FROM REVIEWS TO PERCEIVED PRICING: A SENTIMENT ANALYSIS OF HOTEL EXPERIENCES

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Abstract

Purpose – User-generated content provides valuable insights into customer sentiment, influencing service delivery and pricing decisions. However, limited empirical research has examined how customer sentiment relates to perceived hotel pricing. This study explores the relationship between sentiment expressed in online reviews and customers' perceptions of hotel prices, identifying key service attributes associated with these perceptions.
Methodology/Design/Approach – This study employs an innovative approach using Synthesio, an AI-powered social intelligence platform, to conduct large-scale sentiment analysis. A dataset of 30,500 TripAdvisor reviews was analyzed to examine how sentiment toward specific service attributes relates to perceived pricing.
Findings – Five attributes—room, staff service, food experience, location, and hotel facilities—were identified as key factors associated with price perceptions. Room quality, particularly cleanliness, showed the strongest association with pricing sentiment. Although staff service was generally positive, it did not consistently offset dissatisfaction caused by poor room quality. Location, as a relatively fixed attribute, influenced sentiment primarily when expectations were unmet.
Originality of the research – This study contributes to data-driven pricing research by applying attribute-level sentiment analysis to examine perceived pricing, offering both methodological innovation and practical implications for the hospitality industry.
Keywords sentiment analysis, online customer reviews, pricing, hotel price, Synthesio

Original research paper
Received 21 August 2025
Revised 22 January 2026
01 April 2026
https://doi.org/10.20867/thm.33.1.4
Accepted 09 April 2026

INTRODUCTION

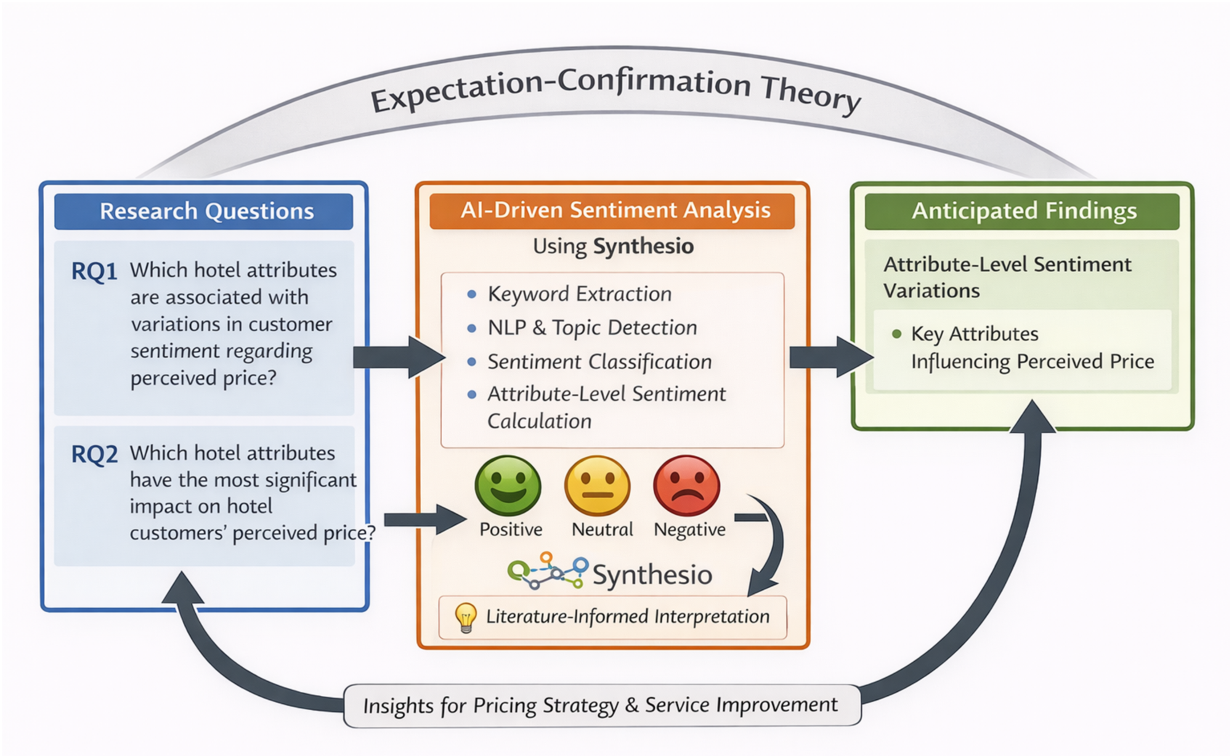
In the dynamic and competitive hospitality industry, it is crucial to have a thorough understanding and effective use of customer feedback, especially with the rise of digitalization in consumer interactions and opinions (Xie et al., 2014; Zhao et al., 2019). User-generated content, such as online reviews from customers, plays a critical role in providing valuable insights into customer sentiments (Berezina et al., 2016), influencing the shaping of service offerings and pricing strategies. With their significant influence on consumer behavior, online reviews have become a crucial factor for businesses looking to improve their market position through informed decision-making (Filieri et al., 2015; Li et al., 2018). In this context, customer perception plays a central role in the hospitality industry, reflecting how guests assess the benefits they receive compared to the costs they incur (Zeithaml et al., 2018). This perception influences their expectations and satisfaction levels, ultimately affecting hotel pricing decisions. Perception encompasses a wide range of attributes that shape a customer's judgment and is often reflected in their online reviews. As such, understanding these attributes is crucial for gauging consumer sentiment and making informed decisions in the hospitality industry, particularly concerning the setting of prices that align with customers' expectations.

In terms of hotel pricing, several methods come into play, including competition-driven, dynamic, and customer-driven pricing (Finch et al., 1998; Noone & McGuire, 2013; Wang, 2012). Recent literature underscores the importance of customer-driven pricing in driving sales and enhancing customer satisfaction (Moll & Yigitbasioglu, 2022; Shi & Nualnoom, 2022). These approaches are founded on customers' perceived benefits and their willingness to pay, tailored to their needs and preferences, and can be informed by monitoring customer sentiments and preferences through social media. Despite the potential insights available through social media, empirical research on the interaction between price and customers' reviews on these platforms has been limited. Hence, this study seeks to adopt an innovative approach by leveraging Synthesio, an AI-powered social intelligence platform, for conducting sentiment analysis on online hotel reviews (Forrester Research, 2020, 2021; Kotras, 2020; Mariani & Baggio, 2022), with the goal of unravelling the intricate relationship between customer sentiment and hotel pricing.

While prior studies have explored hotel attributes and pricing, our study differentiates itself by employing a large-scale sentiment analysis approach using AI-powered technology. Unlike traditional studies that rely on structured survey data or small-scale content analysis, this research utilizes Synthesio to process a vast dataset of real-world online customer reviews, providing a more comprehensive and dynamic understanding of how different hotel attributes are associated with pricing perceptions. Additionally, this study offers methodological novelty by integrating automated data extraction and analysis, which allows for real-time assessment of consumer sentiments and pricing trends, offering a more actionable perspective for industry stakeholders.

This study aims to investigate how hotel customers perceive price through customer sentiments in online reviews. Specifically, this study addresses two research questions: (1) Which hotel attributes are associated with variations in customer sentiment regarding perceived price? and (2) Which hotel attributes have the most significant impact on hotel customers' perceived price? Through these inquiries, the study endeavors to enhance our understanding of pricing in the hospitality industry, which is closely linked with customer feedback and sentiment analysis. As shown in Figure 1, the conceptual framework illustrates the overarching role of Expectation-Confirmation Theory in guiding the study, linking the research questions, AI-driven sentiment analysis using Synthesio with literature-informed interpretation, and the anticipated outcomes. The framework visually represents how hotel attributes are analyzed for their association on customer sentiment and perceived price, providing insights that can inform pricing strategies and service improvements.

