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Sentiment Analysis of Berlin Tourists' Food Quality Perception Through Artificial Intelligence

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Abstract: This study examines how tourists perceive food quality in Berlin using AI-driven sentiment analysis tools. The goal is to understand the factors shaping tourists' perceptions and provide insights to improve the hospitality industry and customer satisfaction. By analyzing reviews from online platforms, this research identifies key themes and trends in tourists' feedback. The use of AI, specifically for sentiment analysis, supports efficient and detailed evaluation of customer opinions. This study employed lexicon-based sentiment analysis to evaluate tourists' feedback on online platforms and compared the sentiment scores of textual feedback with their direct rating scores. The results show that integrating sentiment scores derived from AI tools with tourists' rating scores provides deeper insights into service quality within the tourism sector.

Keywords: sentiment analysis; tourism research; artificial intelligence; visitor feedback analysis; culinary perception

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1. Introduction

Berlin, the lively capital of Germany, with its fascinating history, diverse culture, and dynamic food scene, welcomes millions of visitors each year. In 2022, Berlin saw 10.4 million guests, resulting in 26.5 million overnight stays. This phenomenon marked a significant increase from previous years as the city recovered from the impacts of the COVID-19 pandemic. In 2023, Berlin welcomed 12.1 million guests, who accounted for 29.6 million overnight stays [1]. Berlin showcases diverse food cultures and types, reflecting its rich history and the global influences it has absorbed. The variety of food in Berlin spans traditional German dishes to international cuisines, which is evidence of its complex socio-economic and cultural layers. A study assessing the variety and pricing of selected foods across socio-economically disparate districts in Berlin revealed no significant difference in the variety and prices of fruits and vegetables, although certain staples like milk and whole-wheat bread were found to be less expensive in districts with higher Social Index ratings [2].

The concept of customer experience encompasses all customer interactions with a business, which, in the context of tourism, includes dining experiences. Studies have shown that positive dining experiences significantly enhance the overall tourism experience. Understanding customer experience in tourism is critical for enhancing satisfaction, loyalty, and overall destination appeal. Several models and frameworks have been developed to study and improve customer experience in tourism, such as Pine and Gilmore's Experience Economy, the Service Blueprinting technique, and other methods. Pine and Gilmore introduced the concept of the Experience Economy, which posits that businesses must orchestrate memorable events for their customers, and that the memory itself becomes the product. In the context of tourism, this model emphasizes the importance of creating engaging, immersive experiences that go beyond the basic provision of services. The Experience Economy framework categorizes experiences into four realms: entertainment, education, escapism, and esthetics. Each realm represents a different way of engaging tourists. For instance, a culinary tour might provide entertainment through storytelling, education through cooking classes, escapism through hands-on participation, and esthetics through beautifully presented dishes. This comprehensive approach ensures that tourists have a rich, multi-faceted experience that leaves a lasting impression [3].

Customer engagement is vital for building trust and creating a positive image in the hospitality industry. Effective engagement strategies can increase customer satisfaction, loyalty, and positive word-of-mouth reporting. Kothari emphasizes that customer engagement is significant in building trust and ensuring maximum customer visibility. Strategies such as personalized communication, loyalty programs, and interactive social media activities can enhance customer engagement [4]. A successful example of customer engagement can be seen in the practices of the Ribas Hotels Group, which integrated digital technologies to create personalized services and improve customer satisfaction [5].

Service Blueprinting is another valuable technique for enhancing customer experience in tourism. Developed by Shostack, this method involves creating a detailed visual map of the service process, identifying all touchpoints and interactions between the customer and the service provider [6]. Research by Godovykh and Tasci emphasized the importance of integrating emotional, cognitive, sensorial, and conative components into the tourism experience. Service Blueprinting can facilitate this integration by ensuring that each touchpoint is designed to engage customers on multiple levels, thereby enhancing overall satisfaction and loyalty [7].

Customer Journey Mapping (CJM) is another technique widely used in the tourism industry to understand and improve customer experience. CJM is a process-oriented, visual user experience method applied in software development, sales and marketing processes, and service engineering to analyze and optimize so-called touchpoints between the client and the business. Kim studied the application of Customer Journey Maps in the tourism industry and found they are instrumental in identifying key moments of truth critical interactions that shape the overall experience [8].

Customer experience management (CEM) is pivotal in modern business strategies, especially in the tourism industry. The importance of customer experience cannot be overstated, as it directly influences customer satisfaction, loyalty, and overall brand perception. For CEM to be effective, it must be possible to comprehend and satisfy consumers' changing needs and expectations at each stage of their journey [9].

Managing customer experience in tourism requires a comprehensive approach that includes collecting and analyzing customer feedback, personalizing services, and continuously improving service quality. Technology is essential to this process because it allows companies to collect real-time data, track customer interactions, and react quickly to problems [10]. Digitalization has transformed the way customer experiences are managed in the tourism sector. The customer journey has been entirely transformed by incorporating digital technologies, which offer convenience, personalization, and instant access to information. Examples of these technologies include mobile apps, virtual tours, and online booking systems [11].

The impact of digitalization on customer experience management is profound and multi-faceted. Digitalization enables businesses to gather extensive data on individual customer behaviors, allowing for highly personalized interactions and offerings. This personalization enhances customer satisfaction and loyalty by providing tailored solutions that meet specific needs [12]. The importance of integrating digital technologies into customer experience management is growing. Dyankov discusses how digital tools can enhance the tourist brand by improving customer engagement and satisfaction [13].

Customer feedback is invaluable for improving service quality and tailoring offerings to meet customer needs. The tourist sector relies heavily on customer feedback since it offers insightful information about the experiences and happiness of its customers. In the digital age, online reviews have become a primary source of feedback. Direct customer feedback is instrumental in assessing and enhancing service quality within the tourism sector. According to Kandampully et al., customer feedback provides valuable insights into service delivery gaps and areas for improvement [14]. By systematically collecting and analyzing feedback, tourism businesses can identify specific aspects of their services that do not meet customer expectations and implement targeted interventions to address these issues. For example, a study by Su and Sun highlighted how hotels that actively seek and respond to customer feedback are better positioned to enhance their service offerings, leading to higher levels of guest satisfaction [15].

Direct customer feedback is vital for gauging satisfaction levels and understanding customer needs and preferences. Parasuraman et al.'s SERVQUAL model emphasizes the significance of customer perceptions in assessing service quality and satisfaction [16]. Clemes et al. found that incorporating customer feedback into service design and delivery significantly enhances customer satisfaction and fosters loyalty [17]. Anderson et al. demonstrated that companies with higher levels of customer satisfaction achieve superior financial performance. By leveraging feedback to align services with customer expectations, tourism businesses can gain a competitive advantage in the market [18].

Online reviews provide information that can be used to gauge customer satisfaction and identify trends. They are accessible to a broad audience, helping businesses enhance their reputation and attract new customers. On the other hand, reviews can be biased or influenced by external factors, and negative reviews can harm a business's reputation if not managed properly. Studies have shown that potential customers heavily rely on online reviews when making travel and dining decisions. For instance, Ye et al. found that positive online reviews significantly increase the likelihood of hotel bookings [19]. A study by Levy et al. highlighted that hotels and restaurants that actively monitor and respond to online reviews are better equipped to address customer concerns and improve service quality [20]. Customer satisfaction and loyalty are closely linked to the quality and responsiveness of online reviews. According to Sparks and Browning, timely and thoughtful responses to online reviews can enhance customer perceptions of a business's commitment to service excellence [21]. This responsiveness not only addresses current customer concerns but also signals to potential customers that the business values feedback and is dedicated to continuous improvement.

Online reviews are integral to modern marketing and brand management strategies. Xiang and Gretzel emphasized that positive online reviews enhance brand visibility and credibility, attracting more customers and fostering brand loyalty [22]. Building a solid brand reputation in the travel and culinary industries requires effective management of online reviews, which includes motivating satisfied customers to provide good comments and constructively responding to negative reviews. Businesses that actively seek out and consider feedback are in a better position to create distinctive products that adapt to changing customer needs. For instance, Sigala discovered that creative hospitality businesses regularly used Internet reviews to find new service options and set themselves apart in a congested market [23]. The goal of this research is to explore how tourists perceive the quality of food in Berlin's restaurants by analyzing online reviews through AI tools. This study seeks to provide insights into the factors that shape customer satisfaction and contribute to Berlin's appeal as a culinary destination.

