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Analysis of Almaty's Restaurant Reviews through Topic Modelling

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This research investigates customers' reviews of the restaurant sector in Almaty, Kazakhstan. Although Kazakhstan offers unique foods, beverages, and establishments, few studies have investigated customers' reviews of the restaurant business. Hence, this is a pioneering study examining problems and concerns of the restaurant sector in the eyes of customers in Almaty, Kazakhstan by implementing big data analysis. The scraped dataset from the TripAdvisor website contains more than 13,000 restaurant reviews in different languages between 2010 through 2023. Generally, English and Russian are the two dominant languages used in reviews in Almaty. Text mining techniques of topic modelling and sentiment analysis are applied in order to derive and understand the main focuses, problems, and concerns of restaurant customers. To do this the collected data between 2010–2023 is split into two roughly equal datasets that cover the periods between 2010–2017 and 2018–2023, respectively. It is revealed that while restaurant customers were less satisfied with the service process, the most positive reviews, written in both English and Russian, were obtained for the topic 'Atmosphere and Events'. Considering the service process as a holistic process, analysing the conditions affecting good service delivery and making improvements will urge restaurant customers to form positive opinions. This study provides an opportunity for managerial, operational, and marketing departments in Almaty to improve the restaurant business in the eyes of customers. Since no precise information about the themes of the restaurants is available on the restaurant pages, no thematic distinction could be provided.

Keywords: *restaurant, online reviews, text mining, topic modelling, Almaty, Kazakhstan*

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Introduction

Attracting a variety of customers and generating high revenue is a core factor for the food and beverage industry (Andersson et al., 2017; Jia, 2020). Restaurants aim to attract the attention of customers by offering high-quality services, a wide range of menus, and affordable prices. Customers with positive opinions are not only known as a factor in increasing the popularity of restaurants but also in boosting revenues. Furthermore, restaurant managers should conduct internal activities and raise the awareness of staff in order to deal with several different types of manageable problems posed by customers (Kukanja & Planinc, 2023). However, it is not an easy task to understand the tendencies of customers' opinions and complaints (Jia, 2020; Ryu et al., 2012). Restaurant customers may be influenced by many different factors such as service quality, diner motivation, interaction with staff, and other related factors. Hence, the literature has put much effort into evaluating and mitigating these factors in order to improve the satisfaction of the customers.

In previous efforts, tools such as DINESERV (Stevens et al., 1995) and SERVQUAL (Hansen, 2014; Lee & Hing, 1995) were developed to evaluate meal service quality. These kinds of tools might help in understanding the satisfaction and dissatisfaction levels of restaurant customers. Although such previous efforts have existed, detection of the satisfaction level of restaurant customers is not a completely known and investigated area. Due to the development in internet technologies worldwide, customers can express their general opinions about the places that they visit and/or the services experienced. Thus, sharing opinions on media platforms about products and services has increased tremendously (Nilashi et al., 2021; Renganathan & Upadhya, 2021; Kukanja & Planinc, 2023, Sedmak et al., 2023). The terminology Word of Mouth (WOM), referring to the transfer of information between two persons face-to-face, is converted to the transfer of information over the internet and called electronic Word of Mouth (eWOM) (Kim & Hwang, 2022). eWOM is a way for customers to share their positive or negative experiences with other customers and business owners. It is a critical communication method between customers for intangible products and services provided by restaurants. For this reason, many customers may be influenced by other customers' reviews via eWOM, and it is therefore currently a common behaviour to review customer opinions before deciding to visit any place (Gao et al., 2018).

Within this concept, a study measuring the effects of online reviews on purchasing restaurant services showed that online reviews with high ratings led to the highest trust perceptions (Park et al., 2021). However, expectations of customers also differ in terms of nationality, location, cultural behaviours, etc. To illustrate, research aimed at understanding the satisfaction and needs of Eastern and Western travellers as hotel guests was conducted (Sann & Lai, 2023). Reviews of 2,965 Western and 1,035 Eastern customers from 47 different countries were obtained from TripAdvisor for hotels in Cambodia. This research revealed that there was a difference in perceptions of service experience among Western and Eastern travellers according to the results of topic modelling. Similarly, there exist some other studies that performed similar research regarding customers from South Korea (Sutherland et al., 2020) and three other European countries, namely France, Germany, and Italy (Jia, 2020).

However, there exists a limited number of studies concerning the countries in Central Asia, which are Kazakhstan, Kyrgyz Republic, Tajikistan, Turkmenistan, and Uzbekistan. In a recent study, the authors collected 8,210 restaurant reviews in the Uzbek language and performed sentiment analysis on this data (Matlatipov et al., 2022). In another study, a questionnaire was applied to 60 guests of a restaurant in Almaty, Kazakhstan, from which the authors aimed to identify the service quality perceptions of customers (Kahl et al., 2019). Nevertheless, a customer-reviewed-based analysis of the restaurant sector in Kazakhstan has yet not been conducted.

To fill this gap in the literature, this study aims to analyse the tendencies of restaurant customers in Almaty, Kazakhstan based on analysis of textual online reviews. To do so, restaurant reviews written in English and Russian were gathered from TripAdvisor in the Almaty region of Kazakhstan, which constitutes most of the restaurant reviews in this region. Then, topic modelling and sentiment analysis were implemented together in order to extract the main focuses and concerns of restaurant customers.

In this study, the following research questions were examined:

1. What are the most common themes expressed in customer reviews of restaurants in Almaty, Kazakhstan?
2. What are the key factors that customers are mostly satisfied and dissatisfied with in restaurants in Almaty, Kazakhstan?
3. Is there any difference in tendencies about the main focuses of customer reviews in terms of language and periods?

The rest of the article is outlined as follows: The second section presents the literature review, the third section is allocated to the methodology that briefly describes topic modelling and sentiment analysis, the fourth section presents the results of the conducted research.

Literature Review

WOM and eWOM in Hospitality

WOM is an intrinsic mode that allows consumers/customers to share their opinions and judgments related to the characteristics of products or services (Lu et al., 2013; Nilashi et al., 2021; Bader et al., 2023). These shared opinions can affect other customers' behaviours either positively or negatively concerning products and services that they consider buying. Due to the swift spread of the internet worldwide, online platforms were quickly developed in order to provide a communication means for customers to share their opinions, so WOM easily transformed into eWOM and has emerged rapidly (Moliner-Velázquez et al., 2019; Nieto-García et al., 2017; Nilashi et al., 2021). While WOM includes face-to-face communication and interaction, eWOM relies on online platforms (Nilashi et al., 2021; Zhou et al., 2020; Šormaz & Ruoss, 2023).

A study aiming to understand the usage of the internet for the selection of restaurants showed that restaurant selection by a tourist mostly relies on recommendations of friends and family rather than advertisements or guidebooks (Litvin et al., 2005). According to the results of a study, feedback from eWOM generates valuable informative resources together with experience from purchases and customer perception (Lee, 2013; Nilashi et al., 2021). Note that managers of hospitality services can allocate more resources to improve the level of eWOM:

Gehrels and Kristanto (2006) suggested that eWOM is an effective mechanism for marketing in culinary restaurants in more than 60 Dutch culinary restaurants. A direct relationship between eWOM and the quality of restaurant services always exists. Hence, restaurant managers should invest in producing better eWOM.

A survey on eWOM containing 323 people indicated that eWOM content is directly associated with the restaurant atmosphere and overall quality of food (Bangsawan et al., 2017). In another study, Kim aimed to determine the underlying concepts that lead customers to provide eWOM (Kim, 2017). According to the survey results, three main components that motivate the spread of experience on the Internet are company-focused, self-focused, and others-focused concepts, respectively. However, the research's results verify that serious consumers mostly distribute negative experiences and consumers having negative experiences tend to negatively influence business organizations through eWOM.