Figure 1: **Conceptual Framework**



1. LITERATURE REVIEW

1.1 Online customer reviews on hotels

Online customer reviews, also referred to as electronic word of mouth, play an essential role in shaping consumer behavior and influencing hotel performance, particularly in the digital era, where consumer-generated content significantly impacts business reputation and revenue (Chakraborty, 2019; Wen et al., 2021; Xie et al., 2014; Zhao et al., 2019). With the growing reliance on online platforms such as TripAdvisor and Google Reviews, prospective customers increasingly depend on past guest experiences to inform their decisions, making online reviews a critical component of hotel management strategies (Zhao et al., 2019). Hotel online review research can be categorized into two primary streams: one focusing on the technical aspects of reviews and the other on review content. The technical stream explores linguistic characteristics such as subjectivity, readability, diversity, review length, and sentiment polarity (Fang et al., 2016; Park et al., 2020; Wu et al., 2017; Xu, 2020). Additionally, studies have examined how different linguistic patterns and tonal variations in online hotel reviews impact consumer perceptions (Liu et al., 2017; Mariani et al., 2019), showing that emotionally charged language influences customer expectations and purchase decisions.

The content-focused stream investigates how hotel attributes shape customer satisfaction and dissatisfaction. Zhang et al.'s (2021) study examined the roles of various hotel service attributes (rooms, location, cleanliness, service, and value) in forming customer overall satisfaction. Similarly, He et al. (2017) identified that while positive experiences often stem from excellent service and amenities, dissatisfaction is frequently linked to subpar cleanliness and unexpected additional costs. These findings highlight the importance of monitoring online reviews to understand consumer sentiment and refine service quality (Alaei et al., 2019; Ma et al., 2018).

Jang and Moutinho (2019) classified hotel attributes into intrinsic (e.g., location, amenities) and extrinsic (e.g., price, food, staff) factors, demonstrating how external influences shape customer perceptions. Berezina et al. (2016) found that while staff-related attributes significantly impact satisfaction, dissatisfaction is more commonly associated with tangible aspects such as outdated furnishings and financial concerns. These studies collectively emphasize the role of sentiment analysis in understanding guest perceptions, leading to a more data-driven approach to customer experience management. More recent studies have employed advanced sentiment analysis techniques to extract meaningful insights from large-scale online reviews. The integration of machine learning and natural language processing (NLP) allows researchers to identify emerging patterns in customer feedback and assess how specific hotel attributes contribute to satisfaction or dissatisfaction (Roy, 2023). Such analyses provide hotel managers with actionable insights to enhance service offerings, streamline operations, and develop more competitive pricing approaches that align with customer expectations (Alaei et al., 2019). Furthermore, by leveraging large-scale review datasets, sentiment analysis enhances predictive analytics, enabling hotels to forecast consumer preferences and market trends more effectively.

Despite the wealth of research on online reviews and hotel attributes, the relationship between customer sentiment and pricing perceptions remains relatively underexplored. While studies have examined the impact of price on booking decisions, few have analyzed how guests articulate their pricing perceptions within online reviews. This study seeks to bridge this gap by leveraging sentiment analysis to examine large-scale hotel reviews, providing a more nuanced understanding of how customers perceive pricing based on their hotel experiences. By focusing on this underexamined aspect, this research contributes to the growing literature on customer feedback and pricing in the hospitality industry.

1.2 Hotel pricing approaches

Hotel pricing is a dynamic and multifaceted process that requires a deep understanding of market conditions and consumer behavior. Traditional pricing models, such as cost-based, competition-based, and demand-driven pricing, have long played a central role in revenue management (Abrate & Viglia, 2016; Choi & Mattila, 2004). However, with the advancement of digital technologies and the increasing accessibility of online consumer data, pricing decisions now incorporate real-time consumer insights obtained from online platforms (Noone & McGuire, 2013; Yang et al., 2020). The emergence of sentiment-driven pricing represents a shift toward customer-centric pricing models that align with consumer expectations and willingness to pay (Kimes & Wirtz, 2015). This approach leverages customer feedback, booking patterns, and sentiment analysis from online reviews to optimize pricing structures. Research indicates that integrating real-time consumer sentiment into pricing decisions enhances revenue performance and improves customer satisfaction (Badmus et al., 2024; Geetha et al., 2017). For instance, sentiment-based pricing models powered by artificial intelligence dynamically adjust price levels in response to shifts in consumer perception (Chenavaz & Dimitrov, 2025).

With the increasing transparency of online pricing platforms, competition among hotels has intensified, driving the adoption of personalized pricing models that cater to distinct customer segments. Dynamic pricing, often powered by machine learning algorithms, enables hotels to adjust rates in response to demand fluctuations, competitor pricing, and guest sentiment trends (Abrate & Viglia, 2016; Gao, 2024). Research underscores that sentiment analysis plays a crucial role in refining these pricing models, allowing hotels to anticipate guest reactions to price changes and optimize revenue strategies accordingly (Guillet & Mohammed, 2015). Furthermore, online reviews significantly influence the relationship between price perception and customer booking decisions, with variables such as brand reputation and hotel classification acting as key moderators (Wen et al., 2021). The interplay between price perception, consumer trust, and sentiment highlights the growing importance of sentiment-based pricing models in hotel revenue management.

Additionally, advances in algorithmic pricing strategies have enabled hotels to integrate machine learning-driven pricing recommendations that dynamically adjust rates based on real-time guest sentiment trends. Research in algorithmic pricing has demonstrated its ability to increase revenue and optimize price elasticity by responding to consumer sentiment fluctuations (Choi et al., 2023). This shift toward algorithmic decision-making highlights the increasing role of big data and AI in pricing models, reinforcing the importance of integrating customer sentiment into pricing approaches for long-term competitive advantage.

1.3 Customer perception and pricing

Customer perception plays a critical role in shaping pricing effectiveness in the hospitality industry. Consumers assess hotel prices based on their expectations, past experiences, and competitor offerings. The Expectation-Confirmation Theory (ECT) (Oliver, 1980) provides a theoretical framework for understanding how customers evaluate pricing. According to ECT, customers form initial expectations before booking a hotel stay, and their post-stay perception of price is determined by whether the actual experience meets, exceeds, or falls short of these expectations. If expectations are met or surpassed, customers perceive the price as reasonable, while unmet expectations may result in dissatisfaction and negative reviews. This evaluation process is frequently reflected in online feedback, where guests express their sentiment regarding the price relative to the experience received.

Sentiment analysis has emerged as a critical tool for capturing how customers articulate pricing perceptions in online reviews. Studies suggest that positive sentiment is associated with greater price acceptance, whereas negative sentiment—especially regarding service quality, unexpected fees, or perceived overpricing—can lead to unfavorable pricing perceptions (Li et al., 2024; Mariani & Predvoditeleva, 2019). Furthermore, research indicates that the relationship between price paid and review ratings follows an expectancy-disconfirmation pattern, where guests paying higher prices tend to be more critical of their stay unless the service and experience justify the cost (Abrate et al., 2021). Beyond expectation confirmation, price presentation techniques influence how customers perceive hotel pricing. Studies highlight that value-added pricing structures, such as bundled offers, loyalty discounts, and flexible booking options, help enhance perceived affordability while encouraging repeat bookings (Choi & Mattila, 2004). Sentiment analysis provides valuable insights into how consumers react to different pricing models, allowing hotels to refine their pricing structures in response to customer sentiment.

The integration of big data and AI-driven sentiment analysis has further advanced hotel pricing models. Personalized pricing, enabled by machine learning algorithms, allows hotels to dynamically adjust rates based on guest profiles, previous booking behavior, and sentiment trends from online reviews (Padma & Ahn, 2020). Despite these advancements, empirical research linking sentiment analysis and pricing perception remains underdeveloped. Existing studies indicate that pricing perception influences not only booking decisions but also customer loyalty and long-term brand perception (Milman & Tasci, 2023). Existing research examines how sentiment insights help in understanding consumer behavior, assessing pricing in relation to guest expectations, and analyzing their impact on customer satisfaction. While studies have explored the influence of online reviews on consumer decisions, there is limited empirical research on how sentiment analysis can be systematically integrated into hotel pricing approaches. This study aims to address this gap by investigating the relationship between customer sentiment in online reviews and pricing perception, contributing to a more data-driven approach for hotels.