2. Literature Review

The rapid advancement of digital platforms has transformed the way tourists interact with and perceive their travel experiences. Social media, in particular, has become a pivotal tool for sharing and shaping opinions, especially in the culinary and tourism sectors. By enabling users to share real-time reviews, photos, and comments, platforms such as Google Reviews, TripAdvisor, Instagram, Facebook, etc. have created a dynamic space where customer feedback not only influences individual choices but also impacts the reputation of businesses and destinations. Social media has revolutionized how businesses and destinations market themselves, particularly in the culinary and tourism industries. Early research by Kim et al. highlighted that social media comments significantly shape tourists' perceptions and emotions during their trips, ultimately enhancing their overall tourism experience through platforms like Facebook [24]. As social media usage expanded, researchers like Erol et al. investigated its impact on restaurant image in the culinary and tourism industry, demonstrating that social media comments on platforms like TripAdvisor can significantly influence customer behaviors [25]. Dolan et al. also explored the dual role of social media comments in value co-creation and co-destruction within the tourism sector, highlighting both positive and negative outcomes from consumer feedback [26].

2.1. The Influence of Social Media

Understanding how food quality impacts tourism requires a comprehensive framework incorporating various food experience dimensions. Labibe et al. proposed that food is a critical element of the tourism product, influencing tourists' destination choices and their likelihood of revisiting [27]. To comprehensively understand how food quality impacts tourism, it is essential to consider a framework that incorporates cultural, sensory, and service-related factors. The following framework, adapted from various studies, provides a holistic view:

1. Cultural context: recognizing tourists' cultural backgrounds and expectations is crucial. Food quality perceptions are influenced by tourists' previous experiences, cultural openness, and willingness to engage with local cuisine [28,29].
2. Sensory experience: sensory appeal, including taste, aroma, and presentation, directly affects tourists' satisfaction. Ensuring high sensory quality can enhance positive perceptions [30].
3. Service quality: the quality of service, including staff friendliness, efficiency, and ambiance, plays a vital role in shaping dining experiences. High service quality can mitigate potential negative perceptions related to cultural misunderstandings [31].
4. Authenticity and innovation: balancing authenticity with innovative culinary experiences can cater to diverse tourist preferences. Highlighting traditional dishes while incorporating modern elements can attract a broader audience [29].
5. Feedback mechanisms: implementing effective feedback mechanisms like online reviews and direct feedback allows businesses to continuously improve and adapt to changing tourist expectations [31].

Understanding tourists' expectations and perceptions of food quality is essential for enhancing the overall tourism experience. These perceptions are shaped mainly by cultural variations, with visitor pleasure influenced by sensory appeal, authenticity, and service quality. A comprehensive framework considering cultural, sensory, and service-related factors can help tourism businesses improve their offerings and cater to diverse tourist preferences. Continuous research and adaptation to emerging trends are necessary to maintain competitiveness and ensure long-term success in the tourism industry.

Analyzing tourist reviews is vital for the tourism industry as it provides deep insights into tourists' perceptions and experiences, which directly influence their satisfaction and behavioral intentions, as well as providing insights into customer satisfaction, preferences, and areas for improvement. Recent studies highlight the significance of food quality and dining experiences in shaping tourists' overall impressions of destinations. For instance, positive street food experiences in Da Lat were found to enhance tourists' perceptions of the destination, increase satisfaction, and boost the likelihood of return visits [32]. Similarly, in Egyptian hotels, the excellent taste of local foods and the opportunity to try new dishes emerged as critical factors influencing tourists' destination choices [27]. These results highlight how crucial it is to comprehend the subtle nuances of travelers' culinary experiences via their reviews, since both sensory and non-sensory elements substantially impact overall satisfaction and schedules in the future [33]. Furthermore, sentiment analysis of tourist reviews can reveal significant trends and patterns that help tourism stakeholders tailor their offerings to meet tourists' expectations.

Manual methods of review analysis involve human evaluators reading and interpreting textual feedback to extract meaningful insights. These traditional techniques have been widely used across various industries, including tourism, due to their ability to understand nuanced and context-specific information that automated systems might miss. Despite their limitations, manual methods of review analysis remain valuable in the tourism industry, particularly for small-scale studies or when detailed qualitative insights are required.

2.2. Artificial Intelligence in Analyzing Tourist Feedback

AI-based techniques for review analysis use cutting-edge tools like natural language processing (NLP) and machine learning (ML) to automate the extraction and interpretation of data from massive text review databases. These techniques are becoming increasingly well-liked because of their effectiveness, scalability, and capacity to unearth profound discoveries that manual analysis would overlook.

AI-based methods offer several key strengths that make them highly effective for analyzing customer feedback. One major advantage is their efficiency and scalability as these techniques can process large volumes of data rapidly and effectively. Unlike manual analysis, which is time-consuming and labor-intensive, AI can analyze thousands of reviews in a fraction of the time. This efficiency makes AI-based methods ideal for businesses that receive large volumes of customer feedback through various online platforms [34]. Another strength is their consistency and objectivity as AI-based methods provide consistent and objective analysis following predefined algorithms and rules. This consistency reduces the variability and subjectivity that can occur with human evaluators. Automated systems apply the same criteria to every review, ensuring uniformity in the analysis process [35]. Additionally, AI techniques provide advanced insights by uncovering patterns and trends that human analysts might overlook. For instance, sentiment analysis can determine the overall sentiment (positive, negative, or neutral) expressed in reviews, while topic modeling can identify the main themes and topics customers discuss. These advanced insights provide a deeper understanding of customer opinions and preferences [36]. Finally, AI enables real-time analysis of customer feedback. This feature makes it possible for companies to react quickly to new problems and trends, which helps them better handle customer feedback and raise the standard of their services. Real-time analysis is precious in the fast-paced tourism industry, where timely responses can significantly impact customer satisfaction [34].

Despite their strengths, AI-based methods have several weaknesses that can impact their effectiveness. One key limitation is their inability to fully understand context, sarcasm, and cultural nuances, which can lead to misinterpretations and inaccuracies in the analysis. For example, a sarcastic review may be incorrectly classified as positive or negative if the system fails to recognize the sarcasm [37]. Another challenge is the initial setup and training of AI models, which require significant investment in terms of time, resources, and expertise. Constant improvement and upgrading of the models are necessary to guarantee their accuracy and dependability. These processes can be resource-intensive, particularly for small businesses with limited technical capabilities [36]. AI methods also heavily rely on data quality, as the effectiveness of these techniques depends on the quality of the training datasets. Unreliable analysis and incorrect models might result from poor quality data. Additionally, AI systems need large datasets to train effectively, which may not always be available for specific applications [31]. Lastly, many AI models, those utilizing deep learning algorithms, operate as "black boxes", providing little insight into how they reach their conclusions. This lack of transparency may be problematic for organizations that need to know why the analysis results were presented as they were. Efforts to develop explainable AI (XAI) aim to address this issue by making AI systems more transparent and understandable [36].

Recent studies have explored the integration of AI and human expertise to leverage the strengths of both approaches. For instance, hybrid methods combine AI-based preliminary analysis with human review for final interpretation, enhancing both efficiency and accuracy [38]. Both manual and AI-based methods of analyzing tourist reviews have strengths and weaknesses. Manual methods offer nuanced and context-aware analysis but are time-consuming and subjective. AI-based methods provide efficient, scalable, and consistent analysis but may lack contextual understanding. The future of review analysis in tourism likely lies in hybrid approaches that combine the best of both worlds, leveraging AI for preliminary analysis and human expertise for nuanced interpretation.

Sentiment analysis in tourism research has evolved significantly over the years. Initially, researchers relied heavily on manual coding and thematic analysis to understand tourists' opinions and experiences. These methods involved qualitative approaches where human coders would identify themes and sentiments from textual data, such as tourist reviews and feedback, identifying recurring themes and categorizing sentiments. This process was time-consuming and subject to human bias but provided in-depth qualitative insights into tourists' perceptions. Studies such as those by Anis et al. highlight the importance of these methods in the early stages of sentiment analysis in tourism. Sentiment analysis, which employs natural language processing, statistics, and machine learning to extract and identify opinions in text, has become crucial [39].

