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ONLINE REVIEWS CAN TELL US HOW THE EXPERIENCE OF THE GUEST WITH THE VIETNAMESE HOTEL

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Abstract: Online booking systems have transformed the travel industry by creating vast information platforms. These platforms enable customers to share their experiences, significantly influencing the destination choices of others. For hoteliers, this wealth of user-generated content is an invaluable resource, offering direct insight into the guest perspective. Consequently, analyzing this feedback has become essential for understanding and improving customer satisfaction. Although many studies have employed machine learning techniques to analyze sentiment in this data, these methods have overlooked the specific context of natural language, failing to capture the specific context and linguistic nuance embedded in customer reviews. This study aims to explore customer satisfaction with Vietnamese hotels using a mixed-methods approach. This approach combines linguistic rules, sentiment corpora, and the Python VADER library to mine the big data of customer reviews effectively. By combining algorithms and formulas, the research can measure guest satisfaction with specific aspects of the hotel. The data for this study were collected from TripAdvisor, and it is a large dataset of 32,447 individual reviews of over one thousand hotels in Vietnam. To achieve a high degree of detail, a granular 1–5 scoring scale was implemented, allowing for the classification of feedback into specific categories ranging from "strongly dissatisfied" to "strongly satisfied" for each distinct aspect of the hotel experience, such as service, staff, and cleanliness. The findings revealed an overall customer satisfaction rate with the hotel's quality at 84.3%. Interestingly, the highest satisfaction score for the "staff" aspect was slightly higher at 84.83%, highlighting a subtle discrepancy between general guest sentiment and their experiences with particular amenities or services. The results confirm that a linguistic rule-based method provides a more detailed and accurate understanding of customer satisfaction. This approach helps hotel management to understand and pinpoint specific operational areas that require improvement or reinforcement. It offers deeper insights into customer preferences and facilitates the creation of customer personas. In a highly competitive hospitality market, this study also provides a clear viewpoint for making targeted enhancements to gain a competitive edge.

Keywords: online reviews, Vietnamese hotel, guest experience, big data analysis, Python, linguistic rule

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INTRODUCTION

Customer experience (CX) has become a key competitive advantage in today's crowded marketplace. Delivering a positive experience not only builds customer loyalty but also contributes directly to business growth. Companies that prioritize CX often see higher customer satisfaction, increased retention, and a stronger brand image (Rahimian et al., 2021; Permatasari et al., 2025; Veloso & Gomez-Suarez, 2023; Altun et al., 2025; Chittiprolu et al., 2021). One of the touchpoints influencing CX is online reviews. Positive reviews can boost a company's credibility and attract new customers, while negative feedback offers valuable insights for improvement (Xu et al., 2025; Zhao et al., 2025). With the growing popularity of sharing experiences on social media and review platforms, customer voices now carry more weight than ever. When customers share positive experiences, it acts as organic, word-of-mouth marketing, helping businesses expand their reach and build trust with potential clients. On the other hand, negative reviews can damage a brand's reputation if not handled effectively (Xu et al., 2025). Some studies emphasized that leveraging online reviews, encouraging positive sharing, and implementing efficient online booking systems are key strategies to enhance CX. By focusing on these elements, businesses can build lasting relationships with their customers and drive long-term success (Sadiasa et al., 2025; Altun et al., 2025; Amoako et al., 2023).

Modern travelers are increasingly utilizing omnichannel approaches for journey planning, drawing from various information sources before making decisions (Mensah et al., 2025). Online reviews, especially from booking platforms, significantly influence their choices (Zheng et al., 2023; Nguyen & Nguyen, 2023; Alhassan, 2025). These reviews offer essential insights into service quality and whether accommodations adhere to international standards (Mensah et al., 2025; Kalnaovakul et al., 2025; Glaveli et al., 2023; Adiningtyas & Millanyani, 2024). Feedback from prior guests assists prospective visitors in evaluating destinations, services, and overall experiences (Glaveli et al., 2023; Chittiprolu et al., 2021; Tango et al., 2024). Consequently, platforms such as Agoda, Airbnb, Trip.com, and Tripadvisor have experienced remarkable global expansion, becoming essential tools in travel planning (Alhassan, 2025; Guttentag et al., 2025; Khorsand

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et al., 2020; Sadiasa et al., 2025). The tourism sector has become more digitally interconnected, with most businesses engaging in a global online ecosystem. This digital evolution has expanded the industry's reach and intensified international competition (Adiningtyas & Millanyani, 2024). In this rapid and interconnected landscape, providing exceptional customer experiences is essential. Companies that prioritize technology services are more likely to thrive in this competitive market, where travelers prioritize transparency, quality, and convenience throughout their journey (Amoako et al., 2023).

The global hotel industry is facing heightened competition, largely driven by the growth of online booking platforms (Alhassan, 2025; Cho et al., 2024). In this competitive environment, customer satisfaction has emerged as a key determinant of success. It directly influences customer loyalty, repeat business, brand reputation, and overall revenue generation (Cho et al., 2024; Glaveli et al., 2023). Given the industry's scale and diversity, numerous researchers have investigated customer satisfaction across hotels of various star ratings, particularly from 3-star to 5-star establishments (Adiningtyas & Millanyani, 2024; Kalnaovakul et al., 2025). In traditional approaches, hotels measure customer satisfaction through structured questionnaire surveys. While useful, this method has several limitations. Surveys typically yield a limited number of responses—often only a few hundred—and are restricted to predefined questions, which may not fully reflect the depth and variety of customer experiences (Rahimian et al., 2021). Recognizing these shortcomings, the hotel industry has turned to more dynamic data monitoring and control methods. One such approach involves analyzing online reviews posted by guests on platforms such as Tripadvisor and Agoda. These reviews offer a more spontaneous and authentic reflection of customer sentiment, providing valuable insights into satisfaction levels and areas for improvement (Bigne et al., 2023). This shift towards leveraging user-generated content has transformed how hotels evaluate performance and adapt to evolving customer expectations (Garner & Kim, 2022; Glaveli et al., 2023; Islam, 2025; Tango et al., 2024).

