



**WHAT ARE THE KEY ATTRIBUTES BEHIND GUEST SATISFACTION
IN AWARD-WINNING ALL-INCLUSIVE HOTELS: AN EMPIRICAL
ANALYSIS FROM TÜRKİYE**

**ÖDÜL ALAN HER ŞEY DAHİL OTELLERDE MİSAFİR
MEMNUNİYETİNİN ARKASINDAKİ TEMEL FAKTÖRLER NELERDİR?
TÜRKİYE ÜZERİNE AMPİRİK BİR ANALİZ**

Egemen Güneş TÜKENMEZ 

Dr. Öğretim Üyesi, Alanya Alaaddin Keykubat Üniversitesi Turizm Fakültesi Turizm
İşletmeciliği Bölümü,
egemen.tukenmez@alanya.edu.tr

Geliş Tarihi: 14.11.2025 *Kabul Tarihi:* 29.12.2025

Abstract: In today's tourism industry, online recommendation systems and user reviews play a crucial role in guest decision-making. These platforms provide valuable insights into hotel service quality and customer satisfaction. This study investigates online reviews of all-inclusive hotels in Türkiye, focusing on the key factors influencing guest satisfaction. Reviews from 15 hotels awarded the "Best of the Best Hotels Travelers' Choice" on TripAdvisor in 2025 are analyzed. The findings reveal that the hotels generally receive high ratings, with most reviews being positive. Among six service attributes (value, service, room, cleanliness, location, and sleep quality), value emerges as the most influential factor in guest satisfaction, with a one-unit increase in value leading to a 3.6 times higher chance of positive reviews. Service also has a significant impact, while room is the least influential factor. Analysis by travel type shows no major differences in overall satisfaction, but couples and business travelers are more critical. Therefore, hotel managers should tailor services to meet the expectations of these groups. Furthermore, location is evaluated independently from other factors.

Keywords: All Inclusive, Customer Satisfaction, Sentiment Analysis, Tripadvisor, eWOM

Özet: Günümüzde turizm sektöründe çevrimiçi öneri sistemleri ve kullanıcı değerlendirme platformları, misafirlerin karar verme süreçlerinde kritik bir rol oynamaktadır. Bu platformlar, otellerin hizmet kalitesini ve müşteri memnuniyetini ölçmek için önemli veriler sağlamaktadır. Bu çalışma, Türkiye'deki her şey dâhil (all-inclusive) otellerin çevrimiçi kullanıcı değerlendirmelerini inceleyerek müşteri memnuniyetini etkileyen temel faktörleri ortaya koymaktadır. TripAdvisor'da 2025 yılında "Best of the Best Hotels Travelers' Choice" ödülünü alan 15 otelin değerlendirmeleri analiz edilmiştir. Bulgulara göre, oteller genel olarak yüksek puanlar almış ve değerlendirmelerin çoğu olumlu olmuştur. Altı temel hizmet niteliği (değer, hizmet, oda, temizlik, konum ve uyku kalitesi) içinde "değer" unsuru misafir memnuniyetini en güçlü biçimde etkileyen faktör olarak öne çıkmıştır. Değer algısındaki bir birimlik artış, olumlu değerlendirme olasılığını yaklaşık 3,6 kat artırmaktadır. "Hizmet" de benzer biçimde yüksek etkili bulunurken, "oda" en düşük etkiye sahip unsur olmuştur. Seyahat türüne göre yapılan analizlerde, genel memnuniyet açısından anlamlı fark görülmemekle birlikte, çift ve iş amaçlı seyahat edenlerin daha eleştirel oldukları tespit edilmiştir. Bu nedenle otel yöneticilerinin, özellikle bu grupların beklentilerine uygun hizmet geliştirmeleri önerilmektedir. Çalışma, konumun diğer faktörlerden bağımsız değerlendirildiğini de ortaya çıkarmıştır.

Anahtar Kelimeler: HerŞey Dahil, Misafir Memnuniyeti, Duygu Analizi, Tripadvisor, eWOM

INTRODUCTION

Tourism sector has been subject to considerable impact in recent years due to advancements in technology, with significant consequences across the economic, cultural, and social domains on a global scale. One of the most important factors that cause these effects is digitalization. Digitalization not only facilitates booking and payment processes but also enhances operational efficiency for businesses, making service delivery more effective for the tourism sector (Tandafatu et al., 2024). Within this context, mobile technologies and internet-based platforms provide tourists quick access to touristic informations and enable them to manage and shape their experiences during their stay in a personalized options (Neuhofer et al., 2015; Adeola & Evans, 2019). The adoption of digital tools by businesses supports tourism sector in data driven decision making processes. Furthermore, it enables them to gain a competitive advantage. Thus, technological adaptation is considered a critical element for sustainable performance in tourism sector (Mariani et al., 2021; Mahabub et al., 2025).

One of the critical element of this kind of development is online travel platforms. Online travel platforms play a significant role in today's tourism market. It helps users to guide through travel planning processes such as destination selection, accommodation booking, and event participation. These platforms can optimize decision making processes by offering personalised recommendations based on users' previous preferences and behaviors (Pencarelli, 2020; Yuan et al., 2022; Abashidze, 2024). Recommendation systems also utilize big data analytics and machine learning techniques to predict user behavior and personalized services (Da'u & Salim, 2020; Chiu et al., 2021). These opportunities also enable tourists to access more reliable information, reduce the margin of wrong choices in their decision-making processes, and increase overall travel satisfaction (Liberato et al., 2018; Ramos et al., 2022). Consequently, online travel platforms and recommendation systems stand out as critical tools that not only improve the user experience but also strengthen customer loyalty for tourism businesses (Chiang & Huang, 2015; Yang et al., 2024).

When looking the importance of recommendation systems, it is evident that not only in the booking process but also in enhancing consumer satisfaction and evaluating service quality (Kaverski & Paladini, 2021). Personalized recommendations are effective in meeting user expectations and positively shaping the perception of service quality. (Filiari et al., 2015). Furthermore, these systems influence users' online review and rating behavior, strengthen electronic word of mouth (eWOM), and have a direct impact on business reputation (Yoon et al., 2019). High satisfaction levels definitely increase positive feedback and repeat visitor numbers. It also affects both consumer behavior and strategic plans of tourism businesses (Nilashi et al., 2022). In this context, tourism recommendation systems are considered a comprehensive strategic tool that supports service quality and optimize the consumer experience of tourism firms (Liu & Shih, 2021; Aakash & Gupta-Aggarwal, 2022).

Within the scope of these developments, consumer reviews such as their ratings and written digital comments on online platforms have become one of the most important indicators of service quality and customer satisfaction for tourism businesses. Within this concept, all-inclusive hotels are consequently evaluated by consumers based on various criteria due to the complex and multi-dimensional nature of the services they offer. For this reason, this study aims to analyse the ratings (satisfaction levels) given by hotel

guests to award-winning all-inclusive hotels by TripAdvisor in Türkiye. In analysis process, it is aimed to reveal that which attributes most strongly influence guests' ratings in a positive direction and thus determine consumer satisfaction. In addition, the study also examined whether there was a difference in the satisfaction level of the guests according to their travel type. For the revealing these effects, Chi-Square and logistic regression methods were used in this research, and the findings revealed that the attributes that most strongly influenced guests to give these hotels positive reviews were service and value. Another finding of the study is that although there are differences between the satisfaction levels of the guests according to their type of travel, this level does not have a significant effect on the satisfaction of the guests in general.

CONCEPTUAL FRAMEWORK

Digital transformation has not only restructured operational processes in tourism sector but also transformed the entire value chain, from destination management to customer relations (Gretzel, 2022; Devahastin et al., 2024). Today, the integration of information and communication technologies enables tourism businesses to shape their marketing and pricing strategies and service designs in a data-driven scope (Hojeghan & Esfangerah, 2011; Nezdoyminov et al., 2019; Awal et al., 2025). This transformation with the expansion of artificial intelligence, big data analytics and cloud-based applications allows businesses to develop their personalized services (Hu & Li, 2023). However, digitalization has also changed the nature of competition. Within this framework, customer experience is now shaped not only at physical touchpoints but also through digital interactions between customer to customer and business to customer (Yang et al., 2024). This technological evolution in the tourism industry naturally creates new opportunities in terms of innovation customer engagement (Sigala et al., 2019; Rahmadian et al., 2022; Sakas et al., 2022).

Within this digitalization process in tourism, online travel platforms have become one of the most important interfaces that shapes consumer decision making processes (David et al., 2018). These platforms inevitably facilitate customers' choices by time saving in complex decision making stages such as destination selection, accommodation preference, and price comparison (Nicoli & Papadopoukou, 2017). In this regard, relevant algorithmic recommendation systems use big data such as users' digital footprint, search behavior, and demographic characteristics to deliver personalized content. This fact enables users to access information that is faster, more reliable, and tailored to their needs (Guo et al., 2021). On the other hand, the transparency and trust dimensions of these systems directly affect consumers' loyalty to related platforms and brand loyalty (Litvin & Dowling, 2018). Therefore, online travel platforms are considered not only a booking tool but also a strategic digital system that reshapes the user experience, perception of trust, and consumer satisfaction (Liu & Shih, 2021).

It is known that with digitalisation, traditional word of mouth communication has moved online over time and it converts this concept to electronic word of mouth (eWOM). eWOM significantly influences purchasing decisions by enabling consumers to share their experiences, satisfaction levels and perceptions with several different digital platforms (Manes & Tchetchik, 2018; Zarifah & Hafiz, 2020). In this respect, online reviews and ratings have become one of the key determinants of consumer trust (Noone & Robson, 2016). Users begin to see different experiences shared by other consumers. This situation strengthens the impact of eWOM on purchase intent, brand reputation, and customer loyalty. However, the content and emotional tone of eWOM create different effects on

consumer perception. Therefore, online reputation management has become a strategic necessity for businesses (Chuang et al., 2023, Shu et al., 2025).