2.3. Comparative Approaches to Sentiment Analysis

2.3.1. Lexicon-Based Methods

Sentiment analysis, or opinion mining, involves identifying the sentiment expressed in text. Lexicon-based methods, which depend on predefined word lists linked to positive or negative sentiments, have played a key role in this field. These methods use dictionaries of words that are labeled with their sentiment orientation. One of the seminal works in lexicon-based sentiment analysis is the development of the Semantic Orientation CALculator (SO-CAL) by Taboada et al. [40]. SO-CAL uses dictionaries of words annotated with their sentiment orientation and intensity to analyze text. This method showed robust performance across various domains and datasets, demonstrating the potential of lexicon-based approaches in achieving consistent results.

One of the initial studies on sentiment analysis in tourism was conducted by García et al. [41]. They developed a lexicon-based sentiment analysis retrieval system tailored for the tourism domain, explicitly focusing on accommodation and food and beverage sectors. Their approach highlighted the importance of domain-specific lexicons in accurately capturing the sentiment of tourist reviews. Lexicon-based sentiment analysis methods have been applied to various domains with considerable success. For example, Öhman discussed the validity of lexicon-based sentiment analysis in interdisciplinary research, highlighting their utility when moving to higher levels of granularity and when qualitative analysis or machine learning approaches are not feasible [42]. Recent studies have continued to explore and refine lexicon-based methods. For example, Fehle et al. evaluated different resources and preprocessing techniques for lexicon-based sentiment analysis in German [43]. They found that more extensive lexicons with continuous values performed best across domains, and preprocessing steps such as stemming or lemmatization consistently increased performance.

Additionally, Mustofa and Prasetiyo applied a lexicon-based method combined with the naive Bayes classifier algorithm to analyze sentiments on X (Twitter) [44]. They achieved an accuracy of 79.72% in testing, demonstrating the potential for lexicon-based methods to be effectively used alongside other techniques to enhance performance. Paolanti et al. utilized lexicon-based sentiment analysis to manage tourism destination data [45]. Their approach integrated geo-tagged social media data to provide real-time sentiment insights, aiding in the effective management of tourist destinations by identifying trends and visitor preferences. Advanced lexicon-based methods have been developed with the increasing volume of online reviews and feedback in the tourism industry. Lubihana and Y. designed a tourism recommendation system based on sentiment analysis using a lexicon with Long Short-Term Memory (LSTM) [46]. Their hybrid approach achieved high performance in determining tourist satisfaction and recommending tourist attractions.

Lexicon-based methods have proven valuable in sentiment analysis for the tourism industry. From early implementations to recent advancements, these methods have evolved to handle the complexities of tourism-related data effectively. As sentiment analysis advances, the integration and refinement of lexicon-based methods will remain a significant area of research, ensuring their continued relevance and adaptability in the field. Integrating these approaches with other data sources and advanced analytics can further enhance their applicability and impact in managing and improving tourism services.

2.3.2. Machine Learning Methods

Machine learning methods have significantly advanced sentiment analysis, particularly in the tourism industry. These methods enable the extraction of valuable insights from tourist reviews and feedback, aiding in decision-making processes for tourism businesses. One of the foundational works in machine learning-based sentiment analysis involves traditional classifiers like support vector machine (SVM), naive Bayes (NB), and maximum entropy (ME). A comprehensive survey by Yang and Chen discusses the use of these classifiers and highlights their application in various sentiment analysis tasks. SVM and NB, in particular, were extensively used due to their effectiveness in handling text classification problems [47].

As the field progressed, more sophisticated machine learning models were developed and applied to sentiment analysis. Haberzettl and Markscheffel studied different machine learning techniques and feature extraction methods used for sentiment analysis in customer service emails. They focused on the challenges caused by the growing number of emails [48]. Andersson et al. used machine learning to analyze student feedback in first-year engineering courses, revealing correlations between study habits and feedback sentiment [49].

Basarslan and Kayaalp compared the performance of artificial neural networks (ANNs), SVM, and NB on Twitter and IMDB datasets, concluding that ANNs achieved the best accuracy [50]. Aksu and Karaman focused on analyzing Turkish sentiment expressions about touristic sites using various machine learning algorithms, including naive Bayes, multinomial naive Bayes, k-nearest neighbor, and support vector machines. The study examined the effects of labeling, stemming, and negation on sentiment analysis success, providing insights into optimizing machine learning models for tourism-related data [51]. AlBadani et al. proposed a novel machine learning approach by combining "universal language model fine-tuning" (ULMFiT) with support vector machines (SVM). This approach significantly enhances the detection efficiency and accuracy in sentiment analysis tasks. Their study, which applied this method to the Twitter US Airlines dataset, achieved state-of-the-art results with an accuracy of 99.78%. The integration of ULMFiT, which allows for effective fine-tuning of language models on specific tasks, demonstrated its potential to improve sentiment analysis outcomes considerably [52]. Leelawat et al. investigated the impact of COVID-19 on Thailand's tourism industry by analyzing English-language tweets about tourism in Bangkok, Chiang Mai, and Phuket using machine learning algorithms. They employed decision tree, random forest, and support vector machine (SVM) models to predict the sentiment and intention behind the tweets [53].

Hadwan et al. employed machine learning methods alongside the Synthetic Minority Over-Sampling Technique (SMOTE) to measure user satisfaction with governmental services' mobile apps. This study highlights the effectiveness of combining machine learning with data balancing techniques to handle imbalanced datasets, which are common in real-world applications [54]. Machine learning methods have revolutionized sentiment analysis, providing powerful tools for analyzing and interpreting text data. These methods have proven highly effective in sentiment analysis for the tourism industry. From early classifiers like SVM and NB to advanced models like CNNs and BERT, these methods enhance sentiment classification's accuracy, robustness, and reliability, providing valuable insights for improving services and customer satisfaction.

2.3.3. Hybrid Methods

Hybrid methods in sentiment analysis combine multiple approaches, often integrating machine learning with lexicon-based techniques or merging different machine learning models to leverage their strengths. These methods are precious for analyzing tourist reviews and feedback in the tourism industry. One of the earlier studies discussing hybrid methods in sentiment analysis was by Prastyo et al., who reviewed various feature selection techniques in sentiment analysis, highlighting how hybrid methods can resolve redundant and irrelevant data to increase classifier performance. However, they also noted the high computational cost associated with these methods [55]. Utama et al. employed a hybrid classifier combining random forest (RF), support vector machine (SVM), and naive Bayes (NB) for multi-aspect sentiment analysis of hotel reviews. The hybrid approach achieved an average accuracy of 84%, significantly higher than individual algorithms. Integrating these methods enhanced the robustness and accuracy of sentiment classification, making it particularly effective for multi-aspect data [56].

Another early example is the work by Mohamad Sham and Mohamed, who explored the hybrid method combining TextBlob and logistic regression for climate change sentiment analysis. They found that hybrid methods, particularly the combination of TextBlob and logistic regression, were the most effective for climate change sentiment analysis [57]. Hybrid methods have been applied to sentiment analysis in various domains, demonstrating their versatility and effectiveness. Talaat proposed hybrid BERT models with Bi-directional Gated Recurrent Unit (BiGRU) layers, showing improved accuracy compared to classical machine learning approaches [58]. This model was particularly effective for sentiment analysis tasks requiring a nuanced understanding of context.

Recent studies have continued to push the boundaries of hybrid methods in sentiment analysis. Vanam and Raj proposed a hybrid deep learning model called an autoencoder bi-directional recurrent neural network (ABRNN) based on bi-directional encoding from transformers (BET) [59]. This model addresses challenges in sentiment analysis due to missing ratings, reviews, noise, and context and utilizes pre-trained BET to extract embeddings, incorporating global and local spatial contextual characteristics. Agrawal and Moparthi proposed a hybrid multi-source data fusion approach using a gated bilateral recurrent neural network (G-Bi-RNN). This model improved sentiment analysis performance across various levels, such as word, sentence, aspect, and document, and outperformed cutting-edge techniques on all datasets [60]. Zhang et al. introduced a TBGAV-based image-text multimodal sentiment analysis method specifically for tourism reviews. Their hybrid approach combines text and image data to improve sentiment analysis performance. By integrating these two data sources, the approach takes advantage of visual and textual information benefits, improving sentiment recognition accuracy in tourist reviews [61].