Vietnam is rapidly emerging as a premier tourism destination, celebrated for its vibrant cultural heritage and natural beauty (Nguyen & Nguyen, 2023; Nguyen et al., 2025; Le et al., 2025). The General Statistics Office of Vietnam (2024) reports that the country is expected to welcome 17.6 million international visitors in 2024, reflecting its growing appeal on the global stage. Vietnam offers a wide array of attractions, from the terraced rice fields of Sapa and the iconic limestone formations of Ha Long Bay to the dynamic urban life of Hanoi and Ho Chi Minh City. This diversity positions Vietnam as a versatile and desirable destination for a broad spectrum of travelers (Nguyen & Nguyen, 2023). Despite this strong potential, Vietnam's tourism industry faces significant competition, both globally and within Southeast Asia (Thuy et al., 2024). Internationally, it contends with neighboring countries like Thailand and Indonesia, while domestically, various regions compete to attract tourists by enhancing their unique cultural and natural assets (Thuy et al., 2024; Nguyen et al., 2025). In this increasingly competitive environment, delivering outstanding customer experiences has become essential (Thuy et al., 2024). Vietnam has to care for service quality that aligns with international standards. Providing memorable and consistent visitor experiences not only helps build a strong reputation but also encourages tourist loyalty and repeat visits. By focusing on customer satisfaction and continuously improving service offerings, Vietnam can strengthen its position as a leading tourism destination, appealing to both international travelers and its growing domestic tourism market (Thuy et al., 2024; Nguyen & Nguyen, 2023).

In recent years, there has been a growing body of research focusing on the analysis of customer review data, which has gained significant attention in the academic and business communities (Park et al., 2020; Shi et al., 2025; Yang et al., 2024; Zarezadeh et al., 2022). Customer reviews offer a rich and easily accessible resource for real-time data mining, reflecting the emotions and opinions of customers following their experiences with hotel services (Ahmad et al., 2025; Bigne et al., 2023; Davoodi et al., 2025; Moreno Brito et al., 2024). These reviews provide valuable insights into customer satisfaction and dissatisfaction (Derco & Tometzová, 2025; Li et al., 2020; Moreno Brito et al., 2024). However, when the volume of reviews grows significantly, traditional analysis methods become insufficient. To overcome this challenge, advanced techniques such as machine learning, artificial intelligence, and natural language processing have been employed (Özen & Özgül Katlav, 2023;). The insights gained from these advanced analyses are not only valuable for researchers but also highly beneficial for hotel managers, as they can be directly applied to enhance business operations (Permatasari et al., 2025; Thuy et al., 2024; Bigne et al., 2023). Despite the growing interest in this area, existing research rarely utilizes linguistic rules to thoroughly investigate the specific factors behind customer dissatisfaction in satisfaction ratings (Lee et al., 2025; Bigne et al., 2023; Nguyen & Nguyen, 2023). Moreover, there has been limited focus on classifying customer satisfaction into 1-5 levels, like the Likert measurement, offering further potential for improvement in analysis methods (Bigne et al., 2023; Nguyen & Nguyen, 2023; Adiningtyas & Millanyani, 2024).

In this research, we developed new customer satisfaction measurement formulas by integrating linguistic rules with inferential statistical methods. To collect the necessary data, we utilized a tool to gather hotel reviews from Vietnam. We then applied the Python VADER (Valence Aware Dictionary and Sentiment Reasoner) Library to analyze customer satisfaction levels from 32,447 reviews. While similar methods have been used in recent studies (Bigne et al., 2023; Nguyen & Nguyen, 2023; Lee et al., 2025), our approach was innovative, as we tested it with a new dataset that combined linguistic rules, the Sentinet corpora, and sentiment analysis techniques. The dataset was collected from a wide range of Vietnamese hotels, from 3-star to 5-star ratings, and included reviews from 1,495 hotels in Vietnam. This dataset allowed us to assess the overall guest experience across various hotel categories, whereas many previous studies focused only on luxury hotels (Moreno Brito et al., 2024). Our approach enabled a systematic evaluation and quantification of customer sentiment, providing valuable insights into satisfaction trends and patterns within the Vietnamese hotel sector. This study not only measures customer satisfaction at both the overall and aspect levels, but it also assigns aspect scores on a 5-level scale, from 1 star to 5 stars. Through this, we aim to establish a process for mining big data to better understand guest experiences with Vietnamese hotels, contributing to the improvement of service quality in the industry. The remainder of this paper is organized into four sections. Section 2 addresses research-related issues, including key concepts, definitions, and a comprehensive review of relevant literature on data analysis. Section 3 outlines the research methodology, detailing the approaches, tools, and techniques used to collect and analyze data. Section 4 presents the research findings, followed by a detailed discussion of the results. Finally, the conclusion summarizes the key outcomes of the study, reflects on its contributions, and suggests potential directions for future research.

LITERATURE REVIEW

1. The importance of hotel big data mining

Big data has become crucial across many industries, including hotels. When analyzed effectively, it offers significant opportunities for hotel managers to improve operations, enhance customer experiences, and drive business growth (Nguyen & Ho, 2023; Olorunsola et al., 2023). By leveraging large datasets, hotels gain valuable insights into customer preferences, booking behaviors, and feedback, enabling them to tailor services and marketing strategies (Olorunsola et al., 2023; Peco-Torres et al., 2025). Additionally, big data supports the optimization of pricing models, the enhancement of workflows, and the prediction of future trends, giving hotels a competitive edge. As the hospitality industry evolves, effective big data utilization will be crucial for hotel managers aiming to meet guest expectations (Zhao et al., 2025).

Online booking platforms have made the modern tourism industry with vast amounts of data, which hotel managers leverage to enhance their services and improve guest experiences. By analyzing customer reviews, hotels gain valuable insights into traveler preferences, enabling them to make informed decisions that better align with guest expectations (Chalupa & Petricek, 2024; Le et al., 2024; Zarezadeh et al., 2022; Yang et al., 2024; Zheng et al., 2023). This process allows hotel managers to assess customer sentiment, improve service quality, and optimize operational costs. Furthermore, reviews serve as a powerful tool for word-of-mouth marketing, strengthening the hotel’s reputation and attracting more customers (Peco-Torres et al., 2025; Permatasari et al., 2025). Compared to traditional methods like surveys, collecting customer feedback from reviews is both cost-effective and efficient, offering a more objective and real-time understanding of customer psychology (Nguyen et al., 2025; Barzizza et al., 2025; Okpa et al., 2025). However, the large volume of data generated requires advanced techniques such as data mining, artificial intelligence, and statistical models to ensure accurate and efficient analysis (Le et al., 2025; Xu et al., 2025; Yang et al., 2024; Zhao et al., 2025; Zhuang et al., 2025; Shi et al., 2025; Cuesta-Valiño et al., 2025). One key problem of using this data is measuring customer satisfaction, both at an overall level and in-service aspects (Veloso & Gomez-Suarez, 2023). By understanding how guests perceive different elements of their stay, hotels can refine their offerings and improve service quality (Baek et al., 2020; Kalnaovakul et al., 2025). A solution for this problem is evaluating hotel service quality through customer reviews (Leal et al., 2019). Analyzing guest feedback helps identify strengths and areas for improvement, leading to better overall customer experiences. Additionally, technological advancements have facilitated the creation of automated destination recommendation systems, which rely on customer feedback to suggest personalized travel options (Yang et al., 2024). Furthermore, customer segmentation plays a crucial role in personalizing services and marketing strategies (Yang et al., 2024; Barzizza et al., 2025). By categorizing guests based on behavior, preferences, or demographics, hotels can tailor their services to meet specific needs, boosting customer satisfaction and fostering loyalty (Chalupa & Petricek, 2024).

