

CUSTOMER SATISFACTION IN KAZAKHSTAN HOTELS: EVIDENCE FOR DIFFERENT CITIES, HOTEL SEGMENTS AND TYPE OF GUEST

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Abstract: Electronic word-of-mouth (eWOM) is increasingly influential in the hospitality industry, shaping customer perceptions and decision-making. This study aims to analyse hotel guest satisfaction and its key determinants based on online reviews of hotels located in the three largest cities in Kazakhstan. The study uses a dataset of guest reviews from a major travel platform and applies statistical analysis, regression models, and content analysis. Six service attributes are examined alongside overall satisfaction, considering differences across cities, hotel star ratings, and guest types. The empirical analysis covers 106 hotels and almost 14,000 reviews, including 7,075 reviews written in English, while the qualitative analysis examines 1,630 recent English-language reviews. The results indicate that “value” and “service” show the strongest correlations with overall satisfaction across all segments. Regression findings highlight “rooms” and “service” as the most significant predictors, although the relative importance of individual attributes varies across hotel categories, cities, and guest types. Satisfaction ratings vary notably by hotel category, location, and type of guest, confirming heterogeneity in the evaluation of hotel experiences. Content analysis further identifies recurring themes related to rooms, staff, breakfast, location, and check-in, with negative feedback mainly associated with room size and facilities, air conditioning, cleanliness, food service, and communication issues. Overall, despite some segment-specific differences, guest experience themes remain consistent across hotel classifications and reviewer profiles. The findings contribute to the literature on eWOM and hospitality in emerging tourism destinations by combining quantitative ratings with qualitative review content and provide actionable insights for hotel managers seeking to improve service quality and enhance guest satisfaction in Kazakhstan.

Keywords: electronic word-of-mouth, user generated content, hospitality, satisfaction differences, Kazakhstan

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INTRODUCTION

Central Asian countries joined the global tourism community after the collapse of the Soviet Union. Among them, Kazakhstan is an interesting case study due to its unique history, strategic geographic position, and size. It is the largest landlocked country in the world, located in the centre of Eurasia. Administrative-territorial units of the Republic of Kazakhstan comprise 17 regions and three cities of republican significance (Astana, Almaty, and Shymkent), which are “*settlements of special national importance or population of more than one million people*” (Bureau of National Statistics, 2024). In the last decade, Kazakhstan has become an attractive destination for leisure and business travellers.

In this context, the country’s tourism sector continues to grow steadily, with an increase in both domestic and international visitors. The number of total tourist arrivals increased to 10,978,555, with 35% (3,864,673) corresponding to arrivals in these 3 main cities. Consequently, the number of served visitors in accommodation establishments in the country has increased to 8,139,270 in 2023, which is 11% higher than in the previous year. The numbers show that these cities have started to gain more international attention. In terms of the number of served visitors in accommodation establishments, Almaty hosted 2,038,417 visitors in 2023, followed by Astana with 1,324,047 and Shymkent with 449,098, all of which were higher than in 2022 (Bureau of National Statistics, 2024). This growth underscores the importance of service quality in the hospitality industry as a driver of competitiveness, especially for emerging tourism markets such as Kazakhstan.

Service quality encompasses the level of satisfaction guests feel throughout their stay and involves various elements, including the professionalism and attentiveness of staff, the cleanliness and upkeep of rooms and shared spaces, the range and accessibility of amenities and activities, the smoothness of check-in and check-out procedures, and the general ambience of the property (Adhikari et al., 2023). Given that in 2023, 47% of all guest stays occurred in the three main cities of Astana, Almaty, and Shymkent, and 20% of all accommodation establishments in the country are located in these cities, which we will analyse in this paper. Focusing on Astana, Almaty, and Shymkent is essential because these three cities operate as the country’s main tourism and hospitality hubs. Service quality in these cities may influence

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visitor satisfaction, repeat visitation, and international perceptions of Kazakhstan's hospitality sector as a whole. It is also a valuable study for the entire country, given that Kazakhstan has undertaken several initiatives to boost its tourism industry over the last few years (Ramazanova et al., 2019), and the ongoing improvement of hotel service quality becomes even more crucial, as it directly impacts the overall visitor experience.

Nowadays, the emergence of new technologies has changed how these impressions are conveyed and perceived by the outside world. Traditional word-of-mouth (WOM) quickly evolved into eWOM (Cantallops & Salvi, 2014; Nilashi et al., 2021). Cantallops & Salvi (2014: 41) state the main differences between WOM and eWOM can be identified in the reach of the reviews' impact (number of people who can be influenced) and the speed of interaction. Hotel managers should focus on improving their electronic word of mouth (eWOM) presence. Guest ratings and reviews play a crucial role in a hotel's profitability, as numerous studies have shown that hotels with higher ratings are perceived as offering superior quality and achieving greater revenue per room (e.g., Ye et al., 2009; Nieto-García et al., 2017). Furthermore, Ahmad & Sun (2018) demonstrate that online reviews serve as the primary source of information influencing customers' purchasing decisions.

Thus, hotel managers should consider these reviews, improve their services, and adopt a customer-centric approach that values clients' needs (Rahimi et al., 2022). Despite the growing body of studies on eWOM and hotel satisfaction, empirical evidence from emerging destinations, particularly Central Asia remains scarce. Kazakhstan's developing tourism industry, characterized by cultural and natural diversity, evolving service quality and digital standards, offers a unique context to examine factors linked to guest satisfaction in its major cities, where most overnight stays are concentrated. Moreover, the Government of the Republic of Kazakhstan (2023) in its recent concept of tourism industry development stresses the importance of developing new clusters, expanding product offers, improving infrastructure and service quality.

Thus, the objective of this paper is two-fold. First, to examine the relationship between overall satisfaction and six specific evaluation attributes—location, sleep quality, rooms, service, value (cost–benefit), and cleanliness - derived from online review data. These attributes are interpreted as observable proxies of broader service quality dimensions, consistent with the SERVQUAL framework. Second, the study analyses the content of hotel guests' written reviews to identify recurring themes and patterns in expressed experiences. This qualitative component is interpreted through the lens of Expectation - Confirmation Theory (ECT), where positive and negative evaluations are understood as indirect manifestations of expectation confirmation or disconfirmation. This combined approach provides a comprehensive understanding of how service quality perceptions translate into overall guest satisfaction (Pacheco, 2017; Stoleriu et al., 2019; Olorunsola et al., 2024).

However, given the nature of secondary review data, expectations and disconfirmation are not directly observed; therefore, both frameworks are used as guiding interpretative structures linking theoretical concepts to observable indicators. To achieve the objectives of this study, we analyse guests' average ratings for 106 hotel units located in Kazakhstan's three principal cities - Astana, Almaty, and Shymkent. The dataset was collected from TripAdvisor (www.tripadvisor.com), one of the world's largest online travel platforms. This research constitutes the first empirical assessment of differences in hotel guest satisfaction within a Central Asian context.

This study contributes to the literature in three main ways. First, rather than simply applying established frameworks such as SERVQUAL and Expectation–Confirmation Theory (ECT) to a new setting, it examines how the relative importance of service quality attributes varies across hotel segments, urban contexts, and guest types, thereby contributing to a more nuanced understanding of service quality heterogeneity in hospitality research. Second, the study integrates quantitative ratings and qualitative eWOM content, providing a complementary perspective on how structured evaluations of service attributes relate to unstructured expressions of guest experience. Third, by focusing on an emerging tourism destination, the paper highlights how context-specific factors (e.g., infrastructure constraints, language barriers, and evolving service standards) shape satisfaction formation, thereby extending existing evidence largely derived from mature tourism markets. In doing so, the study moves beyond a purely contextual application and instead aims to refine existing frameworks by examining how satisfaction formation varies across heterogeneous service environments.

The findings have practical value for industry stakeholders. They can support hotel managers in prioritising investments and allocating resources more effectively by pinpointing the service attributes that most directly shape guest satisfaction. As Kazakhstan seeks to enhance product quality and strengthen competitiveness, such evidence is particularly timely.