One of the most important elements in the scope of eWOM is service quality in the tourism sector. Service quality is recognised as one of the strongest determinants of customer satisfaction in the hospitality industry and has been a central area of research in marketing literature for many years (Garrigos et al., 2019; Park & Jeong, 2019). Traditional service quality measurement models, particularly approaches such as SERVQUAL and SERVPERF, have assessed service quality through dimensions such as tangibles, reliability, empathy, and responsiveness (Bhat, 2012; Rasyida et al., 2016; Puri & Singh, 2018; Yu & Hyun, 2019). However, with digital transformation, this measurement paradigm has started to shift to the online environment. The ratings and reviews determined by consumers on digital tourism platforms have become an important dynamic in terms of attributes that served by different hospitality businesses. Categories such as 'value', 'room', 'cleanliness', 'location', 'service and 'sleep quality' found on platforms like TripAdvisor can be considered digital reflections of service quality dimensions (Limberger et al., 2014; Mao et al., 2018; Silva et al., 2021). In this context, online reviews are not only an expression of individual experiences but also a new service quality measurement tool that makes collective customer perception visible in both numerical and textual form (Zoghi, 2025).

In recent years, studies focusing on the service quality of hotel enterprises and the key areas influencing consumer satisfaction have gained considerable momentum. By employing both textual analyses and quantitative evaluations derived from digital platforms, these studies have elucidated the determinants of hotel satisfaction. By analyzing online data across various destinations and hotel types, researchers have examined how consumers perceive specific hotel services and which aspects are evaluated positively or negatively. For instance, an analysis of TripAdvisor data for the ten most expensive hotels in İstanbul indicated that consumer evaluations were predominantly centered on food and beverage services, front office operations, and housekeeping. In these categories, low service quality, cleanliness issues, and staff attitudes were reported as the most frequently mentioned negative factors (Alrawadieh & Demirkol, 2015). Another panel data study conducted in İstanbul that examined 25 hotels and it identified hotel architecture, cleanliness, food and beverage facilities, service and staff quality, location, and accessibility as the most influential determinants of guest satisfaction (Yılmaz, 2020). A study focusing on hotels in Ankara, using data from five different online platforms, found that most complaints were related to rooms, food and beverage services, and cleanliness (Ceylan & Uzun, 2024). In another study examining five-star chain hotels in Antalya, food and beverage services, rooms, and staff-related factors were found to have significant effects on guest satisfaction (Şahin et al., 2017). A further investigation of 164 hotels in Antalya, analyzing reviews from 2017 to 2018, revealed that room quality was the factor most enhancing satisfaction, while location had the least impact (Tuna et al., 2021). A study also conducted in the same destination reported issues such as slow service, cleanliness problems, and insufficient services for children effect the customer satisfaction mostly (Gençer & Keşkekci, 2023). A study examining four- and five-star hotels in Alanya utilized quantitative variables extracted from TripAdvisor reviews and data from HolidayCheck. The results demonstrated that general satisfaction and recommendation likelihood were most strongly influenced by food and beverage services and staff, while room-related factors had the weakest effect on recommendation levels (Doğan et al., 2020). Another study covering the cities of Antalya and Alanya

employed the fuzzy logic method using qualitative TripAdvisor data. The findings suggested that guests' overall evaluations were influenced not by a single variable but by the combined interaction of multiple factors, indicating a nonlinear relationship (Doğan et al., 2020).

When examining studies conducted outside Türkiye that utilized online travel platform hotel data, it is evident that a variety of factors influence guest satisfaction across different contexts. For instance, the related study employed an factor analysis using TripAdvisor reviews of hotels in Hong Kong revealed that staff performance, service, room quality, and value have the most significant positive effects on guest satisfaction (Choi & Chu, 2001). Similarly, an analysis of resort hotels in Spain using TripAdvisor data found that hotel staff and room quality were the main positive drivers of satisfaction, while hygiene and price were the least satisfactory attributes (García-Barriocanal et al., 2010). A large-scale data analysis involving hotels from sixteen different countries demonstrated that room quality and service standards were the two factors most strongly influencing guest satisfaction (Guo et al., 2017). Another study conducted in Singapore also found that room amenities, value, and location were the most important determinants of guest satisfaction (Hargreaves, 2015).

According to TripAdvisor-based research, shortcomings in service quality and problems related to staff behavior were the most frequently reported issues by hotel guests (Lee & Hu, 2005). Data analyses of five-star hotels further showed that room features contributed significantly to guest satisfaction, while factors such as price and location had relatively weaker effects (Li et al., 2020). Another study also examining TripAdvisor reviews of hotels in Brazil revealed guests most frequently contained positive comments related to value and service, while negative feedback was primarily associated with room-related aspects (Limberger et al., 2014). An analysis of TripAdvisor reviews for hotels in Slovakia revealed that room quality, sleep quality, cleanliness, and service jointly influenced guest satisfaction, whereas location was evaluated independently from these factors (Uslu Cibere et al., 2020). An evaluation of hotels in the Bavarian region showed that assessing multiple hotel attributes together, particularly food and beverage services combined with room quality, had a stronger effect on guest satisfaction than evaluating a single attribute alone (Başaran et al., 2020).

A survey-based research conducted in Spain also confirmed that service quality and staff behavior were the most influential factors shaping guests' overall experiences (Rivera et al., 2019). A study covering 100 cities in the United States found that hygiene, cleanliness, staff service, and food and beverage offerings were positively evaluated by guests, whereas sleep quality and room features were assessed more negatively (Stringam & Gerdes Jr., 2010). Similarly, a text-mining analysis of six luxury resorts in the southwestern United States identified recurring complaints regarding insufficient service delivery, unmet requests, service delays, and staff behavior and room conditions (Zheng et al., 2009).

As can be seen, studies examining guest satisfaction of hotels have shown that key factors such as staff, room, price, sanitation and location affect guest satisfaction in different ways. In this context, studies on all-inclusive hotels reveal similar results. For example, a related study conducted on four and five star all-inclusive hotels in the Algarve region in Portugal revealed that staff performance, price, and hotel atmosphere were the factors most strongly influencing guest satisfaction, whereas service quality was interestingly among the lowest-rated elements (Rassal et al., 2024). In another study

carried out in Cape Verde and the Azores Islands using TripAdvisor data, room quality and price were identified as the most influential factors affecting guest satisfaction (Oliveira-Cardoso et al., 2025).

An analysis focusing on mass tourism destinations such as Antalya, Mallorca, and Sharm El-Sheikh found that rooms, staff, and food and beverage services is the most, while location appeared to be a less significant factor for determining the guest's satisfaction in all-inclusive hotels (Atabay & Çizel, 2020). A survey study of all-inclusive hotels in Antalya revealed that location and accessibility received high ratings, whereas price and food and beverage services scored relatively lower (Yolal et al., 2017). A research examined also the relationship between all-inclusive hotels and destination loyalty demonstrated a positive association, showing that accommodation quality, food and beverage services, and cleanliness were among the key determinants of guest satisfaction (Özdemir et al., 2012). On the other hand, a study of all-inclusive hotels in Crete found that hotel prices and economic affordability had the strongest influence on guest satisfaction (Koronios et al., 2020).

Another analysis of TripAdvisor reviews indicated that hotel location, staff performance, and product variety were the most frequently mentioned aspects in guest evaluations (Çizel et al., 2015). Likewise, a further TripAdvisor-based study identified service quality, room features, and staff-related factors as the most important elements valued by guests staying at all-inclusive hotels (Javadpour & Joseph-Mathews, 2023). A survey also conducted in Antalya's all-inclusive hotels emphasized that accommodation quality, food and beverage services, and hygiene were the most critical factors, significantly influencing destination loyalty (Özdemir et al., 2012).

In recent years, research in the hospitality industry has increasingly focused on hotel guest satisfaction according to travel type. Satisfaction levels can vary based on hotel features and services, as well as the type of travelers, including friends, solo travelers, business travelers, families, and couples. For example a study comparing chain and independent hotels revealed that guest expectations were generally higher in chain hotels, where staff and front desk services emerged as the most critical evaluation factors for all type of travelers (Banerjee & Chua, 2016). On the other hand, a study conducted based on Booking.com data showed that solo travelers and couples placed greater emphasis on hotel location, whereas families tended to give higher ratings to the range and quality of services provided by the hotel (Radojevic et al., 2015).

Similarly, a comparative study of hotels in New York and Singapore found that solo travelers provided higher overall ratings for service quality, whereas accompanied travelers tended to give lower overall ratings. However, when assessing service quality specifically, companions such as couples and friends assigned higher scores (Gim et al., 2025). Another study examining the travel behavior of different groups revealed that couples, friends, and families reported higher satisfaction levels compared to solo and business ones, although cleanliness, comfort, location, services, and staff were consistently rated as highly important across all groups (Ahn et al., 2017).

In a study conducted in major U.S. cities, families rated hotel location positively but evaluated Wi-Fi access negatively, while friends placed greater emphasis on room quality yet tended to give lower overall ratings due to high costs of hotels (Xu, 2018). A TripAdvisor analysis of the five most-reviewed hotels in India showed that all traveler types tended to evaluate similar hotel attributes, particularly rooms, staff, and location (Yadav & Roychoudhury, 2019). In Brazil, an assessment of five-star hotels revealed that

friends and couples prioritized service quality, whereas cleanliness and hygiene were most important for families and business travelers. Location, on the other hand, was found to be a less significant factor for solo and business travelers (Almeida & Pelissari, 2019). Another study examined the effects of travel purpose demonstrated that business travelers tended to provide lower hotel ratings compared to leisure travelers (Schiessl et al., 2024).

METHODOLOGY and FINDINGS

This study examined data from the TripAdvisor platform for 15 accommodation establishments that received the "Best of the Best Hotels" award in the 2025 Travelers' Choice Awards in Türkiye for all-inclusive accommodations (TripAdvisor, 2025). Logistic regression analysis is used to investigate which attributes impacted customer satisfaction. Furthermore, the purpose of this study is also to examine whether there are differences and impacts based on travel types in the collected reviews. Within this concept, following hypothesis has constructed as:

H1: Guest reviews of hotel service attributes (value, service, room, cleanliness, location, and sleep quality) significantly influence the likelihood of guests leaving positive reviews.

H1a: Value attribute positively and significantly influences the likelihood of guests leaving positive reviews.

H1b: Service attribute positively and significantly influences the likelihood of guests leaving positive reviews.

H1c: Room attribute positively and significantly influences the likelihood of guests leaving positive reviews.