2. Text mining and Python tool

Text mining is an essential branch of data mining that draws significant insights from textual data. By employing statistical and machine learning techniques, it uncovers patterns and trends, transforming complex information into simpler tasks. These tasks include categorization, classification, clustering, concept extraction, sentiment analysis, summarization, and relationship modeling. Sentiment analysis, a prominent text mining application, is crucial for businesses aiming to enhance customer service (Ahmad et al., 2025). It deciphers the emotional tones within the text, particularly in customer reviews, revealing customer preferences and behaviors. Hotel managers leverage sentiment analysis to make data-driven decisions. Specifically, analyzing sentiment-laden adjectives within reviews allows for accurate assessments of customer satisfaction, providing a deeper understanding of their emotional responses and overall perceptions. This process helps organizations tailor their services and improve customer experiences.

Most of the customer reviews on online booking platforms are unstructured data. Although this data can be understood, it requires aggregation for effective analysis and information extraction. Reviews often convey customers' sentiments and opinions regarding their hotel service experiences (Kalnaovakul et al., 2025; Nguyen et al., 2025; Baek et al., 2020; Bigne et al., 2023). Hotel managers typically seek to comprehend customer psychology through these reviews, necessitating manual reading. However, with large volumes of data, manual reading becomes difficult, so they need a tool to automatically mine and analyze information, summarizing the results (Yang et al., 2024; Veloso & Gomez-Suarez, 2023). Following this way, hotel managers can determine whether customers are satisfied or dissatisfied with the provided hotel services and aspects. This process is also referred to as aspect-based extraction in customer sentiment analysis. To extract attributes and aspects from customer review data regarding service quality, it is essential to identify keywords that reflect their perceptions of hotel attributes. Nouns primarily represent the mentioned hotel services in customer reviews; hence, if many customers refer to them, then their occurrence frequency will be high (Nguyen & Nguyen, 2023).

Python is a programming that is widely used in text mining and sentiment analysis. One of its powerful tools is the VADER (Valence Aware Dictionary and Sentiment Reasoner) library, specifically designed for sentiment analysis. VADER excels at analyzing text data, particularly social media content, by evaluating the sentiment expressed in words and phrases. It assigns sentiment scores to text, identifying whether the tone is positive, negative, or neutral. Vader is optimized for social media data and can yield good results with data from Twitter, Facebook, and more. As the above results show, words' polarity and probabilities are pos, neg, neu, and compound words (Hutto & Gilbert, 2022). By leveraging Python and VADER, businesses and researchers can efficiently mine text data, extract meaningful insights, and understand customer emotions, making it a valuable tool for enhancing decision-making and improving customer experiences.

3. Big Data analysis for understanding customer experience

The Internet customer experience refers to how individuals perceive and interact with products or services in an online environment, as well as how they express these perceptions through digital platforms. Unlike traditional customer experiences, online interactions occur rapidly, allowing businesses to manage customer feedback in real time (Alhassan, 2025; Garner & Kim, 2022; Khorsand et al., 2020). The ease and speed of digital communication make it simpler for companies to respond to concerns, resolve issues, and engage with customers quickly. However, this immediacy also means that negative experiences can have swift and far-reaching consequences. A single poor online interaction can significantly impact a customer's perception, sometimes leading them to abandon a brand entirely. Even reading a negative review or encountering difficulties navigating a company's website can cause customers to disengage instantly (Xu et al., 2025; Adiningtyas & Millanyani, 2024). Therefore, businesses must strongly focus on delivering a seamless and positive online experience. A well-managed internet customer experience is key to building customer loyalty and sustaining competitive advantage in the digital age (Cho et al., 2024; Kalnaovakul et al., 2025).

In recent years, the study of text mining applied to customer-generated content has gained increased attention, particularly in the hotel industry, where online reviews play a crucial role in shaping potential customers' choices (Moreno Brito et al., 2024; Nguyen & Ho, 2023; Ahmad et al., 2025; Tango et al., 2024). Numerous studies have demonstrated the effectiveness of text mining as a robust approach for analyzing extensive amounts of customer feedback. Even when handling datasets with millions of records, the text mining process remains efficient and manageable (Chalupa & Petricek, 2024; Le et al., 2025; Zarezadeh et al., 2022). This technique has become vital for big data analysis in the hospitality industry, especially for assessing customer sentiment and satisfaction. Customer-generated content is prevalent across various digital platforms, including prominent booking websites like Booking. com, Hotels. com, Google Maps, TripAdvisor, and online travel forums (Lee et al., 2024; Garner & Kim, 2022; Islam, 2025; Okpa et al., 2025). TripAdvisor, in particular, is a popular choice in academic research due to its reliable algorithms that help identify and filter fake reviews, ensuring the datasets are more trustworthy (Islam, 2025). Researchers often concentrate on reviews from specific hotel groups to gain in-depth insights into customer satisfaction within certain regions or localized establishments, such as eco-friendly hotels. In Lee's study (Lee et al., 2024), the quality of user-generated content was explored regarding aspects like readability, polarity, word length, and diversity, along with their implications for guest satisfaction in luxury gaming resorts in Las Vegas. They analyzed 12,940 textual reviews from six luxury hotels located in these prestigious gaming destinations, utilizing regression analysis to establish the relationship between the variables in the customer reviews and overall satisfaction. Furthermore, Yang's research (Yang et al., 2024) proposed a ranking of 11 hotels in Chengdu on Tripadvisor. com, accompanied by a comparative analysis to validate the effectiveness of their model. Management implications are discussed for practitioners aiming to enhance hotel management quality. The use of text mining provides a more comprehensive understanding of service quality and traveler expectations (Chalupa & Petricek, 2024). Identifying the topic has been a central focus in customer sentiment analysis (Özen & Özgül Katlav, 2023). This process involves extracting relevant entities, such as identifying aspects of hotel services like "room" or terms that convey sentiment, such as "good" or "terrible." Various techniques, including Latent Dirichlet Allocation (LDA), have been employed to achieve this extraction (Shi et al., 2025; Kalnaovakul et al., 2025). In Shi's study, a sentiment dictionary specific to the cruise industry is created using online reviews.