The next section presents a literature review, and the subsequent sections present the data and methodology and the results. The fifth section discusses the results, and the last section presents some concluding remarks.

LITERATURE REVIEW

Conceptual framework: service quality and customer satisfaction

This study is framed by two complementary frameworks, such as the SERVQUAL and Expectation–Confirmation Theory (ECT) to explain how perceived service quality shapes customer satisfaction. SERVQUAL, developed by Parasuraman et al. (1988), conceptualizes service quality as the gap between customers' expectations and their perceptions of actual service using five dimensions such as tangibles, reliability, responsiveness, assurance, and empathy. In the context of online review platforms, these dimensions are not directly measured through structured survey instruments but are instead approximated through user-generated ratings of specific attributes. Accordingly, variables such as “rooms” and “cleanliness” can be associated with the tangible dimension, while “service” reflects responsiveness and empathy, and “value” captures the perceived trade-off between expectations and actual performance. The ECT model by Oliver (1980) points out that satisfaction is a cognitive outcome of comparing expected and experienced service performance. However, unlike traditional applications of ECT, this study does not directly measure pre-consumption expectations or post-consumption disconfirmation. Instead, it infers these mechanisms indirectly from observed ratings and review narratives.

Positive evaluations are interpreted as indicative of expectation confirmation, while negative comments reflect perceived disconfirmation. Therefore, ECT is applied here as an interpretative framework rather than as a directly testable model. Taken together, these frameworks provide a conceptual basis for linking observable review-based indicators to underlying constructs of service quality and satisfaction. The empirical strategy adopted in this study reflects this approach by combining attribute-level ratings (as structured proxies of service quality dimensions) with textual analysis (as expressions of perceived experience), thereby operationalising theoretical concepts within the constraints of secondary data.

Both frameworks are widely used in the tourism and hospitality industries to better understand service quality, and in recent years they have been supplemented by new technological and cultural aspects (Kaveski Peres & Pacheco Paladini, 2021; Pacheco, 2017; Olorunsola et al., 2024; Stoleriu et al., 2019). Adhikari et al. (2023) contextualized SERVQUAL for Nepali resorts, demonstrating that local cultural and operational factors influence how guests evaluate tangibility, reliability, responsiveness, assurance, empathy, and expectation. Similarly, Ayvaz-Çavdaroğlu et al. (2024) extended the model by integrating “smart service quality,” emphasizing technology-enabled interactions as key components of guest satisfaction. Building upon these conceptual foundations, the study recognizes the growing role of electronic word-of-mouth (eWOM) as an indirect yet powerful reflection of guests’ perceptions of service quality. It is especially relevant for service quality assessment in the tourism and hospitality sectors, as user-generated reviews serve as a key source of information for travellers looking for unbiased assessments. User-generated reviews provide travellers with experience-based insights into services where quality can only be fully assessed after use (Lopes et al., 2014; Ye et al., 2011). Mukhopadhyay et al. (2023), through bibliometric analysis, documented the increasing academic attention devoted to eWOM in hospitality over the past two decades. Hotels are particularly affected by online reviews (Cantalops & Salvi, 2014), and travellers increasingly rely on them when planning trips. Studies show that most travellers check online reviews before booking, perceiving them as more accurate and up to date than traditional information sources (Lu & Stepchenkova, 2012; Vermeulen & Seegers, 2009; Xiang & Gretzel, 2010; Yoo & Gretzel, 2008). Furthermore, individuals are more likely to place trust in information provided by other consumers, as such sources are perceived to enhance decision-making by reducing the likelihood of suboptimal choices (Stringam et al., 2010; Ye et al., 2009).

New eWOM channels such as review sites, blogs, virtual communities, Twitter, Pinterest, and online travel agency websites are rapidly evolving, offering guests various ways to communicate with each other (Melián-González et al., 2013). Web technologies have transformed how users search for and exchange information, providing innovative communication channels that enable them to share their opinions instantly and efficiently, without time or location restrictions. On the other hand, the growing use of social media, online review platforms, and other user-generated content increases the risk of consumers becoming overwhelmed by the excessive amount of eWOM information (Park & Lee, 2008). Another concern is the difficulty consumers face in assessing the credibility of messages coming from strangers. Regarding fears that user-generated content may be compromised by fake comments made under the cover of anonymity, O’Connor (2010) argues that such fears are unfounded, as research has found little evidence of fake reviews—only isolated cases. For this reason, many online intermediaries – including TripAdvisor – require reviewers to register and provide some additional personal information including name, residence, nationality or gender (Jeong & Jeon, 2008; Xie et al., 2011; Filieri et al., 2021). TripAdvisor (2023) positions itself as “*the world’s largest travel guidance platform based on user-generated content (UGC) and shared experiences*”. It is widely used in previous scientific studies, and it is considered a reliable platform that minimizes misleading reviews (Taecharungroj & Mathayomchan, 2019). Some seminal studies used TripAdvisor or other sites as a source of data, collecting it either manually or automatically (Gerdes & Stringam, 2008).

While SERVQUAL and ECT provide well-established foundations for analysing service quality and satisfaction, their application in the context of online reviews requires careful interpretation. In particular, user-generated content does not directly measure expectations or disconfirmation but instead reflects post-consumption evaluations and expressed experiences. Therefore, in this study, these frameworks are used as interpretative lenses to structure the analysis of rating attributes and review content, rather than as fully operationalized causal models.

Electronic word-of-mouth and hotel satisfaction

Previous studies using online reviews highlight several core attributes that influence overall satisfaction. For example, Limberger et al. (2014a) analysed 660 TripAdvisor reviews and found strong correlations between satisfaction and room quality, service, and location. Jiang et al. (2014) analyse English-speaking traveller reviews posted on TripAdvisor about hotels in Mainland China. The authors compare brand image across hotel types and star rating levels, finding that brand image can vary based on specific hotel characteristics, emphasizing different areas of service. For instance, the authors find that a certain star level does not necessarily imply a predetermined type of review, a feature that highlights the importance of distinguishing ratings between star levels. Pacheco (2017) showed that rooms, service, and cost-benefit are the main drivers associated with overall satisfaction in Portuguese hotels and those attributes are common across hotel segments and regions. Other studies identified attributes related to value, culture and sustainability. Jeong & Jeon (2008) analyse the consistency of posted reviews with the expected level of service and room rate. Using guests’ reviews of hotels in New York City posted on TripAdvisor, their results indicate that “value” is one of the key predictors for guest satisfaction, which leads to return intentions. Regardless of hotel segment and average daily rate (ADR), location appears to have the highest mean value among seven performance attributes and hotel segments (i.e., number of stars) and ADR appears to influence the relationships of selected hotel performance attributes with both overall guest satisfaction and return intentions. To understand satisfaction and needs of Eastern and Western travellers, Sann & Lai (2023) analyse 2,965 reviews from Western tourists in Cambodia and compare them with 1,035 reviews from Eastern tourists, representing a

total of 47 countries. Their research reveals differences in the perception of service experiences between the two groups of travellers. Recent research of Gim et al. (2026) shows Eastern consumers use contextual thinking, amplifying the horn effect and negative spillovers in hotel evaluations. This means that one negative experience in a hotel can influence how guests see everything else, even things that are not directly related. As a result, this negative feeling spreads across the whole stay and leads to a much lower overall evaluation.

Pacheco et al. (2024) examine TripAdvisor reviews of Portuguese environmentally certified hotels to assess the presence of sustainability concerns. Their findings show that environmental issues are largely absent and that there is no clear link between eco-certification and guests' reviews.