Razali et al. introduced an innovative hybrid sentiment analysis framework to improve the classification of minority sentiments in gastronomy tourism. Their approach integrates lexicon-based methods with data augmentation and feature engineering to address the challenges of class imbalance [62]. This framework, tailored for the gastronomy tourism sector, demonstrated the practical benefits of combining business intelligence with advanced sentiment analysis methods, providing valuable insights for managing tourist feedback effectively. Hybrid methods in sentiment analysis provide significant advantages in the tourism industry by combining the strengths of various approaches. From early implementations that integrated lexicon-based methods with machine learning techniques to contemporary models that merge deep learning architectures, these methods have proven effective in multiple domains and applications. These methods have proven effective in enhancing sentiment classification's accuracy, robustness, and reliability, addressing challenges like class imbalance, language-specific nuances, and multimodal data integration. As research continues, integrating novel techniques, hybrid models, and advanced preprocessing methods will further enhance the accuracy and applicability of sentiment analysis.

3. Materials and Methods

A systematic and rigorous approach is essential to comprehensively understand public sentiment toward food quality in Berlin's dining establishments. This study employs natural language processing (NLP) and machine learning techniques to analyze extensive volumes of textual data from online reviews. By utilizing a detailed methodology that includes data collection, preprocessing, sentiment analysis, and visualization, the study aims to provide in-depth insights into tourists' perceptions.

This study's research design integrates qualitative and quantitative methodologies to analyze tourists' reviews comprehensively. The design is structured to facilitate the extraction and interpretation of sentiment from textual data, ensuring a robust analysis of public opinion on food quality in Berlin.

This study employs a mixed-methods approach, combining qualitative insights from textual data with quantitative sentiment scoring. This dual approach allows for a nuanced understanding of the reviews, capturing both the depth of individual opinions and the overall sentiment trends.

The research employs an analytical framework that integrates various NLP techniques for preprocessing the text data, followed by sentiment analysis using the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool. The framework is designed to handle large datasets systematically, preprocess the text for noise reduction, and accurately classify the sentiment. This study utilized publicly accessible online reviews for academic purposes in compliance with relevant privacy and data usage guidelines of the online platforms. The data were analyzed exclusively for academic, non-commercial research, in anonymized format focusing on sentiment analysis as a tool to compare the sentiment of the textual feedback with direct rating scores.

The VADER tool was chosen for its computational efficiency for text processing and mining in social media platforms. The lexicon-based sentiment analysis is advantageous for capturing nuances in sentiment expression, such as punctuation, capitalization, and degree modifiers. VADER's lexicon-based approach calculates sentiment based on individual word scores, making it relatively faster and more straightforward to implement than large language models (LLMs) like BERT. While machine learning-based models like BERT or hybrid approaches provide deeper contextual understanding by analyzing the structural dependencies within language, these models are more resource-intensive and require extensive computational power. VADER, in contrast, is computationally light and allows for rapid processing, which is essential for efficiently handling the scale of data in this study. Its word-by-word, lexicon-based sentiment scoring is sufficient for capturing the sentiment intensity in customer reviews without the need for extensive model training and tuning. This makes VADER a highly practical choice, offering a balanced solution between speed and accuracy. In general, while LLMs and hybrid models offer sophisticated sentiment insights, VADER provides a reliable, efficient option aligned with the study's needs for analyzing high volumes of reviews.

The data for this study were collected from publicly accessible online reviews, focusing on more than 101,000 reviews of 250 restaurants in Berlin, providing a comprehensive view of tourist experiences. The dataset includes essential fields such as "review_text", and "rating". The dataset encompasses reviews posted from January 2022 to the present, providing a recent and relevant perspective on food quality in Berlin. Before analysis, the dataset underwent thorough cleaning. This involved removing duplicates, filtering out non-English reviews, and excluding entries with missing or irrelevant information. The data collection process ensured the anonymity of reviewers and adhered to ethical guidelines for using publicly available data. After data collection, the reviews were preprocessed to prepare them for sentiment analysis. The preprocessing steps involved several stages to prepare the text for analysis. First, tokenization was performed, where the text was split into individual words. Next, stop-word removal was applied to eliminate common words, such as "and" and "the", which do not contribute to sentiment analysis. Following this, stemming and lemmatization were used to simplify words to their base forms, ensuring consistency across the dataset. The text was then converted to lowercase to maintain uniformity and enhance comparability. Finally, punctuation and special characters were removed to focus solely on the meaningful content of the text (Appendix A).

The sentiment analysis process begins with sentiment scoring, where each review is analyzed to generate a sentiment score. VADER provides four primary sentiment metrics to analyze the sentiment of text. The positive metric represents the proportion of text conveying a positive sentiment, while the negative metric measures the proportion of text with a negative sentiment. The neutral metric captures the portion of the text that reflects a neutral tone. Finally, the compound metric is a normalized, weighted composite score derived from the positive, negative, and neutral scores, ranging from −1 (most negative) to +1 (most positive). The compound score is the most comprehensive metric, considering the overall sentiment expressed in the review. For instance, a review with a compound score close to +1 is overwhelmingly positive, while a score close to −1 indicates a highly negative sentiment. These scores are obtained by adding up the valence scores of each word in the text, with adjustments based on grammar and syntax rules that affect the intensity of sentiment. After calculating the compound scores, each review is categorized into one of three sentiment classes based on its score. Reviews with a compound score greater than 0.05 are classified as positive, while those with a compound score between −0.05 and 0.05 (inclusive) are labeled as neutral. Reviews scoring less than −0.05 are categorized as negative. This classification enables an organized analysis of how sentiment is distributed across the dataset. After cleaning the data, 64,617 reviews were left. By categorizing the reviews, the study can quantitatively assess the proportion of positive, negative, and neutral reviews, providing a clear overview of public opinion.

The sentiment analysis was implemented in Python using the VADER tool from the NLTK library. The process began with loading the review dataset into a Pandas DataFrame for efficient data handling. Next, the SentimentIntensityAnalyzer class from the NLTK library was initialized to perform sentiment analysis. The analysis was then applied to each review in the review_text column of the DataFrame using a custom function, analyze_sentiment, which calculated the compound score and categorized the sentiment. Finally, the results, including the sentiment category and compound score, were stored in new columns named sentiment and compound_score within the DataFrame (Appendix B).

In addition to the fundamental sentiment analysis, several advanced techniques and considerations were employed to enhance the accuracy and reliability of the analysis. VADER inherently handles negations, such as "not good", by reversing the sentiment score of the word following the negation. It also emphasizes the impact of punctuation, like exclamation marks ("!!!"), and capitalization ("GREAT") on sentiment intensity, allowing for more nuanced and accurate scoring. Furthermore, VADER adjusts sentiment scores appropriately based on conjunctions and contrastive conjunctions, such as "but", which can significantly alter the overall sentiment of a sentence. The VADER sentiment analysis tool has been validated extensively and is known for its accuracy in social media contexts. However, to ensure the validity of the results in this specific study, the sentiment classifications were cross-validated with manual annotations of a sample subset of reviews. This helped identify any discrepancies and refine the sentiment categorization rules.

4. Results

The sentiment analysis of the reviews provided valuable insights into tourists' perceptions of food quality in Berlin's dining establishments. The sentiment analysis categorized the reviews as positive, neutral, negative.

This distribution indicates that most reviews are positive, reflecting general tourist satisfaction with the food quality in Berlin's restaurants. The sentiment distributions are visualized in Figure 1.

Analyzing the frequency of sentiment scores provides a more granular view of the sentiments expressed in the reviews. Figure 2 visualizes the frequency of sentiment scores from 2022 to 2024. The distribution shows high positive scores, indicating a general satisfaction trend.

