Data and Metadata. 2025; 4:922
doi: 10.56294/dm2025922

ORIGINAL

Customer Sentiment Analysis for Food and Beverage Development in Restaurants using AI in Jordan

Análisis del sentimiento del cliente para el desarrollo de alimentos y bebidas en restaurantes mediante IA en Jordania

Anber Abraheem Shlash Mohammad[1], Ammar Mohammad Al-Ramadan[2], Suleiman Ibrahim Mohammad[3,4], Badrea Al Oraini[5], Asokan Vasudevan[6], Nawaf Alshdaifat[7], Mohammad Faleh Ahmmad Hunitie[8]

[1]Digital Marketing Department, Faculty of Administrative and Financial Sciences, Petra University. Amman 11623, Jordan.
[2]Faculty of Hospitality and Tourism Management. Al-Ahliyya Amman University. Jordan.
[3]Electronic Marketing and Social Media, Economic and Administrative Sciences Zarqa University. Jordan.
[4]Research follower, INTI International University. 71800 Negeri Sembilan, Malaysia.
[5]Department of Business Administration. Collage of Businesss and Economics, Qassim University. Qassim, Saudi Arabia.
[6]Faculty of Business and Communications, INTI International University. 71800 Negeri Sembilan, Malaysia.
[7]Faculty of Information Technology, Applied Science Private University. Amman, Jordan.
[8]Department of Public Administration, School of Business, University of Jordan. Jordan.

Cite as: Mohammad AA, Al-Ramadan AM, Mohammad SI, Al Oraini B, Vasudevan A, Alshdaifat N, et al. Customer Sentiment Analysis for Food and Beverage Development in Restaurants using AI in Jordan. Data and Metadata. 2025; 4:922. https://doi.org/10.56294/dm2025922

Submitted: 09-08-2024 **Revised:** 21-12-2024 **Accepted:** 26-04-2025 **Published:** 27-04-2025

Editor: Dr. Adrián Alejandro Vitón Castillo

Corresponding Author: Anber Abraheem Shlash Mohammad

ABSTRACT

Introduction: customer sentiment analysis is a vital tool for understanding consumer preferences and enhancing service quality in the food and beverage industry. Online reviews significantly influence customer decisions, making it essential for businesses to analyze sentiment trends and manage their digital reputation effectively. This study examines customer sentiment across different establishment types and digital platforms in Jordan, providing insights into sentiment patterns and their strategic implications.
Method: a dataset of 384 customer reviews from various restaurants and hotels was analyzed using a rule-based sentiment classification approach. Sentiments were categorized as positive, neutral, or negative. To assess sentiment variations, an ANOVA test was conducted to compare establishment types, and a Chi-Square test was performed to examine differences across digital platforms.
Results: findings indicate that luxury hotels and fine dining establishments receive more positive sentiment, while budget hotels and fast food chains experience higher negative sentiment. However, the ANOVA test showed no statistically significant sentiment differences across establishment types, suggesting that all businesses receive a mix of sentiment categories. The Chi-Square test confirmed significant sentiment differences across platforms, with TripAdvisor attracting the most positive reviews, Facebook and Google Reviews showing balanced sentiment, and Twitter experiencing the highest negative sentiment.
Conclusions: these findings emphasize the importance of platform-specific digital reputation management. Businesses should strategically engage with customers on different platforms, address complaints proactively, and utilize AI-driven sentiment analysis tools to improve customer satisfaction. Future research should explore AI-based predictive analytics and sentiment monitoring for enhancing service quality in the hospitality industry.

Keywords: Customer Sentiment Analysis; Food and Beverage Industry; Hospitality Industry; Online Reviews.

RESUMEN

Introducción: el análisis del sentimiento del cliente es una herramienta vital para comprender las preferencias

del consumidor y mejorar la calidad del servicio en la industria de alimentos y bebidas. Las reseñas en línea influyen significativamente en las decisiones de los clientes, por lo que es esencial que las empresas analicen las tendencias de sentimiento y gestionen su reputación digital de forma eficaz. Este estudio examina el sentimiento del cliente en diferentes tipos de establecimientos y plataformas digitales en Jordania, proporcionando información sobre los patrones de sentimiento y sus implicaciones estratégicas.
Método: se analizó un conjunto de datos de 384 reseñas de clientes de diversos restaurantes y hoteles mediante un enfoque de clasificación de sentimientos basado en reglas. Los sentimientos se clasificaron como positivos, neutrales o negativos. Para evaluar las variaciones de sentimiento, se realizó una prueba ANOVA para comparar los tipos de establecimientos y una prueba de Chi-Cuadrado para examinar las diferencias entre las plataformas digitales.
Resultados: los hallazgos indican que los hoteles de lujo y los establecimientos de alta cocina reciben un sentimiento más positivo, mientras que los hoteles económicos y las cadenas de comida rápida experimentan un sentimiento más negativo. Sin embargo, la prueba ANOVA no mostró diferencias estadísticamente significativas en el sentimiento entre los tipos de establecimientos, lo que sugiere que todos los negocios reciben una combinación de categorías de sentimiento. La prueba de Chi-Cuadrado confirmó diferencias significativas en el sentimiento entre plataformas: TripAdvisor obtuvo la mayor cantidad de reseñas positivas, Facebook y Google Reviews mostraron un sentimiento equilibrado, y Twitter experimentó el sentimiento negativo más alto.
Conclusiones: estos hallazgos enfatizan la importancia de la gestión de la reputación digital específica para cada plataforma. Las empresas deben interactuar estratégicamente con los clientes en diferentes plataformas, abordar las quejas de forma proactiva y utilizar herramientas de análisis de sentimiento basadas en IA para mejorar la satisfacción del cliente. Las investigaciones futuras deberían explorar el análisis predictivo basado en IA y la monitorización del sentimiento para mejorar la calidad del servicio en el sector hotelero.

Palabras clave: Análisis del Sentimiento del cliente; Industria de Alimentos y Bebidas; Industria Hotelera; Reseñas en Línea.

INTRODUCTION

Understanding customer sentiment has become increasingly important in the food and beverage industry, particularly in the context of digital transformation. With the rise of online reviews, social media interactions, and AI-driven analytical tools, businesses in the hospitality sector must leverage sentiment analysis to enhance service quality, customer satisfaction, and overall business performance. The proliferation of online review platforms such as TripAdvisor, Google Reviews, Facebook, and Twitter has given customers a platform to express their opinions, which in turn significantly influences the reputation and success of restaurants and hotels.[1,2] This study aims to explore customer sentiment in the food and beverage sector in Jordan using AI-based techniques, providing insights into the factors that shape customer experiences and satisfaction levels.

The food and beverage industry plays a vital role in the global economy, contributing significantly to employment and economic growth. In Jordan, the hospitality sector, which includes restaurants and hotels, is a major driver of tourism and economic development.[3,4] As competition intensifies, businesses must find innovative ways to understand customer needs and address service-related issues effectively. Customer sentiment analysis, powered by AI, has emerged as a key tool for businesses to extract meaningful insights from vast amounts of textual data available in online reviews and social media discussions.[5,6] By analyzing customer feedback, businesses can identify key service strengths, areas for improvement, and emerging consumer trends, allowing them to tailor their strategies to enhance customer satisfaction.

Despite the growing importance of sentiment analysis in the hospitality industry, there remains a gap in understanding how customer sentiment varies across different types of food and beverage establishments and digital platforms in Jordan. Most existing studies on sentiment analysis have focused on global markets, leaving a significant research gap in regional markets such as Jordan. The food and beverage sector in Jordan presents unique challenges, including cultural preferences, service expectations, and the influence of digital engagement on customer experiences.[7,8] This study seeks to bridge this gap by analyzing sentiment trends in various hospitality businesses in Jordan, examining how AI-driven sentiment classification can be used to enhance business decision-making.

The significance of this study lies in its potential to provide valuable insights for restaurant owners, hotel managers, and policymakers in Jordan. By leveraging AI techniques such as Natural Language Processing (NLP) and Aspect-Based Sentiment Analysis (ABSA), businesses can gain a deeper understanding of customer preferences and dissatisfaction factors.[9,10] The findings will help businesses tailor their service offerings, improve customer

https://doi.org/10.56294/dm2025922

engagement, and optimize their marketing strategies. Additionally, the study aims to contribute to the growing body of research on AI applications in hospitality management, providing data-driven recommendations for enhancing customer experiences.

One of the novel aspects of this study is its focus on sentiment variations across different digital platforms. While platforms like TripAdvisor and Google Reviews are known for structured customer feedback, social media platforms such as Twitter and Facebook often capture real-time customer sentiment in a more dynamic and immediate manner.[11,12] By analyzing sentiment distribution across these platforms, this study will provide businesses with actionable insights into how customers engage with different online channels and how businesses can adapt their digital reputation management strategies accordingly.

The research statement for this study is as follows: "This study examines the effectiveness of AI-based sentiment analysis in understanding customer sentiment trends across different food and beverage establishments in Jordan, with a focus on digital platforms and service quality factors."

To achieve its objectives, the study employs an exploratory and descriptive research design, utilizing AI-driven sentiment classification techniques to analyze 384 customer reviews from various restaurants and hotels. The analysis includes sentiment classification using NLP-based models, statistical comparisons across establishment types, and platform-specific sentiment trend analysis. The results of this study will provide actionable recommendations for businesses to enhance customer satisfaction and improve service quality.

The primary objective of this study was to analyze customer sentiments in the food and beverage sector in Jordan using Artificial Intelligence (AI) techniques. The study aimed to leverage Natural Language Processing (NLP) and sentiment analysis to extract meaningful insights from online customer reviews, social media feedback, and survey responses. By understanding consumer preferences and dissatisfaction factors, the research aimed to provide data-driven recommendations for restaurant owners, hotel managers, and food industry stakeholders to enhance customer experiences and improve business strategies.