The Effect of Customers' Online Reviews on Restaurant Selection

Online review tools or platforms are frequently utilized by consumers to communicate with other potential customers, where they share their experiences about specific products or services (Nilashi et al., 2021; Wang et al., 2019). Considering a result of a survey performed in 2017, 97% of customers take into account online reviews for their decisions on their purchases (Wang et al., 2019). There exist accessible online reviews for various products and services such as restaurants, hotels, etc. (Kim et al., 2016). The number of visits and positive reviews can show the reputation and popularity of the restaurants and the probable demand for products. Both customer reviews and reviews of experienced editors or professionals are essential types of reviews on websites (Zhang et al., 2010).

Generally, online review platforms include customer-generated ratings and textual reviews. However, reviews left by professional evaluators for restaurant services are different from those left by regular customers and these two types of reviews may not reflect the same tendency for consumers. Zhang et al. (2010) evaluated the reviews generated by both customers and professionals for restaurant services. According to the results, there is a positive association between the volume of online customer reviews and the popularity of restaurants but there is an inverse relationship between the number of professional reviews and customers who tend to review a restaurant.

Online reviews seem to be the main data source that affects customers' decisions about purchases (Ahmad & Sun, 2018). In this relevant study analysing customers' restaurant selections, 180,000 customer reviews on an online platform were examined. The main factors affecting the decision of customers were people's preferences, customer expectations regarding expenses, and the restaurant's popularity. Results showed that the platform could guess the customers' potential preferences with the help of their previous consumers' behaviours and recommend reviews from customers with identical preferences (Zhang et al., 2018).

The Quality Assessment of Food and Beverages in Restaurants through eWOM

The quality of food is considered an important factor for loyalty of customers/consumers (Nilashi et al., 2021). Online reviews produced by other consumers are trustworthy sources that help consumers assess the quality of foods. According to the findings of a study, restaurant service quality is the most focused part of eWOM communication (Jeong & Jang, 2011). Furthermore, a study undertaken in Slovenia claims that physical evidence such as the cleanliness of a restaurant is the highest-rated 7P indicator for both restaurant managers and customers after a pandemic period (Kukanja, 2022). In Korea, a survey performed among 218 restaurant patrons indicates that there is a positive correlation between satisfaction level and loyalty of consumers and probable revisits (Lee et al., 2005). There exist many studies in the literature focusing on eWOM communication for evaluating the quality of restaurants worldwide (Nilashi et al., 2021). However, there are almost no studies to assess the restaurant business in the eyes of customers in Central Asia, especially Kazakhstan. There also exist few studies that achieved face-to-face communication for determining the satisfaction levels of tourists in Kazakhstan (Kahl et al., 2019; Tagmanov & Ulema, 2023).

Methodology

The main aim of the study is to analyse textual reviews of restaurant customers in Almaty, Kazakhstan based on conducting topic modelling and sentiment analysis. Topic modelling is a type of statistical modelling that employs unsupervised machine learning approaches to group data into a pre-defined number of topics and put similar customer reviews into the same cluster. It functions as a clustering approach that can put relevant words into the same cluster. So, users' reviews in the form of texts will be put into topics to understand the main concerns of restaurant customers in Amalty. There exist several methods used for extracting topics in topic modelling, such as Non-negative Matrix Factorization (NMF) (Obadimu et al., 2019) and latent Dirichlet Allocation (LDA) (Blei et al., 2003). In this study, the NMF method is used for extracting topics when reviews of restaurant customers are collected. On the other hand, sentiment analysis aims to infer the polarity of textual reviews/documents that show a document's or a sentence's emotional structure and its level such as positive, neutral, or negative. VADER method is one of the examples to sentiment analysis tools which uses a kind of lexicon and some rules. To reveal the sentiment of the collected data, the VADER method is used to understand the polarities of each sentiment (Hutto & Gilbert, 2014).

Topic Modelling with Non-Negative Matrix Factorization (NMF)

The logic behind NMF is that it works on TF-IDF (term frequency-inverse document frequency) weighted data by breaking down a matrix into two lower-ranking matrices (Obadimu et al., 2019). The NMF decomposes its input into a product of a terms-topics matrix and a topics-documents matrix (Chen et al., 2019). Note that it is necessary to apply some pre-processing steps to textual data in order to obtain TF-IDF-weighted data. These steps generally include lowercase conversion, stemming/lemmatization, whitespace removal, etc. Then, textual data is transformed into numeric form by implementing a bag-of-words approach and vector space model (Uysal & Gunal, 2014). When converting textual data to numeric form, TF-IDF weighting is generally applied.

Sentiment Analysis with the VADER Method

Sentiment analysis extracts emotional tone from text data. The emotional tone may be positive, negative, or neutral in most cases. There exist many different methodologies that focus on this task. The VADER tool is a method developed for sentiment analysis and is a kind of lexicon and rule-based approach (Hutto & Gilbert, 2014). Lexicon-based sentiment analysis is known as a popular technique for extracting the emotional polarity of text and relies on predefined dictionaries of words associated with different emotional tones, namely, positive, negative, and neutral.

Results

In this part, the data collection methodology is presented initially and the pre-processing steps applied to raw text data (customer reviews) are explained. Then, the results of the experiments (topic modelling and sentiment analysis) are presented.

The Collection and Pre-processing of the Data

Text data is obtained from the TripAdvisor platform. This platform houses a huge amount of text data for restaurants, hotels, and accommodations. The consumers/customers share their previous experiences via the reviews. The processing and collection of the data was accomplished via a customized web crawler.

The collected data is composed of restaurant reviews in Almaty, Kazakhstan. Note that only reviews in English and Russian are considered since these two languages are the most dominant ones in this region. The constructed dataset contains 4,652 and 8,556 restaurant reviews in English and Russian, respectively. Furthermore, translations of Russian reviews into English are conducted in order to process data in the experiments. Restaurants with five or more reviews were included in the study, so data from more than 400 restaurants were collected. The number of total restaurant reviews was 13,208. In Table 1, the distribution of all data by year is presented. As some reviews do not include the date of visit, the year field is marked as 'UNK'. Note that the reviews whose year field was marked as 'UNK' were not used in experiments.

Similarly, in Tables 2 and 3, the number of reviews in English and Russian are presented. Note that the

Table 1 Distribution of all Restaurant Reviews of Almaty by Years

Year	2023	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	UNK
Count	354	659	724	809	2,464	1,840	1,739	1,777	1,281	677	333	141	46	4	354

Table 2 Distribution of Restaurant Reviews of Almaty in the English Language by Years

Year	2023	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	UNK
Count	188	135	110	164	714	685	689	667	515	241	215	112	38	4	175

Table 3 Distribution of Restaurant Reviews of Almaty in the Russian Language by Years

Year	2023	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	UNK
Count	166	524	614	645	1,750	1,155	1,050	1,110	766	436	118	29	8	–	185

number of reviews in Russian is more than the number of reviews in English.

In the pre-processing stage, lemmatization is applied to all review texts. For this purpose, we used English lemmatizer implementation in spaCy (Srinivasa-Desikan, 2018) for processing texts. Lemmatization/stemming is used for grouping words with similar root forms. For example, when the words 'shops' and 'shop' are converted to root forms, both words will be regarded as the same. We preferred using lemmatization instead of stemming. Stemming may also group words into a common form but the constructed words may not be meaningful sometimes. For example, stemming may transform the word 'changing' into the word 'chang' instead of the word 'change'. In this task, we need to produce meaningful lemmas/root forms in order to interpret the results of topic modelling.

After lemmatization, data is fed into the Orange data mining tool (Demšar et al., 2013) and then this tool is used for further data processing and performing experiments, including topic modelling and sentiment analysis.