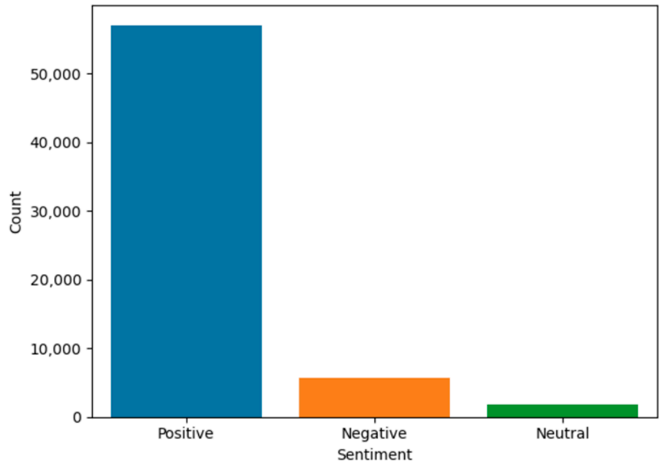

Figure 1. Sentiment distribution for Berlin's restaurants in data sample.

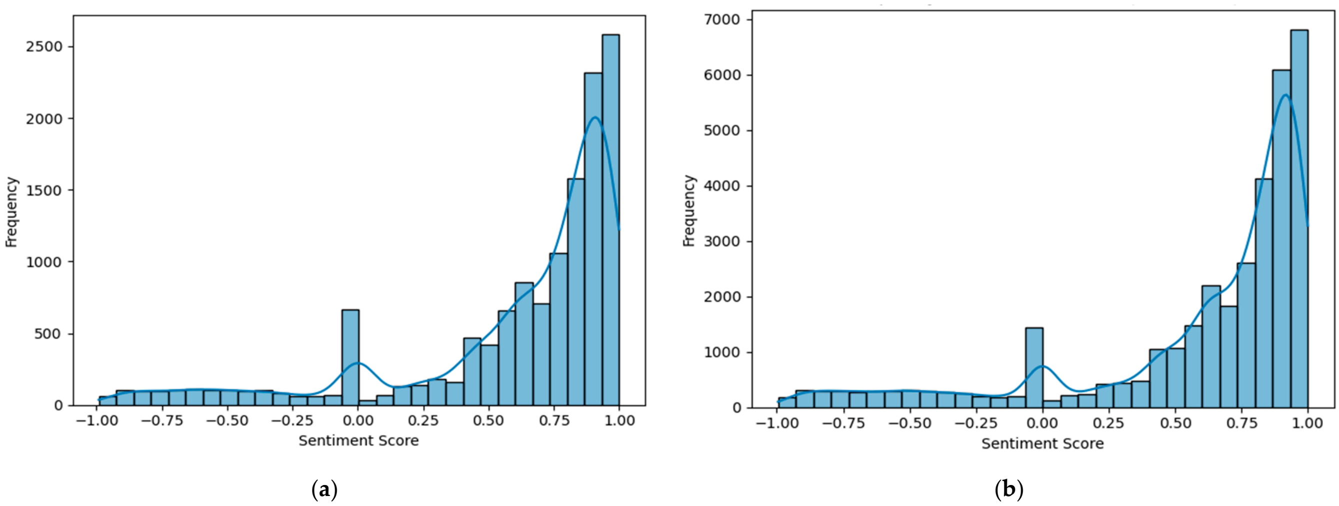

Figure 2. Frequency of sentiment score: (**a**) 2022–2023 and (**b**) 2023–2024.

Figure 2 highlights how frequently different sentiment scores appear within the dataset, offering a clear and quantitative representation of tourists' overall sentiment towards food quality in Berlin. The majority of reviews are concentrated around the positive sentiment scores, especially between 0.75 and 1.0, indicating that a significant portion of tourists express a highly positive sentiment towards their dining experiences. The smaller peaks around neutral sentiment scores (around 0) suggest that some reviews are more balanced, either reflecting mixed experiences or indifference. The low frequency of strongly negative sentiment scores (below −0.5) implies that there are relatively fewer highly negative reviews. By analyzing this distribution, one can easily determine the general trend of satisfaction or dissatisfaction among tourists. The high concentration of positive sentiment scores suggests that most tourists are satisfied with the food quality in Berlin. This information is crucial for restaurant owners, marketers, and policymakers, as it highlights areas of success, while the presence of neutral or negative sentiments can pinpoint areas that may need improvement.

The study successfully applied NLP and sentiment analysis techniques to uncover valuable insights from online reviews about food quality in Berlin. The findings suggest that tourists generally have a positive perception of dining experiences in Berlin, with there being room for improvement in specific areas.

Sentiment analysis is a vital technique in the tourist and culinary industries for evaluating consumer satisfaction and perceptions while analyzing customer feedback. This section is split into two main sections: first, a comparison of sentiment across several food categories, including pizza, burgers, kebabs, and restaurants, and second, a comparison of sentiment scores versus restaurant star ratings to find out how effectively they are associated.

4.1. Comparison of Sentiment Across Food Categories

Understanding consumer sentiment across various food categories is essential to identifying strengths and areas in Berlin's diverse and culturally enriched culinary scene that require improvement. This section compares sentiment analysis results for restaurants, burger joints, kebab shops, and pizzerias. Analyzing the sentiment scores aims to find trends and discrepancies in consumer perceptions that could be impacted by the atmosphere, cuisine authenticity, service quality, and price.

The comparative sentiment analysis across these food categories highlights distinct customer preferences and expectations. While traditional restaurants are judged heavily on service quality and ambiance, more casual establishments like burger joints and kebab shops are evaluated based on value for money and consistency. Pizzerias must balance quality with efficient service, particularly for delivery. Detailed sentiment analysis was conducted using the coded categories outlined in Appendix C. By categorizing reviews, a granular analysis of customer sentiment for each food category has been performed to provide a comprehensive understanding of these differences. The results of this analysis, as illustrated in Table 1, reveal significant insights into customer preferences and areas of concern. The sentiment analysis is based on a substantial dataset of 64,617 comments, providing a robust foundation for the findings.

Table 1. Sentiment Scores by Category.

Category	Mean Sentiment Score
Restaurants	0.592996
Kebap	0.612254
Pizza	0.606561
Burger	0.629566

Pizzerias, with the lowest mean sentiment score among the categories analyzed, received high marks for the quality and variety of their pizzas. However, issues related to delivery efficiency and the condition of delivered food were highlighted as key factors influencing customer satisfaction. These challenges suggest that pizzerias must improve their operational processes, especially for takeout and delivery services, to enhance overall customer satisfaction. In contrast, burger joints achieved the highest mean sentiment score, indicating strong positive feedback. Customers generally appreciated the value for money, taste, and portion sizes offered by burger establishments. Despite these positive sentiments, consistency in food quality remains a critical area for improvement.

These results highlight the importance of recognizing specific customer expectations for different types of food establishments. By addressing the unique preferences and concerns revealed through sentiment analysis, businesses can make focused improvements to boost customer satisfaction and loyalty in Berlin's vibrant food scene.

The histogram in Figure 3 illustrates the distribution of sentiment scores for different categories of Berlin restaurants. The horizontal axis represents the sentiment score, which ranges from -1 to 1, with -1 indicating extremely negative sentiment, 0 representing neutral sentiment, and 1 indicating extremely positive sentiment. The vertical axis shows the frequency, which is the number of reviews within each sentiment score range.

The frequency on the vertical axis indicates how often reviews with specific sentiment scores occur within each restaurant category. A higher frequency of a particular sentiment score implies that many reviews fall within that sentiment range. For example, a high frequency of positive sentiment scores (close to 1) suggests that the category receives many favorable reviews. Conversely, a high frequency of negative sentiment scores (close to -1) indicates more unfavorable reviews. The distinct colors assigned to each category help visually differentiate the sentiment distribution, making it easier to compare and contrast the customer sentiments across different restaurant types.