2. METHODS

2.1 Data collection and procedures

The hotel customers' review data were extracted from TripAdvisor, the most well-known review platform in the tourism industry for users. TripAdvisor reviews contain rich information with the system to avoid false reviews, and it hence has been widely used as a comprehensive and trustworthy data source in the research community (Filieri et al., 2015; Jang & Moutinho, 2019; Lee et al., 2018; Li et al., 2018; Marcolin et al., 2021; Ray et al., 2021; Roy, 2023; Valdivia et al., 2017; Zhao et al., 2019). Ma et al. (2018) noted that TripAdvisor is the most frequently used data source for sentiment analysis in the hospitality context. The dataset includes customer reviews from hotels across all categories, ranging from budget to luxury, as retrieved by Synthesio. This comprehensive approach allows for a more holistic analysis of customer sentiment across different hotel segments, rather than limiting insights to a specific category. By incorporating reviews from diverse hotel types, we can capture variations in price and identify common and unique sentiment trends.

To ensure that all retrieved reviews referred specifically to hotels, the data extraction process was restricted to the "Hotels" category within the TripAdvisor platform. TripAdvisor classifies user-generated content according to business categories (e.g., hotels, restaurants, attractions), and Synthesio allows the data query to be limited to a specific category. Consequently, only reviews posted on hotel listing pages were included in the dataset. Reviews associated with other categories, such as restaurants or attractions, were excluded during the initial data extraction stage.

Particularly, its social listening platform and data dashboard interface are specialised in extracting, transforming and loading data into a central data store. Synthesio not only features the widest selection of mainstream data sources, but also provides cleaner data than other automated web data extraction tools, thanks to its first-of-its-kind Noise Reducer technology (www.synthesio.com). Recent reviews of big data-based research in hospitality and tourism indicated that most studies in the research field either developed their own crawlers or employed application programming interface (API) to collect user-generated content (UGC) data (Li et al., 2018; Lu & Stepchenkova, 2015; Mariani & Baggio, 2022; Mariani et al., 2018). These authors noted the research limitations as far as methods and techniques are concerned and thus suggested widening the data collection techniques. Our study is the first that uses Synthesio – a global leading AI-powered social intelligence SaaS platform (Forrester Research, 2020, 2021; Kotras, 2020) – in big data analytics in tourism research. By utilizing the latest technologies, we, therefore, address the aforementioned research limitation and contribute to methodological novelty.

As we aim to investigate hotel customers' opinions and sentiments on price perception, we set up the keywords "hotel AND (price OR money)" in our search query to extract all the hotel reviews on TripAdvisor containing these keywords. In addition to keyword filtering, Synthesio's Noise Reducer technology and built-in filtering functions were applied to remove irrelevant or duplicated content, ensuring that the dataset only included meaningful user-generated reviews related to hotel price perceptions. The time period was set between July 2022 and July 2023. This timeframe was selected to capture a full 12-month period of post-pandemic travel recovery, during which hotel pricing and consumer perceptions of value were undergoing significant adjustments due to increased travel demand, inflation, and changes in tourism supply. By covering one full year, seasonal fluctuations in travel patterns were also considered. Moreover, examining customer price perceptions during this recovery period provides valuable insights into how consumers evaluate hotel value under conditions of market disruption and rapid change. As similar global disruptions or demand shocks may occur again in the future, the findings from this period can offer useful reference points for understanding consumer responses to pricing dynamics during periods of industry recovery and adjustment.

Therefore, by selecting the three sentiment categories—positive, negative, and neutral—and limiting the dataset to English-language reviews, a total of 30.5K reviews were retrieved through Synthesio.

2.2 Treatment and analysis of data

After scrapping all the reviews containing the words "hotel AND (price OR money)", we carried out sentiment analysis using Synthesio Report Dashboard to produce key attributes affecting hotel customers' perceived price being mentioned in a positive, negative and/or neutral context. This study could consider aspect-based sentiment analysis, which enables sentiment classification at the attribute level (e.g., room experience, staff service, food experience, location, facilities & amenities). This approach would provide a more granular understanding of customer preferences by identifying sentiments associated with specific hotel attributes, offering deeper insights into how customers evaluate their price.

Sentiment analysis, also known as opinion mining (Hemmatian & Sohrabi, 2019; Liu, 2012; Pang & Lee, 2008), is a type of text mining that uses automatic computations to measure people's 'sentiments' on whether they are positive or negative toward a particular topic through extracting and analyzing people's subjective information (Ma et al., 2018). Sentiment is subjective feelings, rather than facts, and includes people's attitude, thought, emotions, and judgment (Fang & Zhan, 2015). Sentiment analysis has been widely used in many disciplines since the early 2000s, and in the recent decade, the interest in this technique has enjoyed a huge burst (Ligthart et al., 2021; Ma et al., 2018; Shaik et al., 2023; Valdivia et al., 2017). In hospitality and tourism research, sentiment analysis of online reviews has been increasingly employed to examine customer experiences, service quality, and satisfaction (Geetha et al., 2017; Ray et al., 2021; Roy, 2023). This study contributes to the literature by applying attribute-level sentiment analysis to investigate customers' perceptions of hotel pricing.

To raise wider awareness and application of sentiment analysis in the hospitality discipline, Ma et al. (2018) provided an easy-to-follow guide for using this innovative research method. The steps for conducting sentiment analysis usually involve data preparation, sentiment classification (i.e., positive, negative, or neutral), and visual presentation (Ma et al., 2018). There are different types of sentiment analysis tools such as SentiStrength, Leximancer, and VADER that have been currently used in hospitality and tourism research (Kirilenko et al., 2018; Ma et al., 2018). Although there are no readily available guidelines for researchers in selecting the most appropriate sentiment analysis software for their big data research, the prime consideration is that analytic techniques should be suited to data characteristics and research objectives (Li et al., 2018).

To facilitate the analysis, we utilised Synthesio as the analytical platform. Synthesio is a social listening and consumer intelligence platform that enables the collection, organisation, and analysis of large volumes of user-generated content from online sources. In this study, Synthesio supported the extraction and pre-processing of review data, allowing the dataset to be organised in a consistent format for analysis. The platform also provides interactive analytical dashboards that allow researchers to identify frequently mentioned attributes and examine their associated sentiment distributions.

In the Data Dashboard, the raw data were retrieved and pre-processed into clean data, and then in the Report Dashboard we used Synthesio's analytic tools to conduct analysis and visually present the results. The use of Synthesio in this study therefore served primarily as an analytical infrastructure to support large-scale review analysis, while the methodological contribution lies in the attribute-level examination of price-related sentiments in hotel reviews.

2.3 Identification process of key attributes with sentiment proportions

The key attributes were identified using a combination of Synthesio's AI-driven social listening and social analytics tools, along with the authors' interpretation based on prior literature. Synthesio's Social Intelligence Suite played a crucial role in detecting and refining these attributes through its advanced AI-driven capabilities. By leveraging natural language processing (NLP), Synthesio identifies and surfaces the most relevant topics and trends within the dataset (Synthesio, n.d.). Through topic clustering and trend analysis, the platform uncovers recurring themes and discussions central to customer feedback, automatically identifying keywords, even when expressed in varied contexts or with different phrasing. And by analyzing the order of frequency, the platform determines the most discussed keywords, highlighting dominant themes in customer sentiment.

Synthesio's automated sentiment analysis further enhances this process by classifying sentiment associated with each keyword as positive, negative, or neutral. The system's ability to process large volumes of data from diverse sources (in this study, TripAdvisor) ensures comprehensive coverage, enabling a detailed understanding of customer sentiment towards specific keyword.