This involves selecting initial sentiment words based on their frequency and further expanding the dictionary through Word2vec and pointwise mutual information for semantic orientation. Additionally, they employ the latent Dirichlet allocation topic model to examine online reviews and pinpoint the 10 urgent issues that concern cruise customers. Studies indicate that key topic words in customer reviews are often nouns. Consequently, researchers have concentrated on extracting frequently mentioned words that signify important aspects of the customer experience (Nguyen & Nguyen, 2023). These words are categorized as hotel service topics (or aspects), including "restaurant," "breakfast," "food," "pool," "reservation," "buffet," "lounge," "bar," "check-in," "floor," "view," "cleanliness," "bed," "bathroom," and "staff." These aspects help define the essential elements that shape a guest's overall hotel experience. There are some challenging issues in this field. A majority of the previous studies have focused on measuring overall customer satisfaction and the level of satisfaction with each aspect of hotel services (Adiningtyas & Millanyani, 2024; Barzizza et al., 2025). One key area of focus in these studies is aspect extraction and analysis (Özen & Özgül Katlav, 2023). The common approach involves the use of statistical techniques based on frequency analysis to identify customer preferences for specific services. For example, customers frequently mention certain aspects such as Location, Room, Service, Dining & Food, Value, and Facility Availability in their reviews (Nguyen & Nguyen, 2023). Kalnaovakul found that eight dimensions of service quality were identified, including leisure activities, tangibles and surroundings, reliability, responsiveness, service process, food, empathy, and ambiance. The study highlights that the service process is the only dimension displaying negative sentiment (Kalnaovakul et al., 2025).

Conversely, other studies use negative sentiment analysis to identify aspects that lead to customer dissatisfaction (Xu et al., 2025; Adiningtyas & Millanyani, 2024). Customer reviews frequently highlight complaints regarding facilities, rooms, and pricing. Adiningtyas suggested that hotels focus on enhancing particular areas needing improvement (Adiningtyas & Millanyani, 2024). Although statistical frequency methods are commonly employed, other research has investigated the links between particular factors and polarity words to evaluate satisfaction through inferential statistics (Zheng et al., 2023;

Derco & Tometzová, 2025; Amoako et al., 2023; Rahimian et al., 2021; Nguyen & Nguyen, 2023). Traditional machine learning techniques, like Support Vector Machines and Naïve Bayes, are frequently used in different sentiment analysis contexts (Le et al., 2025). Moreover, some machine-learning techniques combined with statistical methods can improve classification accuracy and provide actionable insights into the factors driving customer satisfaction, making them valuable tools for the hospitality industry. Deep learning has gained significant traction as a powerful alternative to traditional machine learning models. These advanced methods have delivered remarkable results, especially in Aspect-Based Sentiment Analysis (ABSA). Unlike traditional models, deep learning techniques are trained end-to-end, allowing them to automatically learn and extract meaningful features from large volumes of text data. Some studies used Long Short-Term Memory (LSTM) networks and selected some of the most widely used transformer-based models for sentiment classification, including BERT, DistilBERT, XLNet, and RoBERTa (Bigne et al., 2023; Cuesta-Valiño et al., 2025; Xu et al., 2025; Yang et al., 2025; Alqusair et al., 2025; Adiningtyas & Millanyani, 2024; Zhuang et al., 2025). This shows that a more nuanced and diverse range of review methods can provide a clearer picture of customer satisfaction and dissatisfaction. These findings emphasize the importance of considering various factors and methodologies, such as sentiment analysis, frequency analysis, and regression models, when assessing customer satisfaction in the hotel industry.

Most studies have employed various approaches to text mining. However, few studies have used lexical rules or examined how to combine aspects with SenticNet to improve results and reduce the complexity of the algorithms (Ahmad et al., 2025). Moreover, these studies lack a clear, overall process with step-by-step for solving the problem effectively. This highlights the need for further research to develop comprehensive, standardized methodologies for measuring customer satisfaction that integrate aspects and polarity words while considering the structure and length of customer reviews.

METHODOLOGY

1. Fundamentals of concepts

This study will use some definitions and notations Table 1. Below are definitions and notations. Some of them are extended from a study by Nguyen & Nguyen (2023), and others are developed on our own.

Definition 1. Reviews:

A review is the feedback of a customer when they share their experience on TripAdvisor. The set of reviews is expressed by:

$$R = \{r_1, r_2, \dots, r_n\} \quad (1)$$

Definition 2. Customers:

The customers are a set of guests who have had experiences with Vietnamese hotels (Nguyen & Nguyen, 2023). A set of customers is expressed by (2):

$$G = \{g_1, g_2, \dots, g_m\} \quad (2)$$

Definition 3. Aspect

Aspects are the set of attributes and services that are provided by hotels. They are created by extracting nouns from reviews and fit with the attributes of the hotel. For example, location, staff, room, and surroundings.

$$A = \{a_1, a_2, \dots, a_l\} \quad (3)$$

With a_k is the aspect of the hotel.

Definition 4. Aspect groups

Aspect groups are sets of words that have the same meaning. Aspect groups are used to describe hotel attributes.

$$F = \{w_1, w_2, \dots, w_s\} \quad (4)$$

Definition 5. Overall Satisfaction

Overall satisfaction is described by the feelings of guests g_j with hotel services. who wrote a review r_i (Nguyen & Nguyen, 2023) and it is expressed by the equation (5) below:

$$Sas_{overall} = \frac{\text{number of positive reviews}}{\text{total of reviews}} x100\% \quad (5)$$

Definition 6. Aspect Satisfaction

Customers are satisfied with each aspect of the service provided by the hotel and are denoted by $Sas(a_k)$ With a_k is the aspect of the hotel (Nguyen & Nguyen, 2023).

$$Sas(a_i) = \frac{\text{number of positive reviews that contain aspect } (a_i)}{\text{total of reviews that contain aspect } (a_i)} x100\% \quad (6)$$

Definition 7. Satisfaction level for hotel aspect:

The satisfaction level for the hotel aspect is scored on a scale of 1 to 5. For example: 1= very dissatisfied, 2= dissatisfied, 3= neutral, 4= satisfied, 5= very satisfied. This scale is determined by the degree of polarity of the polarity words.

$$Sas\_Scale = [1..5] \quad (7)$$

Definition 8. Polarity words:

Polarity words refer to adjectives or adverbs that express a positive or negative sentiment in language. These words play a crucial role in sentiment analysis, helping to determine whether a statement conveys a positive, negative, or neutral tone. Positive polarity words indicate approval, happiness, or praise. Examples include adjectives like excellent, beautiful, and delightful and adverbs like wonderfully, brilliantly, and happily. Negative polarity words convey disapproval, criticism, or negativity. Examples include adjectives like terrible, ugly, and disappointing and adverbs like poorly, badly, and unfortunately.

Definition 9. Levels of Sentiment Based on Polarity Words:

This study defined and divided the levels of sentiment into five levels:

- Level 5: Highly Positive: Contains multiple strong positive polarity words (e.g., fantastic, incredible, wonderful).

