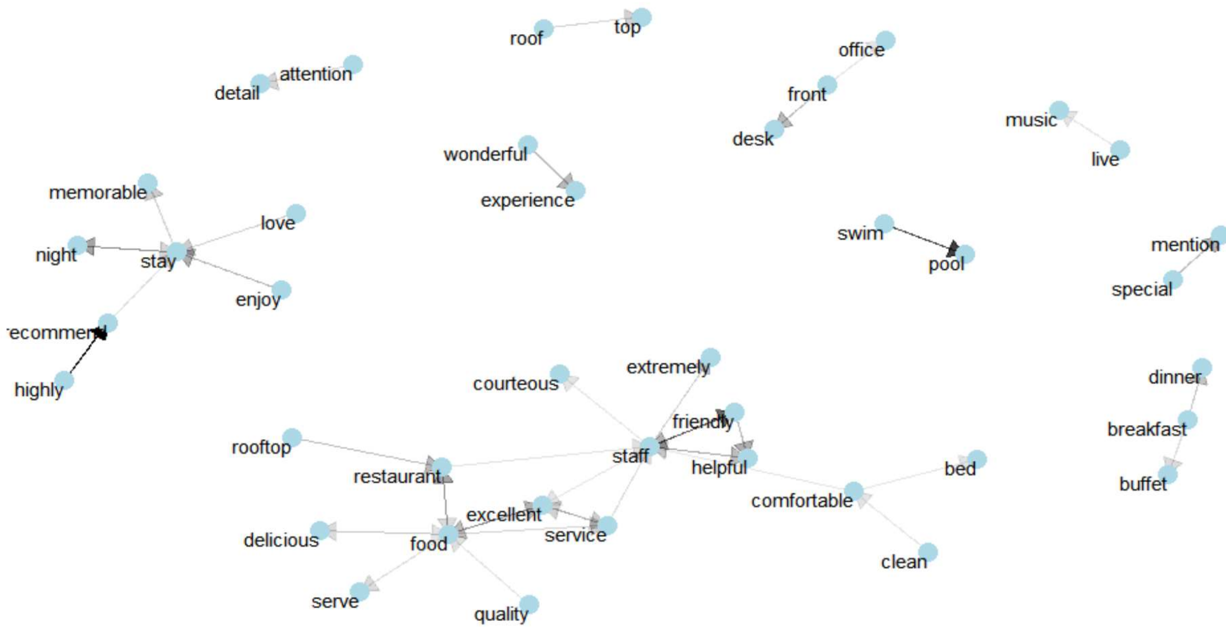
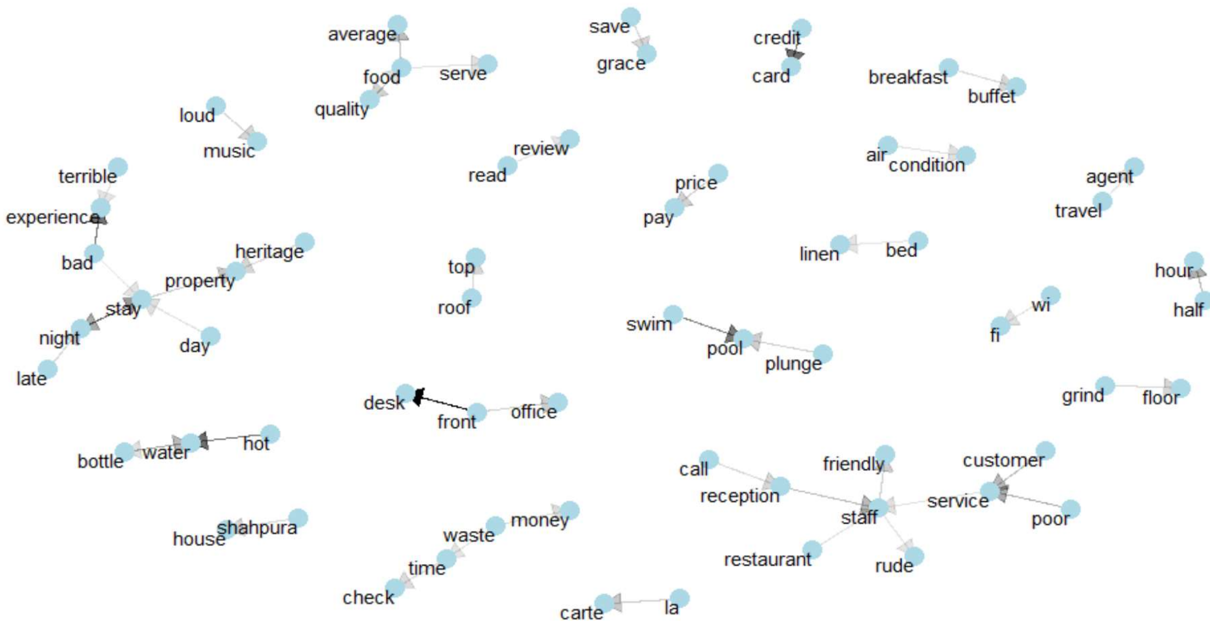