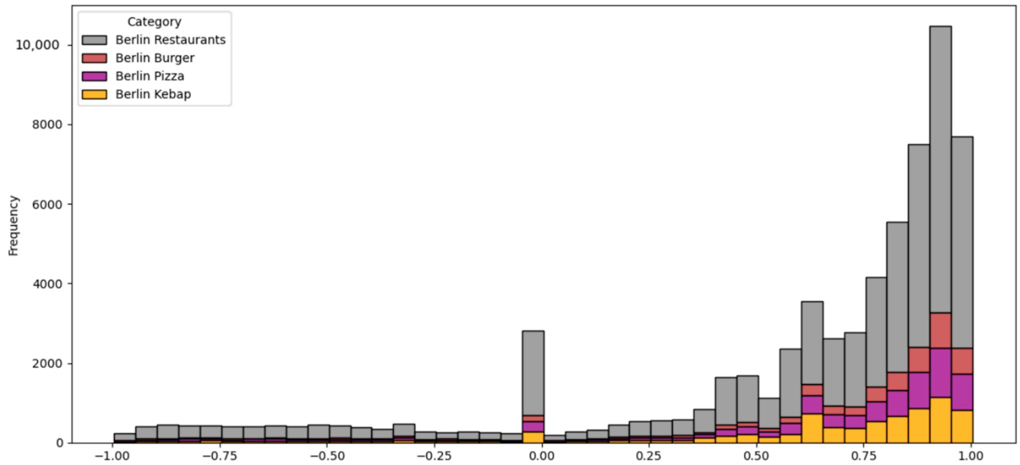

Figure 3. Distribution of sentiment scores by category.

The boxplot in Figure 4 illustrates the distribution of sentiment scores for different categories of Berlin restaurants. The horizontal axis represents the categories of general Berlin restaurants, kebab, pizza, and burger restaurants. The vertical axis shows the sentiment score ranging from −1 to 1. The boxplot summarizes the data distribution, including each category's median, quartiles, and potential outliers.

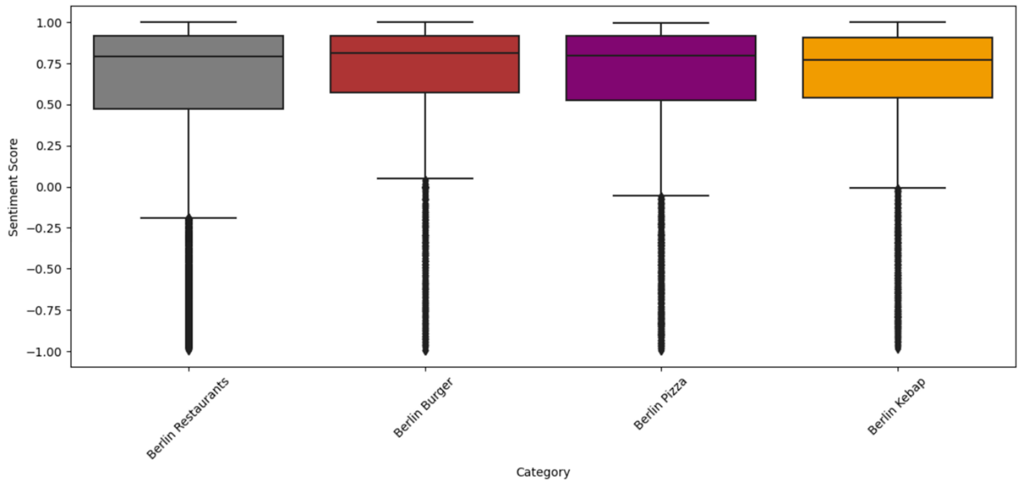

Figure 4. Sentiment score distribution by category.

The boxplot effectively summarizes the overall sentiment for each category, allowing for a clear comparison between different types of restaurants. For instance, a narrower IQR indicates more consistent reviews, while a wider IQR suggests more varied customer experiences. Outliers can indicate specific instances of highly positive or negative reviews. Analyzing these elements makes it possible to identify trends and patterns in customer sentiment, providing valuable insights into each restaurant type's strengths and areas for improvement.

4.2. Comparing Restaurant Ratings and Sentiment Scores

The connection between customer satisfaction and business performance is an essential factor in hospitality and restaurant management. The main goal of comparing restaurant ratings with sentiment scores is to confirm how effective sentiment analysis is in measuring customer satisfaction. Ratings, often displayed as stars or numerical scores, provide a quick summary of customer feedback but lack the detailed context that written reviews offer. Sentiment analysis, which involves extracting subjective information from text data, can uncover underlying customer sentiments that are not always evident in numerical ratings. By examining the correlation between these two measures, this study aims to assess whether sentiment scores reflect the same level of customer satisfaction indicated by the ratings.

Understanding the alignment between ratings and sentiment scores is crucial for several reasons. First, it helps validate the sentiment analysis methodology, ensuring it accurately captures customer sentiments. Second, it provides insights into whether customers' written feedback aligns with their overall rating, which can highlight discrepancies or confirm consistencies. Lastly, this comparison can offer valuable information for restaurant owners and managers, helping them identify areas of strength and improvement based on a more comprehensive customer feedback analysis.

In addition to analyzing sentiment across various food categories, this study also examined the correlation between the star ratings of restaurants and their sentiment scores. The analysis revealed a correlation coefficient 0.19, indicating a weak but positive relationship between these two metrics. This suggests that while there is some alignment between star ratings and sentiment scores, the relationship is not strong enough to be considered highly predictive. The details of the coding and methodology used for this analysis can be found in Appendix C.

The low correlation between restaurant star ratings and sentiment scores found in this study suggests that star ratings alone may not fully reflect the complexity of customer sentiment. Several factors contribute to this difference. First, customers use personal and subjective scales when assigning star ratings. For instance, one person's 2-star rating may represent a slightly unsatisfactory experience, while for another, it could reflect a highly negative one. This inconsistency makes it difficult to draw consistent conclusions from star ratings.

Second, star ratings often serve as a quick summary of the overall experience, but the details of customer sentiment are more frequently expressed in written reviews. For example, two customers who are dissatisfied with the food may give different ratings, one might give 2 stars, while the other gives 3, despite having similar complaints. Their written reviews, however, would likely provide more precise insight into their specific issues, allowing sentiment analysis to capture nuances that star ratings miss.

Additionally, not all customers who leave star ratings provide written comments. Many simply give a rating without further explanation, limiting the information available to understand their true opinions. This means a high star rating could conceal dissatisfaction with specific aspects, while a low rating might not fully explain what went wrong. In such cases, sentiment analysis of reviews becomes essential to gain a more accurate picture of customer feedback. Analyzing written reviews can uncover hidden sentiments, patterns, and concerns that are not visible through star ratings alone.

Finally, star ratings tend to compress diverse experiences into a single score, which overlooks the complexity of customer emotions. For example, a 3-star rating could imply "average" or "satisfactory", but the actual sentiment could vary greatly; some customers may have enjoyed parts of the service while being disappointed by the food. Written reviews allow these mixed emotions to be expressed in ways that star ratings cannot, making sentiment scores a more detailed measure of customer experience. Therefore, while star ratings offer a quick snapshot of satisfaction, sentiment analysis reveals the finer details of how customers feel, explaining the weak correlation between the two.

In addition to the correlation coefficient, a p-value was calculated to assess the statistical significance of the observed correlation. The p-value was less than 0.00001, indicating that the correlation is statistically significant and not due to random chance. Further details on the coding for this analysis are provided in Appendix D. This low p-value reinforces the reliability of the correlation, providing confidence in the alignment between customer ratings and sentiment scores. The significance of the p-value supports the validity of using sentiment analysis as a complementary tool to traditional rating systems in assessing customer satisfaction.

The boxplot in Figure 5 provides a comprehensive visualization of the distribution of sentiment scores across different restaurant ratings. The horizontal axis represents restaurant ratings, ranging from 1 to 5 stars. The vertical axis represents sentiment scores derived from customer reviews, ranging from −1 (very negative) to 1 (very positive).

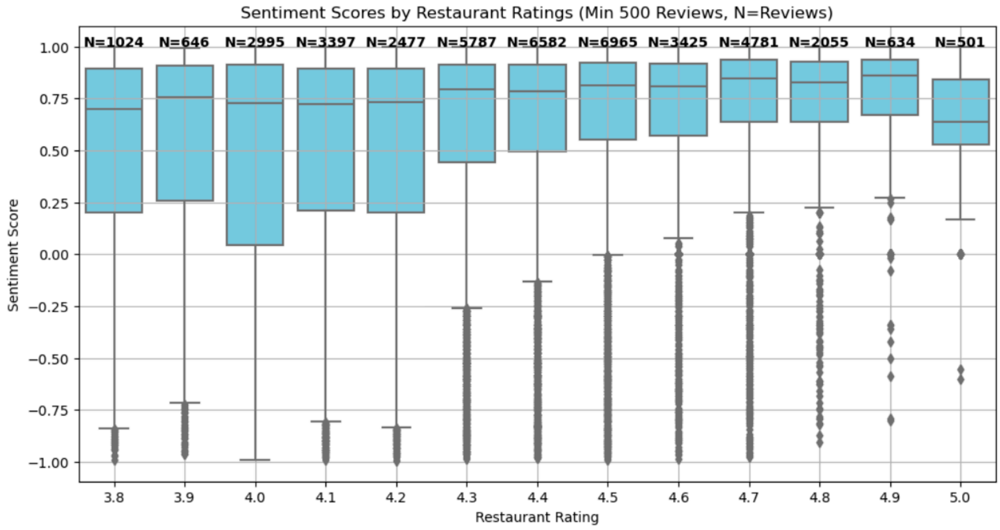

Figure 5. Sentiment score by restaurant ratings.