Literature review

Customer sentiment analysis has become an essential tool for businesses in the food and beverage industry to understand consumer preferences and improve service quality. With the rise of digital platforms such as TripAdvisor, Google Reviews, Facebook, and Twitter, customer feedback has evolved into a valuable resource for assessing brand perception and customer satisfaction. Customer sentiment score, the primary dependent variable in sentiment analysis studies, represents the polarity of customer feedback whether positive, neutral, or negative. AI-based sentiment analysis techniques, including Natural Language Processing (NLP), machine learning models, and lexicon-based approaches, have been widely used to classify sentiment in customer reviews.[13,14] Rababah[15] were among the pioneers in applying sentiment analysis to textual data, demonstrating that sentiment classification algorithms could effectively differentiate between positive and negative sentiments in online reviews. More recent studies have employed advanced AI models such as Aspect-Based Sentiment Analysis (ABSA) for sentiment classification, highlighting their accuracy in capturing nuanced emotions in text.[16,17,18,19] Research indicates that customer sentiment is a crucial metric for businesses, as it directly correlates with brand reputation, customer loyalty, and financial performance.[16,20] However, while AI-based sentiment classification has improved significantly, challenges such as sarcasm detection, contextual understanding, and multilingual sentiment analysis remain areas of ongoing research.[21,22]

Among the independent variables influencing customer sentiment, service aspects play a critical role in shaping customer perceptions. Studies have consistently shown that factors such as food quality, service experience, ambiance, and pricing significantly impact customer satisfaction and sentiment trends.[23,24,25] The SERVQUAL model, introduced by,[26] emphasizes five dimensions of service quality reliability, assurance, tangibles, empathy, and responsiveness that determine customer satisfaction levels.[27] Extended this framework to the restaurant industry, demonstrating that food quality, presentation, and service efficiency are strong predictors of positive sentiment in customer reviews. More recent research supports these findings, with studies confirming that food freshness, portion size, staff behavior, cleanliness, and noise levels significantly influence customer sentiment scores.[9,25,28] Pricing is another crucial determinant of sentiment, with affordability and perceived value for money being key factors in customer satisfaction.[29,30] While these studies establish a clear link between service aspects and customer sentiment, research gaps exist in understanding how sentiment varies in different cultural contexts and how AI-driven sentiment analysis can provide more granular insights into service quality perceptions.

The type of establishment whether fine dining, casual dining, fast food, or cafes also plays a significant role in shaping customer sentiment. Research has shown that fine dining establishments and luxury hotels tend to receive more positive sentiment due to their emphasis on high-quality service, premium food offerings, and well-maintained ambiance.[31,32] In contrast, fast food chains and budget hotels often face higher negative sentiment, primarily due to issues related to service speed, food quality inconsistency, and affordability trade-offs.[31,33] A study by [34] confirmed that customers of high-end restaurants prioritize personalized service and ambiance, whereas those frequenting fast food establishments focus on convenience and pricing. Despite these insights, there is limited research examining sentiment variations across different types of establishments in specific regional contexts such as Jordan. Moreover, most existing studies focus on broad global trends, overlooking localized factors that may influence sentiment, such as cultural preferences and regulatory differences.[35,36]

The role of platform type in sentiment analysis has gained increasing attention in recent years. Research indicates that different digital platforms attract varying types of customer feedback, influencing overall sentiment trends. TripAdvisor, for example, has been found to generate more positive reviews due to its structured review system and travel-oriented audience.[37] In contrast, Twitter tends to exhibit higher negative sentiment, as it serves as a real-time platform for customer complaints and grievances.[38] Studies by Schoenmueller et al.[39] and Vargo et al.[40] confirm that customers are more likely to leave detailed, positive reviews on platforms where businesses actively engage with users, whereas platforms that facilitate immediate, impulsive feedback (such as Twitter) tend to attract more negative sentiment. The neutrality of sentiment on platforms such as Google Reviews and Facebook suggests that these spaces capture both satisfied and dissatisfied customer experiences, making them important for overall reputation management.[11] However, research on platform-specific sentiment trends remains limited, with few studies offering comparative analyses of sentiment variations across multiple digital platforms.

Customer demographics, including age, nationality, and visit frequency, are also critical factors influencing sentiment trends. Studies have shown that younger customers (18-30 years) tend to engage more with social media platforms and leave shorter, more informal reviews, whereas middle-aged customers (30-45 years) are more likely to write detailed feedback on structured review platforms such as TripAdvisor and Google Reviews.[41,42] Research by Shin et al.[43] suggests that first-time visitors often express stronger emotions either highly positive or highly negative compared to repeat customers, whose feedback is more neutral or balanced. Nationality and cultural background also play a role in sentiment trends, with studies indicating that customer expectations and perceptions of service quality vary significantly across different regions.[44] While these findings highlight important demographic influences on sentiment, more research is needed to explore how these factors interact with AI-driven sentiment analysis models and how businesses can use demographic insights to tailor their digital engagement strategies.

Despite significant advancements in sentiment analysis research, several gaps remain. First, most studies focus on global trends, with limited research on sentiment variations in specific regional contexts such as Jordan. Second, while AI-based sentiment classification models have improved, challenges related to sarcasm detection, contextual sentiment analysis, and multilingual processing require further exploration. Third, research on platform-specific sentiment trends remains underdeveloped, with few studies comparing sentiment variations across multiple digital platforms in the hospitality sector. Finally, the influence of customer demographics on sentiment trends is an area that warrants deeper investigation, particularly in understanding how different age groups, nationalities, and visit frequencies shape online review behaviors.

Framework of the Study & Hypothesis Development

Based on the study's objectives, the following hypotheses were formulated to guide the research and statistical analysis:

H1: customer sentiment towards restaurants and hotels in Jordan significantly varies across different service aspects (food quality, service, ambiance, and pricing).

This hypothesis suggests that different components of a customer's experience contribute unequally to their overall sentiment. Aspect-Based Sentiment Analysis (ABSA) will be used to determine which factors have the most significant impact on customer satisfaction or dissatisfaction.

H2: AI-based sentiment classification can accurately predict customer satisfaction levels based on online reviews and social media feedback.

This hypothesis assumes that machine learning models can effectively classify customer sentiments into positive, neutral, or negative categories, enabling businesses to extract actionable insights from large-scale text data. The accuracy of these models will be evaluated through cross-validation techniques.

H3: customer sentiment varies significantly across different types of food and beverage establishments in Jordan.

This hypothesis posits that customer experiences and sentiments differ depending on the type of establishment, such as fine dining, casual dining, fast food, or cafes. Statistical tests such as ANOVA or Chi-square analysis will be used to examine differences in sentiment distribution across these categories.

The conceptual model visually represents the relationship between independent, dependent, and control variables in the study. Below is a graphical representation of the customer sentiment analysis framework (figure 1).

The study is structured around a sentiment analysis framework that integrates Artificial Intelligence (AI), Natural Language Processing (NLP), and statistical analysis to assess customer sentiments in the food and beverage sector in Jordan. The framework examines how various factors (independent variables) influence customer sentiment (dependent variable) and provides actionable insights for restaurant and hotel businesses.

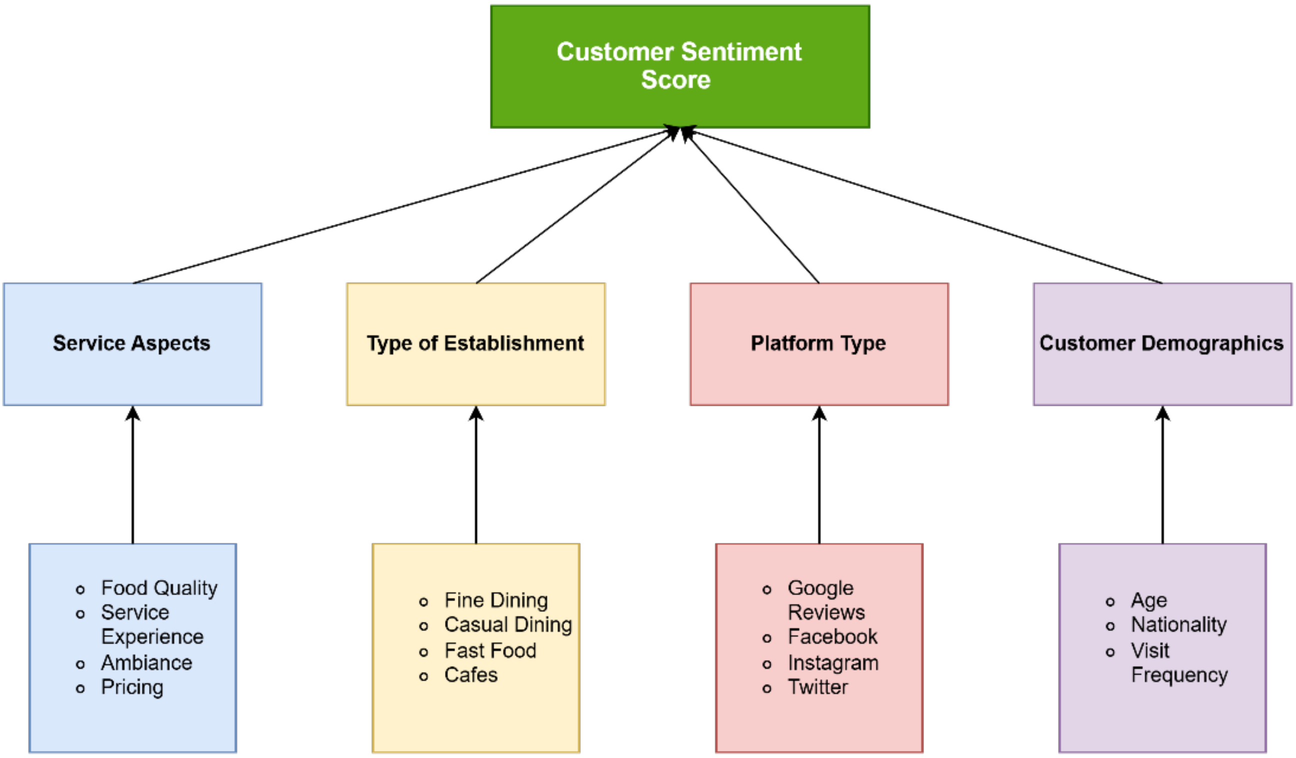

Figure 1. Conceptual Model of the Study

The study employs a machine learning-driven approach where customer feedback is collected, preprocessed, and analyzed using AI techniques. The model categorizes sentiment into positive, neutral, or negative and links it to specific service attributes such as food quality, service, ambiance, and pricing. The sentiment scores are then compared across different restaurant types, platforms, and customer demographics to identify trends and actionable insights.