To enhance transparency regarding the "black box" nature of Synthesio, we provide additional methodological details. Synthesio leverages NLP and machine learning algorithms to detect recurring topics, cluster keywords across varied phrasing, and classify associated sentiment as positive, negative, or neutral. The frequency of each keyword determines its salience, highlighting the most discussed themes within the dataset. These AI outputs were subsequently reviewed and interpreted in conjunction with prior literature (e.g., Jang & Moutinho, 2019; Liu et al., 2017; Ray et al., 2021; Roy, 2023; Zhao et al., 2019; Zhou et al., 2014) to validate the grouping of keywords into the five main hotel attributes, ensuring that both data-driven evidence and theoretical grounding informed the final classification.

By combining AI-driven detection, frequency ranking, sentiment classification, and literature-informed interpretation, this approach allows for a clear and systematic translation of Synthesio outputs into actionable insights. The sentiment distributions of individual keywords were averaged to produce overall sentiment percentages for each attribute, enabling a quantitative understanding of which attributes contribute most to positive, negative, or neutral perceptions of hotel pricing. This integrated method maintains the efficiency and scale of AI analysis while ensuring methodological rigor and transparency, making the process and rationale behind the identification of the five key hotel attributes fully traceable to readers.

3. RESULTS AND DISCUSSION

The findings of this research are expected to assess how customers perceive hotel pricing and identify key factors that are associated with their willingness to pay, based on sentiment analysis of online reviews.

3.1 Sentiment distribution

The overall sentiment distribution is basically balanced between positive reviews (47.5%, n=14,438) and negative reviews (42.5%, n=12,800), and the remaining are neutral reviews (10%, n=3,139). The slightly higher proportion of positive reviews indicates that customer sentiments toward hotel pricing were polarized. Examples of positive sentiment expressed in the reviews include, "Excellent for money", "Good hotel at reasonable price", "Great quality at a competitive price ", "very good quality at an unbeatable price"; examples of negative sentiment expressed in the reviews include, "Much better areas with similar price tags", "Not worth the money", "We were expecting a higher class hotel for the price", "it's not worth the money, not even half the money".

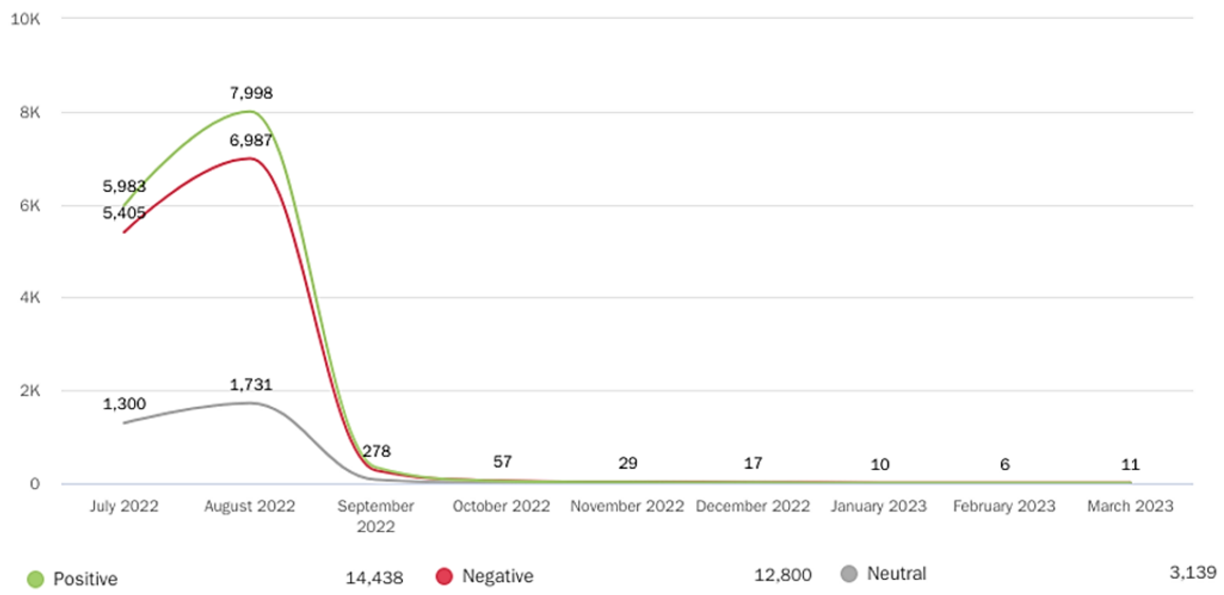
Neutral sentiment only accounted for 10 percent of the data. There are two types of neutral valance, mixed and indifferent (Tang et al., 2014). Mixed neutral reviews include both positive and negative comments in a balanced manner, that is, "with equal amounts of positive and negative claims leading to balanced evaluations, attitudes, and/or emotions" (Tang et al., 2014, p. 44). Whereas indifferent neutral reviews contain neither positive nor negative claims, this is, no feeling appears. Studies have shown that mixed neutral reviews were perceived as more informative because they contain both pros and cons details and are more trustworthy than either strongly positive or negative reviews, which may be perceived as biased (Callarisa-Fiol et al., 2023; Salehan & Kim, 2016). However, because neutral reviews are less prevailing than positive and negative reviews, thus have received little research attention (Roy et al., 2019).

In the context of our study, the mixed neutral reviews usually included both positive and negative comments about various aspects of staying at a hotel and then provided a mixed while balanced conclusion about the hotel's price. For example, the expensive food was the downside of the hotel but also commented that the room rate was reasonable, hence conveying a neutral sentiment. On the other hand, indifferent neutral reviews were simply not clearly indicative of a specific sentiment. For instance, the review though mentioned "a high price" for the most iconic and photographed hotel in the area, it did not imply a specific sentiment.

When examining the different sentiments over time (Figure 2), we noted that over 95 percent of the reviews were posted in July and August 2022. The number of reviews then plunged from 16K in August to 700 in September and remained at less than 100 reviews per month in the following nine months, from October 2022 to July 2023. The reason for the peak volume of reviews in July and August 2022 could be attributed to the summer vacation season. During these months, many people take holidays and travel, leading to a surge in hotel stays, restaurant visits, and tourist attractions. As a result, more individuals are likely to share their experiences and opinions on TripAdvisor, leading to higher review volumes during this period. Prior research in hospitality has demonstrated a strong correlation between hotel occupancy fluctuations and review volumes on platforms like TripAdvisor (Xie et al., 2014; Zhao et al., 2019).

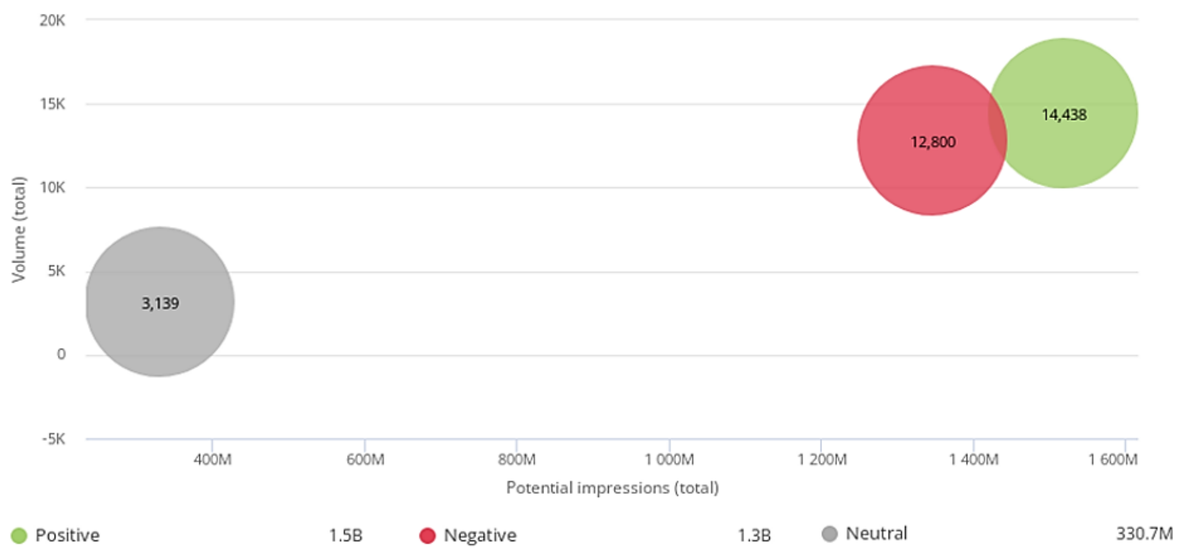
Additionally, with travel restrictions easing in some regions in 2022, more people may have been eager to explore new destinations and share their experiences online. However, the lingering effects of the COVID-19 pandemic may have still influenced travel behaviors in certain months and regions. Although the data collection period (July 2022 – July 2023) falls within the post-pandemic recovery phase, research indicates that ongoing economic uncertainty, fluctuating consumer confidence, and shifting travel priorities continued to impact tourism patterns. These factors may have contributed to irregular hotel bookings and fluctuations in review activity across different months.