The Results of Topic Modelling

The Experiments on All Collected Reviews

In Table 4, topics and representative words with their corresponding weights are listed for all collected data. This data contains reviews from 2010–2023 and the reviews are written either in English or Russian. After executing the NMF method, each textual review is assigned to specific topics with probabilities. The probability of the specific topic being closer to 1 than the others is regarded as the main topic for a textual review. Namely, whichever of the topic possibilities in a review is greater than the others, that topic is classified as the name of the relevant review. The number of the determined topics is 5 and the topic coherence value is 0.54961. The distribution of topics is also presented in parenthesis next to the topic titles. According to the representative words for each topic, the names of the topics were determined as follows: 'Service Process', 'International Cuisine', 'Menu and Price', 'Atmosphere and Events', and 'Local Cuisine and Meat Varieties'. For example, Table 4 depicts that while words such as 'order', 'waiter', 'table', and 'bring' represent the 'Service Process' topic, words such as 'dish', 'Indian', 'lunch', and 'sushi' represent the 'International Cuisine' topic. Some topics include words with potential positive or negative emotions. For example, the 'Atmosphere and Events' topic includes 'great' and 'thank', representing positive emotions.

Next, sentiment analysis is applied to customer reviews in order to obtain user satisfaction and dissatisfaction levels, respectively. Figure 1 depicts that the most positive reviews are obtained for the topic 'Atmosphere and Events'. The topic with the second greatest number of positive reviews is 'International Cuisine'. However, the ratio of positive reviews is the lowest in 'Service Process' when compared to the other topics.

Table 4 Topic Modelling Results for all Restaurant Reviews of Almaty

Service Process (0.203187)		International Cuisine (0.225839)		Menu and Price (0.137378)		Atmosphere and Events (0.292146)		Local Cuisine and Meat Varieties (0.141024)	
order	0.018883	dish	0.021936	burger	0.055945	great	0.018232	meat	0.047938
waiter	0.016676	Indian	0.017027	steak	0.024697	atmosphere	0.016418	horse	0.026414
table	0.016468	lunch	0.014979	pizza	0.021731	thank	0.015879	try	0.022401
bring	0.01525	sushi	0.012717	wine	0.019461	excellent	0.01577	local	0.019399
wait	0.012999	salad	0.012493	Italian	0.017526	cuisine	0.014612	steak	0.018717
minute	0.012858	soup	0.012023	nice	0.016453	place	0.014594	Kazakh	0.01791
time	0.012816	chicken	0.011887	good	0.015866	music	0.014562	English	0.016684
establishment	0.011297	taste	0.010719	price	0.010951	staff	0.014237	Kazakhstan	0.015256
leave	0.009792	order	0.010422	meal	0.010248	Georgian	0.014044	traditional	0.014534
order	0.018883	sauce	0.009015	pasta	0.010048	evening	0.013333	Asian	0.013194

It seems that the customers are not satisfied with the service process, unlike the other topics.

A similar analysis is performed for different periods in the second part of the experiment. To pay attention to reviews collected in different periods, the collected data is partitioned into two periods to understand whether there exist any similarities or differences between topic names and sentiments of these topics and to reveal the tendency according to the dates of the reviews. To do this, two periods, 2010–2017 and 2018–2023, are constructed by considering almost an equal number of the data.

In Table 5, topics and associated words with their corresponding weights are listed for all collected data covering the period of 2010–2017. The number of the determined topics is 5 and the topic coherence score is 0.48441. According to the associated words for each topic, the names of the topics are as follows: 'Service Process', 'International Cuisine', 'Menu and Price', 'Atmosphere and Fine Dining', and 'Local Cuisine and Beverage'. Three topics are the same as the ones ob-

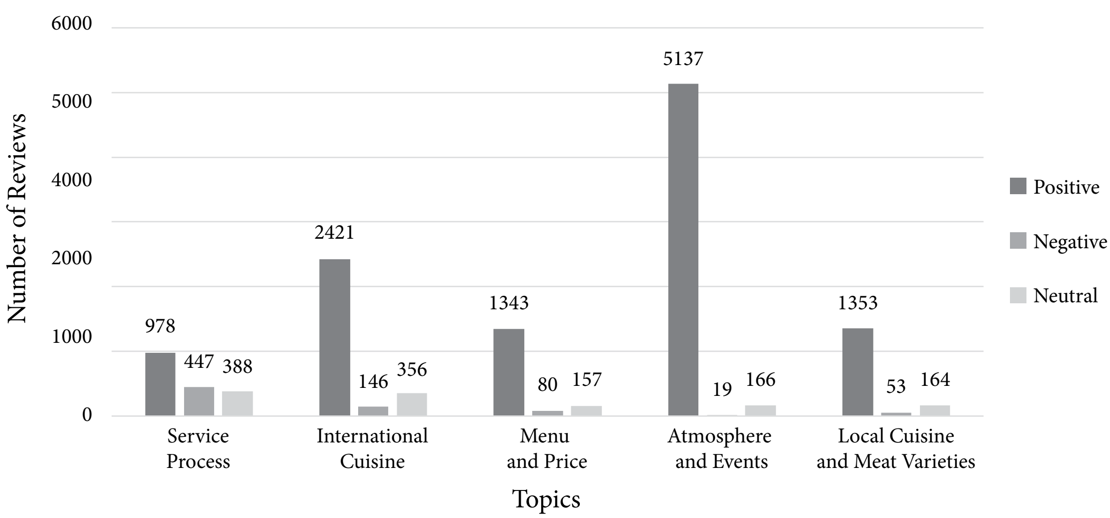

Figure 1 Distribution of Sentiments According to the Topics for all Restaurant Reviews

Table 5 Topic Modelling Results for Restaurant Reviews of Almaty for the 2010–2017 Period

Service Process (0.206667)		International Cuisine (0.208924)		Menu and Price (0.254688)		Atmosphere and Fine Dining (0.212642)		Local Cuisine and Beverage (0.116619)	
waiter	0.017597	dish	0.018017	Russian	0.020186	steak	0.028722	beer	0.047295
table	0.014618	Georgian	0.015669	menu	0.016378	burger	0.023934	pub	0.036709
child	0.013256	soup	0.01434	English	0.01632	breakfast	0.021366	meat	0.024112
time	0.012305	Indian	0.014162	food	0.01541	place	0.019467	horse	0.019094
order	0.011404	order	0.013814	great	0.014096	good	0.014834	bar	0.010905
bring	0.010947	sushi	0.012977	good	0.012662	café	0.0142	drink	0.010869
pizza	0.010575	kebab	0.012095	nice	0.012483	coffee	0.012782	local	0.010851
wait	0.010038	salad	0.011162	local	0.010312	nice	0.012139	meal	0.01048
minute	0.009585	chicken	0.010983	price	0.00988	atmosphere	0.011945	brew	0.010299
leave	0.008797	spicy	0.010139	Kazakh	0.009633	Italian	0.01104	good	0.010019

tained previously using the whole data set. However, 'Fine Dining' and 'Beverage' emerge as new topics for the 2010–2017 period.

Then, sentiment analysis is applied to customer reviews in order to obtain user satisfaction and dissatisfaction levels for data covering 2010–2017 for the determined topics. Figure 2 depicts that the positive reviews are attained for the topic 'Menu and Price' for 2010–2017, unlike results obtained for all data. The topic with the next most positive reviews is 'Atmosphere and Fine Dining'. However, similarly, the ratio of positive reviews is the lowest for the topic 'Service Process' when compared to the others.