In addition to factors of satisfaction, several studies have analysed the relationship between online reviews and hotel performance. For instance, Ye et al. (2009) conducted an empirical study using data from China's largest travel website to examine the influence of online consumer-generated reviews on hotel room sales. They used the volume of reviews on the platform as a proxy for sales performance. The findings reveal that favourable online reviews have a substantial positive effect on hotel business outcomes, although greater variability in customer ratings tends to negatively affect overall room ratings. Drawing on data from the Expedia website, Stringam et al. (2010) explores the relationship between guests' overall satisfaction and specific dimensions of hotel quality, including service, physical condition, room cleanliness, and comfort. Analysing over 60,000 traveller reviews, the study finds that most ratings across all four categories, as well as overall satisfaction, were favourable. Furthermore, approximately 75% of respondents expressed a willingness to recommend the hotel. Each of the four quality dimensions demonstrated a similarly strong correlation with both overall satisfaction and likelihood of recommendation. However, correlation analysis revealed that hotel service and room comfort were the most influential factors, followed by the condition of the hotel and room cleanliness. Previous research highlights the critical role of customer satisfaction with tourism experiences in general, both in the hotel industry and when visiting cultural attractions in shaping visitor loyalty (Pacheco et al., 2026; Phan et al., 2025).

Stringam & Gerdes (2010) evaluate 60,648 consumer ratings and comments from Expedia to determine what factors drive consumer ratings of hotels. Specifically, the paper yields information about the most frequently used words, as well as the pattern of word usage with either high or low guest ratings. It also explores the hotel guests' choice of words when assigning lower ratings versus higher ratings. Wilson et al. (2012) examine the influence of nationality both on the motivation to post (or not) and on where and what type of content consumers share in the context of a recent trip. The method used is an online survey of 568 respondents located in Switzerland, the United Kingdom and Spain, and the results reveal differences in national attitudes and motivations for posting. Respondents in Switzerland and the United Kingdom are more likely to post photos or travelogues on Facebook, but respondents from Spain prefer to post on TripAdvisor with the goal of making recommendations to other travellers. Li et al. (2013) analyse the content of 42,668 online reviews from 774 hotels, showing on one hand that transport facilities, food and beverage management, proximity to tourism destinations and amount paid are the most valued factors, independently of the hotel segment. On the other hand, customers are less satisfied with the bed, reception desk services, room decoration and size. In particular, the authors show that 97% of satisfaction variance can be explained by only four variables: room, value, cleanliness and check-in/out. The authors conclude that individuals from different countries have diverse reasons to post comments, so hotel managers should consider those behavioural differences.

Analysing both the content and volume of electronic word-of-mouth (eWOM) across a substantial sample of 16,680 hotels, Melián-González et al. (2013) identify a link between the valence of reviews (i.e., positive versus negative) and their volume. Their findings suggest that early reviews tend to be predominantly negative. However, as the number of reviews increases, average ratings improve and variability decreases, indicating a higher level of consensus among reviewers and a dilution of initial negative impressions. A key implication of the study is that hotel managers should encourage a greater volume of reviews to achieve a more balanced and representative evaluation of their establishments. As stated by Peres & Paladini (2021) attributes with a negative review should be prioritised, as negative feedback directly influences customer decisions and can have a considerable impact on hotel revenue.

The literature using online reviews confirm that hotel satisfaction is largely shaped by attributes aligned with SERVQUAL dimensions such value, cleanliness, location and rooms. Viewed through Expectation–Confirmation Theory (ECT), positive evaluations indicate confirmation of guests' expectations, whereas complaints about room size or cleanliness represent disconfirmation. Differences observed across guest types and cultures demonstrates ECT's basis that varying expectations shape satisfaction outcomes. The attributes available on review platforms such as TripAdvisor can be conceptually aligned with SERVQUAL dimensions. For example, "rooms" and "cleanliness" reflect tangible aspects, "service" captures elements of responsiveness and empathy, while "value" reflects a perceived trade-off between expectations and performance. This mapping allows us to interpret attribute-level ratings within an established theoretical framework, while acknowledging that these measures are simplified representations of broader service quality constructs.

Although the literature on eWOM and hotel satisfaction is extensive, most studies focus on identifying average effects of service attributes on overall satisfaction, often in mature tourism destinations. Less attention has been given to how these relationships vary across different service contexts, hotel segments, and types of guests, particularly in emerging markets (for instance, in Central Asia). As a result, the heterogeneous nature of service quality evaluation remains underexplored. This study addresses this gap by analysing both rating patterns and review content across multiple dimensions of heterogeneity, thereby providing a more differentiated understanding of satisfaction formation.

We use only reviews posted in English, so we are focusing our analysis on a foreign perspective on Kazakhstan's hotels. Although not explicitly considered here, different cultural backgrounds lead to different consumption concepts,

perceived satisfaction and ratings (Ayoun & Moreo, 2008; Chen et al., 2012; Li et al., 2013). Several studies focus on the relationship between cultural factors and personality traits with hotel reviews and ratings (Hsieh & Tsai, 2009; Tse & Ho, 2009; Yoo & Gretzel, 2011, among others, or Schuckert et al., 2015a, for a literature review).

In this exploratory paper we follow the papers from Chaves et al. (2013), Li et al. (2013), Limberger et al. (2014a, 2014b), Pacheco (2017) and Pacheco et al. (2024), among others, analysing the reviews from a sample of 106 Kazakhstani hotels from its major cities (Astana, Almaty and Shymkent) in order to identify the most important drivers of overall satisfaction and considering differences in terms of location, hotel segments and types of guest. Thus, the three main research questions that we try to answer in the following sections are:

- 1) Are there significant differences in average ratings between hotel segments, cities and types of guests?
- 2) What are the main drivers of overall satisfaction in global terms, and in terms of hotel segments, cities and types of guests?
- 3) What are the main themes and issues in guests' reviews?

Data and methodology

This study combines different levels of analysis. The quantitative analysis is conducted at the hotel level, using average ratings for each attribute and overall satisfaction. In contrast, the content analysis is performed at the review level, based on individual textual comments. This dual approach allows us to capture both aggregated evaluation patterns and the underlying qualitative expressions of guest experience. The data used in this study were manually retrieved from TripAdvisor. TripAdvisor provides a mechanism that enables users to submit reviews of their hotel stays and share their experiences, assigning ratings from 1 (very unsatisfied/terrible) to 5 (very satisfied/excellent). These scores represent eWOM in a straightforward manner. As of November 2024, TripAdvisor listed reviews for more than 2,500 hotels and similar accommodation units in Kazakhstan, distributed across different categories according to their star ratings.

This paper analyses reviews written by hotel guests in the three main cities of Kazakhstan: Astana, Almaty, and Shymkent. Russian and English are generally the dominant languages used in the reviews. Only hotels with more than 50 total reviews and at least 5 reviews in English were included, resulting in a sample of 106 hotels comprising almost 14,000 reviews. The analysis focuses on reviews written in English, which are assumed to reflect the perceptions of international guests. This choice enhances comparability across hotels but may introduce a selection bias, which is acknowledged as a limitation. Nevertheless, this criterion ensures a minimum level of representativeness and reduces the influence of extreme or idiosyncratic evaluations. The main characteristics of the analysed hotels are presented in Table 1.

Table 1. Main characteristics of the hotels analysed (Source: Data obtained from TripAdvisor in November 2024. Own calculations)

	Number of hotels	Number of reviews	Number of reviews in English	Average review	Location	Rooms	Value	Cleanliness	Service	Quality of sleep
5 stars	17	4,997	3,005	4.147	4.341	4.318	3.971	4.588	4.335	4.312
4 stars	57	6,994	3,244	3.833	4.095	3.979	3.730	4.133	3.975	3.853
3 stars	31	1,849	826	3.688	4.031	3.800	3.847	4.153	3.916	3.947
Total	106	13,840	7,075	3.889	4.115	3.979	3.804	4.212	4.015	3.955

In global terms, and as expected, the average rating and some specific reviews present decreasing values when starting from the higher-quality 5-star hotels and descending to the lower-quality ones. This is particularly evident in the categories' "location", "rooms" and "service". Notice that 51% of the reviews are written in English, with that percentage increasing with the hotels' quality (60% in 5-star hotels).