H1d: Cleanliness attribute positively and significantly influences the likelihood of guests leaving positive reviews.

H1e: Location attribute positively and significantly influences the likelihood of guests leaving positive reviews.

H1f: Sleep Quality attribute positively and significantly influences the likelihood of guests leaving positive reviews.

H2. Guest satisfaction levels differ significantly depending on the type of travel (solo, with friends, family, couple, business).

H3. Travel type has a significant impact on the likelihood of guests leaving positive reviews when hotel service qualities are checked.

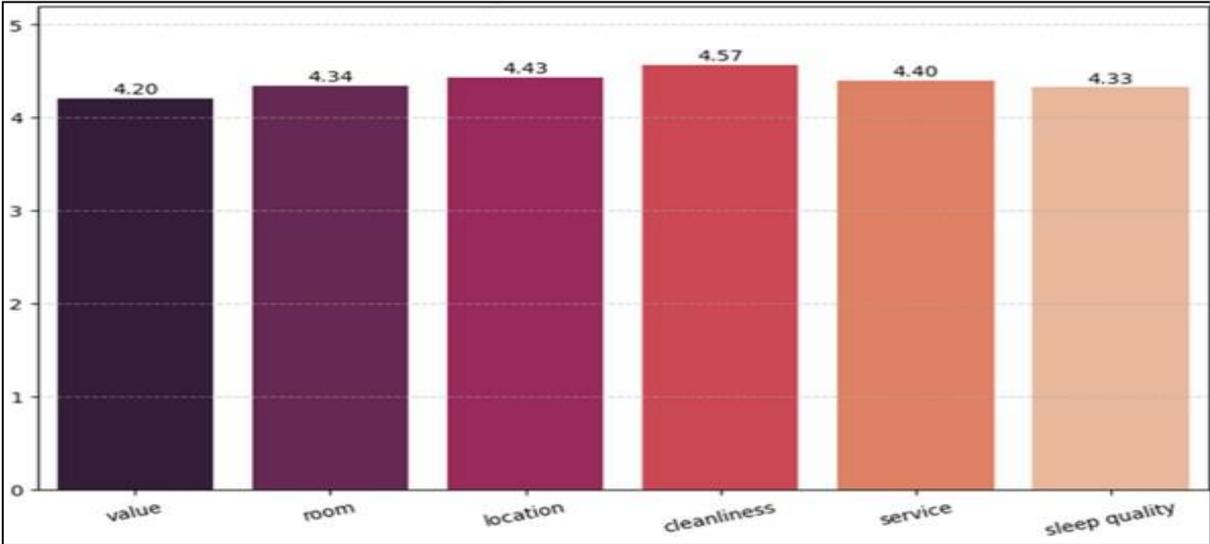
Tripadvisor allows users to rate their reviews based on six numerical variables: value, room, service, sleep quality, cleanliness, and location. Users can rate these attributes on a scale of 1-5. However, rating these attributes is not mandatory for reviewers. Therefore, reviews without this numerical rating were eliminated from the dataset. Additionally, it was observed that most reviews included only three or four attributes, rather than all six. However, because the logistic regression analysis aimed to obtain more meaningful results using complete data, reviews that rated all six attributes were included. Tripadvisor also allowed users to specify their travel type: friends, solo, business, couples, and family. However, specifying the travel type is optional and not mandatory. At this point, reviews in which users specified their travel type with 6 attributes were used in the analysis. After completing this phase, 4178 solid reviews were included in the study. The data cover the period from 2006 to 2025. All analyses were

performed using the Google Colab platform, which was designed according to the Python programming language.

Figure 1 presents the mean scores of the attributes included in the analysis. Among these, cleanliness recorded the highest average rating, whereas value received the lowest. However, when considered overall, all attributes exhibit high average ratings, as only reviews of award-winning hotels were analyzed.

Figure 1.

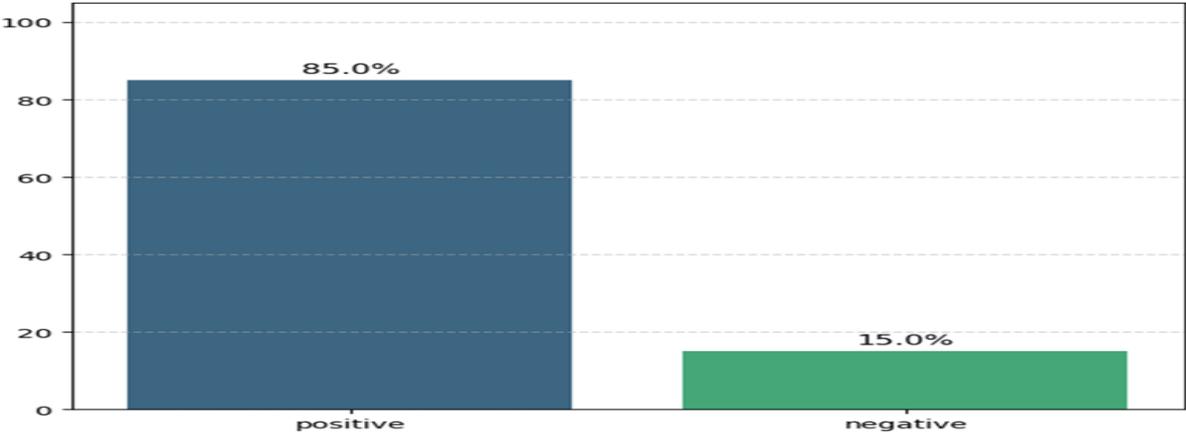
Mean of each Attributes in Dataset



As is known, on the TripAdvisor platform, users also rate their overall experience on a scale of 1-5 in their review. Before implementing logistic regression analysis, the overall rating scores provided by users were transformed into a categorical variable. Consequently, the numerical values assigned by reviewers were recoded into a binary classification for analytical purposes. As is well known, hotel reviews written by consumers inherently contain certain degrees of subjectivity. For instance, a reviewer who experienced a negative issue related to the room may assign a relatively low score, such as 1 or 2, whereas another reviewer may place greater emphasis on problems associated with staff behavior, which is reflected accordingly in their ratings and comments. To minimize this subjectivity to a certain extent, a sentiment analysis was conducted. Sentiment analysis is a process that identifies the emotional tone or opinion orientation contained within a text by applying methods from natural language processing, text mining, and machine learning. This method is started to widely used in social media and recommendation systems in recent years. This technique also determines whether the sentiment expressed in a review is positive, neutral, or negative. In this study, a lexicon-based approach was employed using the TextBlob method in Python. Sentiment polarity scores ranging from 0 to +1 were classified as positive, while those between 0 and -1 were categorized as negative. Since the research will be conducted in a binary manner, reviews were classified only as negative and positive. Based on these classifications, the resulting sentiment variable was incorporated into the model as the dependent variable. As illustrated in Figure 2, the sentiment distribution revealed that 85% of the reviews exhibited a positive tone, whereas 15% were classified as negative. Accordingly, these results defined the target class used in the logistic regression analysis. For the dependent variable is defined as the likelihood of leaving a positive review, Guest reviews were

classified into a binary outcome based on sentiment polarity scores obtained through sentiment analysis. Reviews with positive polarity scores were coded as 1 (positive review), whereas reviews with negative polarity scores were coded as 0 (negative review); neutral reviews were excluded from the analysis to ensure a clear binary classification. The sentiment analysis was conducted on all guest reviews retrieved from TripAdvisor which contain all six attributes. Prior to analysis, all reviews were translated into English. After that, proper preprocessing techniques were obtained into raw data for reveal significant sentiment score of each review. For preprocessing, NLTK library was used to removal of punctuation, stopwords, convert all letters to lowercase and normalizing the accents and non-informative symbols and lemmatizing in order to enhance the accuracy of sentiment classification.

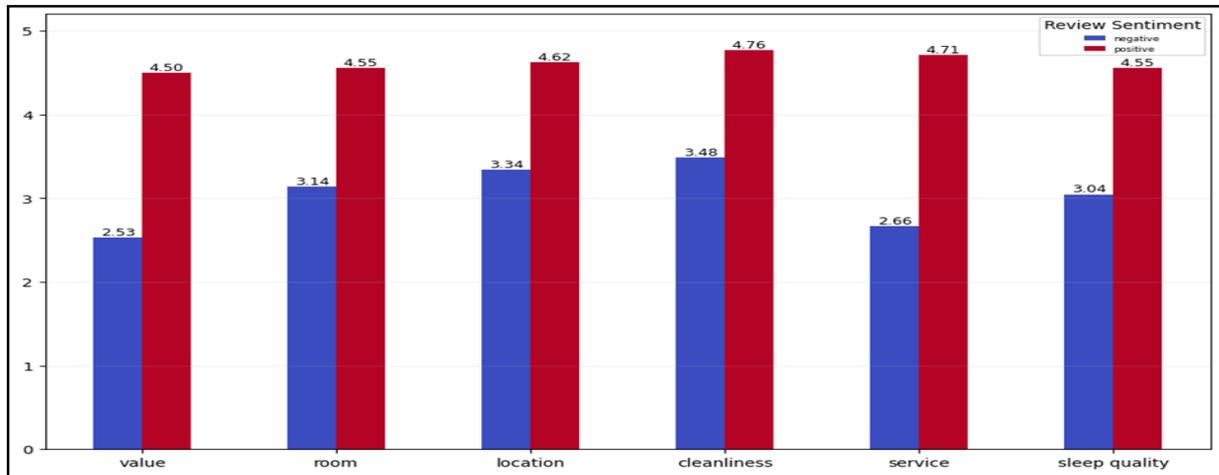
Figure 2.
Distribution of Positive and Negative Reviews in Dataset.



Following this initial phase, where each review was classified as either positive or negative, the average scores for the contained attributes such as value, room, location, cleanliness, service, and sleep quality were calculated according to their respective classes and presented in Figure 3. This figure illustrates that the attributes most frequently associated with positive expression are cleanliness and service. Conversely, the lowest-rated attributes in negative reviews appear to be within the value and service categories. Crucially, an analysis of the distribution across both positive and negative comments reveals that the most significant difference between the means of the respective independent variables is observed in the value and service categories.

Figure 3.