Figure A 11 Negative Word Cloud: Heritage hotels

Figure A 12 Negative Bigram: Heritage hotels



Luxury hotels:

Figure A 13 Positive word cloud: Luxury hotels

Figure A 14 Positive bigrams: Luxury hotels

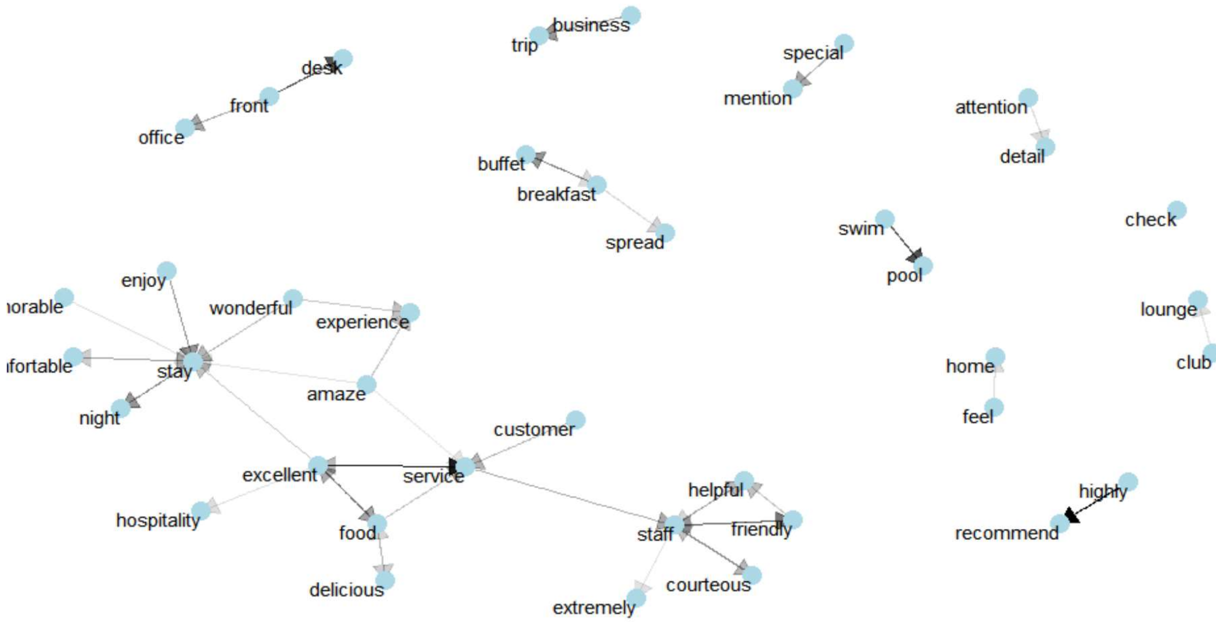
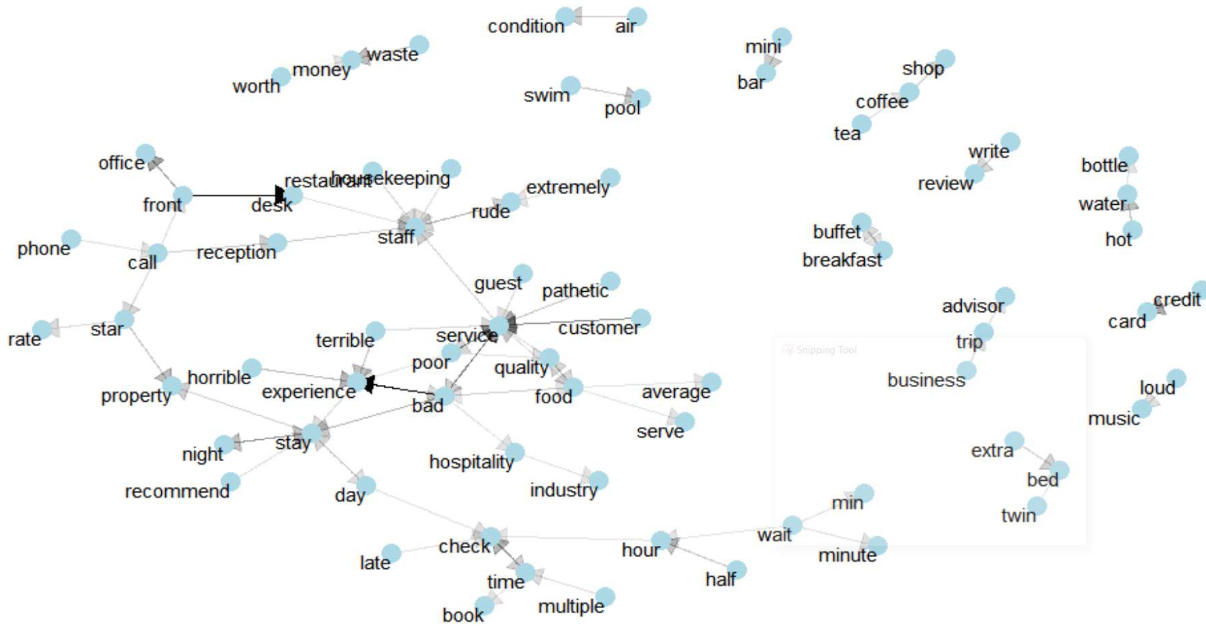