In Table 6, topics and associated words with their corresponding weights are listed for all collected data covering the 2018–2023 period. The number of the determined topics is 5 and the topic coherence score is 0.53467. According to the associated words for each topic, the names of the topics are as follows: 'Service Process', 'International Cuisine', 'Menu', 'Atmosphere and Fine Dining', and 'Bars and Pubs'. Two topics are the same as the ones previously obtained from the

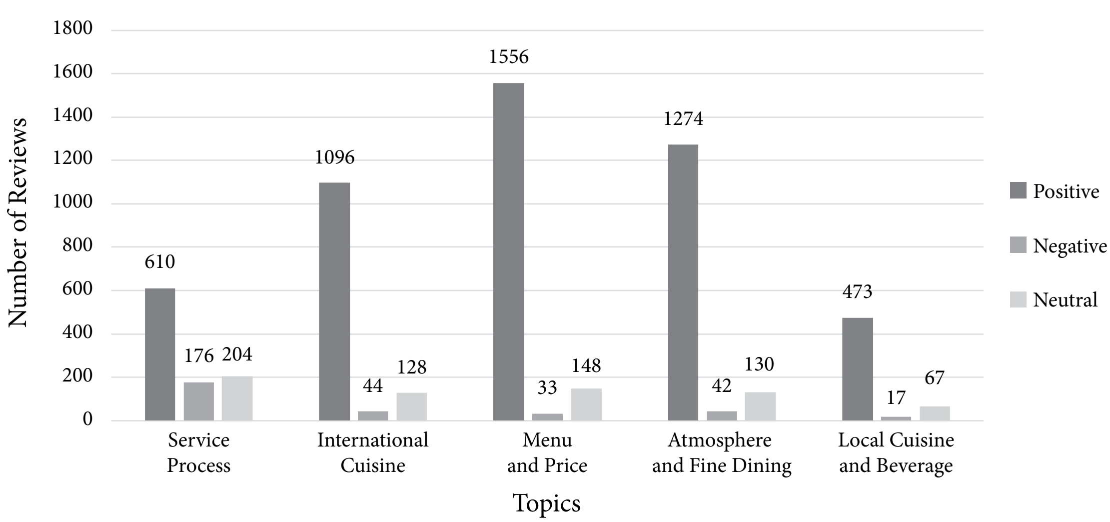

Figure 2 Distribution of Sentiments According to the Topics in the 2010–2017 Period

Table 6 Topic Modelling Results for Restaurant Reviews of Almaty for the 2018–2023 Period

Service Process (0.178847)		International Cuisine (0.105638)		Menu (0.174583)		Atmosphere and Fine Dining (0.302881)		Bars and Pubs (0.237687)	
order	0.023792	sushi	0.059421	meat	0.026222	burger	0.027413	Beer	0.023976
bring	0.01852	eat	0.017981	salad	0.018429	great	0.023288	pub	0.015315
waiter	0.015896	minute	0.017283	steak	0.017738	wine	0.02282	dish	0.014893
table	0.015803	wait	0.016303	eat	0.016717	excellent	0.02099	menu	0.012778
establishment	0.015586	order	0.016218	dish	0.016124	place	0.017896	table	0.011955
minute	0.01518	pizza	0.014649	order	0.015828	recommend	0.016013	check	0.011742
time	0.015025	roll	0.013482	make	0.012289	delicious	0.015748	good	0.01127
wait	0.014898	food	0.011216	cook	0.010999	good	0.014899	nice	0.011172
bad	0.012729	delivery	0.01035	breakfast	0.010927	wonderful	0.014143	waiter	0.010646
hour	0.012309	hour	0.010061	coffee	0.010894	atmosphere	0.013904	music	0.009967

whole data set. However, 'Fine Dining' and 'Bars and Pubs' are obtained for the 2018–2023 period. It seems that customers frequently tend to provide reviews for issues like fine dining, bars, and pubs in addition to the other topics for the 2018–2023 period.

Next, sentiment analysis is applied to customer reviews in order to obtain user satisfaction and dissatisfaction levels for data covering 2018–2023. Figure 3 depicts that the most positive reviews are obtained for the topic 'Atmosphere and Fine Dining' for 2018–2023. This finding is similar to the previous results obtained from all data. The topic with the next most positive reviews is 'Bars and Pubs'. However, similarly, the ratio of positive reviews is the lowest in 'Service Process' when compared to the other topics.

The Experiments on English-Language Reviews

In Table 7, topics and relevant words with their corresponding weights are listed for only English reviews from 2010–2023. Note that the NMF method is used for topic modelling. The number of the determined topics is 5 and the topic coherence score is 0.48873.

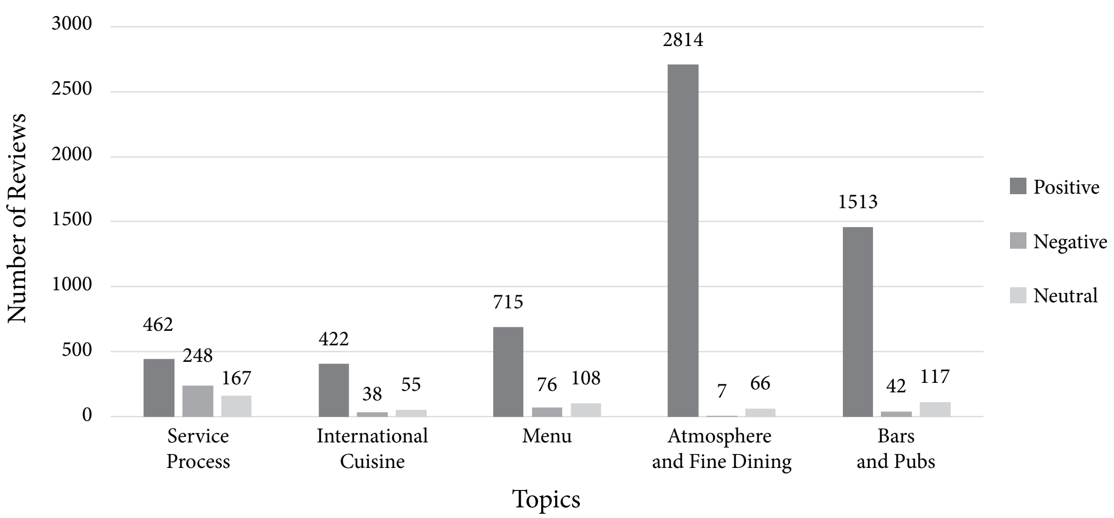

Figure 3 Distribution of Sentiments According to the Topics in the 2018–2023 Period

Table 7 Topic Modelling Results for Restaurant Reviews of Almaty in English

Service Process (0.179359)		Local Cuisine and Meat Varieties (0.135074)		Ethnic Food Varieties (0.186836)		Breakfast and Snacks (0.249554)		Quality of Food and Beverage (0.248719)	
waiter	0.02074	burger	0.047103	Indian	0.044815	pizza	0.022374	steak	0.027548
order	0.019432	meat	0.032844	pub	0.019071	Russian	0.015413	beer	0.022857
bill	0.014145	horse	0.018285	authentic	0.014562	menu	0.013875	wine	0.01841
table	0.012937	try	0.013208	visit	0.014138	English	0.013137	price	0.014057
wait	0.012575	Asian	0.012382	excellent	0.013388	breakfast	0.011817	good	0.012462
minute	0.010667	fry	0.011757	food	0.013069	coffee	0.011603	place	0.012034
arrive	0.010457	traditional	0.011637	local	0.012426	make	0.010139	service	0.010686
leave	0.010419	sauce	0.011452	great	0.012273	experience	0.009928	great	0.010473
time	0.010288	central	0.010834	place	0.011475	staff	0.009649	high	0.009986
bring	0.009473	lamb	0.010804	try	0.010835	Turkish	0.009608	nice	0.009771

The distribution of topics is also presented in parenthesis next to the topic titles. According to the representative words for each topic, the titles of the topics are as follows: 'Service Process', 'Local Cuisine and Meat Varieties', 'Ethnic Food Varieties', 'Breakfast and Snacks', and 'Quality of Food and Beverage'. For example, while words such as 'waiter', 'order', 'bill', and 'table' represents the 'Service Process' topic, words such as 'burger', 'meat', and 'horse' represents 'Local Cuisine and Meat Varieties' topic. Some topics include words with potentially positive or negative emotions. For example, the 'Quality of Food and Beverage' topic includes 'good' and 'great', representing positive emotions.