- Level 4: Moderately Positive: Has some positive words but with lower intensity (e.g., good, nice, pleasant).
- Level 3: Neutral: Lacks significant positive or negative polarity words.
- Level 2: Moderately Negative: Contains some mild negative words (e.g., bad, unsatisfactory, lacking).
- Level 1: Highly Negative: Has multiple strong negative words (e.g., horrible, disastrous, terrible).

The level of satisfaction in sentiment analysis is influenced by the intensity of descriptive words, particularly when modifiers like “very” accompany adjectives. These modifiers, known as gradable adjectives or adverbs, enhance the expression of sentiment. For instance, the word “good” conveys satisfaction, but adding “very” to form “very good” strengthens the positive sentiment, indicating a higher level of satisfaction. The same principle applies to other adjectives, where their intensity can be amplified by degree words, making the sentiment more pronounced. Besides, negation plays a crucial role in altering the meaning of polarity words. Negative words such as "not" or "no" reverse the intended sentiment of an adjective. For example, while “happy” expresses a positive sentiment, the phrase “not happy” weakens or even negates that positivity, shifting the meaning towards dissatisfaction or neutrality. Similarly, "not bad" can suggest a moderate level of positivity despite containing a negation.

The combination of large language models and Sentinet corpora has been demonstrated to be highly accurate in sentiment analysis problems at the deep semantic and lexical levels (Wu et al., 2023). The study by Nguyen (Nguyen & Nguyen 2024) did not explain how to calculate the value of the sentiment words. Therefore, in this study, we have chosen the solution of large language models combined with the Senticnet corpora to understand customer experiences in more detail. In this study, we rely on the sentiment dictionary (SenticNet) to calculate the sentiment of each review. This SenticNet dictionary already has adjectives and adverbs with their sentiment value. Based on the sentiment values, we used a formula to calculate values from 1-5, like a 1-5 star rating. Table 1 below shows a part of the sentiment dictionary with its sentiment value and rate. This SenticNet has 164 adjectives and 276 adverbs.

Table 1. Sentiment dictionary (Source: Authors’ data analysis)

Adjectives	Score	Rated	Adverbs	Score	Rated
good	1.9	4	well	1.1	4
great	3.1	5	fast	0.4	3
nice	1.8	4	straight	0.9	3
excellent	2.7	4	hard	-0.4	2
friendly	2.2	4	loudly	-1.3	2
clean	1.7	4	proudly	2.6	4
helpful	1.8	4	suspiciously	-1.7	2
comfortable	2.3	4	strangely	-1.2	2
best	3.2	5	kindly	2.2	4
beautiful	2.9	4	easily	1.4	4

Definition 10. Aspect substring:

Aspect substrings are smaller segments of the original text that contain specific aspects. These substrings are created through a structured process to ensure that relevant aspect-related information is extracted accurately. They are generated using specific rules, identifying aspects in a sentence, and determining their surrounding context. The extraction process considers factors like the presence of polarity words, sentence structure, and punctuation. The process to create substrings is shown in Figure 1. Below. This study takes a deeper and more detailed approach to measuring customer satisfaction compared to previous research. Our work involves three key tasks. First, we employ Python programming to assess overall customer satisfaction. Next, we apply linguistic rules to segment text into shorter substrings and group them by aspect.

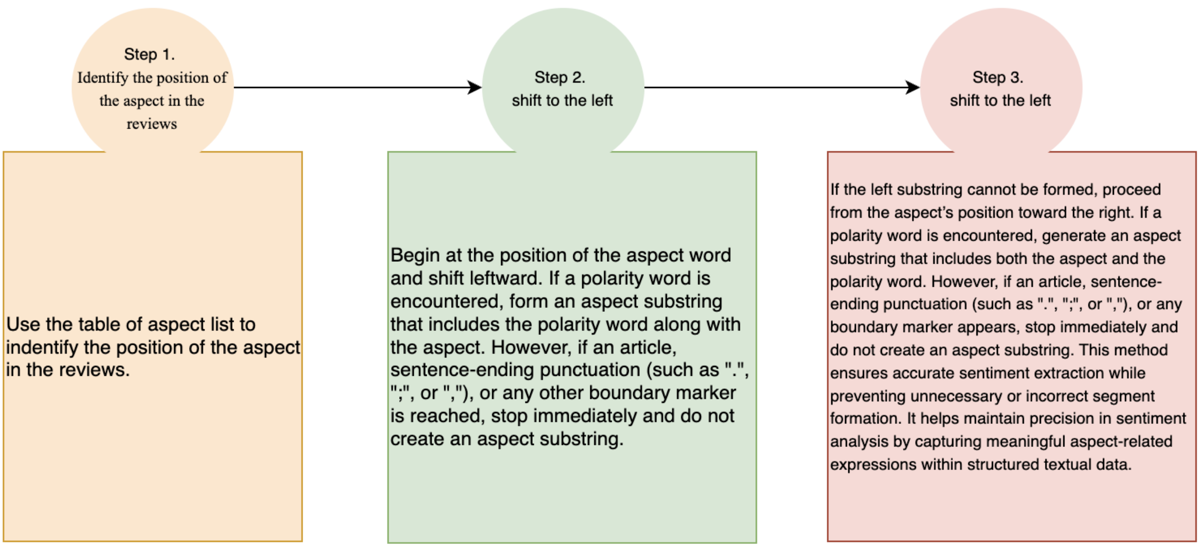

Figure 1. Three steps to create a substring from original reviews (Source: Authors’ data analysis)

This study analyzes satisfaction levels for each specific aspect, identifying aspects of dissatisfaction that may not be evident in overall satisfaction and rates satisfaction of aspects that have not been addressed in prior studies. Finally, this research compiles a list of common polarity words from the dataset, categorizing them into different satisfaction levels: very dissatisfied, dissatisfied, neutral, satisfied, and very satisfied. This classification enables a more precise measurement of satisfaction based on sentiment intensity. This approach, which combines linguistic rules with inferential statistics, introduces a new perspective in sentiment analysis, providing deeper insights into customer satisfaction beyond general ratings.

2. Measuring customer satisfaction with hotel services

The Python language provides a VADER library that can easily measure the sentiment score of reviews, which we have used to measure overall customer satisfaction with hotel services. Overall satisfaction shows the percentage of customers who are satisfied with the whole hotel services in Vietnam and it is calculated by the following formula (5).

3. Measuring customer satisfaction with hotel aspects

In a sentence expressing overall satisfaction, there may still be aspects of the service that the customer is dissatisfied with. The VADER library, however, is unable to analyze satisfaction levels for each individual hotel aspect. To address this, we applied linguistic rules to separate each service aspect into substrings and then used the VADER library to assess satisfaction for each aspect. For measuring satisfaction, we utilized a predefined set of hotel aspects. This approach allows for a more detailed analysis of customer feedback by evaluating satisfaction levels for specific elements of the hotel experience.

