

REVIEW ARTICLE

Section: *Literature, Linguistics & Criticism*

Emotion detection and sentiment dynamics in customer-generated reviews: A corpus-based study of Saudi Arabian food delivery applications

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ABSTRACT

The rapid growth of online food delivery platforms has resulted in large volumes of user-generated feedback, creating a critical need for automated systems that can extract meaningful insights for service improvement. Traditional sentiment analysis methods mostly rely on polarity classification, which frequently falls short of capturing the complex emotional elements that influence customer satisfaction and discontent. The emotion-aware feedback analysis system presented in this study is intended to convert customer reviews into practical suggestions for Saudi Arabian restaurant owners and food delivery services. The suggested system classifies customer reviews submitted in structured Excel format at the sentence level using a transformer-based deep learning model. Batch-based inference and lightweight text preprocessing are used to guarantee computational efficiency and practical usability. In order to produce understandable recommendations that focus on important operational areas like food quality, delivery performance, hygiene, pricing, and customer support, detected emotional patterns are combined with domain-specific service rules. The system incorporates geographic visualization to contextualize major food delivery platforms, including Marsool, Talabat, and HungerStation, within Saudi Arabia. The system successfully detects dominant emotional trends and generates useful insights that go beyond conventional sentiment polarity, according to experimental evaluation using actual customer review data. The findings show that emotion-aware analysis offers a deeper and more insightful comprehension of customer feedback, facilitating data-driven decision-making for service enhancement. The suggested method emphasizes the usefulness of emotion-aware natural language processing and computational linguistics in practical service-oriented applications.

KEYWORDS: Samuel Beckett, Waiting for Godot, modern drama, absurdism, existentialism, waiting, uncertainty, deferred meaning, human agency, modernity

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Introduction

The rapid advancement of digital technologies has significantly transformed the way businesses interact with consumers and deliver products and services. Over the past decade, the widespread adoption of smartphones, high-speed internet connectivity, and mobile applications has contributed to the growth of various forms of electronic commerce, creating new opportunities for businesses to reach customers more efficiently. Among the sectors that have experienced remarkable growth is the online food delivery industry, which has become an integral component of modern consumer lifestyles. Through dedicated mobile applications and web-based platforms, customers can conveniently browse restaurant menus, place orders, make payments, and track deliveries in real time. The convenience, accessibility, and efficiency offered by these platforms have contributed to their increasing popularity among consumers worldwide.

The growth of online food delivery services has generated substantial amounts of customer-generated content in the form of reviews, ratings, comments, and feedback. Every day, thousands of customers share their experiences regarding food quality, delivery speed, customer service, pricing, application usability, and overall satisfaction with the services they receive. These reviews represent a valuable source of information because they provide direct insights into customer perceptions, expectations, and experiences. Unlike traditional customer satisfaction surveys, which often involve structured questions and limited response options, online reviews allow customers to freely express their opinions in their own words. As a result, they offer rich and detailed information that can help businesses better understand customer needs and identify opportunities for service improvement.

The increasing volume of customer reviews presents both opportunities and challenges for organizations. On one hand, the availability of large amounts of customer feedback enables businesses to gain a comprehensive understanding of customer experiences and preferences. On the other hand, manually analyzing thousands of reviews is time-consuming, expensive, and often impractical. Organizations therefore require automated methods capable of processing and interpreting large volumes of textual data efficiently and accurately. This need has led to the growing importance of sentiment analysis, which has emerged as one of the most widely used techniques for extracting meaningful information from customer-generated content.

Sentiment analysis, often referred to as opinion mining, is a branch of natural language processing that focuses on identifying, extracting, and classifying opinions expressed in textual data. The primary objective of sentiment analysis is to determine whether a particular piece of text conveys a positive, negative, or neutral sentiment. By automatically categorizing customer opinions, sentiment analysis enables organizations to understand public attitudes toward products, services, brands, and business practices. In recent years, advancements in machine learning, deep learning, and artificial intelligence have significantly enhanced the accuracy and effectiveness of sentiment analysis systems, allowing them to process increasingly complex and nuanced forms of language.

The importance of sentiment analysis extends across numerous industries, including retail, healthcare, education, tourism, finance, and hospitality. Businesses use sentiment analysis to monitor customer satisfaction, evaluate marketing campaigns, assess brand reputation, and identify emerging consumer trends. Within the online food delivery industry, sentiment analysis has become particularly valuable because customer satisfaction directly influences customer retention, loyalty, and long-term business success. Since consumers can easily switch between competing delivery platforms, understanding customer opinions and addressing service deficiencies have become critical strategic priorities for organizations operating in this sector.