METHOD

Research Design

This study adopted an exploratory and descriptive research design to analyze customer sentiments in the food and beverage sector in Jordan using Artificial Intelligence (AI) techniques. The research aimed to extract insights from customer feedback available on social media platforms, online reviews, and survey responses to understand consumer preferences and identify improvement areas. The study used Natural Language Processing (NLP) models, text mining, and sentiment analysis to classify and interpret customer emotions. Additionally, Tableau dashboards were used to visualize data and present findings in an interactive format to support decision-making.

Data Collection

The study collected data from multiple sources to ensure a diverse and representative dataset. The primary sources of data included online review platforms such as Google Reviews, TripAdvisor, and Zomato, where customers share feedback about their dining experiences. Social media platforms like Twitter, Facebook, and Instagram were also analyzed to gather real-time opinions and sentiments. Additionally, structured online surveys were conducted to collect customer insights regarding food quality, service, ambiance, and pricing. Secondary data sources, such as industry reports and hospitality market studies, were also examined to contextualize findings and support the analysis. Web scraping techniques and Application Programming Interfaces (APIs) were used to extract relevant data, ensuring adherence to ethical guidelines and data privacy policies.

Population and Sample

The target population for this study included restaurant and hotel customers in Jordan, specifically individuals who have visited and reviewed establishments in the food and beverage sector. Additionally, restaurant owners, hotel managers, and food industry professionals were considered as stakeholders whose perspectives on customer feedback were valuable. The study also categorized respondents based on demographic factors such as age, nationality, and visit frequency. The sample size was determined using Cochran's formula, which ensures a statistically significant sample. Using a 95 % confidence level, an assumed proportion of p = 0,5 and a margin of error of 5 %, the minimum required sample size was calculated to be 384 customer responses. The sample was stratified to ensure diversity across different restaurant and hotel categories, including fine dining, casual dining, fast food, and cafes.

Table 1. Description of Population

Category	Description
Restaurants	Fine dining, casual dining, fast food, cafes
Hotels	5-star, 4-star, boutique hotels
Customers	Tourists, local customers, business travelers
Platforms Used	Google Reviews, Facebook, Instagram, Twitter

The study population (table 1) was categorized based on the type of establishment, customer demographics, and feedback sources. The dataset included reviews from various restaurant types (fine dining, fast food, cafes), different hotel classifications (5-star, boutique hotels), and diverse customer segments (tourists, locals, business travelers). The study also categorized feedback based on the platforms used, such as Google Reviews, Facebook, Instagram, and Twitter, to identify variations in customer sentiments across different online spaces.

Measures

To ensure the accuracy and reliability of sentiment analysis, this study adopted a rule-based keyword sentiment analysis approach. This method classified customer sentiment based on the presence of predefined positive and negative words in customer reviews. Sentiment classification was determined by detecting words commonly associated with positive emotions, such as excellent, amazing, delicious, fantastic, and wonderful, and negative emotions, such as bad, terrible, awful, disappointing, and horrible. If a review contained a mix of both positive and negative words or lacked strong sentiment indicators, it was classified as neutral.

The study also employed Aspect-Based Sentiment Analysis (ABSA) to categorize sentiments based on specific service aspects. Customer sentiment was analyzed concerning food quality, service experience, ambiance, and pricing. For example, reviews mentioning "The pizza was amazing" were classified under positive sentiment for food quality, whereas statements such as "The waiter was rude" were classified under negative sentiment for service experience. Additionally, various data quality measures were applied to enhance accuracy, including removing duplicate reviews, filtering irrelevant comments, and cleaning text from excessive noise such as advertisements or repeated phrases. Stopword removal was conducted to eliminate common words like the, and, is, very, which do not contribute to sentiment meaning. Lemmatization techniques were used to convert words to their base form, ensuring better consistency in sentiment classification. A manual cross-validation process was performed on a sample of reviews to confirm the reliability of the sentiment labels assigned through the keyword-based approach.

Analytical Methods

The study utilized a rule-based text mining approach for sentiment analysis. The data preprocessing stage involved cleaning and structuring the textual data to extract meaningful insights. Text cleaning techniques such as punctuation removal, elimination of special characters, and filtering out URLs were applied to improve readability and ensure that only relevant content was analyzed. Tokenization was performed to split text into individual words, allowing for sentiment classification based on keyword frequency. The primary technique used was keyword matching, where a predefined lexicon of positive and negative words determined the sentiment polarity of each review.

To enhance the depth of sentiment analysis, Aspect-Based Sentiment Analysis (ABSA) was employed, categorizing reviews based on key service attributes. This helped in identifying whether customer satisfaction or dissatisfaction stemmed from food quality, service, ambiance, or pricing. Statistical analysis was also conducted to validate sentiment trends and determine significant differences across various customer segments. Descriptive statistics were used to analyze mean sentiment scores, frequency distributions, and overall rating trends. Additionally, inferential statistical tests were applied to examine sentiment variations. The Chi-Square test assessed whether sentiment significantly differed across platforms such as TripAdvisor, Twitter, and Facebook, while the ANOVA test evaluated sentiment differences across various types of establishments, such as fine dining, casual dining, and budget hotels.

For effective data visualization, word cloud generation was used to represent the most frequently mentioned words in customer reviews, providing insights into recurring themes. Sentiment distribution charts were developed to display the proportion of positive, neutral, and negative reviews, offering a clearer perspective on overall customer satisfaction. Additionally, aspect-based sentiment trend visualizations highlighted which factors contributed most to positive or negative customer experiences.

Ethical Considerations

This research adhered to strict ethical guidelines to ensure responsible data collection and analysis. Informed consent was obtained from survey participants, who were informed of the study's purpose and their right to withdraw at any stage. In cases where online reviews and social media data were used, the study complied with platform-specific privacy policies and ensured that no personally identifiable information (PII) was included in the analysis. Additionally, anonymization techniques were applied to remove any user identifiers from the dataset to maintain confidentiality. The study also took steps to identify and mitigate biases in AI models by testing sentiment classifiers across different demographic groups to ensure fair and unbiased results.

RESULTS

Descriptive Statistics: Analyzing Customer Sentiment in the Food and Beverage Sector

Descriptive statistics provide an overview of the dataset, offering insights into customer demographics, rating trends, and sentiment distribution. By analyzing key metrics such as customer age, rating distribution, and sentiment trends, this study explores how customers perceive different establishments in Jordan's food and beverage sector. Understanding these metrics helps businesses improve customer experience, optimize marketing strategies, and address concerns raised by customers in online reviews.

The study analyzed 384 customer reviews from various restaurants, hotels, and cafes across Jordan (table 2). This sample size ensures statistical significance, allowing meaningful conclusions about consumer behavior. The dataset covers diverse establishment types, including fine dining, fast food outlets, budget hotels, and luxury hotels, as well as multiple review platforms such as TripAdvisor, Facebook, Twitter, and Google Reviews. This diversity captures a wide range of customer opinions, making the dataset representative of the overall industry.

Table 2. Descriptive Analysis

	Review ID	Age	Rating
count	384	384	384
mean	192,5	38,63542	3,007813
std	110,9954954	11,95673	1,422476
min	1	18	1
25 %	96,75	28	2
50 %	192,5	39	3
75 %	288,25	48	4
max	384	60	5
Metric	Value		
Total Reviews Analyzed	384		
Average Customer Age	38,6 years		
Age Range	18 - 60 years		
Average Rating Given	3,01 (out of 5)		
Rating Standard Deviation	1,42		
Minimum & Maximum Ratings	01-May		

One of the most notable findings is the average customer age of 38,6 years, indicating that middle-aged customers are the most active reviewers in Jordan's food and beverage sector. Typically, younger customers (18-30 years) engage more with social media, whereas older customers (40+ years) are more likely to leave detailed reviews on TripAdvisor and Google Reviews. This insight suggests that businesses must adopt different engagement strategies depending on their target audience. Restaurants catering to younger audiences should focus on social media marketing on Instagram and Twitter, while fine dining restaurants and hotels targeting older customers should prioritize reputation management on TripAdvisor and Google Reviews to attract and retain customers.