We follow a systematic process to analyze customer satisfaction with hotel services:

- Step 1: Identify aspects of the reviews

We begin by identifying key aspects mentioned in the customer reviews, such as "food," "room," "staff," "location," and "service." These are the focal points that are typically used to evaluate hotel experiences.

- Step 2: Create aspect substrings:

Once the aspects are identified, we create substrings for each aspect within the reviews. This allows us to isolate relevant information for further analysis.

- Step 3: Gather aspect substrings into aspect groups:

After creating the substrings, we organize them into specific aspect groups. These groups will help categorize feedback related to each hotel service area, facilitating more accurate analysis.

- Step 4: Use the VADER library to measure satisfaction:

Finally, we apply the VADER library, a sentiment analysis tool, to evaluate customer satisfaction with each aspect of the hotel service. The VADER library measures sentiment, allowing us to quantify satisfaction levels for each aspect identified in the previous steps. Measure the rate of customer satisfaction according to the service aspects extracted in the previous step, according to the formula (6).

4. Determining the satisfaction level with each hotel aspect

The level of customer satisfaction with each service aspect is measured on a scale from 1 to 5. To achieve this, we build upon the previous results and perform a pairing process between aspects and polarity words as outlined below:

- Step 1: Gather aspect substring groups:

We begin by collecting the groups of aspect substrings according to their respective aspects. This step ensures that each aspect is appropriately categorized.

- Step 2: Extract pairs of polarity words and aspects:

Next, we extract pairs of polarity words (positive or negative words) associated with each aspect. We also remove any unrelated or irrelevant words that may interfere with the analysis. Each word pair is then recorded along with its frequency of occurrence in the reviews.

- Step 3: Calculate the satisfaction score:

In this step, we use the frequency of polarity word pairs to calculate a satisfaction score for each aspect. The score is determined by a predefined formula that considers the occurrence and sentiment of the polarity words. Based on the calculated score, we then assign a satisfaction level (ranging from 1 to 5) to each aspect. Calculate the score and determine the satisfaction level of each aspect according to the formula that was proposed by the authors.

$$Level\_Sas\ (a_i) = \frac{1*\theta_1(a_i)+2*\theta_2(a_i)+3*\theta_3(a_i)+4*\theta_4(a_i)+5*\theta_5(a_i)}{n} \tag{7}$$

In which: $Level\_Sas\ (a_i)$: Level of satisfaction with aspect a_i

$\theta_1, \theta_2, \theta_3, \theta_4, \theta_5$: The number of occurrences of polarity word and aspect pairs is equivalent to the score 1, 2, 3, 4, 5.

n: Total number of side-by-side occurrences of polarity word and aspect

RESULTS

1. Description of data

The research data was gathered from the TripAdvisor website, a trusted source for travel advice from actual travelers. It is regarded as the world's largest travel community, with over 60 million visits each month, 44 million registered members, and upwards of 100 million reviews contributed by genuine travelers. The site serves users in numerous countries, now operating in 49 markets and offering content in 28 distinct languages. We used the TripAdvisor crawler add-on function on Chrome to collect data on the TripAdvisor site. The data is collected from 1,438 hotels in Vietnam, ranked from 3 to 5 stars. The structure of a customer review includes the following key information:

Reviewer name, Review date, Free text review, customer ID, overall star rating, and rating by some aspect of hotel service. The total number of reviews is 32,447, and Figure 2 below shows the customer types when they booked hotels for the purpose: Business, Friends, Family, Couples, Solo, and None. This data showed clearly that Couples dominate, making up 40.5% of the total. Family groups also hold a significant portion at 23.3%. Solo at 6.3% and None at 12.7%. Business accounts for a much smaller share, only 3.3%. This is proven that couples care about their experiences when they stay in a hotel. Next, we store the data in .csv format. Then, we used Python to preprocess the data; after processing, it has 32,447 reviews. In which 5 stars: 23,158 reviews, 4 stars: 5,325 reviews, 3 stars: 2,110 reviews, 2 stars: 984 reviews, 1 star: 870 reviews. Figure 3 shows the distribution of star levels in this data. From a total of 32,447 reviews collected from 3-5 star hotels in Vietnam. The longest review is 20,362 words. The shortest is one word.

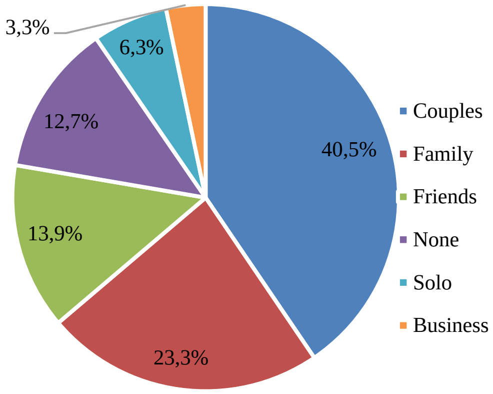

Figure 2. Distribution of customers who comment on TripAdvisor (Source: Authors' data analysis)

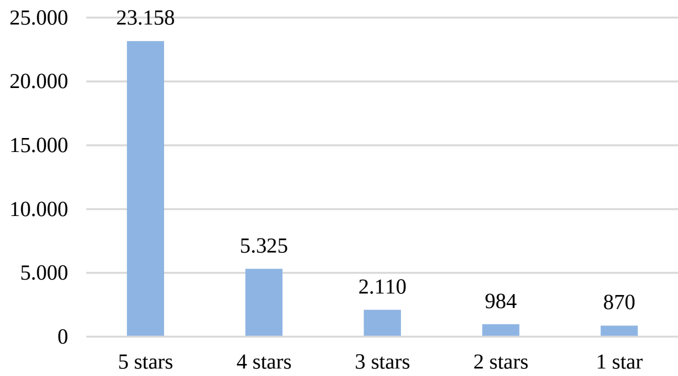

Figure 3. Description of data that were collected from the TripAdvisor site (Source: Authors' data analysis)

2. Measuring customer satisfaction with hotel services

This study utilized the VADER (Valence Aware Dictionary and Sentiment Reasoner) library, which is equipped with tools to assess sentiment scores in sentences. The library calculates scores that categorize sentiments into three distinct types: positive, negative, and neutral. Additionally, it computes a compound score, which aggregates these individual scores into a single value that provides an overall sentiment measurement. Based on the compound score, the sentiments were further classified into three categories: satisfied, dissatisfied, and neutral. The categorization helps to evaluate the general sentiment expressed in the reviews more clearly than the star rating Based on the compound score, we classify it into three categories: satisfied, dissatisfied, and neutral. The number of reviews for each class is 27,353 reviews for satisfaction, 2,985 reviews for dissatisfaction, and 2,110 reviews for neutral. Calculate the satisfaction and dissatisfaction rates of customers equivalent: satisfied: 84.3%, dissatisfied: 9.2% and 6.5% are not clearly expressed attitudes. The measurement results are shown in Figure 4.