Figure A 15 Negative word cloud: Luxury hotels

Figure A 16 Negative bigrams: luxury hotels



Budget Hotels:

Figure A 17 Positive word cloud: Budget hotels

Figure A 18 Positive Bigrams: Budget hotels

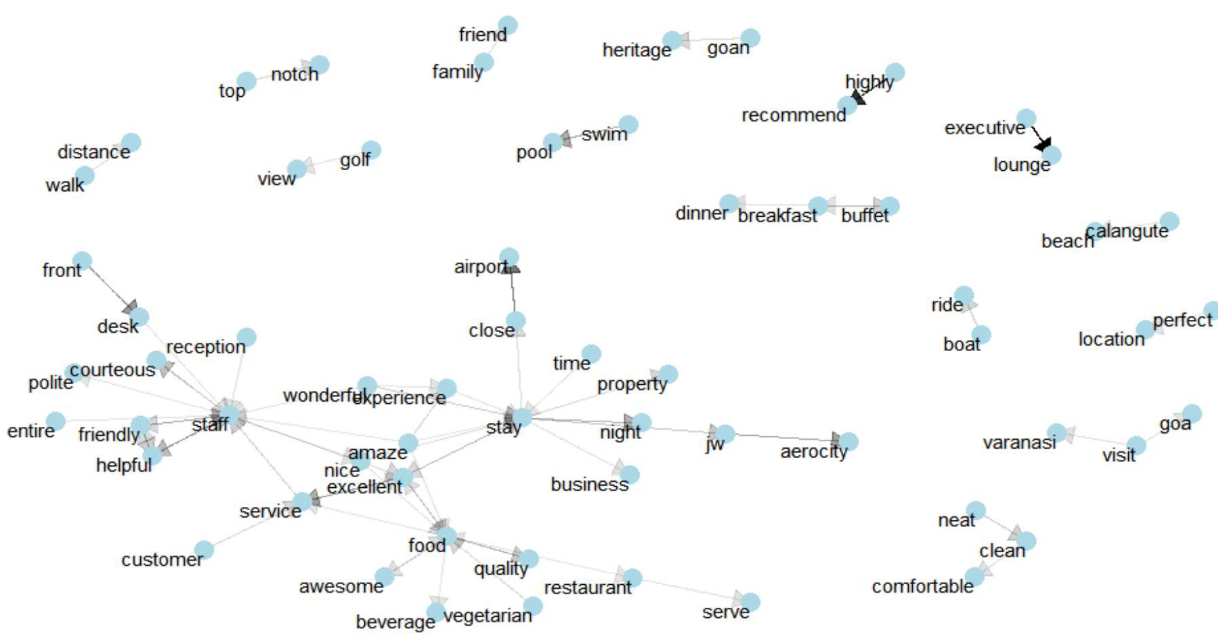
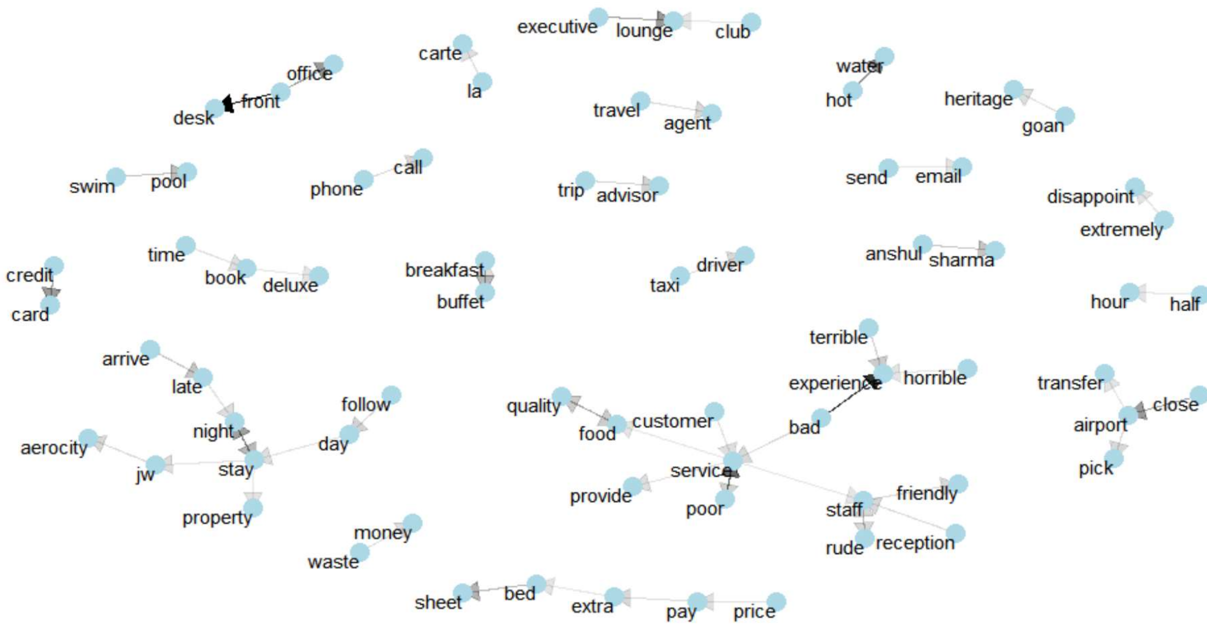


Figure A 19 Negative word cloud: Budget hotels

Figure A 20 Negative Bigram: Budget hotels



Course Work results:

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REG.NO : 16MBPH13 SEMESTER : 1

EXAMINATION : Ph.D. / Management Studies

MONTH AND YEAR : Nov 2017

NAME OF THE STUDENT : VINAY CH

FATHER'S NAME : VENKANNA/LAKSHMI

COURSE NO.	TITLE OF THE COURSE	CREDITS	RESULTS
BA802	Statistics for Business Analytics	3.00	PASS
BA803	Quality Measurement and Quality Systems	3.00	PASS
BA805	Service Operations Management	3.00	PASS
	** END OF STATEMENT **		

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SECTION OFFICER

EXAMINATIONS

Date of Issue : 5/1/2018

UNIVERSITY OF HYDERABAD
NOTIFICATION OF RESULTS

Course: Ph.D.
Subject: M.B.A.