Then, sentiment analysis is applied to customer reviews in order to obtain user satisfaction and dissatisfaction levels. Figure 4 depicts that the most positive reviews are obtained for the topic 'Quality of Food and Beverage'. The topic with the next most positive reviews is 'Breakfast and Snacks'. However, the ratio of positive reviews is the lowest for 'Service Process' when compared to the other topics. It seems that the customers are less satisfied with the service process, unlike the other topics.

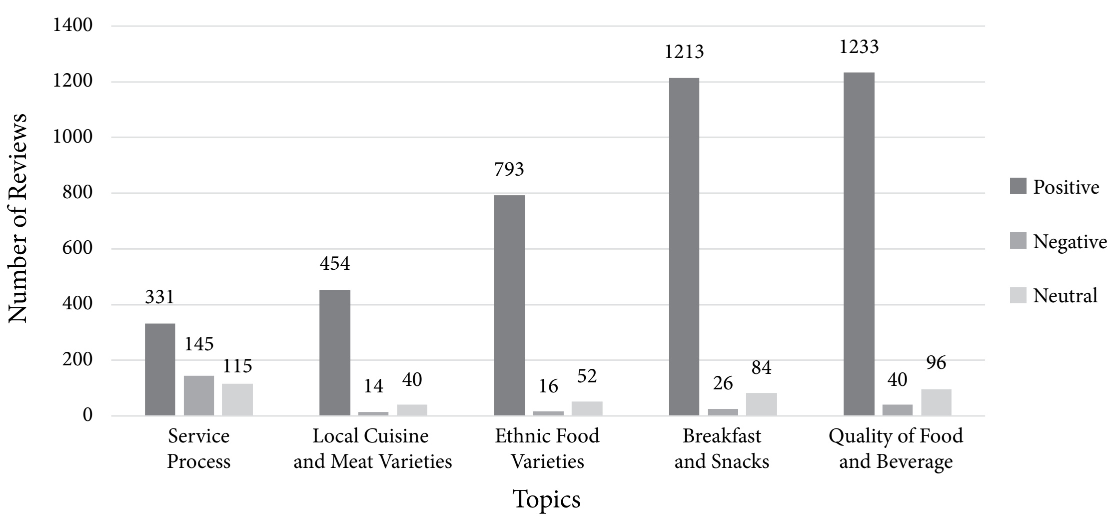

Figure 4 Distribution of Sentiments According to the Topics for Restaurant Reviews in English

Table 8 Topic Modelling Results for Restaurant Reviews of Almaty in English for the 2010–2017 Period

Service Process (0.181268)		Local Cuisine and Meat Varieties (0.181381)		Ethnic Food Varieties (0.179478)		Fine Dining (0.22373)		Regional Cuisine (0.233702)	
order	0.018545	burger	0.031145	door	0.0135182	pub	0.0280774	Indian	0.022768
pizza	0.018325	meat	0.020041	shashlik	0.0134266	steak	0.0234481	time	0.01373
waiter	0.016414	horse	0.017039	Turkish	0.0125129	English	0.0139542	visit	0.013608
table	0.014705	local	0.012152	beer	0.011709	nice	0.0130075	meal	0.013601
dish	0.01211	well	0.011141	Chinese	0.0111444	wine	0.0120582	traditional	0.010765
bill	0.011563	Kazakh	0.010996	great	0.0110179	sushi	0.0116791	Georgian	0.010395
soup	0.010018	try	0.010994	table	0.0100663	Italian	0.0110945	order	0.010316
wait	0.009684	menu	0.010919	place	0.00989791	good	0.0106863	food	0.009824
give	0.009522	Russian	0.010258	cafe	0.0097946	night	0.00946928	bit	0.009723
bad	0.009449	floor	0.009878	brew	0.00961037	staff	0.00918334	tea	0.009389

A similar analysis is performed for different periods in the second part of the experiments. To have almost the same number of reviews for different periods, the collected data is segmented into two periods, which are 2010–2017 and 2018–2023, respectively, for the English reviews.

In Table 8, topics and associated words with their corresponding weights are listed for the collected data in English covering the 2010–2017 period. The number of the determined topics is 5 and the topic coherence score is 0.37413. According to the relevant words for each topic, the names of the topics are as follows: 'Service Process', 'Local Cuisine and Meat Varieties', 'Ethnic Food Varieties', 'Fine Dining', and 'Regional Cuisine'. Three topics are the same as the ones obtained from all data. However, the topics 'Fine Dining' and 'Regional cuisine' are obtained for the 2010–2017 period, unlike all data in English.

Then, sentiment analysis is applied to customer reviews in order to obtain user satisfaction and dissatisfaction levels. Figure 5 depicts that positive reviews were obtained for the topic 'Regional Cuisine' for the 2010–2017 period, unlike all data in English. The succeeding topic in terms of positive reviews is 'Fine

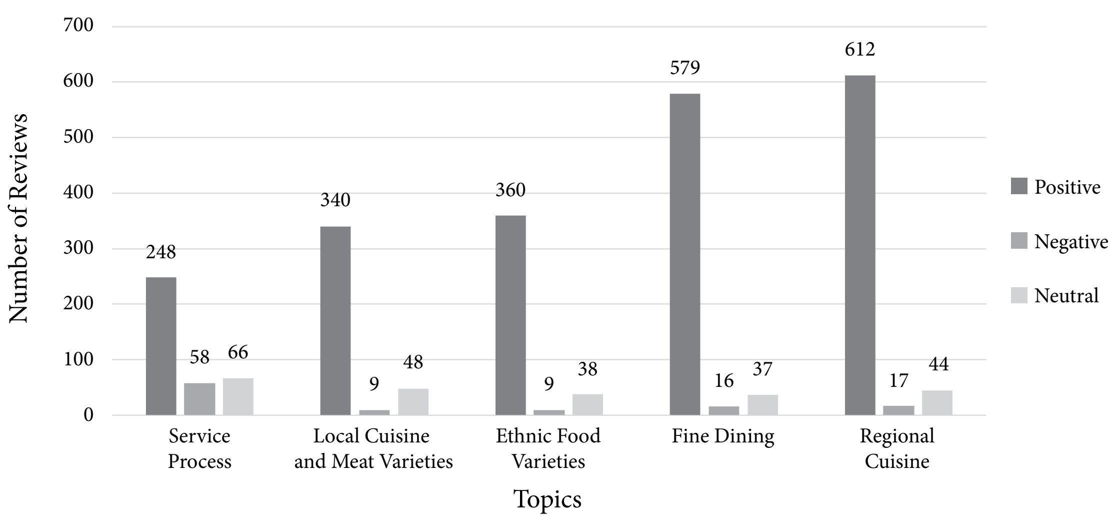

Figure 5 Distribution of Sentiments According to the Topics for Restaurant Reviews in English for the 2010–2017 Period

Table 9 Topic Modelling Results for Restaurant Reviews of Almaty in English for the 2018–2023 Period

Service Process (0.158042)		Local Cuisine and Meat Varieties (0.202183)		Ethnic Food Varieties (0.160219)		Fine Dining (0.193919)		Quality Assessment (0.285267)	
waiter	0.027456	burger	0.026965	beer	0.023036	coffee	0.031833	English	0.014342
order	0.016426	meat	0.019622	Indian	0.020918	steak	0.025716	great	0.014292
arrive	0.014097	try	0.01473	breakfast	0.013221	wine	0.01734	menu	0.012898
experience	0.013555	sauce	0.013172	see	0.012414	meat	0.016892	dish	0.010154
table	0.013128	horse	0.01087	order	0.011682	Turkish	0.011948	visit	0.009641
dish	0.0126	think	0.009505	back	0.011269	service	0.010727	find	0.009592
could	0.011603	perfect	0.008785	craft	0.010677	place	0.009893	local	0.009079
main	0.011351	attentive	0.007983	eat	0.010643	bill	0.008874	café	0.008923
another	0.011165	beef	0.007946	Georgian	0.009678	nice	0.008637	food	0.008887
wait	0.011031	fry	0.00793	something	0.009013	selection	0.008607	real	0.008697

Dining'. However, similarly, the ratio of positive reviews is the lowest in 'Service Process' when compared to other topics.