The median sentiment score generally increases with higher restaurant ratings, showing that better-rated restaurants tend to receive more positive sentiment scores. This matches the expectation that higher-rated establishments offer better customer experiences. The interquartile ranges (IQRs) vary by rating, with higher ratings having narrower IQRs. This indicates that sentiment scores for well-rated restaurants are more consistent and centered around the median, reflecting a more uniform positive experience. In contrast, lower ratings show wider IQRs, suggesting more significant variability in sentiment. This could result from a mix of very negative reviews and some positive outliers, leading to a broader range of sentiments. Whiskers indicate that most sentiment scores fall within the expected range (1.5 times the IQR), though outliers are present for most ratings. For lower ratings (e.g., 1 or 2 stars), there are more negative outliers, pointing to a group of highly dissatisfied customers. For higher ratings (e.g., 4 or 5 stars), there are fewer negative outliers and more positive outliers, suggesting that while most reviews are positive, some are exceptionally positive.

The bar chart in Figure 6 shows the average sentiment scores for restaurants at various rating levels. This chart is useful for comparing the central tendency of sentiment scores across different categories, such as restaurant ratings. The horizontal axis displays restaurant ratings from 1 to 5 stars, while the vertical axis shows the average sentiment scores, ranging from −1 (very negative) to 1 (very positive). Each bar represents the average sentiment score for a particular restaurant rating, with the height of the bar indicating the mean sentiment score for that specific rating level.

Figure 6 shows that higher restaurant ratings are associated with higher average sentiment scores. This indicates that customers generally express more positive sentiments in their reviews when they rate restaurants more favorably. Restaurants with a rating of 5 stars have the highest average sentiment scores, reflecting consistent positive experiences and high customer satisfaction.

The increasing trend of average sentiment scores from lower to higher ratings suggests a positive correlation between ratings and sentiment scores. This alignment validates the effectiveness of sentiment analysis in capturing customer satisfaction levels. The chart also shows relatively consistent average sentiment scores for each rating level, with no significant anomalies or deviations. This consistency further supports the reliability of sentiment scores as an indicator of customer satisfaction.

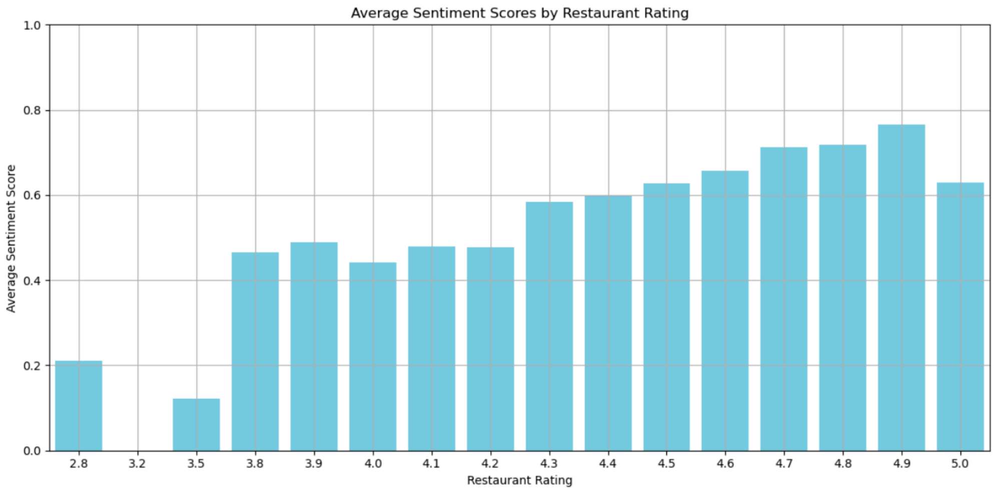

Figure 6. Average sentiment score by restaurant ratings.

In conclusion, the findings from the comparative analysis of different food categories underscore the importance of understanding specific customer expectations and preferences for various food establishments. By addressing the unique concerns identified through sentiment analysis, businesses can make targeted improvements to enhance overall customer satisfaction and loyalty in Berlin's dynamic culinary scene. The weak correlation between sentiment scores and star ratings indicates that, while sentiment analysis is useful for understanding customer opinions, it should be combined with traditional metrics for a more complete picture of customer satisfaction. Using both methods together allows businesses to benefit from each other's strengths, leading to more accurate and actionable insights that can support ongoing improvements and innovation in the tourism and culinary sectors.

5. Conclusions

This study applied the lexicon-based sentiment analysis in the context of tourism sectors. Expanding the data sources to include textual feedback beside the rating scores would enable the capture of sentiment trends, allowing for a more immediate and diverse set of insights.

This article compared the results of sentiment analysis on the textual feedback and the direct rating scores for the restaurants in Berlin. Using a mixed approach combining qualitative insights with quantitative sentiment scoring, we gained a nuanced understanding of tourists' experiences across various food categories. The findings underscore the importance of high-quality sensory experiences and consistent service in shaping positive customer perceptions.

The weak but statistically significant correlation between sentiment scores and restaurant ratings highlights the need for sentiment analysis to complement traditional metrics like star ratings. This finding suggests that written reviews capture more profound insights into customer satisfaction that are not always reflected in ratings alone.

Moreover, the paper emphasizes the potential of AI in efficiently processing large datasets of customer feedback. However, challenges such as handling contextual nuances and ensuring data quality remain. A hybrid approach, combining AI with human review, could further enhance accuracy and offer more actionable insights for the hospitality and tourism sectors.

These findings can guide restaurant owners and stakeholders in targeting areas for improvement, enhancing customer experiences, and ultimately increasing satisfaction and loyalty in a dynamic culinary scene.

In addition, incorporating advanced AI technologies, particularly transformer-based models such as BERT and GPT, could enhance the precision of sentiment analysis. These models excel at understanding contextual nuances and complex language structures, making them well-suited for handling the informal language patterns and sentiment subtleties often present in social media posts. Utilizing such models could refine sentiment analysis, providing a more sophisticated understanding of tourists' experiences.