For the qualitative analysis, we collected in November 2024 the 20 most recent reviews written in English for each hotel, obtaining a total number of 1,630 reviews. This approach balances recency and comparability across units, while limiting potential bias from outdated reviews. Although this choice reduces the total number of reviews analysed, it ensures that the content reflects more recent guest experiences. Hotels with fewer than 5 English-language reviews were excluded to maintain consistency, resulting in a relatively smaller number of reviews in the 3-star segment. As can be seen in Table 2, and roughly reflecting the distribution presented in Table 1, around 54% of the hotels are 4-star hotels (57 out of 106), with the higher and lower categories representing, respectively, 16% and 30% of the sample. The city of Almaty presents the higher number of hotels, followed by Astana, with Shymkent presenting a small number of hotels.

Table 2. Number of hotels (and number of reviews) analysed in the three cities

(Note: Hotels classified from five to three stars according to the TripAdvisor's classification system. Data retrieved in November 2024)

	Almaty	Astana	Shymkent	Total
5 stars	8 (152)	7 (130)	2 (24)	17 (306)
4 stars	33 (488)	18 (287)	6 (92)	57 (867)
3 stars	17 (292)	13 (154)	2 (11)	32 (457)
TOTAL	58 (932)	38 (571)	10 (127)	106 (1,630)
% of the sample	55% (57%)	36% (35%)	9% (8%)	

The reviews were saved in Excel (CSV, comma-delimited) format for subsequent content analysis. Prior to analysis, the textual data were pre-processed to ensure consistency. This included correcting spelling errors, standardising punctuation, and removing irrelevant symbols. While these procedures improve the performance of text analysis software, they may slightly alter the original phrasing. However, care was taken to preserve the semantic content of the reviews.

Table 3. Main characteristics of the data sample (Source: Data obtained from TripAdvisor in November 2024. Own calculations)

	Number of reviews	Average rating (n=1630)	Location (n=769)	Cleanliness (n=386)	Service (n=967)	Value (n=794)	Rooms (n=375)	Sleep quality (n=386)
5 stars	306	4.42	4.63	4.72	4.52	4.28	4.38	4.60
4 stars	867	4.29	4.55	4.62	4.46	4.25	4.40	4.51
3 stars	457	4.07	4.39	4.40	4.21	4.23	3.76	4.00
Total	1,630							

Not all reviews include ratings for every attribute. Therefore, the number of observations varies across variables, as indicated in Table 3. The analysis uses all available observations for each attribute, without imputing missing values, to avoid introducing artificial bias.

As expected, average reviews tend to decrease according to the hotel category, generally with a more evident difference between five/four-star hotels and lower-category hotels, aligned with results of Schuckert et al. (2015b). Although not presented in Table 3, this trend appears in all cities with the exception of Shymkent, where 5-star hotels appear behind 4-star hotels in almost all attributes. This can be explained that guests expect much more from 5-star hotels and when these high expectations are not fully met, reviews tend to become more critical (Carneiro & Costa, 2000; Li et al., 2013).

Table 4 shows the sample distributed according to the type of guest. Independently of the hotel category, the majority of review types of guests are 'business' (n=603, or 41% of total reviews), 'couple' (n=280, or 19%), and 'alone' (n=237, or 16%).

Table 4. Type of guest by hotel segment (Source: Data obtained from TripAdvisor in November 2024; own calculations)

(Notes: Percentages were computed considering only the 1,484 reviews presenting this characteristic)

	Couple	Family	Alone	Friends	Business
5 stars (n=281)	17,4%	15,7%	8,2%	8,5%	50,2%
4 stars (n=801)	19,5%	10,4%	16,5%	14,7%	39,0%
3 stars (n=402)	18,7%	10,9%	20,4%	12,7%	37,3%

We consider this sample to be adequate since the cities of Almaty and Astana have higher weights which reflect their national weights in terms of the number of arrivals (Almaty with 2,084,578 and Astana with 1,324,099 out of 10,978,555) and stays (Almaty with 2,038,417 and Astana with 1,324,047 out of 8,139,270) in 2023.

As for the city of Shymkent, albeit being the third city in terms of dimension, has a relatively smaller population and lacks the allure of the capital or the mountains and landscapes of Almaty. Besides that, data demonstrates a growing tourism demand in its scale in terms of total arrivals, stays and investment in accommodation (455,996 arrivals and 449,098 stays) (Bureau of National Statistics, 2024). In 2023, the country registered a total of 3,992 accommodation establishments with an average annual growth rate of 8% over the past 10 years. By comparison, in 2014, there were 2,056 establishments.

Out of these 3,992 establishments, three cities under study represents 19% (757 establishments), 28% of all rooms (24,132 rooms out of 85,512) and 56% of revenue (Bureau of National Statistics, 2024). Concerning the distribution by segments (according to the number of stars in the official classification system), the sample reflects a higher preponderance of four-star hotels and a relatively lower number of five-star hotels. To examine the relationship between overall satisfaction and its component attributes, we employ an Ordinary Least Squares (OLS) regression model.

This approach is consistent with prior studies using online review data, where overall ratings are analysed in relation to attribute-specific evaluations (e.g., Pacheco, 2017). However, it is important to note that both the dependent variable (overall satisfaction) and the explanatory variables (attribute ratings) originate from the same platform, which may lead to mechanical correlations and inflated explanatory power. Therefore, the results should be interpreted as indicating associations rather than causal relationships. The relatively high adjusted R^2 values are consistent with this structure and reflect the fact that overall satisfaction is partially constructed from similar underlying evaluations. To address this issue, we interpret the coefficients cautiously and complement the regression analysis with subgroup analyses to assess the robustness of the results across different hotel segments, cities, and types of guests. Prior to regression, we compute some descriptive statistics (means, standard deviations and correlations), and to better understand the main characteristics of the sample we perform statistical tests to analyse the presence of differences in mean ratings across cities, hotel segments and types of travel. Finally, using the Maxqda and Leximancer software we perform a content analysis of the reviews, as an increasingly used scientific method in tourism (e.g., Camprubí & Coromina, 2016; Sánchez-Vargas et al., 2022).

RESULTS AND DISCUSSION

Statistical analysis and regression

This section presents the main empirical findings, structured around the three research questions. To enhance clarity and avoid repetition, we focus on the most relevant results, while additional descriptive details are reported in supplementary tables. The discussion emphasises the patterns that directly contribute to understanding the relationship between service attributes and overall satisfaction, as well as the main themes emerging from guest reviews.

Table 5 shows that higher-category hotels systematically receive higher ratings across most attributes, confirming a consistent quality gradient. Differences across cities are also evident, with Astana presenting relatively higher evaluations, particularly in "value" and "location". Table 6 presents the Spearman's rank correlation coefficients between overall satisfaction and the different attributes for different cities. As can be seen from the table, correlations are all significant and positive, presenting values around the 0.3-0.9 range.

Table 5. Means and standard deviations (Note: n = 106 (total) and according to Table 2)

	Overall satisfaction	Location	Rooms	Value	Cleanliness	Service	Quality of sleep
Mean (Standard dev.)							
Total	3.75 (1.30)	4.12 (1.06)	3.79 (1.22)	3.80 (1.31)	4.08 (1.15)	3.85 (1.28)	3.84 (1.24)
5 stars	3.92 (1.25)	4.45 (1.00)	4.05 (1.15)	3.95 (1.22)	4.52 (0.93)	4.03 (1.22)	4.14 (1.10)
4 stars	3.73 (1.27)	4.11 (1.02)	3.78 (1.23)	3.77 (1.30)	4.02 (1.13)	3.82 (1.29)	3.74 (1.25)
3 stars	3.69 (1.30)	3.92 (1.06)	3.66 (1.22)	3.74 (1.32)	3.95 (1.16)	3.80 (1.29)	3.84 (1.24)
Astana	3.95 (1.22)	4.18 (1.03)	4.02 (1.10)	4.11 (1.12)	4.31 (0.94)	4.12 (1.14)	4.09 (1.07)
Almaty	3.62 (1.34)	4.09 (1.08)	3.61 (1.26)	3.59 (0.49)	4.18 (0.39)	4.10 (0.32)	4.33 (0.40)
Shymkent	3.85 (1.23)	4.03 (0.96)	3.93 (1.25)	3.88 (1.10)	4.10 (1.01)	3.89 (1.24)	3.74 (1.38)
Business	3.68 (1.30)	4.03 (1.06)	3.67 (1.22)	3.71 (1.31)	3.92 (1.15)	3.78 (1.28)	3.67 (1.24)
Couple	3.82 (1.29)	4.22 (1.05)	3.93 (1.21)	3.83 (1.29)	4.41 (1.12)	3.86 (1.28)	3.77 (1.23)
Alone	3.97 (1.29)	4.21 (1.05)	3.97 (1.21)	4.13 (1.29)	4.25 (1.13)	4.11 (1.28)	4.09 (1.22)