In Table 9, topics and relevant words with their corresponding weights are listed for all collected data covering the 2018–2023 period. The number of the determined topics is 5 and the topic coherence score is 0.48364. The names of the topics are presented as follows: 'Service Process', 'Local Cuisine and Meat Varieties', 'Ethnic Food Varieties', 'Fine Dining', and 'Quality Assessment'. Three topics are the same as the previous ones obtained from all data. However, 'Fine Dining' and 'Quality Assessment' are obtained for the 2018–2023 period. It seems that customers frequently tend to provide reviews for issues like fine dining and quality assessment in addition to the other topics for the 2018–2023 period.

Next, sentiment analysis is utilized in customer reviews to attain user satisfaction and dissatisfaction levels. Figure 6 depicts that the most positive reviews are obtained for the topic 'Quality Assessment' for 2018–2023. This situation is similar to the results obtained from all data. The succeeding topic in terms of positive reviews is 'Fine Dining'. However, similarly,

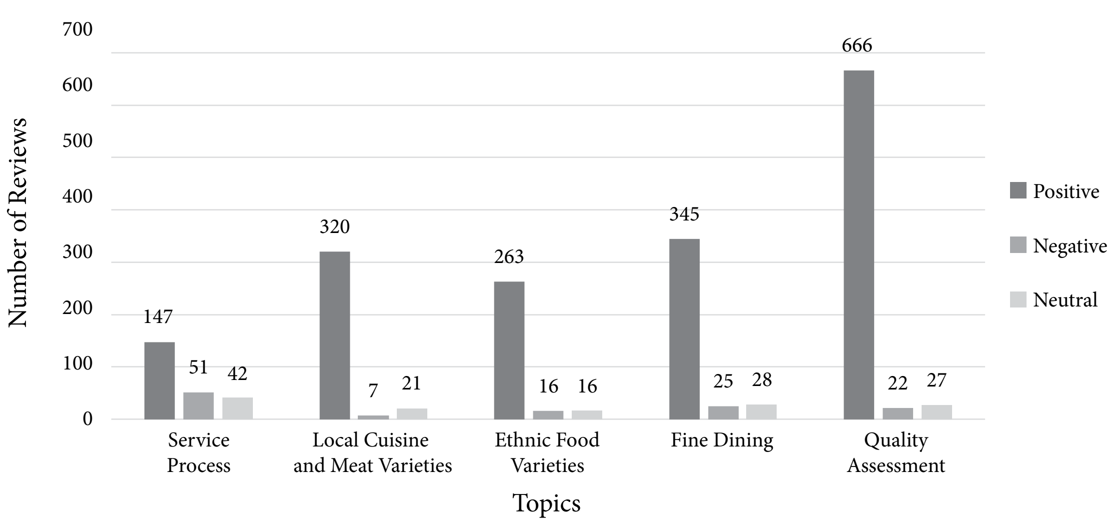

Figure 6 Distribution of Sentiments According to the Topics for Restaurant Reviews in English for the 2018–2023 Period

Table 10 Topic Modelling Results for Restaurant Reviews of Almaty in Russian

Service Process (0.186961)		Menu and Price (0.185447)		Quality of Food and Beverage (0.227884)		Atmosphere and Events (0.227053)		Pubs and Bars (0.172228)	
order	0.030365	lunch	0.020732	meat	0.022452	music	0.025723	pizza	0.025293
bring	0.017497	dish	0.017804	wine	0.021437	great	0.02301	beer	0.024864
minute	0.016994	national	0.016955	steak	0.018911	birthday	0.022436	pub	0.014624
wait	0.016898	tenge	0.016424	staff	0.015293	friend	0.021633	eat	0.013588
waiter	0.015679	pilaf	0.015771	cozy	0.014441	thank	0.018513	well	0.012809
time	0.014833	cuisine	0.013696	delicious	0.014306	evening	0.017766	establishment	0.012039
table	0.014656	large	0.01231	excellent	0.013794	atmosphere	0.01685	drink	0.011371
hour	0.013494	portion	0.01212	place	0.013627	live	0.01607	taste	0.010492
call	0.013075	price	0.012068	recommend	0.012956	celebrate	0.014484	cheese	0.009936
administrator	0.011674	Kazakh	0.011821	friendly	0.012925	good	0.014162	bar	0.009739

the ratio of positive reviews is the lowest in 'Service Process' when compared with other topics.

The Experiments on Russian-Language Reviews

In Table 10, topics and relevant words with their corresponding weights are listed for only collected data in Russian reviews from 2010–2023. Note that the topic model applies the NMF methodology. The number of the determined topics is 5 and the topic coherence score is 0.54403. The distribution of topics is also presented in parenthesis next to the topic titles. The names of the topics were determined as follows: 'Service Process', 'Menu and Price', 'Quality of Food and Beverage', 'Atmosphere and Events', and 'Pubs and Bars'. For example, while words such as 'order', 'bring', 'minute', and 'wait' represents the 'Service Process' topic, words such as 'lunch', 'dish', 'national', and 'tenge' represents the 'Menu and Price' topic. Some topics include words with potential positive or negative emotions. For example, the 'Quality of Food and Beverage' topic includes 'delicious' and 'excellent', representing positive emotions.

Then, sentiment analysis is implemented in customer reviews to attain user satisfaction and dissatis-

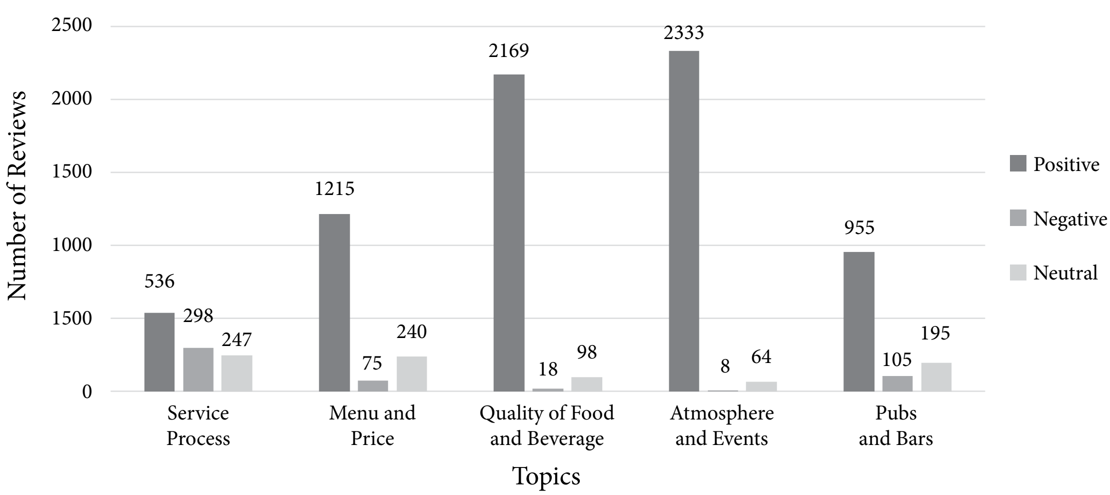

Figure 7 Distribution of Sentiments According to the Topics for all Restaurant Reviews in Russian