Month & Year: April'2017
Semester: I

Sl. No	Regn.No.	Name of the Student	Course No. Credits 4	Course No. Credits 4	Course No. Credits 4	Course No. Credits 4	Course No. Credits 4	Course No. Credits 4	Course No. Credits 4
			EG-825	BA- 872	Core Course	Seminar Course	BA-574	Course Work	Course Work
1	13MBPH05	A.Rohit Kumar	-	-	-	-	PASS	-	-
2	14MBPH03	Raja Debashis	-	-	-	-	PASS	-	-
3	14MBPH04	Kanika Sharma	-	-	-	-	PASS	-	-
4	14MBPH06	Ishfaq Hussain Bhat	-	-	-	-	PASS	-	-
5	15MBPH05	B.Ashish		-	-	-	-	PASS	Pass
6	15MBPH06	Bramhani	PASS	-	PASS	-	-	-	-
7	16MBPH01	Mohan Venkatesh Palani	PASS	-	PASS	-	-	-	-
8	16MBPH02	Moturi Sairam	PASS	-	PASS	-	-	-	-
9	16MBPH03	Om Naraian Srivastava	-	-	AB	-	-	-	-
10	16MBPH04	Parmeshwari	-	-	AB	-	-	-	-
11	16MBPH05	Rejendra Mahanandia	PASS	PASS	PASS	-	-	-	-
12	16MBPH06	Ram Kumar R	-	-	AB	-	-	-	-
13	16MBPH07	Rhulia Nukhu	PASS	-	PASS	-	-	-	-

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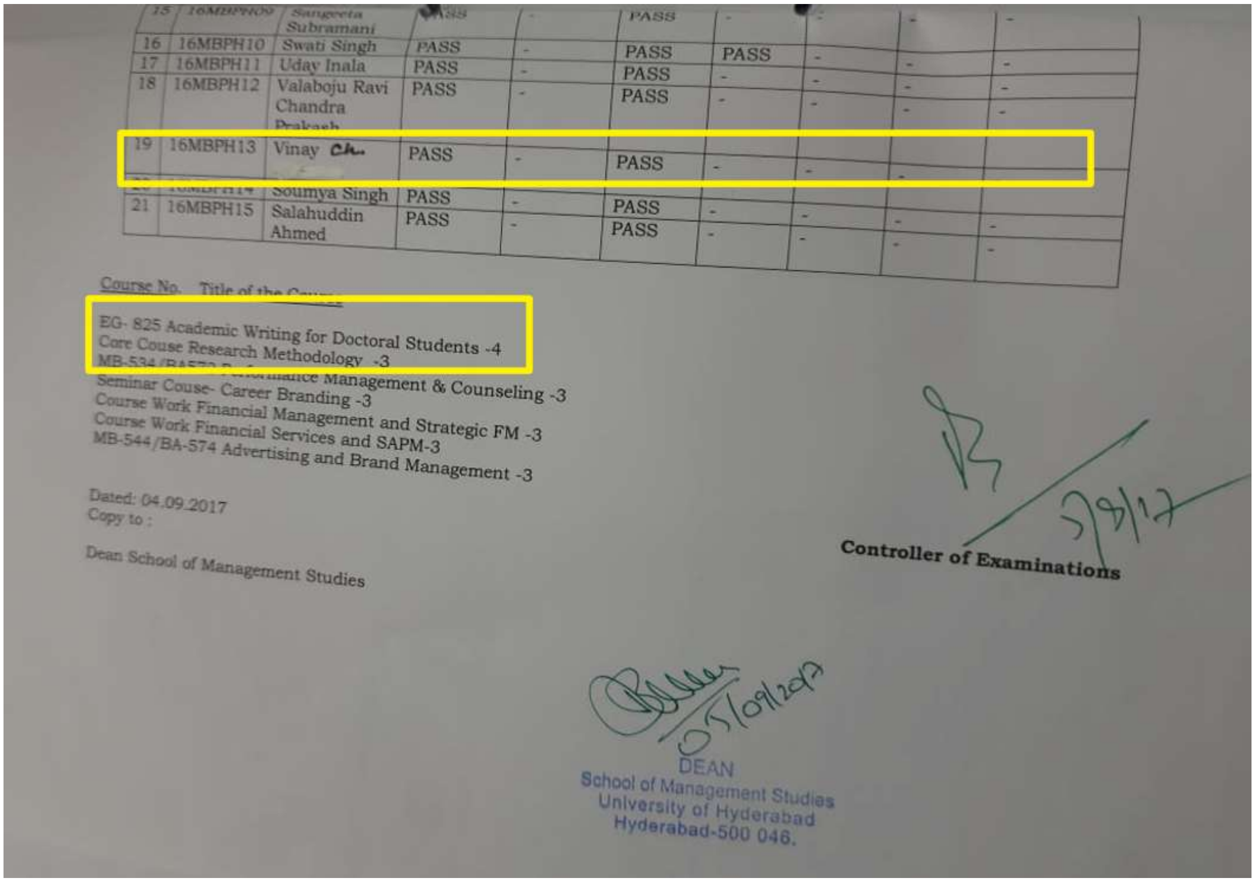