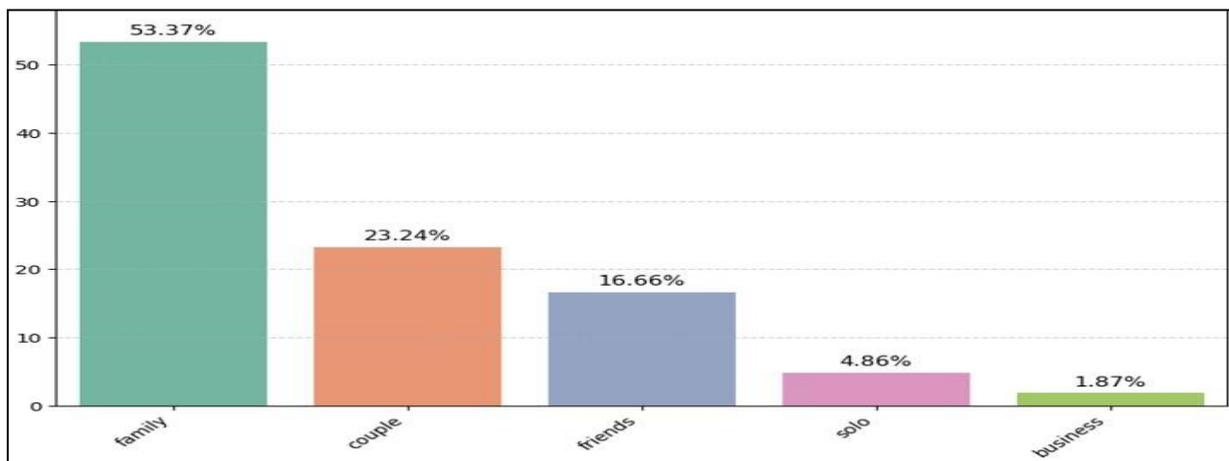
Mean of each Attributes in Negative and Positive Reviews



In this research, the type of travel was additionally incorporated into the analysis as a dummy variable. The primary objective was to determine whether there is a statistically significant difference between different traveler types and to assess the magnitude of its potential effect within the forthcoming logistic regression model. The distribution of travel types within the dataset is presented in Figure 4. According to the figure, families constitute the group that most frequent in awarded all-inclusive hotels, almost made up more than half of the entire dataset. Families are sequentially followed by couples and friends. Individuals such as traveling solo or business are observed at the lowest levels of frequency. These data collectively indicate that individuals traveling in groups larger than one person predominantly use all-inclusive hotels in Türkiye.

Figure 4.

Distribution of the Traveller Types

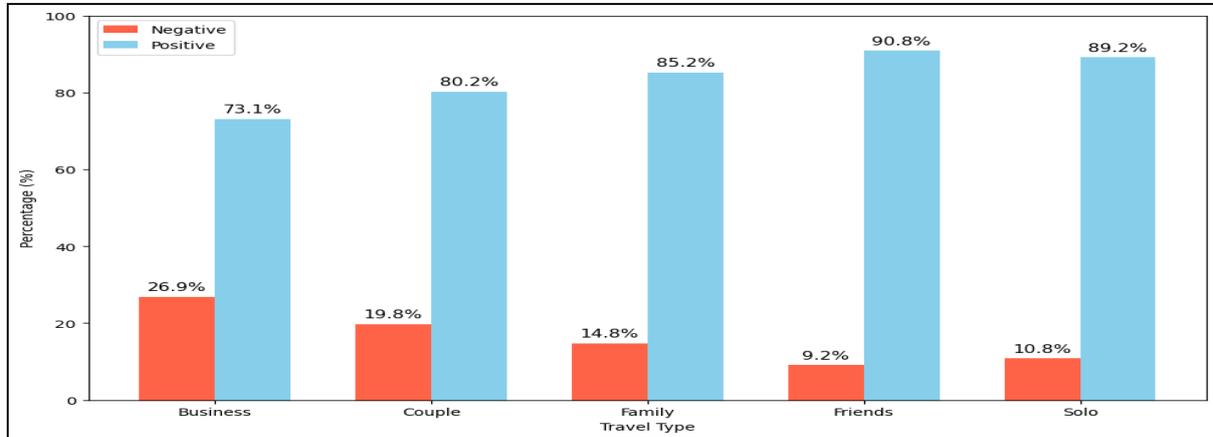


An examination of the sentiment distribution across different travel types reveals that, positive sentiment is dominant across all groups. However, it is noteworthy that the level of positive sentiment varies depending on the type of travel. The highest positive rates were observed in reviews from individuals traveling with friends (90.8%) and those traveling alone (89.2%). While high levels of positive sentiment are maintained among families (85.2%) and couples (80.2%), a marked decrease in positive sentiment and a

conspicuous increase in the rate of negative reviews (26.9%) are evident in the business travel (73.1%) segment compared to other groups.

Figure 5.

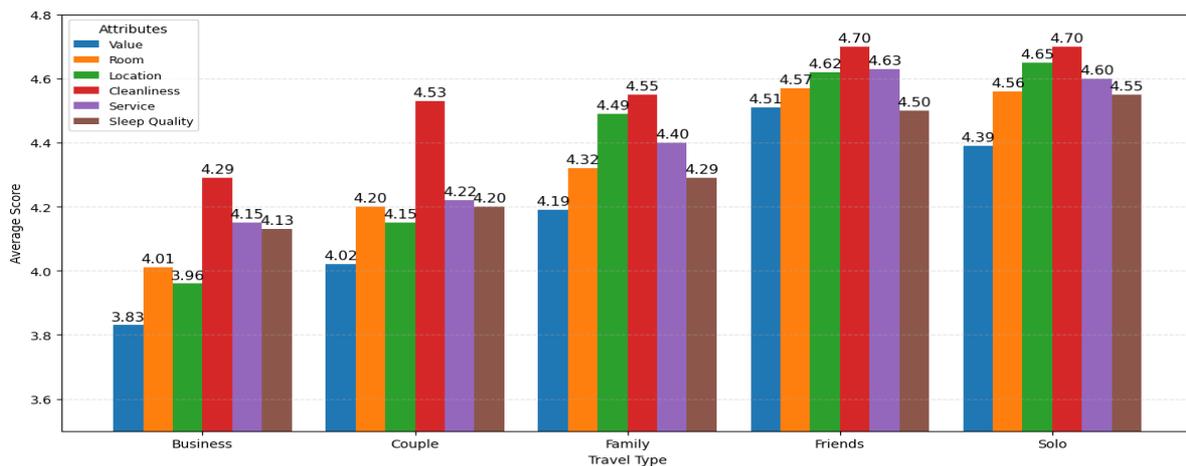
Sentiment Distribution of Traveler Types



A general examination of the values presented in the table indicates that hotels receive relatively high scores across all traveler types in terms of cleanliness, service, and sleep quality. In contrast, the variable value exhibits comparatively lower averages. This suggests that, while guests are generally satisfied with the service and physical conditions, their expectations regarding the price performance balance are not fully met. Notably, business travelers tend to assign the lowest ratings across all categories, which may reflect a more critical evaluation of the hotel experience. Conversely, groups of friends and couples emerge as the highest-scoring segments.

Figure 6.

Average Ratings of Attributes of each Traveler Types



Prior to conducting the logistic regression, the presence of multicollinearity among the variables was examined. For this purpose, a Variance Inflation Factor (VIF) analysis was performed, and the results ranged between 1 and 3. This indicates that there are no strong correlations among the independent variables included in the model, suggesting that the constructed model can be considered reliable.

Table 1.*Variance Inflation Factor (VIF) Results*

<i>Independent Variable</i>	<i>VIF</i>
<i>Service</i>	2.28
<i>Value</i>	2.08
<i>Room</i>	2.04
<i>Cleanliness</i>	1.94
<i>Sleep Quality</i>	1.75
<i>Location</i>	1.37

Additionally, Hosmer–Lemeshow test, one of the most commonly used methods for assessing the goodness of fit in logistic regression models, was applied to the dataset. The results indicate that there is no significant difference between the model’s predictions and the observed outcomes, suggesting that the model demonstrates a good fit.

Table 2.*Hosmer–Lemeshow Goodness-of-Fit Test Results*

<i>Test Statistic</i>	<i>Value</i>	<i>Degrees of Freedom</i>	<i>p-value</i>	<i>Model Fit Interpretation</i>
<i>Chi-square (χ^2)</i>	11.12	8	0.1948	<i>Model fits the data well ($p > 0.05$)</i>

As a result of the logistic regression analysis, the effects of the independent variables on the dependent variable defined as positive/negative overall evaluation (Y_binary) were examined. The model was estimated using the Maximum Likelihood Estimation (MLE) method and was based on 4178 observations. The Pseudo R² value, which indicates the model’s goodness of fit, was 0.6252, suggesting a strong performance in explaining the variance of the dependent variable. When comparing the model’s log-likelihood value (-604.02) to the LL-null (-1,611.50) and considering that the LLR test yielded $p < 0.001$, it is evident that the model captures the contribution of the independent variables in a statistically significant manner. Furthermore, the model converged successfully for all observations, and the predictions are reliable. These results indicate that the independent variables such as value, room, location, cleanliness, service, and sleep quality) significantly influence the likelihood of guests providing a positive or negative overall evaluation. Therefore, these sub-dimensions of hotel services can be considered critical factors in determining customer satisfaction.

Table 3.*Logistic Regression Model Summary*

<i>Model Information</i>	<i>Values</i>
<i>Dependent Variable</i>	<i>Y_binary</i>
<i>No. of Observations</i>	4178
<i>Model</i>	<i>Logit</i>
<i>Method</i>	<i>Maximum Likelihood Estimation (MLE)</i>
<i>Degrees of Freedom (Model)</i>	6
<i>Degrees of Freedom (Residuals)</i>	4175
<i>Pseudo R²</i>	0.6252
<i>Log-Likelihood</i>	-604.02
<i>LL-Null</i>	-1611.50
<i>LLR p-value</i>	0.000
<i>Model Convergence</i>	<i>True</i>

The logistic regression results also presented in Table 4 highlight the most critical factors influencing overall guest satisfaction (positive or negative evaluation). The analysis indicates a particularly striking effect of perceived value with a coefficient of $\beta = 1.282$ ($p < 0.001$) and an odds ratio of 3.60, a one-unit increase in value is associated with approximately a 260% higher likelihood of guests providing a positive evaluation. This finding underscores the central role of price performance perception in customer satisfaction and clearly suggests that hotel management should prioritize pricing and packaging strategies in their strategic decision making. Following value, service emerges as the second strongest determinant ($\beta = 0.927$, OR = 2.53, +152.8%), indicating that guests evaluate their experiences not only based on price but also on the quality of services provided. Other factors, namely location, sleep quality, cleanliness, and room facilities and/or conditions were also found to be significant, serving as supportive elements that increase the likelihood of a positive evaluation.