Table 6. Correlations between overall satisfaction and attributes

(Note: n = 106 (total) and according to Table 2. * p<0.05; ** p<0.01 and *** p<0.001)

	Location	Rooms	Value	Cleanliness	Service	Quality of sleep
Total	0.59 ***	0.83 ***	0.88 ***	0.77 ***	0.84 ***	0.76 ***
5 stars	0.57 ***	0.76 ***	0.91 ***	0.69 ***	0.85 ***	0.63 ***
4 stars	0.30 ***	0.84 ***	0.88 ***	0.82 ***	0.83 ***	0.79 ***
3 stars	0.55 ***	0.87 ***	0.86 ***	0.72 ***	0.84 ***	0.76 ***
Astana	0.64 ***	0.82 ***	0.88 ***	0.77 ***	0.85 ***	0.76 ***
Almaty	0.50 ***	0.85 ***	0.86 ***	0.74 ***	0.83 ***	0.75 ***
Shymkent	0.50 **	0.77 ***	0.89 ***	0.92 ***	0.80 ***	0.69 ***

To test our first research question, we perform a t-test to determine whether there are significant differences in means for the different attributes. Table 7 presents the results for the t-test while differentiating between hotel segments, cities and type of guest, comprising three combinations each. Since the t-test needs to consider an assumption regarding the equality of variances or not, before this test we tested whether the different pairs presented equal variances to perform the appropriate test for differences in means. Notice that a parametric test is used, since after computing the Doornik-Hansen test it was found that more than half of the data series followed a normal distribution.

Table 7. T-test for differences in review ratings between hotel segments, cities and type of guest

(Note: n = 106 (total) and according to Table 2. * p<0.05; ** p<0.01 and *** p<0.001)

	Overall satisfaction	Location	Rooms	Value	Cleanliness	Service	Quality of sleep
	t-test (p-value)	t-test (p-value)	t-test (p-value)	t-test (p-value)	t-test (p-value)	t-test (p-value)	t-test (p-value)
5 vs. 4 stars	2.13 (*)	3.50 (***)	1.59	1.22	4.20 (***)	1.70	2.59 (*)
5 vs. 3 stars	2.46 (**)	4.51 (***)	2.26 (*)	1.30	4.34 (***)	1.69	1.87
4 vs. 3 stars	0.74	1.72	1.03	0.23	0.58	0.15	0.75
Almaty vs. Astana	5.00 (***)	0.98	3.63 (***)	4.78 (***)	4.16 (***)	5.09 (***)	3.51 (***)
Almaty vs. Shymkent	1.98 (*)	0.31	1.46	1.58	0.98	1.38	0.22
Astana vs. Shymkent	0.85	0.76	0.45	1.18	1.21	1.19	1.22
Business vs. Couple	1.54	1.35	1.49	0.82	3.60 (***)	0.63	0.58
Business vs. Alone	1.78	0.50	0.91	1.07	0.06	1.73	0.30
Couple vs. Alone	2.76 (**)	0.58	1.81	1.50	2.14 (*)	1.98 (*)	0.15

Overall, these results provide evidence that guest evaluations differ significantly across hotel segments and, to a lesser extent, across cities and guest types, thereby supporting the presence of heterogeneity in satisfaction patterns.

Ratings generally increase from lower to higher hotel segments, suggesting that guests in five-star hotels report higher satisfaction levels compared to those in lower-category establishments. Consistent with previous research (Schuckert et al., 2015b), lower-category hotels also exhibit greater dispersion in ratings, indicating more heterogeneous guest experiences. This variability is particularly pronounced among ‘business’ travellers. Statistically significant differences are also observed between five-, four-, and three-star hotels, as well as between Almaty and the other cities. Differences between “couple” and “alone” travellers are also evident. At the attribute level, notable variation is found in “location” and “cleanliness”, both across hotel categories and, in the case of “cleanliness”, across guest types.

These findings address the first research question by evidencing that satisfaction patterns are not homogeneous. The differences observed in Almaty may be partly associated with specific local characteristics, such as geographical features and traffic congestion, which can affect accessibility and perceived convenience. In order to answer our second research question, Table 8 presents the results for the OLS regression for the entire sample and the three hotel segments, followed by the regressions for different cities and types of travel. It should be noted that the regression results reflect relationships between overall satisfaction and its component ratings derived from the same platform.

Therefore, the coefficients should be interpreted as associations rather than causal effects, and the high explanatory power partly reflects the structure of the data.

Table 8. Regression results (Note: Robust standard errors (HC1). VIFs consistent with the absence of multicollinearity. Due to the small sample Shymkent is not considered. * $p < 0.05$; ** $p < 0.01$ and *** $p < 0.001$)

	Entire sample		5 star hotels		4 star hotels		3 star hotels			
	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig		
Constant	- 0.4012	***	0.3557		- 0.5199	***	- 0.2469			
Location	0.1089	**	- 0.2002		0.1513	**	0.0760			
Rooms	0.2123	***	0.0156		0.2521	**	0.3641	***		
Value	0.3261	***	0.3997	***	0.1898	*	0.3933	***		
Cleanliness	0.0981		0.1204		0.2234	**	- 0.0782			
Service	0.2828	***	0.4791	***	0.2097	*	0.2249	**		
Quality of sleep	0.0472		0.1281		0.0567		0.0769			
R ²	0.88		0.95		0.87		0.91			
R ² adjusted	0.88		0.94		0.87		0.90			
F	378.99	***	133.89	***	214.04	***	160.32	***		
	Astana		Almaty		Business		Couple		Alone	
	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig
Constant	- 0.4540		- 0.4145	**	- 0.4407	*	- 0.7649	*	- 0.4065	
Location	0.0450		0.1767	***	0.1423	**	0.3212	***	0.0440	
Rooms	0.3436	**	0.1801	**	0.2634	**	0.2626	**	0.3603	**
Value	0.2539	**	0.3411	***	0.1296		0.2107	**	0.8734	***
Cleanliness	0.0976		0.0861		0.0444		0.1574		0.3554	**
Service	0.1697		0.3082	***	0.2920	***	0.2749	**	- 0.0580	
Quality of sleep	0.1811		- 0.0151		0.2142	**	- 0.0526		- 0.5566	**
R ²	0.88		0.88		0.89		0.93		0.94	
R ² adjusted	0.86		0.87		0.88		0.91		0.92	
F	88,14	***	291.06	***	272.87	***	105.22	***	42,54	***

Table 9. Most determinant attributes (by hotel segment, city or type of guest)
(Note: only the significant variables for each regression are presented. VIFs consistent with the absence of multicollinearity)

	Astana	Almaty	Business	Couple	Alone
Total	rooms, value	location, rooms, value, service	location, rooms, service, quality of sleep	location, rooms, value, service	rooms, value, cleanliness, quality of sleep
5 stars	...	location, value, service	service	rooms, value, cleanliness	...
4 stars	rooms, quality of sleep	location, rooms, service	rooms, service, quality of sleep	cleanliness	location, rooms
3 stars	rooms, cleanliness	rooms, value, service	rooms, service	...	value

Across specifications, “rooms” and “service” emerge as the most consistently significant attributes, while “value” also plays an important role, particularly in lower hotel segments and certain guest categories. Table 9 summarises these patterns, highlighting the attributes most strongly associated with overall satisfaction across different subsamples.