15	16MBPH09	Sangeeta Subramani	PASS	-	PASS	-	-	-	-
16	16MBPH10	Swati Singh	PASS	-	PASS	PASS	-	-	-
17	16MBPH11	Uday Inala	PASS	-	PASS	-	-	-	-
18	16MBPH12	Valaboju Ravi Chandra Prakash	PASS	-	PASS	-	-	-	-
19	16MBPH13	Vinay Ch.	PASS	-	PASS	-	-	-	
20	16MBPH14	Soumya Singh	PASS	-	PASS	-	-	-	-
21	16MBPH15	Salahuddin Ahmed	PASS	-	PASS	-	-	-	-

Course No. Title of the Course

EG- 825 Academic Writing for Doctoral Students -4
Core Couse Research Methodology -3
MB-534/BA572 Performance Management & Counseling -3
Seminar Couse- Career Branding -3
Course Work Financial Management and Strategic FM -3
Course Work Financial Services and SAPM-3
MB-544/BA-574 Advertising and Brand Management -3

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THE ANTECEDENTS OF CUSTOMERS' COMPLIMENTS AND COMPLAINTS TOWARDS DIFFERENT CATEGORIES OF HOTELS IN INDIA: MINING MEANING FROM BIG DATA USING LATENT DIRICHLET ALLOCATION

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Published papers:

Heritage hotels and customer experience: a text mining analysis of online reviews

Authors	Vinay Chittiprolu, Nagaraj Samala, Raja Shekhar Bellamkonda
Publication date	2021/3/5
Journal	International Journal of Culture, Tourism and Hospitality Research
Publisher	Emerald Publishing Limited

Description

Purpose

In business, online reviews have an economic impact on firm performance. Customers' data in the form of online reviews was used to understand the appreciation and service complaints written by previous customers. The study is an analysis of the online reviews written by the customers about Indian heritage hotels. This study aims to understand the dimensions of service appreciation and service complaints by comparing positive- and negative-rated reviews and find the patterns in the determinants of the satisfaction and dissatisfaction of the customers.