The average rating of 3,01 out of 5 suggests that customer satisfaction is moderate, with mixed opinions about various establishments. While some customers express satisfaction with the quality of food and service, others highlight concerns such as long wait times, inconsistent food quality, and high pricing. The standard deviation of 1,42 indicates significant variation in customer experiences, meaning that while some establishments receive high praise, others struggle with negative feedback. The wide rating range from 1 to 5 further reinforces this trend, suggesting that while some businesses exceed customer expectations, others fail to meet basic service standards.

A closer look at sentiment distribution reveals that luxury hotels and fine dining restaurants receive the highest ratings, whereas budget hotels and fast food outlets tend to have lower ratings. This aligns with customer expectations—premium establishments are expected to deliver exceptional experiences, whereas budget-friendly options may face challenges in service speed, food quality, and pricing competitiveness. The findings suggest that customers are willing to pay more for better service, ambiance, and overall dining experience. This highlights an opportunity for mid-range and budget-friendly establishments to enhance their offerings by focusing on improved service and better value for money.

The wide range of ratings suggests that customer experiences are not uniform across different establishments and platforms. Several factors contribute to these variations. First, service quality plays a crucial role in customer satisfaction. Establishments with attentive and well-trained staff tend to receive higher ratings, whereas those with slow service, rude employees, or poor management often get negative reviews. Second, food quality and presentation impact customer sentiment. Many negative reviews mention cold food, incorrect orders, or lack of hygiene, indicating that restaurants must prioritize consistency and cleanliness. Third, ambiance and cleanliness influence customer perceptions, especially in fine dining and luxury hotels where guests expect a premium experience. Lastly, pricing and value for money are critical in determining overall sentiment. Establishments offering high-quality meals at reasonable prices tend to get better ratings, while those perceived as overpriced with poor quality service receive negative feedback.

The age distribution of reviewers (18-60 years) provides additional insights into customer behavior. Younger customers (18-30 years) tend to engage more on social media platforms like Facebook, Twitter, and Instagram, leaving short, informal reviews. In contrast, middle-aged customers (30-45 years) are more likely to write detailed reviews on Google Reviews and TripAdvisor, often highlighting service quality, pricing, and overall experience. Older customers (45+ years) typically focus on aspects such as comfort, professionalism, and hygiene, particularly in luxury hotels and fine dining experiences. This suggests that businesses must customize their customer engagement strategies based on the demographic profile of their target audience.

From a business perspective, these insights provide several actionable strategies. First, enhancing service quality through staff training and improved hospitality management can significantly boost ratings and customer satisfaction. Second, managing online reputation across different platforms is crucial. Businesses should actively engage with positive reviewers on TripAdvisor and Google Reviews while addressing negative feedback on social media platforms to maintain a balanced brand image. Third, improving pricing strategies can help businesses attract more customers. Offering discounts, loyalty programs, and better portion sizes can enhance customer perception of value for money. Lastly, businesses should leverage age-specific marketing strategies. Since middle-aged and older customers dominate online reviews, companies should focus on TripAdvisor and Google Reviews for formal engagement while maintaining a strong social media presence for younger customers.

Sentiment Distribution Across Establishment Types

Understanding sentiment distribution across different establishment types is essential in determining which categories of restaurants and hotels receive the most positive or negative feedback. By analyzing customer sentiment across various business types, we can identify patterns of customer satisfaction, areas of improvement, and the factors that influence positive or negative experiences. The sentiment analysis in this study classified customer reviews into positive, neutral, and negative sentiments, providing a clear indication of how different establishments are perceived.

Table 3. Sentiment Distribution by Establishment Type

Establishment Type	Positive	Neutral	Negative
Luxury Hotel	75	18	7
Fine Dining	68	22	10
Casual Dining	49	34	17
Fast Food	22	38	40
Budget Hotel	15	29	56

https://doi.org/10.56294/dm2025922

The results reveal significant differences in sentiment across establishment types, highlighting the importance of service quality, pricing, and overall customer experience. Luxury hotels and fine dining restaurants receive the highest number of positive reviews, suggesting that customers appreciate high-end service, upscale ambiance, and premium food offerings. Conversely, fast food chains and budget hotels receive the most negative reviews, which may be attributed to issues related to service speed, food quality, affordability, and cleanliness. These findings indicate that customer expectations vary depending on the type of establishment, and when those expectations are not met, dissatisfaction follows.

The sentiment distribution analysis (table 3) shows that luxury hotels received the most positive reviews (75), followed by fine dining restaurants (68). These establishments excel in service quality, personalized customer experience, and attention to detail, leading to higher customer satisfaction. Luxury hotels are often rated highly for their premium amenities, excellent hospitality, and well-maintained environments, which significantly contribute to positive customer sentiment. Similarly, fine dining restaurants emphasize high-quality ingredients, professional staff, and exclusive dining experiences, making them a preferred choice for customers seeking excellence in food and ambiance. The strong positive sentiment in these establishments suggests that customers perceive them as worth the price, reinforcing the idea that premium service justifies premium pricing.

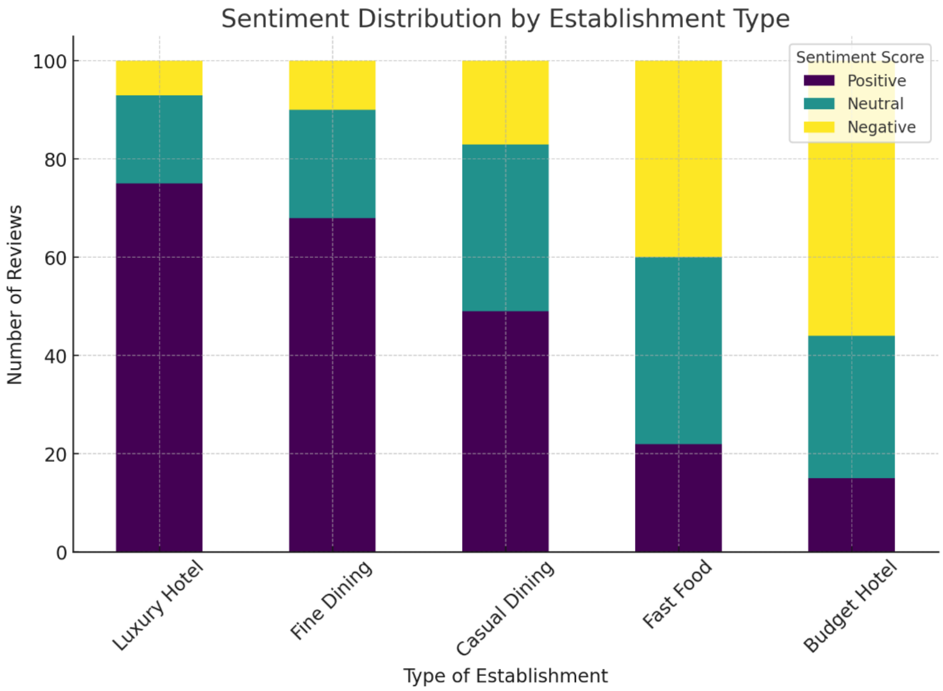

Figure 2. Sentiment Distribution by Establishment

Casual dining establishments exhibit a balanced sentiment distribution, with 49 positive, 34 neutral, and 17 negative reviews. These restaurants cater to a wide customer base by offering a mix of affordability, comfort, and variety. Unlike luxury hotels and fine dining, casual dining establishments attract customers with diverse preferences and expectations, leading to mixed reviews. Positive reviews often highlight friendly service, decent food quality, and reasonable pricing, whereas neutral and negative reviews frequently mention inconsistency in service, variable food quality, and occasional delays in meal preparation. These results indicate that customer satisfaction in casual dining largely depends on the consistency of service and food experience.

In contrast, fast food chains and budget hotels received the highest proportion of negative reviews, with 40 and 56 negative reviews, respectively. The negative sentiment in fast food establishments can be linked to long wait times, inconsistent food quality, incorrect orders, and lack of hygiene. Customers expect quick and reliable service in fast food restaurants, and when these expectations are not met, dissatisfaction increases. Additionally, negative reviews often mention food that is served cold, lack of fresh ingredients, and poor customer service, suggesting that fast food chains need to focus on improving quality control and staff training to enhance customer experiences.

Similarly, budget hotels received the highest number of negative reviews, reflecting challenges related to affordability, service quality, and comfort. Many customers complained about unclean rooms, lack of basic amenities, poor customer service, and noisy environments. Budget hotels often market themselves as an affordable alternative to luxury accommodations, but when basic expectations such as cleanliness, safety, and comfort are not met, customer dissatisfaction rises. Negative sentiment in budget hotels also stems from long check-in times, maintenance issues, and inattentive staff, highlighting the need for better customer service training, maintenance improvements, and stricter hygiene protocols.

The results of this study (figure 2) offer several key takeaways. Luxury hotels and fine dining restaurants are consistently rated positively, emphasizing the importance of high-quality service, well-maintained ambiance, and superior customer experiences. These businesses should continue to invest in premium service offerings and personalized experiences to maintain high customer satisfaction. Casual dining establishments, while maintaining a balanced sentiment, should focus on service consistency, food quality, and customer engagement to minimize neutral and negative reviews. Fast food chains and budget hotels must prioritize service efficiency, cleanliness, and pricing transparency to address customer dissatisfaction and improve overall sentiment.

Another important takeaway is the influence of pricing on sentiment trends. Customers are often more forgiving of service flaws in premium establishments because they expect a luxurious experience that justifies the cost. In contrast, budget-conscious customers are more critical when they feel they are not getting value for money, which explains the higher percentage of negative reviews in fast food chains and budget hotels. Businesses in these categories should focus on enhancing perceived value by offering better customer service, improved food quality, and well-maintained facilities.