Overall, these findings suggest that value and service constitute the two main dimensions driving guest satisfaction. Prioritizing strategies related to price performance and service quality can play a critical role in enhancing customer satisfaction and consequently loyalty. These results reinforce the importance of the relationship between service quality and perceived value in the literature while providing concrete managerial implications for the hospitality industry.

Table 4.*Logistic Regression Model Coefficients and Odds Ratios*

<i>Variable</i>	<i>Coefficient (β)</i>	<i>Std. Error</i>	<i>z-value</i>	<i>p-value</i>	<i>95% Confidence Interval</i>	<i>Odds Ratio Exp(β)</i>	<i>Effect Interpretation (%)</i>
<i>Constant</i>	-13.4127	0.632	-21.219	0.000	[-14.652, -12.174]	–	–
<i>Value</i>	1.2816	0.100	12.824	0.000	[1.086, 1.478]	3.6025	260.25
<i>Room</i>	0.2301	0.103	2.224	0.026	[0.027, 0.433]	1.2587	25.87
<i>Location</i>	0.6159	0.084	7.361	0.000	[0.452, 0.780]	1.8513	85.13
<i>Cleanliness</i>	0.3141	0.102	3.082	0.002	[0.114, 0.514]	1.3691	36.91
<i>Service</i>	0.9273	0.082	11.331	0.000	[0.767, 1.088]	2.5277	152.77
<i>Sleep Quality</i>	0.4680	0.087	5.349	0.000	[0.297, 0.639]	1.5967	59.67

In addition to the findings, it was aimed to examine the predictive power of the created LR model. Table 5 indicates that the model achieved an overall accuracy of 0.924, with a recall of 0.968 for positive evaluations and a specificity of 0.737 for correctly classifying negative evaluations. Additionally, a precision of 0.941 and an F1-score of 0.954 indicate that the model provides balanced and reliable predictions across classes. These findings demonstrate that the model represents a robust and practical tool for forecasting tourist satisfaction.

Table 5.*Classification Performance Metrics*

<i>Metric</i>	<i>Values</i>
<i>Accuracy</i>	0.9241
<i>Sensitivity / Recall</i>	0.9675
<i>Specificity</i>	0.7368
<i>Precision</i>	0.9407
<i>F1-Score</i>	0.9539

Furthermore, The Omnibus Test and model summary metrics presented in Table 6 were used to assess the overall fit and explanatory power of the logistic regression model. The Omnibus Test (Chi-Square = 2014.86, df = 6, p < 0.001) indicates that the independent variables included in the model are jointly significant, demonstrating a statistically significant improvement over the null model. The log-likelihood values (-604.02 for the model, -1611.45 for the null) and the likelihood ratio test statistic (-2LL = 2014.86) further show that the model provides substantially better fit compared to the baseline model without independent variables. Additionally, the Cox & Snell Pseudo R² (0.625) and Nagelkerke Pseudo R² (0.730) values suggest that the model explains

approximately 63–73% of the variance in the dependent variable, highlighting its strong explanatory capability. Taken together, these metrics indicate that the logistic regression model is both statistically significant and practically reliable as a predictive tool.

Table 6.

Omnibus Test and Model Summary Metrics

<i>Metric</i>	<i>Values</i>
<i>Chi-Square Statistic (Omnibus / LRT)</i>	2014.86
<i>Degrees of Freedom (df)</i>	6
<i>P-value</i>	0.000
<i>Log-Likelihood (Model)</i>	-604.0208
<i>Log-Likelihood (Null)</i>	-1611.4512
<i>-2 Log-Likelihood (LRT Statistic)</i>	2014.8607
<i>Cox & Snell Pseudo R²</i>	0.6252
<i>Nagelkerke Pseudo R²</i>	0.7303
<i>Number of Observations</i>	4178

After ensuring the significance of the model, it was aimed to see whether there was a significant difference between travel types. The Chi-Square test indicated a strong association between traveler type (solo, friends, families, business, couples) and sentiment (positive vs. negative), $\chi^2(4) = 47.22$, $p < 0.001$, suggesting that the likelihood of positive or negative reviews varies by travel group. Complementing this, the t-Test showed that the average sentiment scores differed significantly among these groups ($t = 61.99$, $p < 0.001$), indicating that certain traveler types tend to provide higher positive ratings than others. Together, these results demonstrate that traveler type plays a meaningful role in shaping guests' perceptions of hotel services, with distinct patterns of satisfaction observed across solo, friends, business, and couple travelers.

Table 7.

Chi-Square and t-Test Results for Travel Type vs. Rate (Post-hoc Analysis)

<i>Test Type</i>	<i>Statistic</i>	<i>Degrees of Freedom (df)</i>	<i>p-value</i>
<i>Chi-square Test</i>	47.22	4	1.37×10^{-9}
<i>t-Test</i>	61.99	—	0.000

The standardized residuals heatmap presented in Figure 7 highlights significant differences between travel types and customer satisfaction. In terms of negative evaluations, groups of friends provided significantly fewer negative comments than expected (residual = -3.97*), whereas couples and business travelers contributed more negative evaluations than expected (residuals = 3.81* and 2.71*, respectively), indicating a more critical perception of the hotel experience among these groups. For solo and family travelers, negative evaluations closely aligned with expected distributions, showing no significant differences. Regarding positive evaluations, residual values across all groups did not exhibit significant differences, suggesting that positive assessments are generally evenly distributed across travel types. These findings underscore the importance of travel type as a determinant, particularly in the context of negative evaluations

Figure 7.

Heatmap of Standardized Residuals for Travel Type and Customer Satisfaction

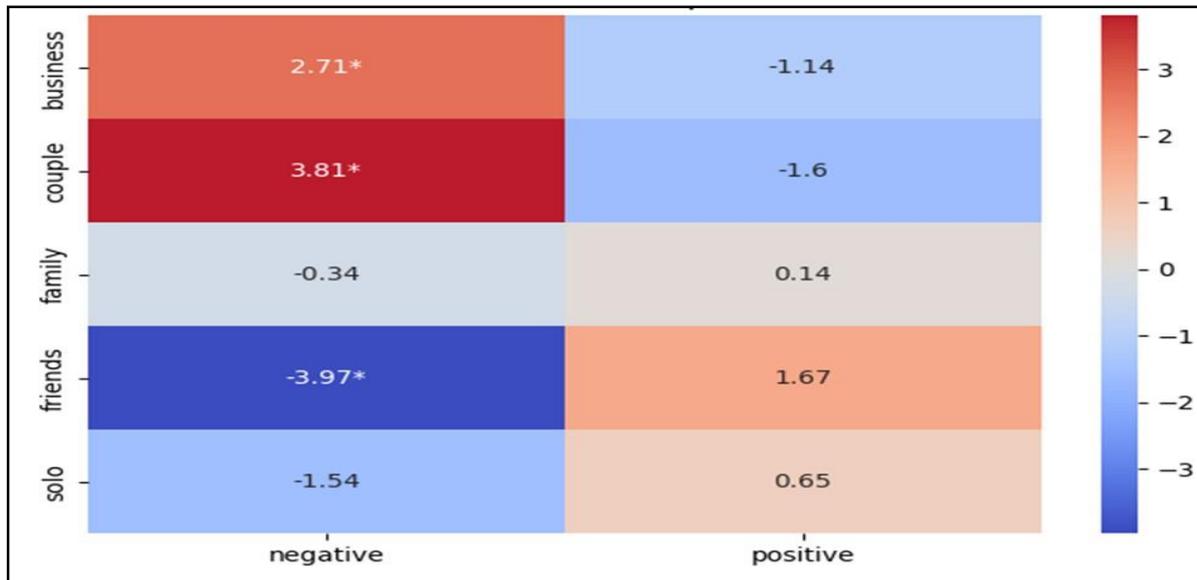


Table 8 shows the model significance level after traveler type dummy variable was included in logistic regression equation model. The inclusion of travel type dummy variables in the model resulted in a slight increase in the log-likelihood value; however, this change was not statistically significant. This indicates that travel type is not a strong predictor of positive/negative evaluation when other independent variables value, service, room, sleep quality, cleanliness, location are considered. While the Chi-square analysis revealed significant differences in the distribution of positive and negative evaluations across travel types ($p < 0.001$), suggesting that certain groups perceive the hotel experience more critically or positively than others, the addition of travel type dummy variables to the logistic regression model did not significantly improve model fit, as indicated by the Likelihood Ratio Test ($\chi^2 = 4.55$, $df = 4$, $p = 0.3365$). This implies that although travel type reflects distributional differences on its own, it does not serve as an independent determinant when other variables particularly value and service are controlled for. Consequently, while travel type may create notable differences in some observations, hotel attributes remain the primary predictors for forecasting guest satisfaction in the model.

Table 8.

Effect of Traveler Type on Logistic Regression Model Fit

<i>Model / Metric</i>	<i>Value</i>
<i>Baseline Model (Without Type)</i>	-604.021
<i>Full Model (Including Type)</i>	-601.745
<i>Likelihood Ratio Statistic (Chi-square)</i>	4.5512
<i>Degrees of Freedom (df)</i>	4
<i>p-value</i>	0.3365

Furthermore, Spearman correlation analysis was conducted to examine the ordinal relationships among the independent variables. The results indicate a particularly positive correlation between service value (0.53), suggesting that guests who perceive higher

priceperformance value also tend to report greater satisfaction with service. Additionally, positive correlations were observed between room and both cleanliness and sleep quality indicating that physical comfort is closely associated with room based satisfaction. The location variable exhibited lower, yet significant, positive correlations with other variables implying that satisfaction with location may exert a more independent influence compared to other experiential factors.