Figure 2: **Monitoring over time of the different sentiments**



We also examined sentiment in potential impressions of the reviews. Potential impressions refer to the number of times a review was viewed (or clicked) (Liu, 2007). Impressions are about exposure to content; therefore, the greater potential impressions a review reaches, the more influential it is (Liu et al., 2021; Marin et al., 2018). As shown in Figure 3, the positive reviews received approximately 1.5B potential impressions, the negative reviews received roughly 1.3B potential impressions, and the neutral reviews received nearly 330.7M potential impressions. This means that the review could potentially reach all of those who search for information through TripAdvisor and/or use TripAdvisor for their hotel booking. In essence, these potential impressions of the reviews are associated with the credibility of a business or destination, leading to electronic word-of-mouth (eWOM) recommendations from those who have read the reviews (Mathews et al., 2022).

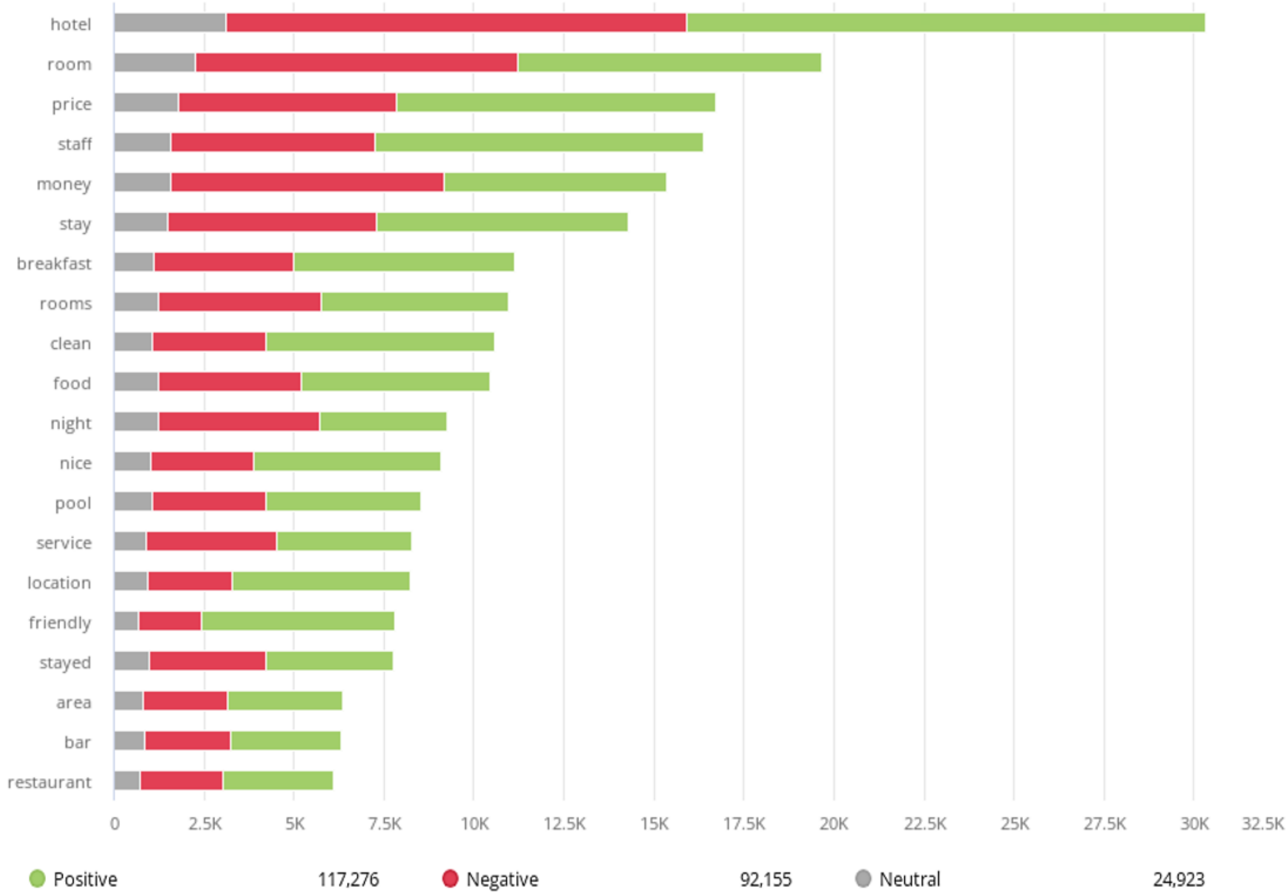
Figure 3: **Sentiment in potential impressions**



3.2 Sentiment analysis of key attributes affecting hotel pricing perception

We analyzed the main attributes affecting hotel customers' perceived price being mentioned in a positive, negative, and neutral context. From 30.5K reviews, total 117,276 positive mentions, total 92,155 negative mentions, and total 24,923 neutral mentions were distributed across the top 20 keywords. As shown in Figure 4, the sentiment distribution of each keyword is largely consistent with the overall sentiment distribution, that is, positive sentiment is the most dominant among the 17 keywords, while negative sentiment is the most dominant among 3 keywords (i.e., room, money, night).

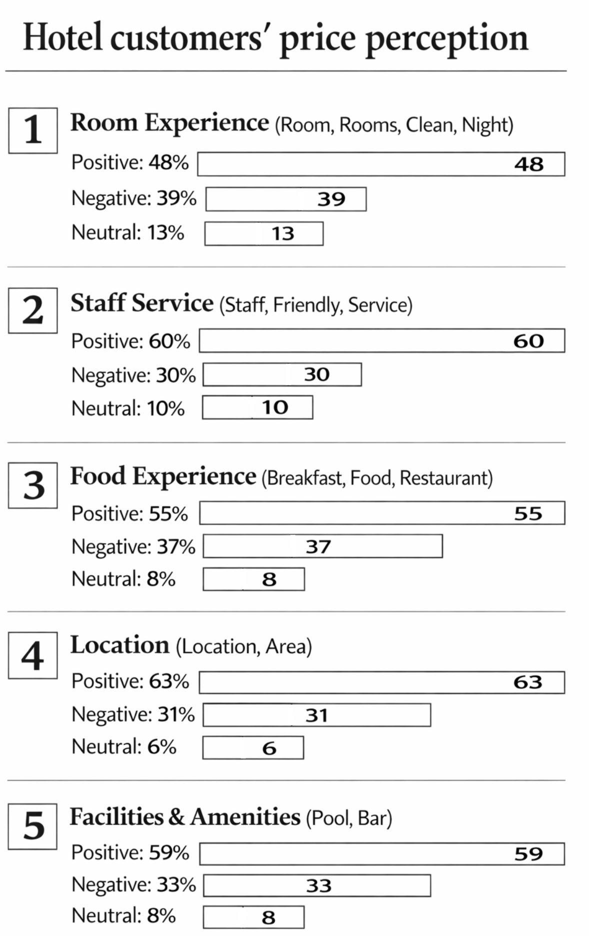
Figure 4: **The top 20 keywords by sentiment**



For the eligibility of the generated keywords to group into main themes, we first excluded the three search query words “hotel”, “price”, and “money” which were included in all the hotel reviews on TripAdvisor. We also perused the three keywords “stay”, “stayed”, and “nice”. The words “stay/stayed” were frequently used to describe staying in a hotel. The word “night” was similarly used to describe how many night(s) people stayed in a hotel or the price of per night. However, because “night” was also mentioned in reviews when people describing sleep, so we associated the word with the room attribute and included in the room theme. The high occurrences of “stay/stayed” were merely about general descriptions of hotel experience but not particularly related to specific hotel attributes. The word “nice” was used to describe something nice in a general manner, including place, people, food, view, and weather. Because it was all-present, we did not include it in any theme.