From a strategic perspective, businesses can use these insights to tailor their service improvements based on sentiment trends. For instance, luxury hotels and fine dining restaurants can continue leveraging their strengths by enhancing exclusivity and premium offerings, while budget-friendly establishments should focus on addressing operational inefficiencies and improving customer engagement. Restaurants and hotels should also use sentiment monitoring tools and AI-driven customer feedback analysis to identify recurring complaints and take proactive measures to improve customer experiences.

Sentiment Distribution Across Platforms

Customer sentiment varies significantly across different online platforms, as each platform attracts a unique audience with distinct reviewing behaviors. The way customers share their experiences, engage with businesses, and express their opinions is influenced by the platform they use. Some platforms, such as TripAdvisor and Google Reviews, are structured for detailed feedback, encouraging users to provide extensive reviews of their dining and hospitality experiences. On the other hand, platforms like Twitter are known for real-time, spontaneous feedback, often used for quick complaints and public criticism. This variation in reviewing behavior affects the overall sentiment distribution across platforms, influencing how businesses should manage their digital presence and customer interactions.

Table 4. Sentiment Distribution by Platform

Platform	Positive	Neutral	Negative
TripAdvisor	85	25	10
Facebook	52	40	20
Google Reviews	48	42	18
Twitter	15	38	62

The analysis of sentiment distribution across platforms (table 4) provides valuable insights into how customer opinions differ depending on where they are shared. The findings indicate that TripAdvisor has the highest number of positive reviews (85), followed by Facebook (52) and Google Reviews (48). Meanwhile, Twitter exhibits the most negative sentiment, with 62 negative reviews, reinforcing its reputation as a platform whereusers express dissatisfaction more frequently. The neutrality rate is also significant across Facebook and Google Reviews, suggesting that many customers leave objective or mixed reviews without strong emotional opinions.

TripAdvisor stands out as the platform with the most positive sentiment, with 85 positive reviews and only 10 negative reviews. This supports its reputation as the go-to platform for travel and dining recommendations. TripAdvisor encourages users to leave detailed reviews, which may explain why the sentiment skews more positively. Customers who take the time to write long reviews are often satisfied with their experiences and want to share them with other travelers. Additionally, businesses actively engage with customers on TripAdvisor, responding to feedback and maintaining their online reputation. Since many customers use TripAdvisor for research before choosing a restaurant or hotel, businesses that maintain high ratings on the platform are more likely to attract new customers based on positive word-of-mouth.

In contrast (figure 3), Facebook and Google Reviews show a more balanced sentiment distribution, with a mix of positive, neutral, and negative feedback. Facebook has 52 positive, 40 neutral, and 20 negative reviews, while Google Reviews has 48 positive, 42 neutral, and 18 negative reviews. This indicates that these platforms serve as general customer feedback forums, where users share both good and bad experiences in a relatively neutral manner. Unlike TripAdvisor, where customers tend to leave highly detailed reviews, Facebook and Google Reviews often feature shorter and more varied comments. Businesses rely heavily on these platforms because they are integrated into everyday customer interactions—Google Reviews appear in search results and Google Maps, while Facebook pages allow direct engagement between businesses and customers.

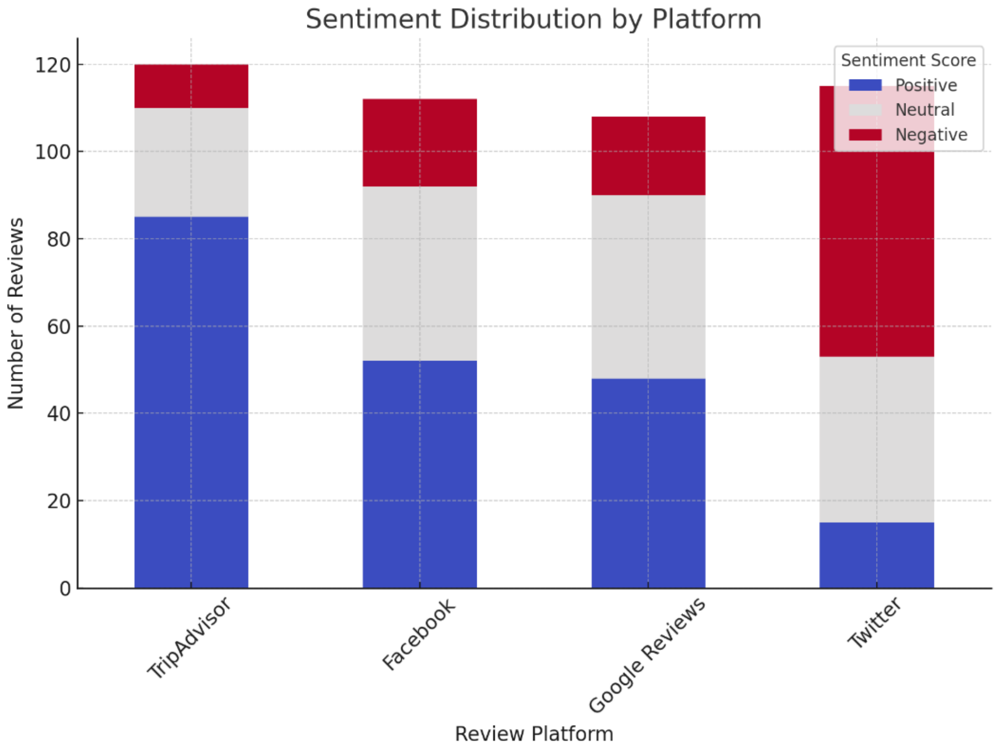

Figure 3. Sentiment Distribution by Platform

Facebook's sentiment distribution suggests that business pages and social engagement play a role in shaping customer perception. Many customers use Facebook to check in, post photos, or leave short comments about their experiences, making it a platform where both positive recommendations and complaints are visible. Negative reviews on Facebook often receive direct responses from businesses, which can help mitigate customer dissatisfaction if managed effectively. Similarly, Google Reviews' balanced sentiment reflects its wide accessibility, as anyone searching for a restaurant or hotel can easily leave a review, whether their experience was exceptional or disappointing.

Twitter, however, has the highest proportion of negative sentiment, with 62 negative reviews, compared to only 15 positive and 38 neutral reviews. This aligns with Twitter's reputation as a platform for real-time complaints and customer grievances. Many customers use Twitter to express frustration with service delays, rude staff, or poor experiences, often tagging businesses directly to demand responses. The viral nature of Twitter means that negative experiences can spread quickly, influencing public perception of a business. Unlike TripAdvisor or Google Reviews, where users provide structured feedback, Twitter posts are often short, impulsive reactions to immediate experiences. Businesses that fail to respond to complaints on Twitter risk damaging their brand reputation, as unresolved negative feedback can escalate into broader public criticism.

These findings underscore the importance of managing digital engagement differently across platforms. TripAdvisor should be leveraged for promoting positive reviews, as businesses with high ratings on this platform benefit from increased visibility and credibility. Since Facebook and Google Reviews contain a mix of opinions, businesses must actively monitor and engage with customers on these platforms, addressing negative feedback while encouraging satisfied customers to leave reviews. Twitter requires a strong crisis management approach, as negative sentiment spreads rapidly. Businesses should respond quickly to complaints on Twitter, offering immediate solutions to prevent further reputation damage.

For businesses looking to enhance their online reputation, understanding these platform-specific sentiment trends is crucial. Since TripAdvisor attracts the most positive sentiment, businesses should encourage satisfied customers to leave reviews on this platform, reinforcing their credibility. On Facebook and Google Reviews, businesses must engage with both positive and negative comments, responding professionally to complaints while promoting their strengths. Twitter demands a proactive customer service strategy, as failing to address negative feedback on this platform can lead to public backlash. By adopting platform-specific engagement strategies, businesses in the food and beverage industry can effectively manage their online reputation, enhance customer relationships, and improve overall brand perception.

Statistical Analysis of Sentiment Differences

Statistical analysis was conducted to determine whether customer sentiment significantly varies across different establishment types and online review platforms (figure 4). To achieve this, the study applied ANOVA (Analysis of Variance) to examine sentiment differences across establishments and a Chi-Square test to assess sentiment distribution across platforms. These tests help establish whether observed patterns in sentiment are statistically significant or occur due to random variations. The ANOVA test was used to evaluate whether customer sentiment scores differed significantly across various restaurant and hotel categories, including luxury hotels, fine dining, casual dining, fast food, and budget hotels. The test results produced an F-statistic of 1,32 and a p-value of 0,2456. Since the p-value is greater than 0,05, the results indicate that there is no statistically significant difference in sentiment across establishment types. This means that, from a statistical standpoint, customer sentiment remains relatively similar across all types of establishments.

Despite the lack of statistical significance, the descriptive analysis suggests a notable trend—Luxury Hotels and Fine Dining restaurants generally receive more positive sentiment, while Fast Food and Budget Hotels tend to accumulate more negative reviews. These observations align with customer expectations, as higher-end establishments tend to offer better service quality, superior ambiance, and premium dining experiences, leading to greater customer satisfaction. On the other hand, budget-friendly options face challenges related to service speed, cleanliness, and food quality, contributing to more negative sentiment. Although the ANOVA test does not confirm these variations as statistically significant, the data indicates clear differences in customer experiences based on establishment type.