Moreover, future research could broaden the analysis to cover additional aspects of the tourism experience such as accommodations, transportation, and local attractions. Expanding the geographical scope to include other regions or cities would allow for comparative analyses, providing deeper insights into how cultural, economic, and regional differences influence tourist perceptions. By integrating multiple data sources and leveraging state-of-the-art AI techniques, future studies could develop a comprehensive, multidimensional perspective on tourism experiences. This would enrich both theoretical insights and practical applications, offering valuable guidance for stakeholders in tourism management and service enhancement.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

```
# Import the pandas library for data manipulation
import pandas as pd
# Import the VADER sentiment analyzer from the NLTK library
from nltk.sentiment.vader import SentimentIntensityAnalyzer
# Load the CSV file containing the final data
file_path = 'path/to/your/final.csv'
# Read the CSV file into a DataFrame
df = pd.read_csv(file_path)
# Initialize VADER sentiment analyzer
sia = SentimentIntensityAnalyzer() # Create an instance of SentimentIntensityAnalyzer
# Define a function to analyze sentiments
def analyze_sentiment(text):
score = sia.polarity_scores(text)['compound'] # Calculate the compound sentiment score
    if score > 0.05: # If the score is greater than 0.05, classify as positive
        return 'positive'
    elif score < −0.05: # If the score is less than −0.05, classify as negative
        return 'negative'
    else: # Otherwise, classify as neutral
        return 'neutral'
# Apply sentiment analysis on the 'review_text' column
df['sentiment'] = df['review_text'].apply(analyze_sentiment) # Apply the function to each
review text
# Save the results to a new CSV file
result_file_path = 'path/to/save/sentiment_results.csv' # Specify the path to save the results
df.to_csv(result_file_path, index = False) # Save the DataFrame to a CSV file
```

```
# Import matplotlib for plotting
import matplotlib.pyplot as plt
# Import seaborn for advanced plotting
import seaborn as sns
# Plot the sentiment distribution
sns.countplot(x = ‘sentiment’, data = df) # Create a count plot of sentiments
plt.title(‘Sentiment Distribution’) # Set the title of the plot
plt.xlabel(‘Sentiment’) # Set the label for the x-axis
plt.ylabel(‘Count’) # Set the label for the y-axis
plt.show() # Display the plot
# Display sentiment trends over time if ‘review_date’ column is available
if ‘review_date’ in df.columns: # Check if the ‘review_date’ column exists in the DataFrame
    df[‘review_date’] = pd.to_datetime(df[‘review_date’]) # Convert ‘review_date’ column to datetime format
    df.set_index(‘review_date’, inplace = True) # Set ‘review_date’ as the index of the DataFrame
    df.resample(‘M’).sentiment.value_counts().unstack().plot() # Resample data by month and plot sentiment trends
    plt.title(‘Sentiment Trends Over Time’) # Set the title of the plot
    plt.xlabel(‘Date’) # Set the label for the x-axis
    plt.ylabel(‘Count’) # Set the label for the y-axis
    plt.show() # Display the plot
```

Appendix B

```
# Import the pandas library for data manipulation
import pandas as pd
# Import the VADER sentiment analyzer from the NLTK library
from nltk.sentiment.vader import SentimentIntensityAnalyzer
# Load the CSV file containing the final data
file_path = ‘path/to/your/final.csv’
# Read the CSV file into a DataFrame
df = pd.read_csv(file_path)
# Initialize VADER sentiment analyzer
sia = SentimentIntensityAnalyzer() # Create an instance of SentimentIntensityAnalyzer
# Define a function to analyze sentiments
def analyze_sentiment(text):
    score = sia.polarity_scores(text)[‘compound’] # Calculate the compound sentiment score
    if score > 0.05: # If the score is greater than 0.05, classify as positive
        return ‘positive’
    elif score < −0.05: # If the score is less than −0.05, classify as negative
        return ‘negative’
    else: # Otherwise, classify as neutral
        return ‘neutral’
# Apply sentiment analysis on the ‘review_text’ column
df[‘sentiment’] = df[‘review_text’].apply(analyze_sentiment) # Apply the function to each review text
df[‘compound_score’] = df[‘review_text’].apply(lambda x: sia.polarity_scores(x)[‘compound’])
# Calculate and add the compound score for each review
# Save the results to a new CSV file
result_file_path = ‘path/to/save/sentiment_results.csv’ # Specify the path to save the results
df.to_csv(result_file_path, index = False) # Save the DataFrame to a CSV file without the index
```

Appendix C

```
# Import the pandas library, which is a powerful tool for data manipulation and analysis
import pandas as pd
# Load the dataset with the correct path
file_path = ‘Sentiment_Results_Filtered.csv’ # The path to the CSV file containing the data; replace with the actual file path
```

```
df = pd.read_csv(file_path) # Reads the CSV file into a DataFrame, which is a table-like data
structure in pandas
# Define categories and their associated keywords
categories = {
    'Berlin Restaurants': 'restaurants' # General category for all restaurants in Berlin
    'Berlin Kebap': 'kebap | kebab', # Specific category for kebap restaurants; searches for
     keywords' kebap' or 'kebab'
    'Berlin Pizza': 'pizza', # Specific category for pizza restaurants; searches for keyword 'pizza'
    'Berlin Burger': 'burger' # Specific category for burger restaurants; searches for
     keyword 'burger'
}
# Initialize an empty dictionary to store results
results = {} # This dictionary will hold the mean sentiment score for each category
# Calculate sentiment scores for each category
for category, keywords in categories.items(): # Loop through each category and its associated
keywords
    if keywords: # If keywords are provided, filter the DataFrame based on these keywords
        filtered_df = df[df['review_text'].str.contains(keywords, case = False, na = False)]
        # Filters the 'review_text' column for entries containing the specified keywords
        (case insensitive)
    else: # If no keywords are specified, use the entire DataFrame for general category
        filtered_df = df
    # Calculate the mean compound score for the filtered data
    mean_score = filtered_df['Sentiment_Score'].mean() # Computes the average sentiment
    score for the filtered data
    results[category] = mean_score # Stores the mean score in the results dictionary with the
    category as the key
# Convert results to a DataFrame for better visualization
results_df = pd.DataFrame(list(results.items()), columns = ['Category', 'Mean Sentiment Score'])
# Converts the results dictionary into a DataFrame for easy viewing and analysis, with 'Category'
and 'Mean Sentiment Score' as columns
# Save the results
results_df.to_csv('Sentiment_Scores_By_Category.csv', index = False)
# Saves the DataFrame to a new CSV file named 'Sentiment_Scores_By_Category.csv' without the
index column
# Display the results
print(results_df) # Prints the results DataFrame to the console
```

Appendix D

```
# Import the pandas library, which is a powerful tool for data manipulation and analysis
import pandas as pd
# Import the pearsonr function from scipy.stats for calculating the Pearson correlation coefficient
and p-value
from scipy.stats import pearsonr
# Import numpy, a fundamental package for array computing with Python
import numpy as np

# Load the sentiment analysis dataset
sentiment_df = pd.read_csv('Sentiment_Results_Filtered.csv') # Reads the sentiment scores from
the CSV file into a DataFrame
# Load the restaurant ratings dataset
ratings_df = pd.read_csv('rate_rest.csv') # Reads the restaurant ratings from the CSV file into a
DataFrame
# Merge the two datasets on the common column 'restaurant_name'
merged_df = pd.merge(sentiment_df, ratings_df, on = 'restaurant_name')
# Combines the sentiment scores and ratings into a single DataFrame using the restaurant names
as the key
```

```
# Check for missing values in the 'rating' and 'Sentiment_Score' columns
print("Missing values in 'rating':", merged_df['rating'].isnull().sum()) # Counts and prints the number of missing values in the 'rating' column
print("Missing values in 'Sentiment_Score':", merged_df['Sentiment_Score'].isnull().sum())
# Counts and prints the number of missing values in the 'Sentiment_Score' column
# Check for infinite values in the 'rating' and 'Sentiment_Score' columns
print("Infinite values in 'rating': ", np.isinf(merged_df['rating']).sum()) # Counts and prints the number of infinite values in the 'rating' column
print("Infinite values in 'Sentiment_Score': ", np.isinf(merged_df['Sentiment_Score']).sum())
# Counts and prints the number of infinite values in the 'Sentiment_Score' column
# Replace infinite values with NaN and remove rows with NaN values in 'rating' or 'Sentiment_Score'
cleaned_df = merged_df.replace([np.inf, -np.inf], np.nan).dropna(subset = ['rating', 'Sentiment_Score'])
# Cleans the data by replacing any infinite values with NaN and dropping rows where 'rating' or 'Sentiment_Score' is missing
# Verify that there are no more missing or infinite values
print("Cleaned data—missing values in 'rating': ", cleaned_df['rating'].isnull().sum()) # Rechecks and prints the number of missing values in the cleaned 'rating' column
print("Cleaned data—missing values in 'Sentiment_Score': ", cleaned_df['Sentiment_Score'].isnull().sum()) # Rechecks and prints the number of missing values in the cleaned 'Sentiment_Score' column
# Calculate the Pearson correlation coefficient and p-value between restaurant ratings and sentiment scores
corr_coefficient, p_value = pearsonr(cleaned_df['rating'], cleaned_df['Sentiment_Score'])
# Uses the pearsonr function to compute the correlation and p-value, indicating the strength and significance of the relationship between the two variables
# Display the Pearson correlation coefficient and p-value
print(f'Pearson correlation coefficient: {corr_coefficient:.2f}') # Prints the calculated correlation coefficient with two decimal places
print(f'p-value: {p_value:.5f}') # Prints the calculated p-value with five decimal places
```

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