Drawn on hotel attributes and customer satisfaction literature using online review data (Jang & Moutinho, 2019; Liu et al., 2017; Roy, 2023; Zhao et al., 2019; Zhou et al., 2014), we grouped the remaining 14 top keywords into five core hotel attributes based on their impact on hotel customers’ sentiments in relation to price perception (see Figure 5). Our sentiment analysis then focused on these five themes of core hotel attributes to explore to what extent and in what way these attributes affected customers’ price sentiments. To give detailed insights into these five attributes, relevant keywords and direct quotes from hotel reviews are provided in Appendix 1. The quotes are amended for grammatical and/or typographical errors and protection of private data and/or anonymity.

Figure 5: **Five main attributes affecting hotel customers' price perception**



"Room" was the most frequently occurring word in our data, with a distribution of 48% positive, 39% negative, and 13% neutral. And room cleanliness ("clean") was the most important aspect of room experience. The word "night" was also mentioned in association with "room", mainly concerning the quality of sleep. Other aspects of the room experience included size, bed, bathroom, room amenities, and furniture and decoration. This theme indicates that hotel customers associated their sentiments towards "money" or "price" closely with their room experience. Previous research has shown that room experience is an important hotel attribute contributing to customer satisfaction or dissatisfaction (Berezina et al., 2016; Guo et al., 2017; Roy, 2023; Xu & Li, 2016).

Our result suggests that room experience also has a direct, significant impact on customers' perceived pricing. Positive room experience likely led to positive sentiment that the price was worth it, and on the other hand, negative room experience likely generated negative sentiment that the hotel overcharged money. Importantly, room cleanliness appeared to function primarily as a basic expectation rather than a differentiating attribute. Consistent with the concept of hygiene factors in service quality (Berezina et al., 2016), a clean room alone did not necessarily generate strong positive sentiment or position a hotel as premium. However, dissatisfaction with cleanliness frequently triggered negative evaluations and complaints about price. This finding suggests that while cleanliness may not elevate perceptions of luxury or premium positioning, its absence can significantly undermine perceived value and lead customers to question whether the price paid is justified.

The second most frequently mentioned word was "staff," along with "service" and "friendly," with a distribution of 60% positive, 30% negative, and 10% neutral. In Figure 4, it shows that "staff" and "service" received a slightly higher number of positive mentions compared to negative ones, in line with the overall sentiment distribution. However, the positive sentiment associated with the word "friendly" was significantly more prominent than the negative sentiment. This is no surprise, given "friendly" being a positive descriptive adjective. The interesting findings were actually unveiled from the negative sentiment related to "friendly" and "staff" or "service". Customers normally expected hotel staff to be friendly and helpful, providing welcoming and hospitable services. Therefore, the comment "not friendly" denoted a strong negative sentiment. In addition, when the hotel service was not up to service expectations (for example, "service was average"), the mild disappointment tended to compound negative views on other aspects of hotel experience, adding to a negative sentiment about hotel price.

However, in the case where friendly staff was the only positive aspect of the hotel, customers also expressed strong negative price sentiment. Notably, those customers made it clear that they appreciated hotel staff's work but complained about everything else. This finding suggests that, similar to room cleanliness but to a lesser extent, the presence of good service was necessary, but not sufficient in itself to impress in terms of perceived pricing. In addition, when comparing the "staff service" theme with the "room experience" theme, we noted that friendly staff was not as important as clean rooms in relation to hotel customers' price sentiments. Not only the frequency of occurrences of "room/rooms" was greater than "service/staff" in the data, but also when customers had different sentiments between room quality and staff service, room-experience-induced sentiments were more determinant to their opinions on hotel price.

The third theme is "food experience," which includes "food," "breakfast," and "restaurant," with a distribution of 55% positive, 37% negative, and 8% neutral. The food attribute usually includes food variety (e.g., Asian food, Western food), food quality, the dining environment, and availability of special food service (e.g., room service; vegetarian and gluten free options; Halal food) (Zhou et al., 2014). Our data demonstrated that customers shared their views on all these various aspects of their food experience in online reviews. In addition, "breakfast" and "restaurant" were two most frequently mentioned aspects that are associated with hotel customers' sentiments towards their perceived hotel pricing. This might indicate that hotel customers are more likely to have breakfast than lunch or dinner at the hotel restaurants, hence having more opinions about breakfast. Noticeably, customers' food experience was often related to restaurant staff's service. These two aspects interconnected and jointly affected customers' sentiments to price, more likely in a generative way.

The fourth theme includes "location" and "area," with a distribution of 63% positive, 31% negative, and 6% neutral. This theme describes the hotel's convenience to major tourist attractions, transportation, or points of interest (e.g., conference venues, museums, stadiums). In addition to the geographical location of a hotel, there were other factors that affected customers' sentiments toward hotel price, such as availability of parking, traffic and safety of the area, and provision of hotel transport service. We noted two interesting findings in this theme of location. First, amongst negative hotel reviews, a large number commented that location was the only positive thing about the hotel, and second, negative comments about the location were actually not centered on geographical location but on other aspects of hotel areas such as parking and traffic.

The final theme was hotel facilities, which included the keywords "pool" and "bar," with a distribution of 59% positive, 33% negative, and 8% neutral. Positive comments about "pool" included being clean and warm, family friendly, attended by lifeguards, having pool amenities (e.g., slides, view, bar) and good changing facilities. Negative comments about "pool" included being crowded or even dirty, limited access, extra charges, no separate pools for kid and adult, and lack of pool amenities such as umbrellas. Comments about "bar" were mainly centered on two aspects, quality of bar service and the price of bar drinks. Bar service included the bartender, selection and quality of drinks, and the environment. The bar service aspect was equally present in both positive and negative comments. The price aspect of bar amenity, however, was more frequently associated with negative comments than positive comments.

Our analysis revealed that customers' sentiments regarding hotel facilities and amenities were relatively aligned with their sentiments to pricing. Interestingly, there were exceptions that negative sentiment of "pool" or "bar" were seen in positive reviews and positive sentiment of those in negative reviews. We also noted that there were positive hotel reviews in which the absence of pool facilities or bar amenities was mentioned. This 'exception' and 'absence' case showed that different types of hotel customers evaluated the relevance and importance of hotel facilities and amenities differently. For example, people on family holidays may consider pool entertainment more than bar drink menus, whereas business travelers would spend more time and money at the bar than around the pool. The finding suggests that, unlike hygiene-factor hotel attributes such as room cleanliness which are essential to all customers and critical to their perceptions of pricing, hotel facilities and amenities are motivator-factors that may create a positive disposition but are not regarded equally across all customers. On the one hand, if customers are not satisfied with rooms or staff service, it is very unlikely they would be interested in or fully appreciate other hotel facilities and amenities such as pool or bar. On the other hand, absent or subpar facilities or amenities do not necessarily affect customers' sentiments in a negative way; however, when provided, these motivator-factor hotel attributes may enhance positive sentiment and pricing perceptions.