In summary, the results of the logistic regression analysis indicate that guest evaluations of hotel service attributes significantly influence the likelihood of leaving positive reviews, thereby supporting H1. All service-related attributes included in the model value, service, room, cleanliness, location, and sleep quality exhibit statistically significant effects on positive review probability. Among these factors, the value attribute demonstrates the strongest positive influence, followed by service quality, whereas room-related evaluations show a comparatively weaker but still significant effect. Accordingly, hypotheses H1a, H1b, H1c, H1d, H1e, and H1f are all supported. In addition, the chi-square analysis reveals statistically significant differences in guest satisfaction levels across travel types, providing empirical support for H2. However, when travel type is incorporated into the logistic regression model alongside hotel service attributes, its effect on the likelihood of leaving positive reviews is not statistically significant. Therefore, H3 is not supported, suggesting that travel type does not exert an independent influence on review positivity once service quality perceptions are taken into account.

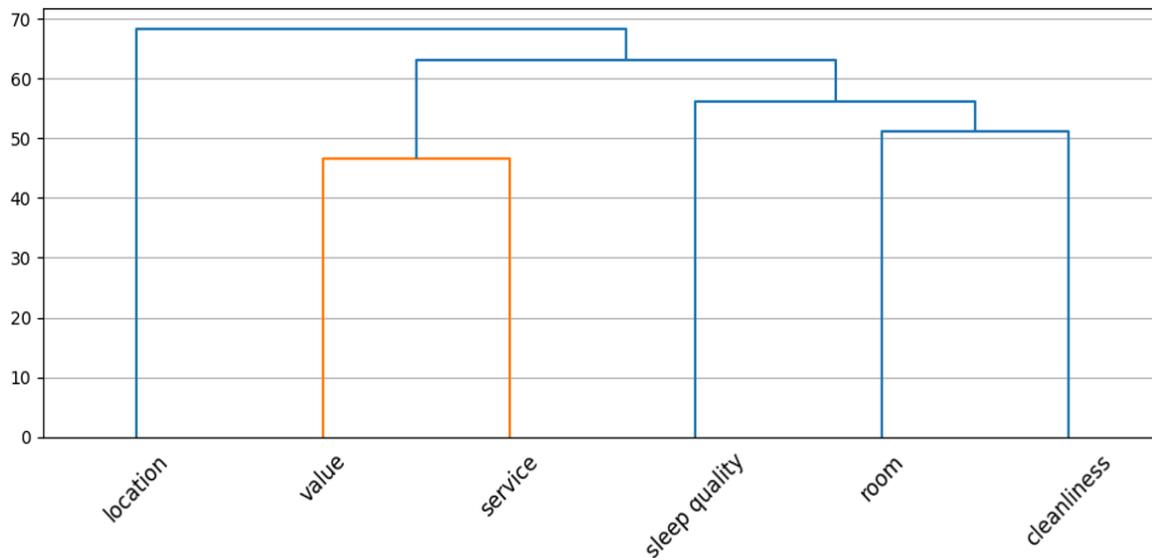
Figure 8. Spearman Correlation Heatmap with Significance of Attributes



To better visualize correlations between attributes, a hierarchical cluster analysis was conducted to examine the relational structure among hotel evaluation variables in Figure 9. The clustering results indicate that value and service form the earliest merged cluster, suggesting that guests tend to evaluate these two aspects in parallel. Room and cleanliness initially formed a separate cluster, which was subsequently joined by sleep quality indicating a moderate association among room, cleanliness, and sleep quality. Finally, location merged with all other variables, highlighting its relatively independent role in shaping the hotel experience. These numerical and visual findings demonstrate that hotel evaluation criteria are interrelated to varying degrees, with certain variables particularly value and service emerging as key determinants.

Figure 9.

Hierarchical Clustering of Attributes



CONCLUSION

This study examined online reviews of award-winning all-inclusive hotels in Türkiye to identify key service attributes influencing guest satisfaction and to derive managerial implications. Accordingly, online reviews of 15 all-inclusive hotels in Türkiye that received TripAdvisor’s 2025 Best of the Best Hotels Travelers’ Choice award were examined. Numerical evaluations of value, service, room, cleanliness, location, and sleep quality, together with travel types, are considered to identify the service attributes that most strongly influence hotel evaluations and to assess whether their importance varies across different travel types.

The findings indicate that the majority of online reviews are positive, reflecting a generally high level of guest satisfaction across all-inclusive hotels. Overall, all six service attributes receive high evaluation scores, with cleanliness rated the highest and value the lowest. Logistic regression results show that guest satisfaction is jointly shaped by these service attributes, with perceived value emerging as the strongest determinant of positive reviews, followed by service quality, while room-related attributes exhibit the weakest effect. Specifically, a one-unit increase in perceived value increases the likelihood of a positive evaluation by approximately 3.6 times, whereas a similar increase in service quality raises this likelihood by about 2.5 times. From a managerial perspective, these findings suggest that although maintaining high standards of cleanliness remains essential, hotel managers should prioritize strategies that enhance perceived value and service quality, as improvements in these dimensions yield the greatest impact on overall guest satisfaction.

The chi-square analysis indicates that satisfaction levels do not differ significantly across travel types in terms of positive evaluations; however, notable differences emerge in negative feedback, with couples and business travelers exhibiting a more critical evaluation pattern. Nevertheless, when travel type is incorporated into the logistic regression model alongside service attributes, it does not exert a statistically significant effect on the likelihood of leaving positive reviews. This finding suggests that guests’ evaluations are primarily driven by perceptions of service quality rather than travel-related characteristics. From a managerial perspective, these results imply that while maintaining

consistent service quality across all guest segments should remain a priority, hotel managers should pay particular attention to reducing dissatisfaction among couples and business travelers through targeted improvements, such as enhancing comfort and privacy for couples and providing efficient operational services, including faster check-in and reliable high-speed internet, for business travelers.

An examination of the six evaluation attributes indicates that guests tend to assess room, cleanliness, and sleep quality jointly, while value and service are also frequently evaluated together and emerge as the most influential determinants of overall service quality. From a managerial perspective, this pattern suggests that hotel managers should prioritize integrated improvement strategies focusing primarily on enhancing perceived value and service quality, as these dimensions exert the strongest influence on customer satisfaction. In contrast, location is evaluated independently from the other attributes, reflecting its largely fixed and uncontrollable nature. Accordingly, while location remains an important factor shaping guest perceptions, managerial efforts should concentrate on controllable service dimensions where operational improvements can more effectively enhance guest satisfaction.

The primary limitation encountered in this study stems from the fact that consumers did not consistently rate all six variables in their reviews, and in some cases provided incomplete evaluations. Additionally, the sample distribution revealed that a large proportion of respondents were family travelers, most of whom tended to provide positive feedback. This concentration likely influenced the logistic regression results, leading to the travel type variable not exhibiting a statistically significant effect. While the chi-square analyses did not reveal significant differences in terms of positive evaluations, meaningful distinctions were identified among three travel-type groups concerning negative evaluations. Nevertheless, the overall findings suggest that travel type does not exert a statistically significant influence on satisfaction levels.

Therefore, future studies could enhance the analytical depth of their findings by labeling the target classes into more than two categories, allowing for a more nuanced interpretation of satisfaction patterns across different travel types. As observed in this study, the majority of reviews were positive, which is expected given that the dataset was composed of award-winning hotels. However, future research could utilize a more balanced dataset such as one that includes an equal proportion of positive and negative reviews, or a similar sampling approach to better capture the differential effects of hotel attributes and travel types on customer satisfaction. Moreover, since this study focused on award-winning all-inclusive hotels in Türkiye, subsequent research could expand the scope to include all-inclusive hotels from various regions within the country. Comparing the quantitative and textual reviews of these hotels with those of award-winning properties could reveal whether significant differences exist between them, thereby contributing to a more comprehensive understanding of customer satisfaction dynamics in the all-inclusive hotel segment.

ETHICAL APPROVAL

As this study uses publicly available secondary data, ethical approval is not required.