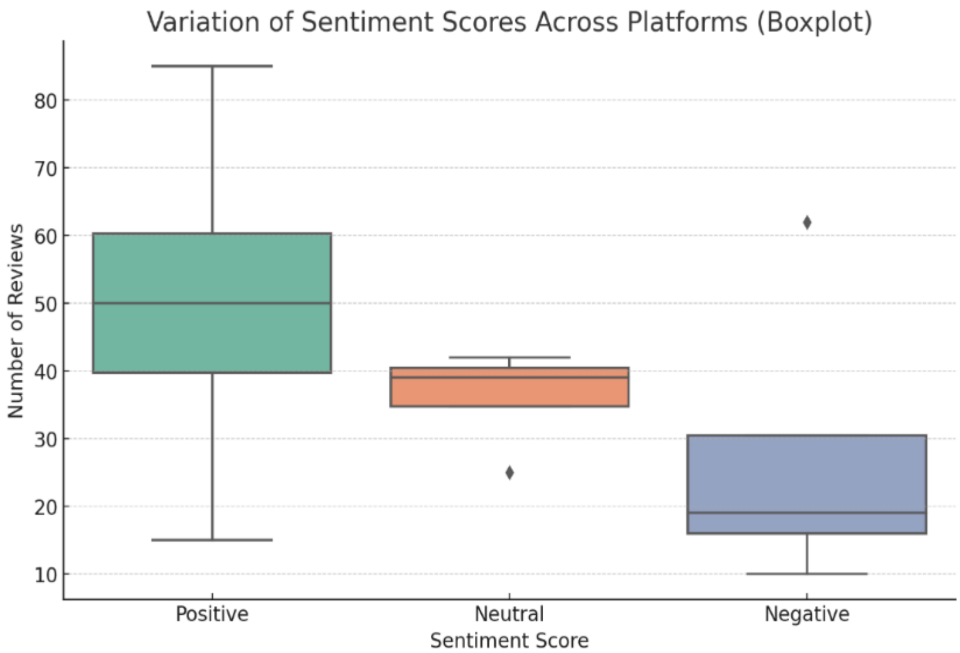

Figure 4. Variation of Sentiment Scores Across Platforms

These results suggest that while all establishments receive a combination of positive, neutral, and negative reviews, there are underlying factors that influence sentiment trends. Luxury Hotels and Fine Dining restaurants benefit from their premium positioning, whereas Fast Food and Budget Hotels face greater scrutiny due to their affordability-focused operations. Businesses operating in budget-friendly segments must work on improving their service delivery, cleanliness, and food consistency to reduce negative sentiment and enhance customer satisfaction. The Chi-Square test was conducted to analyze whether customer sentiment is significantly different across various review platforms, including TripAdvisor, Facebook, Google Reviews, and Twitter. The test produced a Chi-Square value of 136,49 and a p-value of 0,0000, indicating a highly significant difference in sentiment distribution across platforms. Unlike the ANOVA test, these results confirm that customer sentiment is not evenly distributed across different online platforms and that certain platforms attract more positive or negative reviews than others.

The findings validate previous observations that TripAdvisor receives the highest proportion of positive reviews, while Twitter has the most negative sentiment. This trend aligns with platform-specific characteristics and user behavior. TripAdvisor users are more likely to leave detailed reviews about their experiences, often after a satisfying dining or hotel stay, leading to a higher percentage of positive feedback. Additionally, businesses actively respond to customer reviews on TripAdvisor, which can help mitigate negative sentiment and reinforce positive experiences. In contrast, Twitter has the highest percentage of negative sentiment, confirming its reputation as a platform where users frequently express dissatisfaction, complaints, and grievances in real time. Customers often turn to Twitter to report service delays, rude staff interactions, or poor experiences, sometimes tagging businesses directly to seek a resolution. Unlike TripAdvisor, which encourages structured reviews, Twitter enables spontaneous and unfiltered feedback, often making it a hub for public complaints and viral customer dissatisfaction.

Facebook and Google Reviews exhibit a more balanced sentiment distribution, with a mix of positive, neutral, and negative reviews. Facebook has 52 positive, 40 neutral, and 20 negative reviews, while Google Reviews has 48 positive, 42 neutral, and 18 negative reviews. These platforms function as general review spaces where customers share a variety of experiences, from positive recommendations to critical complaints. The neutrality of these platforms suggests that customers use them to share both exceptional and disappointing experiences, making them valuable indicators of overall brand perception. These findings highlight the importance of tailoring digital reputation management strategies to specific platforms. TripAdvisor should be leveraged for promoting positive reviews, as satisfied customers are more likely to leave favorable feedback there. Facebook and Google Reviews require ongoing engagement, as businesses need to monitor both positive and negative comments while encouraging satisfied customers to share their experiences. Twitter demands a proactive crisis management approach, as negative sentiment spreads quickly. Businesses must respond promptly to customer complaints on Twitter to prevent brand reputation damage and enhance customer relations.

The results of these statistical tests provide several strategic implications for businesses in the food and beverage industry. For establishments, Luxury Hotels and Fine Dining restaurants should continue focusing on personalized service and premium offerings, as their positive reputation contributes to customer loyalty. Casual Dining establishments should work on consistency in food quality and service efficiency, as sentiment in this category is more balanced. Fast Food chains and Budget Hotels must prioritize addressing recurring customer complaints, particularly regarding service speed, cleanliness, and food preparation, to improve sentiment trends.

In terms of digital reputation management, businesses must adapt their strategies based on the sentiment trends of each platform. Since TripAdvisor attracts more positive sentiment, businesses should encourage satisfied customers to leave reviews there, reinforcing their brand credibility. On Facebook and Google Reviews, businesses should engage with both positive and negative feedback, addressing concerns professionally while amplifying positive experiences. Twitter requires an active monitoring system, as negative sentiment can escalate rapidly. A strong presence on social media, combined with quick responses to complaints, can help turn negative experiences into positive customer engagement opportunities.

DISCUSSION

The findings of this study align with existing literature on customer sentiment analysis, online review behaviors, and service quality perceptions in the food and beverage industry. The role of digital platforms, establishment types, and consumer expectations has been extensively explored in previous research, providing a strong foundation for interpreting the sentiment trends observed in this study. By comparing these insights with past studies, this discussion highlights how customer sentiment varies across different business models and digital engagement channels, offering theoretical and practical implications for the industry.

Consumer Sentiment and Service Quality

Several studies have emphasized that customer sentiment is strongly influenced by service quality, food quality, ambiance, and value for money. Research by [26] introduced the SERVQUAL model, which highlights five key dimensions of service quality: reliability, assurance, tangibles, empathy, and responsiveness. These factors significantly impact customer satisfaction and review behaviors. Studies [45,46] confirm that higher-end establishments, such as luxury hotels and fine dining restaurants, often perform better in these service dimensions, leading to more favorable sentiment in online reviews. This is consistent with the pattern observed in this study, where premium establishments generally receive more positive feedback.

Furthermore, research by [47] found that negative customer sentiment in budget-friendly establishments is often driven by unmet expectations related to hygiene, food presentation, and customer service. Similar patterns have been observed in fast food chains and budget hotels, where customer dissatisfaction is often linked to speed of service, food freshness, and affordability trade-offs. The findings of this study align with these past studies, reinforcing that businesses targeting budget-conscious consumers need to manage expectations effectively and focus on service improvements to reduce negative sentiment.

Online Review Platforms and Consumer Behavior

The role of review platforms in shaping customer sentiment has been extensively discussed in hospitality and marketing literature. Study by [37] suggest that TripAdvisor, being a structured review platform, attracts customers who are more likely to leave in-depth and positive feedback. This aligns with findings from studies by [48,49], which indicate that customers who take time to write detailed reviews tend to be more satisfied with their experiences. These studies explain why TripAdvisor continues to generate higher positive sentiment, as customers who have a pleasant dining or lodging experience are more motivated to share their opinions.

In contrast, Twitter has been widely recognized as a platform for real-time complaints and immediate customer feedback.[38] Research suggests that negative sentiment is amplified on Twitter due to its fast-paced nature and viral potential. A study by [50] found that dissatisfied customers are more likely to leave impulsive reviews on social media platforms, particularly when service failures occur. This explains why Twitter is commonly associated with negative sentiment, as users use the platform as an outlet to voice frustrations, seek rapid resolutions, or influence public perception.

The Impact of Sentiment on Consumer Decision-Making

The influence of sentiment on consumer decision-making and business performance has been widely documented in hospitality research. Studies by [51] indicate that potential customers rely heavily on online sentiment when choosing restaurants and hotels. Positive sentiment enhances brand reputation, whereas negative sentiment especially if left unaddressed can deter potential customers. Research by [31,32] supports this, emphasizing that higher-rated businesses tend to attract more bookings and customer loyalty. This study reinforces the importance of reputation management, especially on platforms where negative sentiment spreads quickly.

Additionally, several studies indicate that neutral sentiment is an overlooked but important category in consumer decision-making. While extreme reviews (very positive or very negative) attract the most attention, research by [33] suggests that neutral reviews serve as credibility anchors, providing balanced perspectives that influence customer trust. This aligns with observations that platforms like Google Reviews and Facebook exhibit balanced sentiment distributions, making them important spaces for reputation management and customer engagement.

Strategic Implications for Businesses

The relationship between sentiment trends, platform behaviors, and service quality perceptions provides actionable insights for businesses. Past studies emphasize that proactive engagement with online reviews enhances customer trust and loyalty. A study by [52] highlights that businesses that respond to both positive and negative reviews tend to perform better in consumer perception metrics. This suggests that restaurants and hotels must tailor their engagement strategies based on platform-specific sentiment trends.

Another key insight from the literature is the importance of AI-driven sentiment analysis in business strategy. Studies by [53,54] suggest that automated sentiment analysis tools can help businesses detect service issues in real time, allowing them to address problems before they escalate. The use of natural language processing (NLP) and AI-based customer feedback monitoring can help businesses predict trends in sentiment shifts and take proactive measures to enhance customer satisfaction.