Also, in the current digital context, customer experiences are immediately visible and widely disseminated through online reviews and social media, meaning that tangible service quality such as room cleanliness, staff responsiveness, and basic facilities is instantly exposed to a broad audience. This transparency forces a reassessment of the service-profit chain and value hierarchy in hospitality: foundational hygiene factors must be reliably delivered to avoid negative sentiment about pricing, while additional motivator attributes, such as pools or bars, can enhance perceived value. The AI-driven analysis of large-scale customer reviews highlights which attributes are most strongly associated with perceived price, showing that digital visibility accelerates the evaluation of core service quality and amplifies its impact on price perceptions and customer satisfaction.

4. IMPLICATIONS AND CONCLUSION

To reach an overall sentiment on hotel pricing, hotel customers tended to appraise across multiple aspects of hotel experience, commenting on various opinion hotel attributes in their reviews. In addition, we noted that many reviews included both positive and negative comments on different aspects of staying at a hotel, and then, in the end, made either positive or negative sentiment evaluations. These comprehensive reviews, or full reviews as some customers described themselves, were different from neutral reviews because they provided clear sentiment polarity, rather than a mixed or balanced expression of positive and negative sentiment.

This section delves into the implications of the research for both theoretical frameworks and practical applications, focusing on how customer sentiments shape perceptions of hotel pricing. It also addresses the constraints encountered during the study and outlines potential avenues for future research.

4.1 Theoretical implications

This study contributes to the hospitality and tourism literature by offering a refined understanding of how customer perceptions of pricing are shaped by hotel experiences. Existing research has consistently shown that both tangible hotel attributes (e.g., room furnishings and cleanliness) and intangible attributes (e.g., staff attitudes and behaviours) play a significant role in influencing customer satisfaction and online review sentiment (Berezina et al., 2016; Roy, 2023; Xu & Li, 2016; Zhang et al., 2021).While prior studies published in leading hospitality and tourism journals (e.g., Tourism Management, International Journal of Hospitality Management) primarily examine these attributes in relation to overall satisfaction or dissatisfaction (Berezina et al., 2016; Zhang et al., 2021), our findings extend this literature by demonstrating that tangible attributes exert a stronger association specifically on customers' assessments of price fairness and appropriateness.

The results indicate that customers tend to perceive tangible attributes as the core product of the hotel, directly linked to their basic functional expectations, whereas intangible attributes are more frequently interpreted as experiential enhancers. This finding aligns with Berezina et al. (2016) that dissatisfaction is often driven by tangible shortcomings, but extends their work by showing that such shortcomings are also central to negative price perceptions rather than dissatisfaction alone. In doing so, our study provides empirical support for the growing stream of content-focused online review research by linking attribute-level sentiment directly to pricing perceptions.

Moreover, this research builds upon Expectation-Confirmation Theory (ECT) (Oliver, 1980), which has been widely applied in hospitality research to explain customer satisfaction and post-consumption evaluations. According to ECT, when actual hotel experiences meet or exceed pre-stay expectations, customers are more likely to perceive prices as reasonable, whereas expectation disconfirmation leads to negative sentiment. Our findings empirically reinforce this theoretical mechanism by demonstrating that price-related sentiment in online reviews is closely tied to expectation confirmation associated with core attributes such as room quality, cleanliness, staff service, and amenities.

The results further show that discrepancies between expected and actual service standards, particularly regarding room conditions and cleanliness, are major drivers of negative price sentiment. This observation complements sentiment-driven pricing research (e.g., Guillet & Mohammed, 2015; Wen et al., 2021) by providing demand-side evidence of how customers articulate price dissatisfaction in natural language, rather than inferring price sensitivity from booking or transaction data alone. In addition, the findings advocate for expanding existing models used in hospitality research to incorporate experiential and contextual factors more effectively. Our study calls for the adoption of more comprehensive theoretical models in hospitality research, ensuring that pricing perceptions are examined through a multidimensional approach that accounts for how expectation confirmation is associated with consumer assessments.

4.2 Practical implications

This finding suggests that customers' priority of hotel experience, and hence their perceived price, vary at a personal level. Customers' personal preferences more or less played a role in weighing up different hotel attributes in relation to their perceptions of price. This subjective nature of customer perceived price means that what constitutes price appears to be highly personal and idiosyncratic, and can vary from one customer to another (El-Adly, 2019; Jamal et al., 2011). Nevertheless, our findings show that the room attribute, particularly room cleanliness, was seen as a necessary, though not sufficient, condition for positive reviews on price by all customers. Therefore, emphasizing positive reviews in marketing materials and branding efforts, particularly those highlighting room cleanliness and hygiene standards, can position the hotel as a premium or luxury destination. By showcasing testimonials and ratings that commend the hotel's exceptional cleanliness practices, prospective customers are likely to perceive the property as a trustworthy and upscale option. Also, partnering with recognized hygiene certification programs can reinforce the hotel's premium image. Displaying these certifications in marketing materials may further justify price premiums. Implementing AI-driven tools to continuously monitor and highlight positive reviews on cleanliness in real time allows hotels to refine their marketing messages and adjust pricing approach accordingly.

Clean rooms were found to have a stronger association with hotel customers' price sentiments compared to friendly staff. While customers generally anticipated friendly and helpful hotel staff, the absence of friendliness was viewed as a significant negative aspect, indicating a strong negative sentiment. Recognizing that negative reviews about staff unfriendliness can deter potential customers, hotels could opt to tweak their pricing approach to enhance competitiveness within the market. This could involve modest reductions in rates to offset any perceived shortcomings in service quality, thereby increasing the hotel's appeal despite the presence of negative sentiments. Alternatively, investing in staff training programs focused on customer service and hospitality skills can address the root causes of negative feedback. By ensuring that staff members are friendly, helpful, and welcoming, hotels can elevate service standards and justify premium pricing. Additionally, incorporating contactless services such as mobile check-ins, digital room keys, and automated concierge services can help minimize direct staff interactions, reducing the impact of negative sentiments related to unfriendliness. These technologies not only enhance operational efficiency but also cater to guests who prefer seamless, self-service experiences. Combining enhanced service training with contactless solutions allows hotels to strengthen their pricing.

In terms of food experience, this study suggests that customers are more inclined to comment on breakfast offerings compared to lunch or dinner options at hotel restaurants, potentially indicating a greater emphasis on morning dining experiences. In response, hotels may offer breakfast-inclusive room rates or package deals that emphasize the quality, variety, and sustainability of breakfast offerings. By bundling breakfast with accommodations, hotels can justify slightly higher room rates. Also, launching exclusive promotions or discounts for breakfast or restaurant dining can draw guests and encourage them to opt for on-site dining, while incorporating locally sourced, organic, and seasonal ingredients not only enhances the pricing approach but also supports sustainable food systems. Limited-time offers or package deals featuring plant-based or zero-waste meal options, aligned with the growing demand for sustainable hospitality practices, can entice guests to dine at the hotel, reinforcing their pricing.

Customers usually had prior knowledge about location when choosing hotels; in fact, location probably is the first factor to consider when people make decisions about where to stay. Therefore, customers tended to have relatively realistic expectations on the location aspect of the hotel. Even in the case of negative sentiment about the hotel as a whole, customers would still remain positive about location, as long as there were no major discrepancies between their prior knowledge of the location and their experience in person after arrival. When there were such discrepancies, the issues were mostly related to the surrounding areas of the hotel or transportation related issues, rather than the location per se. In this sense, location is an 'experience' attribute because only after staying in the hotel can customers obtain more details about the various aspects of the location attribute (Xu, 2020). In response, offering complimentary parking or shuttle services can improve the hotel's overall pricing appeal. By including these services in the room rate or package deals, hotels can justify their pricing while providing added convenience to guests. Additionally, integrating green parking initiatives (e.g., designated spots for electric vehicles (EV) and EV charging stations) and leveraging smart technology in parking management and shuttle services (e.g., mobile apps that provide real-time updates on shuttle arrivals or parking availability) can strengthen the hotel's pricing approach. These innovations not only enhance operational efficiency but also justify higher room rates by offering additional services to guests, while aligning with the growing trend of digitalization and sustainability in hospitality.