Table 11 Topic Modelling Results for Restaurant Reviews of Almaty in Russian for the 2010–2017 Period

Service Process (0.178379)		Menu and Price (0.238516)		International Cuisine (0.226082)		Events and Fast Food (0.17945)		Fine Dining (0.177186)	
order	0.017476	lunch	0.022901	kebab	0.023835	child	0.02828	beer	0.036484
table	0.017034	breakfast	0.022792	Georgian	0.01871	family	0.014992	burger	0.018807
waiter	0.014771	business	0.016587	cuisine	0.015467	pizza	0.012372	steak	0.015341
minute	0.014674	place	0.013339	try	0.01335	waiter	0.011441	wine	0.014986
bring	0.013689	coffee	0.012466	meat	0.013028	guest	0.011037	bar	0.013871
time	0.012841	atmosphere	0.01192	tasty	0.012651	staff	0.010784	good	0.010539
wait	0.011438	great	0.011861	delicious	0.011466	salad	0.010238	selection	0.010438
hour	0.009954	delicious	0.011595	lamb	0.01126	time	0.010229	order	0.009816
call	0.009864	price	0.010958	shish	0.011247	birthday	0.009464	drink	0.00969
two	0.009207	beautiful	0.010861	recommend	0.011027	establishment	0.009076	taste	0.009676

faction levels. Figure 7 depicts that the most positive reviews are obtained for the topic 'Atmosphere and Events'. The succeeding topic with the most positive reviews is 'Quality of Food and Beverage'. However, the ratio of positive reviews is the lowest in 'Service Process' when compared to the other topics. It seems that customers are less satisfied with the service process, unlike the other topics.

A similar analysis is performed for different periods in the second part of the experiments. To have almost the same number of reviews for different periods, the collected data is partitioned into two periods, which are 2010–2017 and 2018–2023, respectively, for the Russian reviews.

In Table 11, topics and relevant words with their corresponding weights are listed for the collected data in Russian between 2010–2017. The number of the determined topics is 5 and the topic coherence value is 0.49995. According to the relevant words for each topic, the names of the topics are determined as fol-

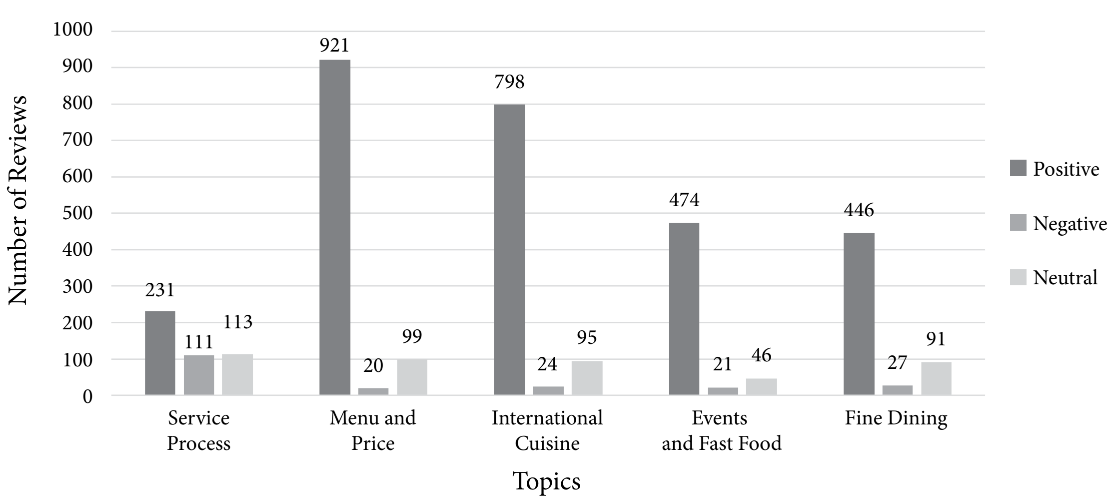

Figure 8. Distribution of Sentiments According to the Topics for Restaurant Reviews in Russian for the 2010–2017 Period

Table 12 Topic Modelling Results for Restaurant Reviews of Almaty in Russian for the 2018–2023 Period

Service Process (0.169675)		Pubs and Bars (0.122826)		Fast Food (0.180599)		Atmosphere and Events (0.269965)		Fine Dining (0.256556)	
order	0.025895	beer	0.043868	pizza	0.022364	thank	0.024644	wine	0.02419
bring	0.018928	order	0.027726	burger	0.016051	pub	0.019771	excellent	0.018212
table	0.014866	wait	0.025863	taste	0.01583	check	0.017989	high	0.018178
dish	0.013485	minute	0.02466	salad	0.015798	birthday	0.016797	table	0.018071
waiter	0.012946	sit	0.021403	sauce	0.013213	evening	0.015846	family	0.017325
call	0.011983	drink	0.018922	cheese	0.013115	great	0.014338	price	0.016867
leave	0.010441	time	0.017984	meat	0.01271	atmosphere	0.014318	level	0.015922
time	0.010342	long	0.017147	fish	0.011458	music	0.014122	steak	0.015592
minute	0.009526	sushi	0.015793	try	0.01145	cuisine	0.012749	place	0.014938
guest	0.009367	hour	0.014725	eat	0.011079	wonderful	0.012211	tasty	0.014377

lows: 'Service Process', 'Menu and Price', 'International Cuisine', 'Events and Fast Food', and 'Fine Dining'. Two topics are the same as the previous ones attained from all data. However, the topics 'International Cuisine', 'Fast Food', and 'Fine Dining' are obtained for the 2010–2017 period, unlike all data in Russian.

Then, sentiment analysis is employed in customer reviews to attain user satisfaction and dissatisfaction levels. Figure 8 depicts that the most positive reviews are obtained for the topic 'Menu and Price' for 2010–2017, unlike all data in Russian. The succeeding topic with the next most positive reviews is 'International Cuisine'. However, similarly, the ratio of positive reviews is the lowest in 'Service Process' when compared to the other topics.

In Table 12, topics and relevant words with their corresponding weights are listed for the gathered daytaset in Russian between 2018–2023. The number of the determined topics is 5 and the topic coherence value is 0.56388. The names of the topics were

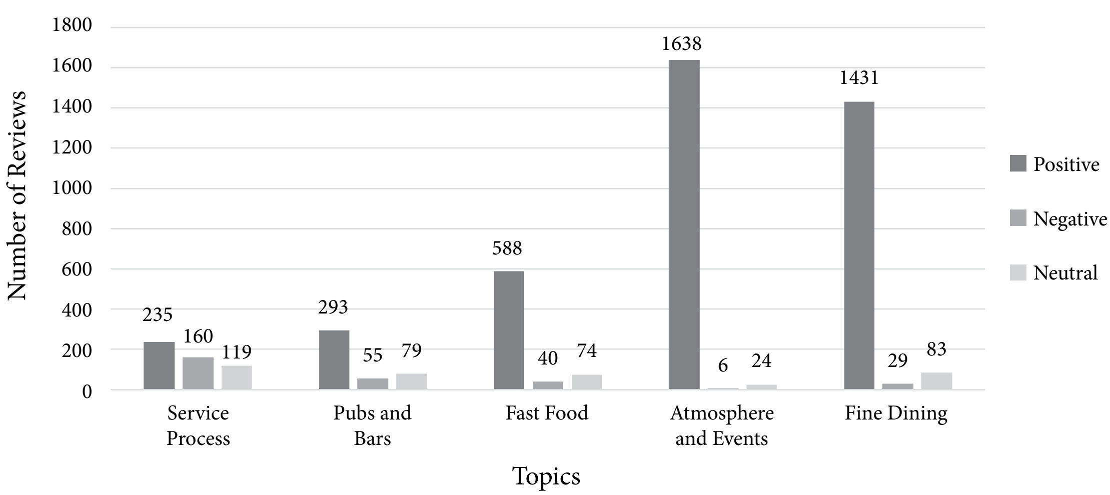

Figure 9 Distribution of Sentiments According to the Topics for Restaurant Reviews in Russian for the 2018–2023 Period

determined as follows: 'Service Process', 'Pubs and Bars', 'Fast Food', 'Atmosphere and Events', and 'Fine Dining'. Three topics are the same as the previous ones obtained from all data. However, 'Fast Food' and 'Fine Dining' are obtained between 2018–2023. It seems that customers frequently tend to review issues like fast food and fine dining in addition to the other topics for the 2018–2023 period.