REFERENCES

- Aakash, A., & Gupta Aggarwal, A. (2022). Assessment of hotel performance and guest satisfaction through eWOM: Big data for better insights. *International Journal of Hospitality & Tourism Administration*, 23(2), 317–346. <https://doi.org/10.1080/15256480.2020.1746218>
- Abashidze, I. (2024). The influence of online platforms on decision-making process and behavioural traits of international travelers. *European Scientific Journal*, 20(37), 51. <https://doi.org/10.19044/esj.2024.v20n37p51>
- Adeola, O., & Evans, O. (2019). Digital tourism: Mobile phones, internet and tourism in Africa. *Tourism Recreation Research*, 44(2), 190–202. <https://doi.org/10.1080/02508281.2018.1562662>
- Ahn, D., Park, H., & Yoo, B. (2017). Which group do you want to travel with? A study of rating differences among groups in online travel reviews. *Electronic Commerce Research and Applications*, 25, 105–114. <https://doi.org/10.1016/j.elerap.2017.09.001>
- Almeida, G. S. D., & Pelissari, A. S. (2019). Customer satisfaction based on the attributes of accommodation services. *Revista Brasileira de Pesquisa em Turismo*, 13(02), 32–53. <https://doi.org/10.7784/rbtur.v13i2.1516>
- Alrawadih, Z., & Demirkol, Ş. (2015). Konaklama işletmelerinde e-şikâyet yönetimi: İstanbul'daki beş yıldızlı oteller üzerinde bir çalışma. *Nişantaşı Üniversitesi Sosyal Bilimler Dergisi*, 3(1), 130–148. <https://doi.org/10.21733/ibad.628032>
- Atabay, L., & Çizel, B. (2020). Comparative content analysis of hotel reviews by mass tourism destination. *Journal of Tourism and Services*, 11(21), 147–166. <https://doi.org/10.29036/jots.v11i21.163>
- Awal, R. I. R., Rahayu, A., Hendrayati, H., Heryana, N., Rahman, S. Y., Deny, M., & Lestari, F. (2025). Digital value-based pricing strategy in tourism marketing: a systematic literature review approach. *Dinasti International Journal of Economics, Finance & Accounting (DIJEFA)*, 5(6). <https://doi.org/10.38035/dijefa.v5i6.3728>
- Banerjee, S., & Chua, A. Y. (2016). In search of patterns among travellers' hotel ratings in TripAdvisor. *Tourism Management*, 53, 125–131. <https://doi.org/10.1016/j.tourman.2015.09.020>
- Başaran, M. A., Dogan, S., & Kantarci, K. (2020). On modeling of responses generated by travel 2.0 implementation: Fuzzy rule-based systems. *International Journal of Contemporary Hospitality Management*, 32(4), 1503–1522.
- Bhat, M. A. (2012). Tourism service quality: A dimension-specific assessment of SERVQUAL. *Global Business Review*, 13(2), 327–337. <https://doi.org/10.1177/097215091201300210>
- Ceylan, U., & Uzun, A. H. (2024). Otel işletmelerine yönelik çevrimiçi şikâyetlerinin incelenmesi: Ankara örneği. *Sinop-e: Turizm Araştırmaları Dergisi*, 1(2), 74–94.
- Chiang, H. S., & Huang, T. C. (2015). User-adapted travel planning system for personalized schedule recommendation. *Information Fusion*, 21, 3–17. <https://doi.org/10.1016/j.inffus.2013.05.011>
- Chiu, M. C., Huang, J. H., Gupta, S., & Akman, G. (2021). Developing a personalized recommendation system in a smart product service system based on unsupervised learning model. *Computers in Industry*, 128, 103421. <https://doi.org/10.1016/j.compind.2021.103421>
- Choi, T. Y., & Chu, R. (2001). Determinants of hotel guests' satisfaction and repeat patronage in the Hong Kong hotel industry. *International Journal of Hospitality Management*, 20(3), 277–297. [https://doi.org/10.1016/s0278-4319\(01\)00006-8](https://doi.org/10.1016/s0278-4319(01)00006-8)
- Chuang, C. M., Wu, C. X., & Stanley Snell, R. (2023). How do online travel reviews facilitate informed purchase decisions?. *Asia Pacific Journal of Tourism Research*, 28(4), 323–340. <https://doi.org/10.1080/10941665.2023.2228939>
- Çizel, B., Çizel, R., & Ajanovic, E. (2015). Which hotel attributes matter for mass tourist: A qualitative research on tourists' review on TripAdvisor. *People: International Journal of Social Sciences*, 1(1), 632–642. <https://doi.org/10.20319/pijss.2015.s21.632642>

- Da' u, A., & Salim, N. (2020). Recommendation system based on deep learning methods: A systematic review and new directions. *Artificial Intelligence Review*, 53(4), 2709–2748. <https://doi.org/10.1007/s10462-019-09744-1>
- David, T., Almedida-Santana, A., Hernández, J. M., & Moreno-Gil, S. (2018). Understanding European tourists' use of e-tourism platforms. *Analysis of Networks. Information Technology & Tourism*, 20(1), 131–152. <https://doi.org/10.1007/s40558-018-0113-z>
- Devahastin, D. D., Sayasonti, S., Aung, C. M., Aung, Z. P., & Wongwaiyut, P. (2024). Digital transformation of supply chain management for tourism industry in Thailand. *Journal of Supply Chain Management: Research and Practice*, 18(2), 28–39. <https://doi.org/10.59160/ijscm.v12i3.6135>
- Doğan, S., Başaran, M. A., & Kantarcı, K. (2020). Konaklama işletmelerinin tavsiye edilmesini etkileyen hizmetlerin belirlenmesi: Alanya'da bir araştırma. *Türk Turizm Araştırmaları Dergisi*, 4(4), 3769–3784. <https://doi.org/10.26677/tr1010.2020.590>
- Doğan, S., Başaran, M. A., & Kantarcı, K. (2020). Determination of attributes affecting price-performance using fuzzy rule-based systems: Online ratings of hotels by travel 2.0 users. *Journal of Hospitality and Tourism Technology*, 11(2), 291–311. <https://doi.org/10.1108/jhtt-07-2018-0067>
- Filieri, R., Alguezaui, S., & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management*, 51, 174–185. <https://doi.org/10.1016/j.tourman.2015.05.007>
- García-Barriocanal, E., Sicilia, M.A., & Korfiatis, N. (2010). Exploring hotel service quality experience indicators in user-generated content: A case using TripAdvisor data. *MCIS 2010 Proceedings*. (33). <https://aisel.aisnet.org/mcis2010/33>
- Garrigos-Simon, F. J., Narangajavana-Kaosiri, Y., & Narangajavana, Y. (2019). Quality in tourism literature: A bibliometric review. *Sustainability*, 11(14), 3859. <https://doi.org/10.3390/su11143859>
- Gençer, K., & Keşkekci, D. (2023). Beş yıldızlı otellerin hizmet hataları ve telafi yöntemlerinin incelenmesi: Antalya otelleri örneği. *Seyahat ve Otellşletmeciliği Dergisi*, 20(2), 142–158. <https://doi.org/10.24010/soid.1231506>
- Gim, J., Kim, S. I., Park, S., & Kim, H. (2025). Traveling alone, reviewing differently: Identifying distinctive hotel evaluation behaviors of solo travelers. *Journal of Travel & Tourism Marketing*, 42(1), 100–117. <https://doi.org/10.1080/10548408.2024.2425103>
- Gretzel, U. (2022). The smart DMO: A new step in the digital transformation of destination management organizations. *European Journal of Tourism Research*, 30, 3002–3002. <https://doi.org/10.54055/ejtr.v30i.2589>
- Guo, X., Pesonen, J., & Komppula, R. (2021). Comparing online travel review platforms as destination image information agents. *Information Technology & Tourism*, 23(2), 159–187. <https://doi.org/10.1007/s40558-021-00201-w>
- Guo, Y., Barnes, S. J., & Jia, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent Dirichlet allocation. *Tourism Management*, 59, 467–483. <https://doi.org/10.1016/j.tourman.2016.09.009>
- Hargreaves, C. A. (2015). Analysis of hotel guest satisfaction ratings and reviews: An application in Singapore. *American Journal of Marketing Research*, 1(4), 208–214.
- Hojeghan, S. B., & Esfangareh, A. N. (2011). Digital economy and tourism impacts, influences and challenges. *Procedia-Social and Behavioral Sciences*, 19, 308–316. <https://doi.org/10.1016/j.sbspro.2011.05.136>
- Hu, H., & Li, C. (2023). Smart tourism products and services design based on user experience under the background of big data. *Soft Computing*, 27(17), 12711–12724. <https://doi.org/10.1007/s00500-023-08851-0>
- Javadpour, L., & Joseph-Mathews, S. (2023). An examination of alignment of hotel brand differentiation and customer priorities: A case study of three unique destinations.

- Journal of Business and Management*, 28(2), 61–88.<https://doi.org/10.1504/jbm.2023.141299>
- Kaveski Peres, C., & Pacheco Paladini, E. (2021). Exploring the attributes of hotel service quality in Florianópolis-SC, Brazil: An analysis of TripAdvisor reviews. *Cogent Business & Management*, 8(1), 1926211.<https://doi.org/10.1080/23311975.2021.1926211>
- Koronios, K., Dimitropoulos, P., Kriemadis, A., Ioannis, D., Papadopoulos, A., & Manousaridou, G. (2020). Tourist satisfaction with all-inclusive packages: The moderating impact of income and family size. *Cultural and Tourism Innovation in the Digital Era: Sixth International IACuDiT Conference*, 597–610. https://doi.org/10.1007/978-3-030-36342-0_46
- Lee, C. C., & Hu, C. (2005). Analyzing hotel customers' e-complaints from an internet complaint forum. *Journal of Travel & Tourism Marketing*, 17(2-3), 167–181.https://doi.org/10.1300/j073v17n02_13
- Liberato, P., Alen, E., & Liberato, D. (2018). Smart tourism destination triggers consumer experience: The case of Porto. *European Journal of Management and Business Economics*, 27(1), 6–25.<https://doi.org/10.1108/ejmbe-11-2017-0051>
- Li, H., Liu, Y., Tan, C. W., & Hu, F. (2020). Comprehending customer satisfaction with hotels: Data analysis of consumer-generated reviews. *International Journal of Contemporary Hospitality Management*, 32(5), 1713–1735.<https://doi.org/10.1108/ijchm-06-2019-0581>
- Limberger, P. F., Dos Anjos, F. A., de Souza Meira, J. V., & dos Anjos, S. J. G. (2014). Satisfaction in hospitality on TripAdvisor.com: An analysis of the correlation between evaluation criteria and overall satisfaction. *Tourism & Management Studies*, 10(1), 59–65.
- Litvin, S. W., & Dowling, K. M. (2018). TripAdvisor and hotel consumer brand loyalty. *Current Issues in Tourism*, 21(8), 842–846.<https://doi.org/10.1080/13683500.2016.1265488>
- Liu, W., & Shih, H. P. (2021). How do search-based and experience-based information matter in the evaluation of user satisfaction? The case of TripAdvisor. *Aslib Journal of Information Management*, 73(5), 659–678.<https://doi.org/10.1108/ajim-03-2021-0093>
- Mahabub, S., Hossain, M. R., & Snigdha, E. Z. (2025). Data-driven decision-making and strategic leadership: AI-powered business operations for competitive advantage and sustainable growth. *Journal of Computer Science and Technology Studies*, 7(1), 326–336.<https://doi.org/10.32996/jcsts.2025.7.1.24>
- Manes, E., & Tchetchik, A. (2018). The role of electronic word of mouth in reducing information asymmetry: An empirical investigation of online hotel booking. *Journal of Business Research*, 85, 185–196.<https://doi.org/10.1016/j.jbusres.2017.12.019>
- Mao, Z., Yang, Y., & Wang, M. (2018). Sleepless nights in hotels? Understanding factors that influence hotel sleep quality. *International Journal of Hospitality Management*, 74, 189–201.<https://doi.org/10.1016/j.ijhm.2018.05.002>
- Mariani, M., Bresciani, S., & Dagnino, G. B. (2021). The competitive productivity (CP) of tourism destinations: an integrative conceptual framework and a reflection on big data and analytics. *International Journal of Contemporary Hospitality Management*, 33(9), 2970–3002.<https://doi.org/10.1108/ijchm-09-2020-1102>
- Neuhofer, B., Buhalis, D., & Ladkin, A. (2015). Smart technologies for personalized experiences: A case study in the hospitality domain. *Electronic Markets*, 25(3), 243–254.<https://doi.org/10.1007/s12525-015-0182-1>
- Nezdoyminov, S., Bedradina, G., & Ivanov, A. (2019). Digital technology in the management of quality service in tourism business. *International Journal of Engineering and Advanced Technology*, 9(1), 1865–1869.<https://doi.org/10.35940/ijeat.a1001.109119>
- Nicoli, N., & Papadopoulou, E. (2017). TripAdvisor and reputation: A case study of the hotel industry in Cyprus. *EuroMed Journal of Business*, 12(3), 316–334.<https://doi.org/10.1108/emjb-11-2016-0031>
- Nilashi, M., Fallahpour, A., Wong, K. Y., & Ghabban, F. (2022). Customer satisfaction analysis and preference prediction in historic sites through electronic word of mouth.