This study found that hotel facilities and amenities function as motivator-factors that can create a positive impression but are not equally considered by all customers. The absence or substandard quality of facilities and amenities may not necessarily lead to negative sentiments among customers. However, when these motivator-factor attributes are present and of high quality, they can significantly enhance positive sentiment and perceptions of price. This finding suggests hotels could adjust their pricing to reflect the quality and availability of these motivator-factors. Offering competitive rates while highlighting desirable amenities and facilities can help hotels justify their pricing. Additionally, promotional offers or package deals that showcase these amenities, such as loyalty program perks, can attract guests seeking enhanced experiences, thereby bolstering revenue. Ultimately, aligning the pricing approach with the presence and quality of motivator-factors can contribute to the overall guest perception of price and profitability.

4.3 Research limitations and future research directions

Our study represents an endeavor to employ Synthesio, a prominent AI-powered social intelligence SaaS platform, for big data analytics within hospitality research. Synthesio is recognized for its ability to provide comprehensive and precise sentiment data from social media users, addressing previous research limitations and introducing methodological innovation. However, reliance on a single AI tool may limit the generalizability of the findings, as the nuances of data extraction, sentiment interpretation, and contextual accuracy depend on the platform's algorithms, which may not capture every aspect of sentiment as effectively as other tools. In addition, while this study leverages AI-driven sentiment analytics to identify the relative salience of hotel attributes based on sentiment volume, polarity, and contextual co-occurrence, it does not employ traditional quantitative models (e.g., survey-based importance–performance analysis) to statistically test causal relationships. Future research could explore comparative studies using multiple sentiment analysis tools and integrate AI-based approaches with quantitative techniques to further quantify attribute influence and triangulate findings across methodologies.

As the study relies solely on TripAdvisor reviews, customer sentiment from other platforms is not captured. Future research would incorporate multiple review and social media platforms to enhance generalizability.

This study's restriction to a particular timeframe could neglect potential fluctuations in customer sentiment over time, thereby constraining the longitudinal validity of the results. To delve into the temporal dynamics of customer sentiment, conducting longitudinal studies becomes essential. Future studies would involve tracking changes in sentiment patterns over an extended period, allowing for an assessment of the enduring efficacy of pricing approach.

Furthermore, future research on neutral reviews would have the potential to advance the understanding of the nuances of consumer perception and behavior in response to different types of neutral reviews, and to inform practical implications for businesses and review platforms in managing their online reputation and influencing consumer decision-making.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

In preparing this paper, the authors used ChatGPT to assist with paragraph structuring, figure creation, and grammar checking. Following the use of this tool/service, the authors have reviewed and edited the content as necessary and take full responsibility for the content of the published article.

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Please cite this article as:
Kim, E., Choi, K., Abbott, L. (2027). From Reviews to Perceived Pricing: A Sentiment Analysis of Hotel Experiences. *Tourism and Hospitality Management, 33*(1), pp. https://doi.org/10.20867/thm.33.1.4

APPENDIX 1. MAIN ATTRIBUTES, RELEVANT KEYWORDS, AND QUOTATIONS

Main attributes	Relevant keywords	Quotations
Room experience	Room, Rooms, Clean, Night	Positive *"Room was spacious and clean…. **Price for the room was worth it."** "The rooms were extremely clean, nicely decorated and **great for the money**."*
		Negative *"… We stayed for 6 nights and the room was never cleaned. Yes, I requested and it was never done... This one **won't respect your money spent**." "… The condition/cleanliness of the room was **not what I would expect to pay $500/night for**…" "Really mediocre. Torn sheets, zero in room amenities like a fridge or mini bar, paint touch ups needed, view of a dirt pit. **Really not worth the money at all**… Incidentally the beds are horrible…"*
Staff service	Staff, Service, Friendly	Positive about staff but still negative about price *"**Really not worth the money at all**…. The staff was friendly, but that's the only thing this place has going for it …" "The only positive are the employees who are friendly and work hard … So in conclusion, if you want to pay $1000 a night to stay at a dirty hotel with old furniture and no pool this is for you. Or, **save the money and stay at a cheaper hotel** with cleaner rooms and a pool…" "The room needed a good clean … That being said the staff were very friendly and accommodating. **Just the quality of that room didn't match the inflated price**."*
		Negative *"…. The valet was friendly (that was expected) nothing I haven't seen before for less money … The hotel culture seems to be on charging and **indeed overcharging** as much as possible instead of concentrating on delivering warm friendly and honest customer service." "We…spent the extra money …. the service was not what you'd expect from a luxury or 5 star hotel. Nothing went wrong but staff certainly didn't go out of their way to be hospitable or helpful."*
Food experience	Food, Breakfast, Restaurant	Positive *"Food was of **great quality for the price** and catered well for both me (meat eater) and my wife vegetarian. Breakfast was really good for a hot full English buffet. The hash browns were best I have ever had." "What sent this hotel over the top for us was Sunday breakfast in a small, gorgeous dining room …Dishes were beautifully presented, super fresh with some unique ingredients, and very creative touches. Service was professional and quick. A little pricey, yes, but restaurants in this area are very pricey, and **here the money spent was well worth** a wonderful dining experience."*
		Negative *"**Do not waste your money on this hotel** … The food is **extremely overpriced**. The coffee is terrible and imported from low grade convenient store. I ordered tamala…. That was the only vegetarian dish offered. It was quarter pound of blob of corn and onion and not fit to eat. Avoid ordering any overpriced food at this hotel." "The food. Room service was quick but unappealing. I ordered the steak frites, but the steak looked like it was only 4 ounces. Breakfast was no better. **Despite the $23 price**, spare yourself from ordering the Signature Breakfast. It is a poor imitation…. Also, they seem to have a problem getting the food to stay hot…"*
Location	Location, Area	Positive *"… The good are the location, free/secure parking… If you need just a safe, clean place to crash but not spend time in this is a great place for that. **I would stay again for the price**!" "A great stay in a central location: … **The price is unbeatable for the location**; only a 15 minutes walk… A plethora of restaurants, stores and nightlife options are just outside the doorstep. Everywhere else can easily be reached by the metro. Wouldn't mind staying here again during future trips to the city of lights. Can recommend!"*
		Negative *"**RIP-OFF**: I don't want to diminish the historical value and importance of the building for the city and area... However, put **a hefty price tag** on the accommodation, that is simply **not worth it**. Parking 60 USD per night?" "**Not worth the price tag**: The location is great if you are not traveling by car. The route to turn into to get the car valet is annoying with all the traffic from the roundabout especially during rush hours. They need a better parking system… The entrance of hotel is catered more to the restaurant than it is to the hotel. Definitely a lot of traffic noise you can hear even on the 14th floor late at night… Just disappointing for the stay with that kind of price tag."*
Facilities &amenities	Pool, Bar	Positive *"The pools were awesome, we spent the majority of our time at the main pool. There was always plenty of things to do such and the pool was warm and had sun shades which was great. Pool towels can be collected at the pool so you don't have to bring any from the rooms. **Excellent for money.**" "Bars were good, plenty of stuff and drinks service. You pay a bit extra for the premium alcoholic drinks but there's still plenty to drink without have to pay for any premium drinks. I've even uploaded a copy of the bar menu for reference. **Good quality for the price**"*
		Negative *"If you only stay for one night then you can only use the pool once your entire stay, and only at your allotted time. They do not allow you to use the pool once a day. **At the price point they are charging this is quite insane**." "Family pool full of screaming kids, adult pool full of guests blasting personal speaker systems." "Don't go the hotel bar before you ask a price of your drink. They **charge an abusive price for the drinks**. Be careful before you place your order! Terrible service!!"*