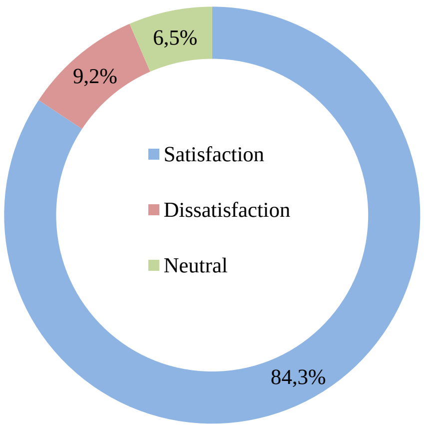

Figure 4. Satisfaction and dissatisfaction rates with 3-5 stars hotels in Vietnam (Source: Authors' data analysis)

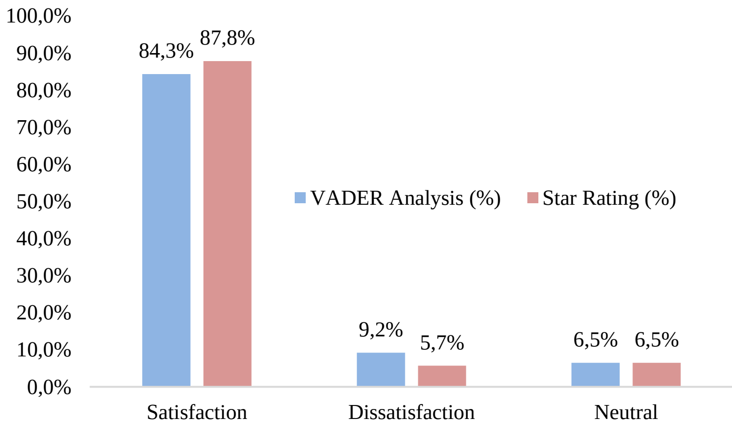

Figure 5. The comparison of customer satisfaction from their rating and from the result of the review analysis (Source: Authors' data analysis)

With a rate of 84.3% of customers satisfied with the 3-5 star hotels in Vietnam, it shows that the overall service quality of 3-5 star hotels has met the requirements of customers. Besides, the dissatisfaction score is 9.2%. So we need to consider carefully what points were not satisfactory.

Figure 5 illustrates a discrepancy between customer satisfaction as indicated by direct ratings and analysis derived from reviews. While 87.8% of customers express satisfaction with their experience, only 84.3% of the review-based analysis aligns with this satisfaction level, highlighting more complex or critical sentiments in written feedback. The rate of dissatisfaction stands at 5.7%, whereas the review analysis reports a greater dissatisfaction at 9.2%.

3. Measuring satisfaction of customer by service aspects

To genuinely grasp what elements of the hotel lead to customer dissatisfaction, we will conduct a detailed analysis of specific factors. Our initial step involves listing these hotel aspects and identifying the corresponding sentiment words for each. The aspect words highlighted in reviews will indicate their significance. Frequent mentions by customers suggest they hold those aspects in high regard, while infrequent mentions imply less concern. The Word Cloud chart in Figure 6 below illustrates the aspects referenced in this data. Figure 7 illustrates the frequency of each aspect that customers mentioned in; it helps highlight the relative importance of various aspects. The chart presents data on how often each aspect was referred to. The aspect of "room" stands out with the highest number of mentions, indicating that it is considered the most important factor by the customers. This emphasizes the value placed on the room experience, suggesting that it plays a crucial role in overall satisfaction. By analyzing these frequencies, we gain a clearer understanding of the priorities and preferences of those surveyed. We identified aspect substrings related to the room, staff, food, service, and location. Table 2 below shows the total count of these substrings derived from 32,447 reviews, demonstrating that each aspect of hotel service is addressed in all reviews. Some aspects may have been mentioned multiple times, resulting in a total count of extracted aspect substrings that exceeds the number of reviews collected.

Figure 6. Word Cloud for the review data (Source: Authors' data analysis)

Table 2. Number of aspect substrings for each aspect (Source: Authors' data analysis)

Aspect	# aspect substring
Food	10246
Room	29963
Staff	14251
location	6561
services	9793
Prices	2346
Facility	3235

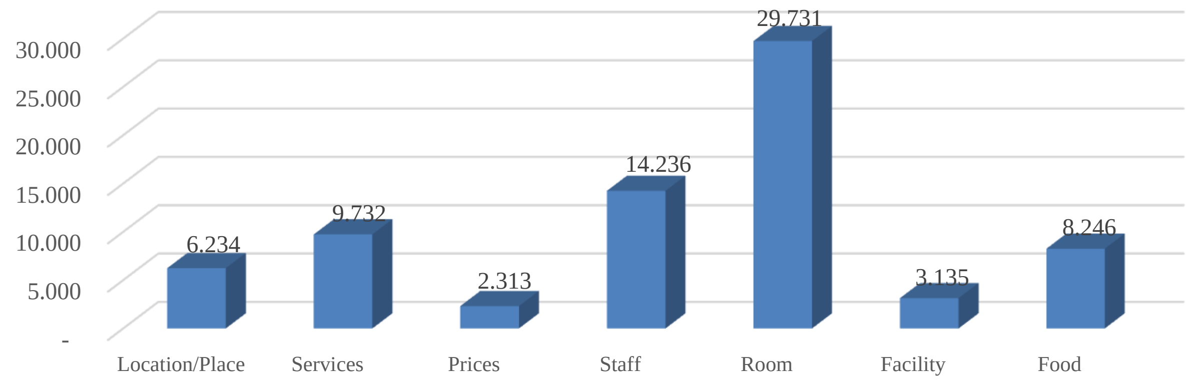

Figure 7. Mentions by Aspect (Source: Authors' data analysis)

Customer satisfaction is evaluated through aspect substrings using the VADER library. The satisfaction levels are categorized into satisfaction, dissatisfaction, and neutrality. Figure 8 below is the chart displaying satisfaction measurements based on various hotel aspects: services, location, staff, room, price, facility, and food.