Across the full sample, “value” and “service” show the strongest associations with overall satisfaction, while “cleanliness” and “quality of sleep” are not statistically significant. At the segment level, only “value” and “service” remain significant for five-star hotels, whereas “rooms” is significant across all hotel categories. At the city level, both “value” and “rooms” are consistently relevant. Differences also emerge across guest types: for example, “location” appears less relevant for ‘alone’ travellers, while “service” and “quality of sleep” are more relevant for ‘business’ guests.

These findings address the second research question by identifying the attributes most strongly associated with satisfaction and highlighting how their importance varies across contexts. Overall, the results reveal a consistent pattern across cities, while also confirming that the relative importance of some attributes varies across segments and guest types. For instance, “rooms” and “service” are particularly relevant for ‘business’ travellers, “value” is more important in lower hotel segments, and “location” plays a stronger role in Almaty. This is consistent with prior studies (Jiang et al., 2014; Pacheco, 2017), which show that the importance of service attributes may vary across destinations within the same country.

More broadly, the findings are consistent with existing literature showing that attributes such as rooms, service, value, cleanliness, and location are central to guest evaluations and are frequently discussed in online reviews (Stringam et al., 2010; Li et al., 2013; Limberger et al., 2014a; Pacheco, 2017; Ali et al., 2023; Pacheco et al., 2024). In the case of Kazakhstan, “value” and “service” appear to be particularly salient, suggesting that guests may be especially sensitive to perceived value for money and service quality in an emerging tourism context. This pattern may reflect structural characteristics of developing tourism markets, including infrastructure limitations, language barriers, and restricted service variety.

Content analysis (word frequency and concept maps)

To complement the statistical analysis, we examine the textual content of reviews to better understand how guests articulate their experiences and evaluations. Following Stoleriu et al. (2019), Olorunsola et al. (2022), and Ali et al. (2023), an exploratory content analysis of the qualitative data was used to identify the main themes and discover the frequency of themes and their relationships. With the objective to answer our third research question, we use Maxqda and Leximancer software to perform a content analysis of guest reviews on TripAdvisor. Besides quantifying the occurrence of words with Maxqda, the Leximancer software was used to eliminate the researcher bias coder reliability and subjectivity (Olorunsola et al., 2022). When handling a large data volume with manual content analysis, the researcher risks committing errors and

bias the results. Leximancer mitigates this problem by avoiding manual intervention (Angus et al., 2013). First, a word frequency analysis was carried out. Only adjectives were considered, being selected as a list of the ten most frequently used words in the reviews of the three hotel categories. That exercise was repeated considering the distribution by average review, by the five types of guests (“business”, “couple”, “family”, “alone”, and “friends”), and by city. Detailed lexical outputs and extended tables are available in the appendix to improve readability of the main text (Tables A1 and A2).

Considering the rankings of the top 10 most mentioned adjectives in each category, words as ‘good’, ‘great’, ‘nice’, and ‘clean’, among others, stand out, pointing to the overall satisfaction of guests with hotel accommodation. Adjectives like ‘small’, ‘hot’, and ‘poor’ appear in the reviews with ratings of 3 or less, denoting problems with room dimension, non-functioning air conditioning or cleanliness. Considering the type of guest or city, the only negative adjective regularly appearing in the top 10 is ‘small’, associated with room dimension. Negative words rank first in lower-category hotels. Negative words are primarily associated with hotel facilities (e.g., room size and air conditioning), staff (e.g., inability to solve a problem and to speak English), and food (e.g. poor quality and absence of vegetarian dishes). Second, Leximancer software was used to group concepts within themes and generate the corresponding concept maps. Several phases were followed to build the concept maps. First, the Excel file with the reviews was uploaded into the software. It then detected the most repeated words and identified word patterns and clusters consistent in the review transcripts, classifying them as concepts.

Finally, the software determines the frequency of co-occurrences and interconnectivity between concepts, displaying them graphically. Concepts are grouped into a more extensive set and classified as themes, represented in colour-coded circles containing interconnected concept links (Olorunsola et al., 2022). The Leximancer maps should be interpreted as visual representations of co-occurring concepts, where proximity and colour intensity indicate stronger relationships and thematic relevance. The concept map for the complete sample (Figure 1) identifies the leading themes and concepts.

A systematic approach was used, and the analysis results showed five themes, further separated into 78 concept seeds and structured in the form of a conceptual framework. The Leximancer analysis yielded the following themes: ‘staff’, ‘room’, ‘breakfast’, ‘location’, and ‘check’. The results of the customer analysis show the service’s distinctive characteristics by focusing on the tangible and intangible elements that comprise the service based on determinants (service experience), showing the importance of staff from check-in to check-out. The following are revealed by the concept analysis (Figure 1). The ‘room’ theme is the most important, showing 100% relevance to the other themes and concepts. This dominance of the ‘room’ theme confirms its central role in shaping guest experience, consistent with the regression results.

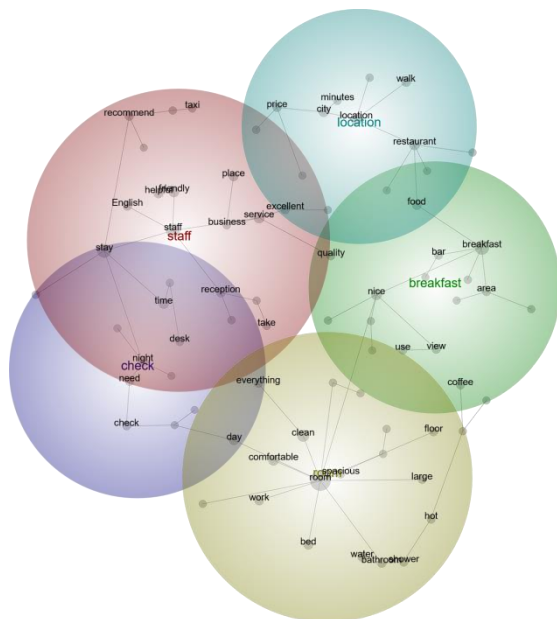


Figure 1. Concept map (complete sample)

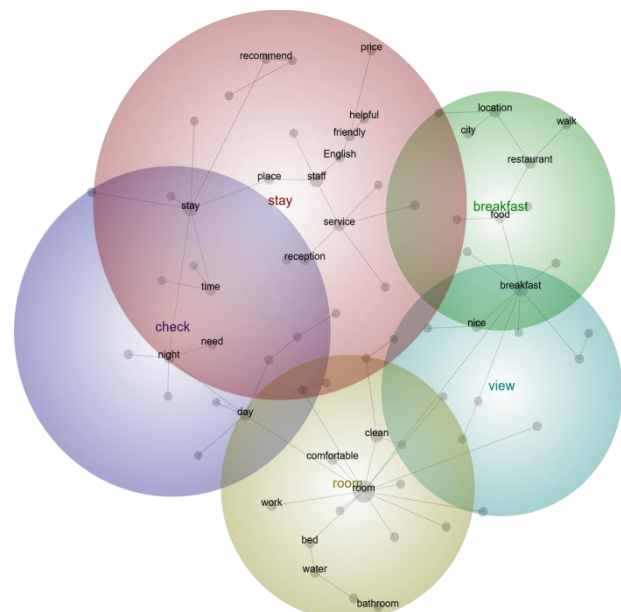


Figure 2. Concept map (hotels from Almaty)

For brevity reasons, not all possible concept maps are presented. Given their relevance in our sample, we present below the concept maps for Almaty hotels, three stars’ hotels, hotels with reviews of 1 or 2 and for business travellers’ reviews.

The concept map for Almaty hotels (Figure 2) identifies five themes, further separated into 71 concept seeds and structured as a conceptual framework. The Leximancer analysis yielded the following themes: ‘stay’, ‘room’, ‘breakfast’, ‘view’, and ‘check’. For instance, the eleven most relevant concepts under the ‘stay’ theme are ‘room’ (1181; 100%), ‘clean’ (328; 28%), ‘day’ (240; 20%), ‘comfortable’ (212; 18%), ‘bed’ (171; 14%), ‘work’ (186; 16%), ‘water’ (165; 14%), ‘bathroom’ (153; 13%), ‘shower’ (119; 10%), ‘hot’ (107; 9%), and ‘use’ (116; 10%).