Design/methodology/approach

A total of 23,643 online reviews about heritage hotels were collected from the TripAdvisor website by using a Web crawler developed in Python. A total of 1000 reviews were randomly selected for further analysis to eliminate the bandwagon effect. Unsupervised text mining techniques were used to analyze reviews and find out …

Scholar articles

Heritage hotels and customer experience: a text mining analysis of online reviews
V Chittiprolu, N Samala, RS Bellamkonda - International Journal of Culture, Tourism and …, 2021
Related articles

A text mining analysis of online reviews of Indian hotel employees

Authors	Vinay Chittiprolu, Swati Singh, Raja Shekhar Bellamkonda, Sita Vanka
Publication date	2020/12/13
Journal	Anatolia
Pages	1-14
Publisher	Routledge
Description	Based on the premise of *Market-focused Human Resource Management* we propose that organizations should attend to employee voice. To this end, online reviews have emerged as a significant source of key information. We performed our analysis on (n = 2751) Glassdoor reviews of 22 hotel chains in India. We employed text mining tools to identify determinants of employee motivation and dissatisfaction. Organizational culture, career growth opportunities, and flexibility-motivated employees. Poor work–life balance, office politics, and high attrition rate de-incentivized employees. Further, the regression analysis of numerical ratings revealed that compensation and work–life balance are hygiene factors; career opportunities and cultural values emerged as dominant predictors of overall employee satisfaction. Practical, policy, and theoretical implications of these findings are discussed.
Scholar articles	A text mining analysis of online reviews of Indian hotel employees V Chittiprolu, S Singh, RS Bellamkonda, S Vanka - Anatolia, 2020 Related articles

DETERMINANTS OF AGRI-HOTEL CUSTOMERS'EXPERIENCE FROM THE PERSPECTIVE OF USER-GENERATED CONTENT: TEXT MINING ANALYSIS

Authors	Vinay Chittiprolu, Mohan Venkatesh Palani, DV Srinivas Kumar, V Venkata Ramana
Publication date	2020
Journal	Academy of Marketing Studies Journal
Volume	24
Issue	2
Pages	1-15
Publisher	Jordan Whitney Enterprises, Inc
Description	In the hospitality industry, majority of the guests depend upon online reviews while choosing the hotels due to intangible services and risks associated with them. So, it is necessary to analyze the online reviews to understand the level of customers' satisfaction and their experiences to improve the services. Moreover, consumer-generated reviews have an economic impact on the hospitality industry. The purpose of this paper is to identify the positive and negative determinants of agritourists' experience by using text mining analysis. A total of 2566 online reviews of agri-hotels reviews were collected from 16 agri-hotels in India, which are listed on tripadvisor. com by using web-crawler developed in Python and NVivo 12, qualitative analysis software, was used to identify the determinants of agritourists' experience. R Software was used to extract the technical features of user-generated content. The results of our …
Scholar articles	DETERMINANTS OF AGRI-HOTEL CUSTOMERS'EXPERIENCE FROM THE PERSPECTIVE OF USER-GENERATED CONTENT: TEXT MINING ANALYSIS V Chittiprolu, MV Palani, DVS Kumar, VV Ramana - Academy of Marketing Studies Journal, 2020 Related articles

What Made You Success: Text Mining Analysis of Trip Advisor Traveler Choice Hotel

Authors	Ch Vinay
Publication date	2019
Journal	Management Today
Volume	9
Issue	3
Pages	139-147
Publisher	Gokaraju Rangaraju Institute of Engineering and Technology
Description	Due to the availability of the reviews in review websites, customers have plenty of choices to proceed with booking. Hospitality industry introduced many innovative technologies to gain customer satisfaction and to do the easy of business. This paper tries to address the factors made to achieve customer loyalty and what made to win the Trip Advisor travelers choice award. We did the text mining analysis of the satisfied and dissatisfied customer reviews of the hotel. We performed frequency analysis, polarity analysis, sentiment analysis, and cluster analysis. The study finds that the positive sentiments are more than negative sentiments. By observing the polarity score, the negative sentiments are negligible by seeing the descriptive statistics, less than 3% of customers rated negatively. We performed sentiment analysis of the reviews by using QSR Nvivo 12 software. The positive sentiments are hotel a place of …
Scholar articles	What Made You Success: Text Mining Analysis of Trip Advisor Traveler Choice Hotel C Vinay - Management Today, 2019