- Neural Computing and Applications*, 34(16), 13867–13881. <https://doi.org/10.1007/s00521-022-07186-5>
- Noone, B. M., & Robson, S. K. (2016). Understanding consumers' inferences from price and nonprice information in the online lodging purchase decision. *Service Science*, 8(2), 108–123. <https://doi.org/10.1287/serv.2016.0141>
- Oliveira-Cardoso, Q. J. D., Martínez-González, J. A., & Álvarez-Albelo, C. D. (2025). Hotel guest satisfaction: A predictive and discriminant study using TripAdvisor ratings. *Administrative Sciences*, 15(7), 264. <https://doi.org/10.3390/admsci15070264>
- Özdemir, B., Çizel, B., & Bato Cizel, R. (2012). Satisfaction with all-inclusive tourism resorts: The effects of satisfaction with destination and destination loyalty. *International Journal of Hospitality and Tourism Administration*, 13(2). <https://doi.org/10.1080/15256480.2012.669313>
- Park, J., & Jeong, E. (2019). Service quality in tourism: A systematic literature review and keyword network analysis. *Sustainability*, 11(13), 3665. <https://doi.org/10.3390/su11133665>
- Pencarelli, T. (2020). The digital revolution in the travel and tourism industry. *Information Technology & Tourism*, 22(3), 455–476. <https://doi.org/10.1007/s40558-019-00160-3>
- Puri, G., & Singh, K. (2018). The role of service quality and customer satisfaction in tourism industry: A review of SERVQUAL Model. *International Journal of Research and Analytical Reviews*, 5(4).
- Radojevic, T., Stanic, N., & Stanic, N. (2015). Solo travellers assign higher ratings than families: Examining customer satisfaction by demographic group. *Tourism Management Perspectives*, 16, 247–258. <https://doi.org/10.1016/j.tmp.2015.08.004>
- Rahmadian, E., Feitosa, D., & Zwitter, A. (2022). A systematic literature review on the use of big data for sustainable tourism. *Current Issues in Tourism*, 25(11), 1711–1730. <https://doi.org/10.1080/13683500.2021.1974358>
- Ramos, C. M., Cardoso, P. J., Fernandes, H. C., & Rodrigues, J. M. (2022). A decision-support system to analyse customer satisfaction applied to a tourism transport service. *Multimodal Technologies and Interaction*, 7(1), 5. <https://doi.org/10.3390/mti7010005>
- Rassal, C., Correia, A., & Serra, F. (2024). Understanding online reviews in all-inclusive hotels servicescape: A fuzzy set approach. *Journal of Quality Assurance in Hospitality & Tourism*, 25(6), 1607–1634. <https://doi.org/10.1080/1528008x.2023.2167761>
- Rasyida, D. R., Ulkhaq, M. M., Setiowati, P. R., & Setyorini, N. A. (2016, August 1). Assessing service quality: A combination of SERVPERF and importance-performance analysis. *MATEC Web of Conferences*, (68), 06003. <https://doi.org/10.1051/mateconf/20166806003>
- Rivera, D. E., Fa, M. C., Sampaio, P., & Villar, A. S. (2019). Exploring the role of service delivery in remarkable tourism experiences. *Sustainability*, 11(5), 1–19. <https://doi.org/10.3390/su11051382>
- Sakas, D. P., Reklitis, D. P., Terzi, M. C., & Vassilakis, C. (2022). Multichannel digital marketing optimizations through big data analytics in the tourism and hospitality industry. *Journal of Theoretical and Applied Electronic Commerce Research*, 17(4), 1383–1408. <https://doi.org/10.3390/jtaer17040070>
- Schiessl, D., Manosso, F. C., Alves, F., & Prado, P. H. M. H. (2024). Hotel ratings: The impact of trip type (business vs leisure). *Tourism Review*. <https://doi.org/10.1108/TR-11-2023-0807>
- Shu, Z., Llorens-Marin, M., Carrasco, R. A., & Romero, M. S. (2025). Customer electronic word of mouth management strategies based on computing with words: The case of spanish luxury hotel reviews on TripAdvisor. *Electronics*, 14(2), 325. <https://doi.org/10.3390/electronics14020325>
- Sigala, M., Rahimi, R., & Thelwall, M. (2019). Big data and innovation in tourism, travel, and hospitality. *Culinary Science & Hospitality Research*, 23(6), 1–11. <https://doi.org/10.1007/978-981-13-6339-9>

- Silva, E. M., Freitas, G. A. D., & Rebouças, S. M. D. P. (2021). Quality of accommodation in Ceará: A study based on TripAdvisor customer reviews. *Revista Brasileira de Pesquisa em Turismo*, 15, e-2011. <https://doi.org/10.7784/rbtur.v15i3.2011>
- Stringam, B. B., & Gerdes Jr, J. (2010). An analysis of word-of-mouth ratings and guest comments of online hotel distribution sites. *Journal of Hospitality Marketing & Management*, 19(7), 773–796. <https://doi.org/10.1080/19368623.2010.508009>
- Şahin, I., Gulmez, M., & Kitapci, O. (2017). E-complaint tracking and online problem-solving strategies in hospitality management: Plumbing the depths of reviews and responses on TripAdvisor. *Journal of Hospitality and Tourism Technology*, 8(3), 372–394. <https://doi.org/10.1108/jhtt-02-2017-0009>
- Tandafatu, N. K., Ermilinda, L., & Darkel, Y. B. M. (2024). Digital transformation in tourism: Exploring the impact of technology on travel experiences. *International Journal of Multidisciplinary Approach Sciences and Technologies*, 1(1), 55–64. <https://doi.org/10.62207/w3vsg352>
- Tripadvisor. (2025). Travelers' Choice Awards Best of the Best Hotels All-Inclusive - Türkiye. Retrieved from <https://www.tripadvisor.com/TravelersChoice-Hotels-cAllInclusive-g293969>, November 8, 2025.
- Tuna, M. F., Akdoğan, Ş., & Kaynar, O. (2021). Analysis of hotel-related non-review customer feedbacks. *Sciences*, 22(2), 50–81. <https://doi.org/10.37880/cumuiibf.869489>
- Uslu Cibere, G., Başaran, M. A., & Kantarcı, K. (2020). Evaluation of hotel performance attributes through consumer generated reviews: The case of Bratislava. *Advances in Hospitality and Tourism Research (AHTR)*, 8(1), 48–75. <https://doi.org/10.30519/ahtr.592312>
- Xu, X. (2018). Does traveler satisfaction differ in various travel group compositions? Evidence from online reviews. *International Journal of Contemporary Hospitality Management*, 30(3), 1663–1685. <https://doi.org/10.1108/ijchm-03-2017-0171>
- Yadav, M. L., & Roychoudhury, B. (2019). Effect of trip mode on opinion about hotel aspects: A social media analysis approach. *International Journal of Hospitality Management*, 80, 155–165. <https://doi.org/10.1016/j.ijhm.2019.02.002>
- Yang, X., Zhang, L., & Feng, Z. (2024). Personalized tourism recommendations and the E-tourism user experience. *Journal of Travel Research*, 63(5), 1183–1200. <https://doi.org/10.1177/00472875231187332>
- Yılmaz, E. S. (2020). The effects on consumer behavior of hotel-related comments on the TripAdvisor website: An Istanbul case. *Advances in Hospitality and Tourism Research*, 8(1), 1–29. <https://doi.org/10.30519/ahtr.536303>
- Yolal, M., Chi, C. G. Q., & Pesämaa, O. (2017). Examine destination loyalty of first-time and repeat visitors at all-inclusive resorts. *International Journal of Contemporary Hospitality Management*, 29(7), 1834–1853. <https://doi.org/10.1108/ijchm-06-2015-0293>
- Yoon, Y., Kim, A. J., Kim, J., & Choi, J. (2019). The effects of eWOM characteristics on consumer ratings: Evidence from TripAdvisor.com. *International Journal of Advertising*, 38(5), 684–703. <https://doi.org/10.1080/02650487.2018.1541391>
- Yu, M., & Hyun, S. S. (2019). The impact of foreign flight attendants' service quality on behavioral intention toward their home country—Applied SERVPERF model. *Sustainability*, 11(15), 4136. <https://doi.org/10.3390/su11154136>
- Yuan, Y., Chan, C. S., Eichelberger, S., Ma, H., & Pikkemaat, B. (2022). The effect of social media on travel planning process by Chinese tourists: The way forward to tourism futures. *Journal of Tourism Futures*. <https://doi.org/10.1108/jtf-04-2021-0094>
- Zarifah, N., & Hafiz, M. (2020). Help me TripAdvisor! Examining the relationship between TripAdvisor e-WOM attributes, trusts towards online reviews and travellers behavioural intentions. *Journal of Information and Organizational Sciences*, 44(1), 83–112. <https://doi.org/10.31341/jios.44.1.4>
- Zheng, T., Youn, H., & Kincaid, C. S. (2009). An analysis of customers' e-complaints for luxury resort properties. *Journal of Hospitality Marketing & Management*, 18(7), 718–729. <https://doi.org/10.1080/19368620903170240>

Zoghi, F. S. (2025). Hotel performance attributes and consumer complaints in online reviews. *Review of Socio-Economic Perspectives*, 10(1), 27–43.<https://doi.org/10.2478/rsep-2025-0004>