For hotels with 3 stars, the concept analysis identifies five themes, further separated into 62 concept seeds and structured in a conceptual framework (Figure 3). The Leximancer analysis yielded the following themes: ‘room’, ‘breakfast’, ‘stay’, ‘location’, and ‘buffet’. The ten most relevant concepts under the ‘room’ theme are ‘room’ (count = 546; relevance = 100%), ‘clean’ (188; 34%), ‘comfortable’ (106; 19%), ‘time’ (112; 21%), ‘bed’ (104; 19%), ‘day’ (101; 18%), ‘work’ (96; 18%), ‘water’ (73; 13%), ‘shower’ (69; 13%), ‘bathroom’ (75; 14%), and ‘hot’ (44; 8%).

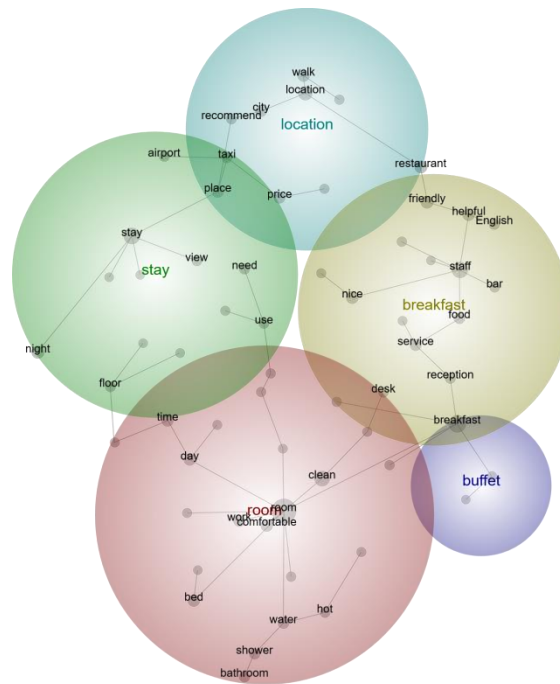


Figure 3. Concept map (3-stars' hotels)

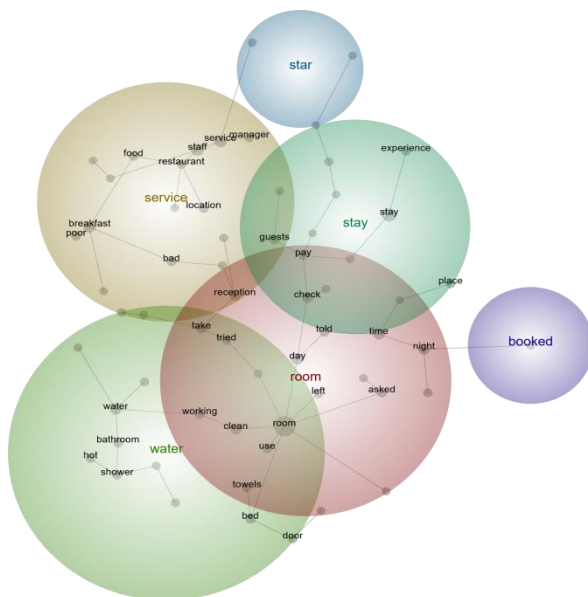


Figure 4. Concept map (hotels with ratings of 1 or 2)

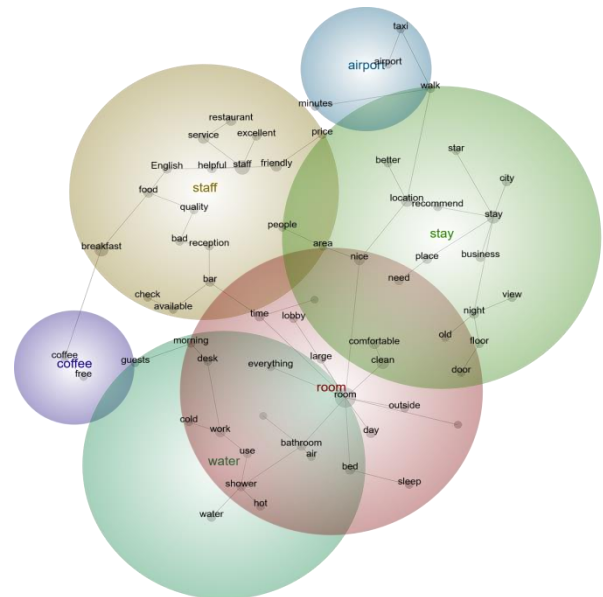


Figure 5. Concept map (Business' guests)

For hotels with ratings of 1 or 2, the concept analysis identifies six themes, further divided into 54 concept seeds and structured within a conceptual framework (Figure 4). The Leximancer analysis yielded the following themes: 'room', 'service', 'water', 'stay', 'booked', and 'star'. For instance, the six most relevant concepts under the 'water' theme are 'water' (count = 85; relevance = 21%), 'working' (77; 19%), 'bathroom' (71; 17%), 'bed' (77; 19%), 'shower' (51; 12%), and 'towels' (49; 12%). These results indicate that the main sources of dissatisfaction associated with lower ratings are related to facility-related issues and inadequate service, particularly in food service. Finally, regarding reviews from business travellers, six themes were identified, divided into 64 concept seeds. The themes revealed by the concept map are: 'room', 'staff', 'stay', 'water', 'airport', and 'coffee' (Figure 5). Notably, the themes 'airport' and 'coffee' appear specifically in this group.

For instance, the 12 most relevant concepts under the 'staff' theme are 'staff' (338; 51%), 'breakfast' (346; 52%), 'service' (197, 30%), 'friendly' (150; 23%), 'restaurant' (152, 23%), 'food' (119, 18%), 'helpful' (98, 15%), 'bar' (90, 14%), 'English' (87, 13%), 'excellent' (79, 12%), 'price' (87, 13%) and 'reception' (71, 11%). These results indicate that staff quality, including communication in English, and food service are particularly relevant aspects for business travellers. The content analysis provides additional insights into guest experiences. The predominant themes identified in the reviews – particularly 'room' and 'staff' – are consistent across hotel categories, cities, and types of guests.

This finding aligns with previous research (Olorunsola et al., 2022; Ali et al., 2023; Pacheco et al., 2024), highlighting the central role of physical facilities and staff interactions in shaping guest perceptions. Negative comments frequently relate to room amenities (e.g., bed and bathrooms), communication issues in English, and operational aspects

such as check-in and out procedures. Although not reported in detail, additional analysis of specific guest segments (e.g., ‘family’ travellers) reveals some variation in thematic emphasis. For example, reviews associated with family travel highlight themes such as ‘location’ and ‘breakfast’, suggesting a greater importance of accessibility and food services for this group. These patterns are consistent with the idea that different guest types prioritise different aspects of the hotel experience, as documented in prior studies (Ali et al., 2023). Regarding the third research question, the results indicate that the dominant themes in guest reviews are largely consistent across contexts, regardless of hotel category, average rating, or type of guest. Similar to previous research (Ali et al., 2023; Pacheco et al., 2024), reviews tend to focus on core aspects of the hotel experience – particularly facilities and staff – while also frequently referencing location and food-related services. Overall, the qualitative findings complement the quantitative results by reinforcing the central role of a limited set of key attributes in shaping guest satisfaction.

CONCLUSION

Theoretical Implications

This exploratory study examines variations in hotel guest satisfaction within a Central Asian context, contributing to the hospitality literature through an analysis of the hotel industry in Kazakhstan. It identifies the key attributes associated with overall satisfaction across a large sample of hotels, covering three quality segments and three cities. The findings indicate that guests’ perceptions of hotel performance vary systematically by hotel segment and city, based on evidence from TripAdvisor reviews. By highlighting which evaluation criteria are most strongly associated with overall satisfaction, the study provides insights relevant for both research and hotel management.