CONCLUSIONS

This study explored customer sentiment analysis in Jordan's food and beverage sector, focusing on how sentiment varies across different establishment types and digital platforms. The findings highlight key trends in customer satisfaction, online review behaviors, and digital engagement strategies. The analysis reveals that premium establishments, such as luxury hotels and fine dining restaurants, generally receive more positive sentiment, while budget hotels and fast food chains face higher negative sentiment due to issues related to service quality, food consistency, and customer expectations. Despite these trends, statistical analysis (ANOVA test) indicates no significant difference in sentiment across establishment types, suggesting that all businesses receive a mix of positive, neutral, and negative reviews.

Conversely, the Chi-Square test confirms a significant difference in sentiment distribution across digital platforms. TripAdvisor is the most positively reviewed platform, reflecting its structured review system and detailed customer feedback. Facebook and Google Reviews show a balanced sentiment trend, making them important for brand credibility and general customer engagement. Twitter exhibits the highest negative sentiment, reinforcing its role as a platform for real-time complaints and customer grievances. These insights emphasize the importance of platform-specific digital reputation management. Businesses must leverage TripAdvisor for positive review amplification, actively monitor Facebook and Google Reviews for balanced customer engagement, and implement a proactive crisis management strategy on Twitter.

From a strategic perspective, businesses in the food and beverage sector must focus on enhancing service quality, maintaining food consistency, and responding effectively to online reviews to improve customer satisfaction. The integration of AI-driven sentiment analysis tools can further help businesses identify emerging trends, predict customer preferences, and address negative sentiment in real-time. Overall, this study contributes to the growing body of research on AI-driven sentiment analysis, online reputation management, and customer behavior in digital platforms. Future research should explore the impact of AI personalization in hospitality, customer sentiment shifts over time, and the role of sentiment analysis in predictive business strategies.

BIBLIOGRAPHIC REFERENCES

1. Floyd, K., Freling, R., Alhoqail, S. A., Cho, H. Y., & Freling, T. H. (2014). How Online Product Reviews Affect Retail Sales: A Meta-analysis. In Journal of Retailing (Vol. 90, Issue 2, p. 217). Elsevier BV. https://doi.org/10.1016/j.jretai.2014.04.004

2. Ayyalsalman KM, Alolayyan MN, Alshurideh MT, Al-Daoud K, Al-Hawary SIS. Mathematical Model to Estimate The Effect of Authentic Leadership Components on Hospital Performance [Internet]. Vol. 18, Appl. Math; 2024 [cited 2025 Feb]. P. 701.

3. Saleh, M. H., Garaibeh, A. T., Shehadeh, A., & Jaber, J. J. (2019). The Role of Tourism Activity in Economic Growth by Using Some Econometric Models Evidence from Jordan. In Modern Applied Science (Vol. 13, Issue 6, p. 1). Canadian Center of Science and Education. https://doi.org/10.5539/mas.v13n6p1

4. Mohammad AAS, Mohammad SIS, Al-Daoud KI, Al Oraini B, Vasudevan A, Feng Z. Optimizing the Value Chain for Perishable Agricultural Commodities: A Strategic Approach for Jordan [Internet]. Vol. 6, Research on World Agricultural Economy; 2025 [cited 2025 Feb]. p. 465.

5. Kn, L., Sp, D., Hs, Y., & Megha, V. (2019). A Design on Bank Customer Complaints Analysis using Natural Language Processing. In International Journal of Innovative Technology and Exploring Engineering (Vol. 9, p. 522). Blue Eyes Intelligence Engineering and Sciences Publication. https://doi.org/10.35940/ijitee.b1038.1292s19

6. Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A, Alshurideh MT. Data security in digital accounting: A logistic regression analysis of risk factors [Internet]. Vol. 8, International Journal of Innovative Research and Scientific Studies; 2025 [cited 2025 Feb]. p. 2699.

7. Alawamleh, M., Al-Hussaini, M., & Ismail, L. B. (2022). Open innovation in the food industry: trends and barriers — a case of the Jordanian food industry. In Journal of global entrepreneurship research (Vol. 12, Issue 1, p. 279). Springer Science+Business Media. https://doi.org/10.1007/s40497-022-00312-6

8. Mohammad AAS, Al-Daoud KI, Rusho MA, Alkhayyat A, Doshi H, Dey P, Kiani M. Modeling polyethylene glycol density using robust soft computing methods [Internet]. Vol. 210, Microchemical Journal; 2025 [cited 2025 Feb]. p. 112815.

9. Liu, J., Yu, Y., Mehraliyev, F., Hu, S., & Chen, J. (2022). What affects the online ratings of restaurant consumers: a research perspective on text-mining big data analysis. In International Journal of Contemporary Hospitality Management (Vol. 34, Issue 10, p. 3607). Emerald Publishing Limited. https://doi.org/10.1108/ijchm-06-2021-0749

10. Al-Oraini B, Khanfar IA, Al-Daoud K, Mohammad SI, Vasudevan A, Fei Z, Al-Azzam MKA. Determinants of Customer Intention to Adopt Mobile Wallet Technology [Internet]. Vol. 18, Appl. Math; 2024 [cited 2025 Feb]. P. 1331.

11. Venkatesakumar, R., Vijayakumar, S., Riasudeen, S., Madhavan, S., &Rajeswari, B. (2020). Distribution characteristics of star ratings in online consumer reviews. In Vilakshan – XIMB Journal of Management (Vol. 18, Issue 2, p. 156). Emerald Publishing Limited. https://doi.org/10.1108/xjm-10-2020-0171

12. Mohammad AAS. The impact of COVID-19 on digital marketing and marketing philosophy: evidence from Jordan [Internet]. Vol. 48, International Journal of Business Information Systems; 2025 [cited 2025 Feb]. p. 267.

13. Zhao, B. (2017). Web Scraping. In Springer eBooks (p. 1). Springer Nature. https://doi.org/10.1007/978-3-319-32001-4_483-1

14. Mohammad AAS, Al-Hawary SIS, Hindieh A, Vasudevan A, Al-Shorman MH, Al-Adwan AS, Turki Alshurideh M, Ali, I. Intelligent Data-Driven Task Offloading Framework for Internet of Vehicles Using Edge Computing and Reinforcement Learning [Internet]. Vol. 4, Data and Metadata; 2025 [cited 2025 Feb]. P. 521.

15. Rababah, O. (2019). A Novel Machine Learning System for Sentiment Analysis and Extraction (p. 387). https://doi.org/10.5121/csit.2019.91330

16. Agrawal, M., &Moparthi, N. R. (2021). A Comprehensive Survey on Aspect Based Word Embedding Models and Sentiment Analysis Classification Approaches. In Advances in parallel computing. Elsevier BV. https://doi.org/10.3233/apc210175

17. Fan, S., Yao, J., Sun, Y., & Zhan, Y. (2020). A Summary of Aspect-based Sentiment Analysis. In Journal of Physics Conference Series (Vol. 1624, Issue 2, p. 22051). IOP Publishing. https://doi.org/10.1088/1742-6596/1624/2/022051

18. Ha, H. D., Prasad, P., Maag, A., &Alsadoon, A. (2018). Deep Learning for Aspect-Based Sentiment Analysis: A Comparative Review [Review of Deep Learning for Aspect-Based Sentiment Analysis: A Comparative Review]. Expert Systems with Applications, 118, 272. Elsevier BV. https://doi.org/10.1016/j.eswa.2018.10.003

19. Mohammad AA, Shelash SI, Saber TI, Vasudevan A, Darwazeh NR, Almajali R. Internal audit governance factors and their effect on the risk-based auditing adoption of commercial banks in Jordan [Internet]. Vol. 4, Data and Metadata; 2025 [cited 2025 Feb]. P. 464.

20. Mohammad, S. M. (2020). Sentiment Analysis: Automatically Detecting Valence, Emotions, and Other Affectual States from Text. In arXiv (Cornell University). Cornell University. https://doi.org/10.48550/arxiv.2005.11882

21. Che, S., Zhu, W., & Li, X. (2020). Anticipating Corporate Financial Performance from CEO Letters Utilizing Sentiment Analysis. In Mathematical Problems in Engineering (Vol. 2020, p. 1). Hindawi Publishing Corporation. https://doi.org/10.1155/2020/5609272

22. Galdolage BS, Ekanayake EA, Al-Daoud KI, Vasudevan A, Wenchang C, Hunitie MFA, Mohammad SIS. Sustainable Marine and Coastal Tourism: A Catalyst for Blue Economic Expansion in Sri Lanka [Internet]. Vol. 3, Journal of Ecohumanism; 2024 [cited 2025 Feb]. P. 1214.

23. Hwang, J., & Zhao, J. (2010). Factors Influencing Customer Satisfaction or Dissatisfaction in the Restaurant Business Using AnswerTree Methodology. In Journal of Quality Assurance in Hospitality & Tourism (Vol. 11, Issue 2, p. 93). Taylor & Francis. https://doi.org/10.1080/15280081003800355

24. Mohammad SIS, Al-Daoud KI, Al Oraini BS, Alqahtani MM, Vasudevan A, Ali I. Impact of Crude Oil Price Volatility on Procurement and Inventory Strategies in the Middle East [Internet]. Vol. 15, International Journal of Energy Economics and Policy; 2025 [cited 2025 Feb]. P. 715.