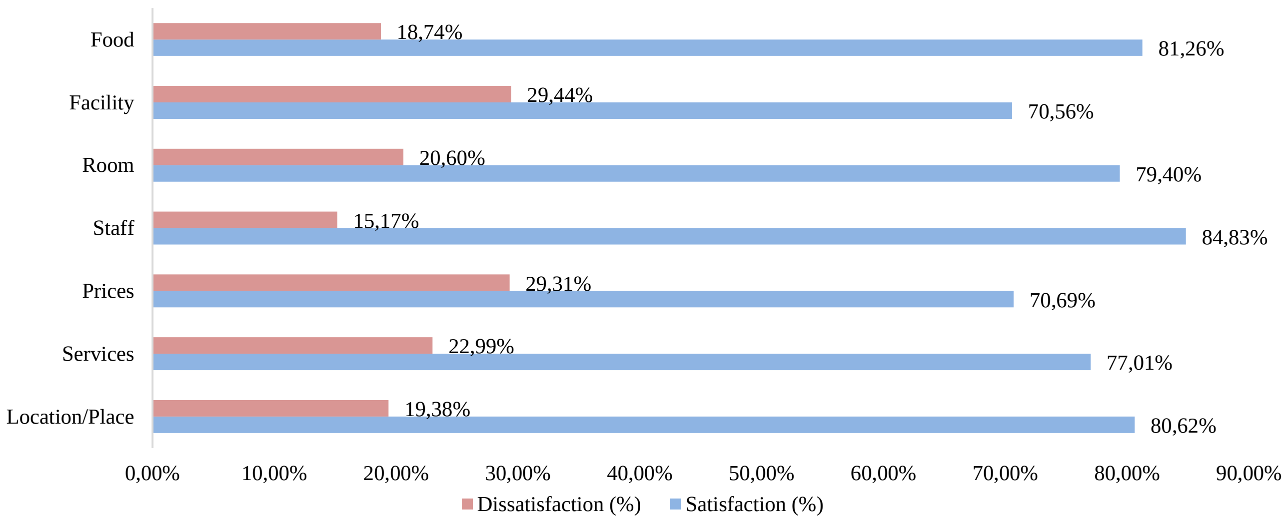

Figure 8. Measuring satisfaction for each aspect by calculating the aspect substring score

The chart presents customer satisfaction and dissatisfaction rates across several aspects of the hotel. The data reveals key insights into the areas where customers feel most satisfied and where improvements might be needed. The aspect "Staff" has the highest satisfaction rate of 84.83%, with a low dissatisfaction rate of 15.17%, reflecting positive customer feedback on the staff provided. For the aspect "Location/Place" the satisfaction rate is high at 80.62%, with a relatively low dissatisfaction rate of 19.38%, indicating that most customers are pleased with the hotel's location. While the aspect "room" with the highest mention, it only reaches 79.4% of satisfied customers. Regarding "prices", only 70.69% of customers were satisfied with the price of the hotel, and the frequency of mentions was the lowest. Which 29.31% are dissatisfied, suggesting that pricing could be a point of contention. The satisfaction rate with "services" is 77.01%, indicating that the hotels have to improve their services.

4. Measuring the satisfaction level with each hotel aspect

The aspect of "Room" generated the most mentions, representing a large part of the total feedback. This indicates that customer experiences related to the room are the most commonly addressed, suggesting that it significantly impacts overall satisfaction or dissatisfaction. The "Food" and "Staff" aspects also garnered substantial mentions, with "Staff" being the second most discussed area following Room, highlighting their importance to customers. On the other hand, the "Service" and "Location" aspects received moderate mentions, implying that while they are relevant, they are not as integral to the customer experience as staff and room quality. In contrast, the aspects of "Price" and "Facility" had very few mentions, suggesting these elements may play a less critical role in customer satisfaction than others. To calculate the rating for each aspect, this study followed two stages. First, we identified the corresponding sentiment words with each aspect and then used the sentiment dictionary to calculate the sentiment value of each aspect. Figure 9 shows the rating of each aspect. Despite the aspect "Room" was mentioned with the highest frequency. But the satisfaction is not the highest. The aspects "Staff" and "Food" have the highest ratings, 4.67 and 4.61, respectively. This indicates that when customers do mention the "staff", they are overwhelmingly positive when reacting to staff, and the dining experience is a strong point for the hotels. The "Price" aspect has a notably low rating of 2.63, which is significantly lower than all other aspects. This indicates a strong dissatisfaction with the pricing. The aspect "room" with a 4.46 score, has slightly lower ratings compared to other aspects like "Location".

Figure 9. Ratings by Aspect (Source: Authors' data analysis)

DISCUSSION AND CONCLUSION

In modern business administration, the customer-centric approach has become a crucial strategy. By prioritizing customer satisfaction, companies can foster customer loyalty, which ultimately drives revenue and profit growth (Luturlean & Anggadwita, 2016; Lee et al., 2020; Rahimian et al., 2021). As we live in an increasingly digital world, the hotel industry in Vietnam has integrated into the global value chain, leveraging online hotel service platforms.

This digital transformation has significantly altered how customers interact with hotel services, making their experiences more diverse, emotional, and complex (Hariandja & Vincent, 2022). In the highly competitive market, customer experience plays a crucial role in a business's success. The rise of online platforms means customers can easily share their experiences, whether positive or negative, influencing the decisions of future customers. A single poor experience can lead to a customer seeking services from a competitor, which underscores the importance of maintaining a consistently high-quality experience. Hotels and businesses must recognize that customers are not just purchasing a service; they are investing in an experience, one that is shaped by emotional connections and technological advancements.

Therefore, hotel managers not only focus on improving physical services but also enhance their online presence and digital interfaces, ensuring that the entire customer journey—both online and offline—is seamless and satisfying. The customer-centric approach requires continuous adaptation to emerging technologies and customer needs, making it vital for companies to stay ahead of the curve in order to retain and grow their customer base (Hu et al., 2019).

This study presents data analysis techniques employing text mining to assess customer satisfaction with hotel services in Vietnam. Customer satisfaction is evaluated through three stages: (1) overall satisfaction with hotel services, (2) satisfaction with particular hotel features, and (3) satisfaction levels regarding individual hotel aspects. By combining text mining with sophisticated language analysis, this approach offers deeper insights into customer preferences and facilitates the development of a more comprehensive customer persona. The satisfaction results show that 84.3% of customers are satisfied with hotel services in Vietnam. Yet, a deeper analysis of the language uncovers some unsatisfactory elements in the general feedback. The highest satisfaction is associated with the "staff" factor, which received over 84.83% satisfaction. This aligns with previous studies, where the "staff" aspect consistently received higher ratings.

While previous research has primarily focused on measuring customer satisfaction, few studies have examined the satisfaction levels associated with specific aspects of hotel services. This study adds to the field by introducing this new dimension, thereby providing a more nuanced understanding of customer satisfaction. Furthermore, this study presents a method for rating these aspects from 1 to 5 stars. This approach can be further explored in future research, enabling a broader application of text-mining techniques to evaluate customer satisfaction across various industries and regions.

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