The results reveal a consistent pattern across cities, with “rooms” and “service” emerging as the attributes most strongly associated with overall satisfaction in Kazakhstan hotels. These findings are consistent with prior studies (e.g., Stringman et al., 2010; Pacheco, 2017; Sann & Lai, 2023), which show that evaluations of specific service attributes are closely related to overall satisfaction. In addition, the “rooms” attribute frequently appears in positive guest comments, reinforcing its central role in shaping the overall experience (Sann & Lai, 2023). These results show how satisfaction attributes operate within evolving hotel industries in emerging tourism destinations.

Differences across cities and hotel categories are also observed. Hotels located in Astana tend to receive higher ratings in terms of overall satisfaction and most specific attributes, particularly “location” and “value”. This pattern may be related to city-specific factors such as accessibility and the concentration of attractions. Furthermore, the results indicate statistically significant differences in average ratings across hotel categories, cities, and guest types (e.g., “couple” versus “alone” travellers). For instance, variations observed in Almaty may be associated with local characteristics such as geographical conditions and traffic congestion, which can affect accessibility and perceived convenience.

From a theoretical perspective, this study contributes to the literature in several ways. First, it complements research on electronic word-of-mouth (eWOM) by illustrating how online reviews function in an emerging tourism market where service standards are still evolving. Second, by comparing attribute-satisfaction relationships across hotel categories and cities, the study contributes to the understanding of service quality heterogeneity, showing that guest evaluations are shaped not only by individual characteristics but also by the contextual factors (Chaves et al., 2012; Hsieh & Tsai, 2009; Kaveski Peres & Pacheco, 2021). Third, the findings highlight the relevance of destination-specific characteristics, such as accessibility, infrastructure and natural environment, in shaping tourists’ assessments.

Practical implications

The findings of this study have several implications for hospitality management, as they identify key attributes associated with overall guest satisfaction. Prior research (e.g., Taecharungroj & Mathayomchan, 2019) shows that positive user-generated content can act as an effective promotional tool, while negative reviews may harm a hotel’s reputation.

Given the visibility and perceived credibility of online reviews, it is important for hotel managers to monitor feedback closely and respond appropriately. In this context, hotel managers should identify the main sources of dissatisfaction and implement targeted actions to improve the guest experience. Encouraging satisfied guests to share positive evaluations and responding constructively to negative feedback, can help strengthen online reputation. In addition, understanding differences across guest segments provides useful insights into customer preferences, which can support service improvements and contribute to higher occupancy rates and profitability. Maintaining strong online ratings is particularly important, as they are closely linked to booking intentions (Ladhari & Michaud, 2015).

The results also highlight specific areas requiring attention, particularly in lower-rated hotels. Negative feedback frequently relates to facilities, staff performance, and food quality—factors that directly influence the guest experience. Investment in these areas, especially in staff training and food service delivery, may contribute to improved satisfaction levels. Hotels serving international guests may particularly benefit from well-trained staff, as employee interactions play a central role in shaping perceptions. Similarly, offering more diverse food options, including healthier and vegetarian choices, may help meet the expectations of a broader range of travellers.

More broadly, the analysis of online reviews provides valuable information for service improvement. Adopting a customer-oriented approach, which prioritises guest needs and preferences (Rahimi et al., 2022), can support more effective management strategies. This is particularly relevant in the context of Kazakhstan, where tourism development is a strategic priority and demand is increasing. Improving service quality in the hotel sector may enhance the country’s competitiveness, attract more visitors, and strengthen its position as a tourism destination in Central Asia. Given the similarities across Central Asian countries, these insights may also be relevant for neighbouring markets with comparable characteristics.

The study has several limitations that should be acknowledged. First, the analysis is based on secondary data from TripAdvisor, which may include biased or non-authentic reviews. Future research could address this issue by combining online data with primary data collection, such as interviews or surveys. Second, the study assumes a linear relationship between service attributes and satisfaction; future work could explore non-linear approaches, such as the Kano Model or the Three-Factor Theory, to better capture asymmetric effects. Third, the importance of attributes may vary according to demographic and cultural characteristics, which are not fully captured in this study. In addition, the analysis focuses only on English-language reviews, which may limit generalization. Fourth, incorporating sentiment analysis or advanced techniques, such as deep learning could provide further insights into guests' emotional responses (Xu et al., 2025).

Finally, the study relies on a single platform. Future research could compare multiple review platforms to validate findings and account for differences in user populations. This issue is especially relevant since different nationalities likely tend to use different services, as happens with nearly every service on the internet.

Table A1. Ten most frequent adjectives (by hotel category, average rating, type of guest, and city) (Source: Own elaboration (using Maxqda))

Five-stars	%	Four-stars	%	Three-stars	%	Rating = 5	%	Rating = 4	%
good	6.49	good	8.08	good	7.92	good	7.52	good	10.69
great	3.83	clean	3.10	clean	3.92	great	4.95	nice	4.05
nice	3.50	nice	2.96	great	2.89	clean	3.69	clean	3.70
excellent	2.59	great	2.72	friendly	2.87	friendly	3.53	great	2.88
friendly	2.16	comfortable	2.58	nice	2.78	comfortable	3.50	friendly	2.63
comfortable	2.06	friendly	2.50	comfortable	2.36	nice	3.45	comfortable	2.50
clean	1.87	helpful	2.14	helpful	2.36	excellent	3.31	helpful	2.48
amaze	1.60	excellent	1.76	small	2.16	helpful	2.57	big	2.04
large	1.47	small	1.74	big	1.54	spacious	1.77	large	1.82
helpful	1.34	big	1.62	excellent	1.33	amaze	1.49	small	1.79
Rating = 3	%	Rating = 1/2	%	Business	%	Couple	%	Family	%
good	7.56	good	3.42	good	8.47	good	7.00	good	6.28
clean	2.45	poor	2.57	clean	3.59	great	3.11	nice	3.11
hot	2.35	bad	2.20	nice	3.12	nice	3.11	great	2.90
comfortable	2.22	wrong	2.09	friendly	2.67	clean	2.73	friendly	2.40
small	2.12	old	2.06	great	2.61	helpful	2.59	clean	2.24
nice	2.05	small	1.91	comfortable	2.23	comfortable	2.46	comfortable	2.02
friendly	1.95	hot	1.65	helpful	1.81	friendly	2.32	excellent	2.02
helpful	1.78	dirty	1.54	big	1.76	excellent	1.78	small	1.86
great	1.55	clean	1.51	excellent	1.61	small	1.60	helpful	1.48
big	1.51	nice	1.43	small	1.61	large	1.57	big	1.31
Alone	%	Friends	%	Shymkent	%	Astana	%	Almaty	%
good	6.81	good	8.40	good	7.48	good	7.98	good	7.63
great	3.76	nice	3.34	clean	4.18	great	3.23	clean	3.02
comfortable	2.90	clean	2.98	nice	3.45	nice	3.16	nice	2.86
clean	2.58	friendly	2.68	great	3.01	friendly	2.99	great	2.83
nice	2.43	great	2.56	friendly	2.79	clean	2.93	comfortable	2.33
helpful	2.35	comfortable	2.03	helpful	2.42	comfortable	2.61	friendly	2.24
excellent	2.31	helpful	2.03	comfortable	2.27	helpful	2.19	helpful	1.91
friendly	2.19	big	1.79	big	1.83	excellent	1.91	small	1.75
small	1.96	hot	1.79	excellent	1.83	big	1.53	excellent	1.74
spacious	1.49	small	1.43	small	1.83	large	1.49	big	1.48

Table A2. Ranking of the top five negative adjectives Source: Data obtained from TripAdvisor in November 2024. Own calculations (using Maxqda)

Five-stars			Four-stars			Three-stars		
Ranking	Word	Frequency (%)	Ranking	Word	Frequency (%)	Ranking	Word	Frequency (%)
20	Old	0.72	9	Small	1.74	8	Small	2.16
23	Bad	0.66	11	Hot	1.41	13	Hot	1.06
23	Poor	0.66	14	Old	1.01	14	Cold	0.96
23	Small	0.66	15	Poor	0.96	18	English	0.76
38	Cold	0.52	19	Bad	0.79	23	Basic	0.71

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