Then, sentiment analysis is applied to customer reviews to obtain user satisfaction and dissatisfaction levels. Figure 9 depicts that the most positive reviews are obtained for the topic 'Atmosphere and Events' for 2018–2023. This situation is similar to the previous results obtained from all data. The succeeding topic with the most positive reviews is 'Fine Dining'. However, the ratio of positive reviews is the lowest for the topic 'Service Process' when compared to the others.

Discussion

The number of analyses regarding customers' restaurant reviews is very limited, not only in Central Asian states but also in Kazakhstan. This study is one of the pioneering efforts to understand customers' main focuses and potential problems in the restaurant sector in the metropolitan city of Almaty, Kazakhstan, and provides substantial insights into the restaurant business. A dataset is constructed by using a customized web crawler from TripAdvisor. A comprehensive analysis was performed with more than 13,000 reviews in two different languages, namely, English and Russian, which are the two dominant languages used by customers when they provide opinions and complaints on TripAdvisor. The text data includes reviews from 2010–2023. After pre-processing unstructured text data, topic modelling and sentiment analyses are applied to derive insights based on different languages and periods.

Customers are generally less satisfied with service processes in the restaurants in Almaty; for the whole dataset, the ratio of positive reviews is the lowest for 'Service Process' when compared to the other topics. For all English and Russian reviews, the most positive reviews are obtained for the topics 'Atmosphere and Events' and 'Quality of Food and Beverage'. Thus, it is claimed that 'Atmosphere and Events' is an important and attractive topic for the restaurant sector in Almaty.

For all data between 2010–2017, the most positive reviews are obtained for the topic 'Menu and Price'. The most positive reviews are obtained for the topics 'Regional Cuisine' and 'Menu and Price' when both the English and Russian languages are under consideration. It can be said that 'Menu and Price' is an important and attractive topic for the restaurant sector in Almaty.

For all data between 2018–2013, the most positive reviews are obtained for the topic 'Atmosphere and Fine Dining'. The most positive reviews are obtained for the topics 'Quality Assessment' and 'Atmosphere and Events' when both English and Russian are considered. Thus, the common keyword 'Atmosphere' is an important and attractive topic for the restaurant sector in Almaty.

This study reveals the underlying concepts that customers focused on in the restaurant sector in Almaty, Kazakhstan between 2010 and 2023, covering both English and Russian texts. While satisfaction levels for the topic 'menu and price' were the highest between the 2010–2017 period, those for the topic 'atmosphere and fine dining' were highest for the 2018–2023 time period for customers. Therefore, it can be said that there is a difference in tendencies concerning satisfaction levels of restaurant customers for various topics during different periods. Similar changes in tendencies were observed for customers leaving reviews in both English and Russian.

Conclusion and Implications

The performance of all types of restaurants serving food and beverages in a decorated ambiance with personnel has been gauged by web-based technology and the results shared for potential and current customers via various platforms. For example, TripAdvisor shares a great chunk of reviews collected from restaurants in any city around the globe. This technology has started to transform the industry, just as is happening in the hotel industry. Hence, the issues of potential areas to develop, and reengineering the business and attracting more customers, especially more tourists, can be detected easily based on deep analyses of the texts, and better solutions can be found to improve the restaurant business. Since the written reviews are remarks, opinions, criticisms, feelings, and compliments, they include sentiments that can be used for analysing the fundamentals of the restaurant business.

In this research, the reviews from TripAdvisor are used, which accommodates the largest number of reviews when compared to other platforms for restaurants in Almaty, Kazakhstan between 2010–2023. The data is split into 2 almost equally represented data sets, so almost equal numbers of reviews are analysed to detect how the topics of the restaurant sector have changed during the whole period. Since Central Asian countries joined the global community after the Soviet Union collapsed, how Kazakhstan's important city Almaty has changed its status and improved in the restaurant business needs to be understanded to develop a better food and beverage service for customers and tourists.

Even though the food and beverage sector has issues expressed by customers and tourists, especially in service quality due to personnel incompetency, it has several advantages such as the variety of meals, tasty foods, and meats, accommodating international cuisines, providing an enriched atmosphere and events, and serving customers and tourists in their languages.

Theoretical Implications

With the increase in digital channels, customers can deliver opinions and complaints about products and services that they experience to businesses and other consumers more quickly and directly with Web 2.0 technologies. Thus, the factors that create service quality and customer satisfaction can emerge from different perspectives, and these elements can be examined effectively and efficiently by businesses to segment the market. In this study, the analysis of customers' reviews for restaurants in Almaty provides substantial insights that can be broadly beneficial to the restaurant business and the tourism industry.

In general, the profile of customer satisfaction is seen as a unified structure. Along with the service marketing mix elements, physical evidence, people, and process elements were revealed as the factors that most affect customer satisfaction in restaurants in Almaty. In addition to the menu, product features, product differences, price, and themes of the restaurants, the atmosphere offered by the restaurants, and the activities they organize are important components that contribute to people's positive reviews. Additionally, different customer segments are also distinctly affected by these factors. However, defects that occur in the service process negatively affect the satisfaction of consumers. The findings can be easily expanded to other Central Asian states that want to develop a robust tourism industry, since they have very similar characteristics.

Practical Implications

This study presents an opportunity to help managerial, operational, and marketing managers when decisions and strategies are developed for the management of restaurants in Almaty, since a very limited number of studies exist. When looking at the general characteristics of the restaurants in Almaty, positive impressions were left in the reviews mostly about the atmosphere, the variety of products, reasonable prices, and menus. Other metropolitan cities can also benefit from these findings as they probably have similar issues.

In addition, the problems and deficiencies that usually occur in the service process appear as a factor that negatively affects the satisfaction of consumers. In this context, considering the service process as a holistic means of analysing the situations that affect good service delivery and making improvements in the relevant area will enable customers to revisit and promote to others in their reviews for the restaurants in Almaty.

Limitations and Suggestions for Future Research

One of the main problems experienced in the topic modelling carried out is the formation of semantic integrity of the words that form the topic clusters. For this reason, the pre-processing phase and the topic modelling algorithm were tried many times to ensure the semantic integrity of the topics, and it is a time-consuming step at this stage to reveal meaningful topics from the obtained dataset. Furthermore, since no precise information about the themes of the restaurants is available on the restaurant pages, no thematic distinction could be added. On the other hand, most of the reviews are built from English and Russian. Since a dataset other than these languages could not be used, topic modelling could not contain other languages.

For future studies and research, reviews of other travel platforms about restaurants or other food and beverage establishments in the Almaty region can be used to make comparisons of these platforms. Furthermore, restaurant reviews in other Kazakh regions can be studied to reveal which topics are addressed more by tourists and how these topics are distributed positively and negatively. Also, other text mining and natural language processing algorithms and machine learning methods can be used to obtain different information and perspectives about the restaurant business.

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