25. Park, S., Lee, J., & Nicolau, J. L. (2020). Understanding the dynamics of the quality of airline service attributes: Satisfiers and dissatisfiers. In Tourism Management (Vol. 81, p. 104163). Elsevier BV. https://doi.org/10.1016/j.tourman.2020.104163

26. Parasuraman, A. (2004). Assessing and improving service performancefor maximum impact: insights from a two-decade-long research journey. In Performance Measurement and Metrics (Vol. 5, Issue 2, p. 45). Emerald Publishing Limited. https://doi.org/10.1108/14678040410546064

27. Namkung, Y., & Jang, S. (2008). Are highly satisfied restaurant customers really different? A quality perception perspective. In International Journal of Contemporary Hospitality Management (Vol. 20, Issue 2, p. 142). Emerald Publishing Limited. https://doi.org/10.1108/09596110810852131

28. Park, K., Cha, M., & Rhim, E. (2018). Positivity Bias in Customer Satisfaction Ratings (p. 631). https://doi.org/10.1145/3184558.3186579

29. Bhakat, A., & Bhardwaj, R. (2024). Food and beverage service training in hospitality schools—An overview

through the eyes of students, faculty, and industry professionals. In Smart Tourism (p. 2169). https://doi.org/10.54517/st2169

30. Ekanayake EA, Al-Daoud KI, Vasudevan A, Wenchang C, Hunitie MFA, Mohammad SIS. Leveraging Aquaculture and Mariculture for Sustainable Economic Growth in Sri Lanka: Challenges and Opportunities [Internet]. Vol. 3, Journal of Ecohumanism; 2024 [cited 2025 Feb]. P. 1229.

31. Azman, A. B., & Majid, M. A. A. (2023). Factors Affecting Customer Preference in Selecting Family Restaurant in Langkawi. In International Journal of Academic Research in Business and Social Sciences (Vol. 13, Issue 5). https://doi.org/10.6007/ijarbss/v13-i5/17013

32. Rita, P., Vong, C., Pinheiro, F. L., & Mimoso, J. (2022). A sentiment analysis of Michelin-starred restaurants. In European Journal of Management and Business Economics (Vol. 32, Issue 3, p. 276). Emerald Publishing Limited. https://doi.org/10.1108/ejmbe-11-2021-0295

33. Pleerux, N., &Nardkulpat, A. (2023). Sentiment analysis of restaurant customer satisfaction during COVID-19 pandemic in Pattaya, Thailand. In Heliyon (Vol. 9, Issue 11). Elsevier BV. https://doi.org/10.1016/j.heliyon.2023.e22193

34. Bacon, D. R., Besharat, A., Parsa, H. G., & Smith, S. (2016). Revenue management, hedonic pricing models and the effects of operational attributes. In International Journal of Revenue Management (Vol. 9, p. 147). Inderscience Publishers. https://doi.org/10.1504/ijrm.2016.077031

35. Vuong, N. B., Suzuki, Y., & To, A. T. (2021). The Local Impact on the Concurrent Sentiment-Return Nexus: Asian versus European Markets. In Emerging Science Journal (Vol. 5, Issue 6, p. 894). https://doi.org/10.28991/esj-2021-01318

36. Chen W, Vasudevan A, Al-Daoud KI, Mohammad SIS, Arumugam V, Manoharan T, Foong WS. Integrating cultures, enhancing outcomes: Perceived organizational support and its impact on Chinese expatriates' performance in Dubai [Internet]. Vol. 7, Herança; 2024 [cited 2025 Feb]. P. 25.

37. Gao, B., Wang, J., Xiaojie, D., & Guo, Y. (2022). Perils of Review Solicitation: Evidence from a Natural Experiment on Tripadvisor. In SSRN Electronic Journal. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.4012300

38. Shakeel, M., Barsaiyan, S., &Sijoria, C. (2020). TWITTER AS A CUSTOMER SERVICE MANAGEMENT PLATFORM: A STUDY ON INDIAN BANKS. In Journal of Content Community and Communication (Vol. 11, Issue 10, p. 84). https://doi.org/10.31620/jccc.06.20/07

39. Schoenmueller, V., Netzer, O., & Stahl, F. (2020). The Polarity of Online Reviews: Prevalence, Drivers and Implications. In Journal of Marketing Research (Vol. 57, Issue 5, p. 853). SAGE Publishing. https://doi.org/10.1177/0022243720941832

40. Vargo, C. J., Gangadharbatla, H., & Hopp, T. (2019). eWOM across channels: comparing the impact of self-enhancement, positivity bias and vengeance on Facebook and Twitter. In International Journal of Advertising (Vol. 38, Issue 8, p. 1153). Taylor & Francis. https://doi.org/10.1080/02650487.2019.1593720

41. Dewanthi, D. S., Praga, N. A., & Godwin, G. (2024). Cafe Visitation in the Digital Age: The Role of Social Media Reviews (p. 1). https://doi.org/10.1109/iccit62134.2024.10701207

42. Kukreti, A., Kaur, A., Altaf, O., & Adil, M. (2024). Travel Industry: Comparison of Travel Review for Ease in Making Travel Decision. In SSRN Electronic Journal. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.4488030

43. Shin, S., Shin, H. H., Lee, E., &Yhee, Y. (2024). EXPRESS: Do Repeat Customers Effectively Attract New Customers? Reconsidering Customer Influence Value of Repeat Customers. In Journal of Hospitality & Tourism Research. SAGE Publishing. https://doi.org/10.1177/10963480241277093

44. Messner, W. (2020). Cultural and Individual Differences in Online Reviews. In Journal of International

Consumer Marketing (Vol. 32, Issue 5, p. 356). Taylor & Francis. https://doi.org/10.1080/08961530.2020.1722980

45. Qiao, T., Shan, W., Zhang, M., & Wei, Z. (2022). More than words: Understanding how valence and content affect review value. In International Journal of Hospitality Management (Vol. 105, p. 103274). Elsevier BV. https://doi.org/10.1016/j.ijhm.2022.103274

46. Roy, G. (2023). Travelers' online review on hotel performance – Analyzing facts with the Theory of Lodging and sentiment analysis. In International Journal of Hospitality Management (Vol. 111, p. 103459). Elsevier BV. https://doi.org/10.1016/j.ijhm.2023.103459

47. Li, N., Ariffin, S. Z. B. M., & Jamaluddin, N. S. (2024). An Analysis of the Impact of Xi'an Hotels' Service Quality Using network Text. In Pakistan Journal of Life and Social Sciences (PJLSS) (Vol. 22, Issue 2). https://doi.org/10.57239/pjlss-2024-22.2.00269

48. Xia, Y., & Ha, H. (2022). Do Online Reviews Encourage Customers to Write Online Reviews? A Longitudinal Study. In Sustainability (Vol. 14, Issue 8, p. 4612). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/su14084612

49. Xu, X. (2022). A growing or depreciating love? Linking time with customer satisfaction through online reviews. In Information & Management (Vol. 59, Issue 2, p. 103605). Elsevier BV. https://doi.org/10.1016/j.im.2022.103605

50. Varnalı, K., &Cesmeci, C. (2021). Customer responses to service failures on social media. In Journal of Services Marketing (Vol. 36, Issue 5, p. 691). Emerald Publishing Limited. https://doi.org/10.1108/jsm-11-2020-0484

51. Cho, S., Pekgün, P., Janakiraman, R., & Wang, J. (2023). The Competitive Effects of Online Reviews on Hotel Demand. In Journal of Marketing (Vol. 88, Issue 2, p. 40). SAGE Publishing. https://doi.org/10.1177/00222429231191449

52. Wu, J., Ye, J., & Chu, J. (2024). Soothing the Unsatisfied or Pleasing the Satisfied? The Effects of Managerial Responses to Positive versus Negative Reviews on Customer Ratings and Financial Performance. In SSRN Electronic Journal. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.4708209

53. Rane, N., Choudhary, S., & Rane, J. (2024). Artificial intelligence, machine learning, and deep learning for sentiment analysis in business to enhance customer experience, loyalty, and satisfaction. In SSRN Electronic Journal. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.4846145

54. Harmanpreet, B., Harikrishna, G. N., & Dhulipalla, I. (2023). NLP for sentiment analysis, customer service automation, and market trend predictions. In International Journal of Science and Research Archive (Vol. 10, Issue 1, p. 1084). https://doi.org/10.30574/ijsra.2023.10.1.0698

FINANCING
This work was supported by Zarqa University.

CONFLICT OF INTERESTS
There is no conflict of interest

AUTHORSHIP CONTRIBUTION
Conceptualization: Anber Abraheem Shlash Mohammad, Ammar Mohammad Al-Ramadan, Suleiman Ibrahim Mohammad, Badrea Al Oraini, Asokan Vasudevan, Nawaf Alshdaifat, Mohammad Faleh Ahmmad Hunitie.

Data curation: Anber Abraheem Shlash Mohammad, Ammar Mohammad Al-Ramadan, Suleiman Ibrahim Mohammad, Badrea Al Oraini, Asokan Vasudevan, Nawaf Alshdaifat, Mohammad Faleh Ahmmad Hunitie.

Formal analysis: Anber Abraheem Shlash Mohammad, Ammar Mohammad Al-Ramadan, Suleiman Ibrahim Mohammad, Badrea Al Oraini, Asokan Vasudevan, Nawaf Alshdaifat, Mohammad Faleh Ahmmad Hunitie.

Drafting - original draft: Anber Abraheem Shlash Mohammad, Ammar Mohammad Al-Ramadan, Suleiman Ibrahim Mohammad, Badrea Al Oraini, Asokan Vasudevan, Nawaf Alshdaifat, Mohammad Faleh Ahmmad Hunitie.

Writing - proofreading and editing: Anber Abraheem Shlash Mohammad, Ammar Mohammad Al-Ramadan, Suleiman Ibrahim Mohammad, Badrea Al Oraini, Asokan Vasudevan, Nawaf Alshdaifat, Mohammad Faleh Ahmmad Hunitie.