The online food delivery market has experienced extraordinary growth over the past several years. Factors such as urbanization, changing consumer lifestyles, increased workforce participation, and technological innovation have contributed to the widespread adoption of food delivery applications. Consumers increasingly prefer the convenience of ordering meals through digital platforms rather than visiting restaurants in person. This trend was further accelerated by the COVID-19 pandemic, which significantly increased reliance on online food delivery services due to movement restrictions, social distancing measures, and health concerns. As a result, the online food delivery market expanded rapidly and reached an estimated global value of approximately USD 154.34 billion by 2023. This substantial growth highlights the economic significance of the industry and underscores the importance of understanding customer experiences within this rapidly evolving market.

As competition among food delivery platforms intensifies, customer satisfaction has become one of

the most important determinants of business success. Customers evaluate their experiences based on multiple factors, including food quality, delivery speed, order accuracy, pricing, packaging, customer service, and the usability of the delivery application. Positive experiences often encourage repeat purchases and customer loyalty, whereas negative experiences can result in customer dissatisfaction, unfavorable reviews, and customer attrition. Consequently, businesses must continuously monitor customer feedback to identify areas requiring improvement and maintain high levels of service quality.

Customer reviews serve as a valuable source of operational intelligence because they often reveal issues that may not be apparent through internal performance metrics alone. For example, while a company may measure average delivery times and order completion rates, customer reviews can provide additional context regarding customer expectations, emotional responses, and perceived service quality. Reviews may reveal recurring complaints about delayed deliveries, poor food quality, incorrect orders, or ineffective customer support. Similarly, positive reviews may highlight strengths such as efficient delivery processes, excellent food quality, or responsive customer service. Analyzing these reviews allows businesses to gain a deeper understanding of customer experiences and develop targeted strategies to improve service performance.

In addition to identifying customer satisfaction levels, sentiment analysis can help organizations uncover the factors that drive customer opinions and behaviors. Research has shown that food quality, delivery reliability, application usability, and customer service are among the most influential determinants of customer satisfaction in online food delivery services. Understanding the relative importance of these factors can assist managers in prioritizing operational improvements and allocating resources more effectively. Furthermore, sentiment analysis can reveal changes in customer perceptions over time, enabling businesses to evaluate the effectiveness of implemented improvements and respond proactively to emerging challenges.

Recent developments in sentiment analysis have moved beyond simple polarity classification toward more sophisticated approaches capable of detecting emotions, contextual meanings, and aspect-specific sentiments. Traditional sentiment analysis typically categorizes reviews as positive, negative, or neutral. While such classifications provide useful information, they may not fully capture the complexity of customer experiences. For example, two customers may both express negative opinions, yet one may feel disappointed due to unmet expectations while the other may feel angry because of a serious service failure. Modern sentiment analysis techniques seek to identify these emotional distinctions, providing businesses with deeper insights into the underlying causes of customer satisfaction and dissatisfaction.

The growing interest in sentiment analysis has resulted in a substantial body of academic research investigating customer reviews in online food delivery services. Researchers have employed a variety of methodologies, including machine learning algorithms, deep learning architectures, lexicon-based approaches, and hybrid models, to analyze customer opinions and predict satisfaction outcomes. These studies have contributed valuable knowledge regarding customer preferences, service quality dimensions, and the effectiveness of different analytical techniques. However, despite the increasing volume of research, findings remain distributed across multiple disciplines and often focus on specific aspects of sentiment analysis without providing a comprehensive overview of the field.

Therefore, there is a need to critically examine and synthesize the existing literature on sentiment analysis in online food delivery services. A comprehensive review can help identify major research trends, evaluate methodological approaches, highlight key determinants of customer satisfaction, and reveal gaps that require further investigation. Such an analysis is valuable not only for researchers seeking to advance knowledge in this area but also for practitioners who wish to leverage sentiment analysis to improve business performance and customer experiences.

This literature review aims to provide a comprehensive examination of sentiment analysis within the context of online food delivery services. Specifically, it seeks to explore how sentiment analysis has been applied to customer reviews, identify the primary factors influencing customer satisfaction, evaluate the methodologies used in previous studies, and discuss opportunities for future research. The review is organized into several sections. The first section provides an overview of sentiment analysis and its applications in online food delivery services. The second section examines previous studies and discusses the key determinants of customer satisfaction identified in the literature. The third section reviews the analytical techniques used in sentiment analysis, including machine learning, deep learning, and natural language processing methods. Finally, the

review concludes by discussing the practical implications of existing research and outlining potential directions for future investigation. Through this comprehensive analysis, the review aims to contribute to a deeper understanding of how sentiment analysis can support service improvement, customer satisfaction management, and strategic decision-making in the rapidly expanding online food delivery industry.

Research Questions

1. How can emotion-aware natural language processing be used to analyze customer feedback from online food delivery platforms?
2. To what extent does fine-grained emotion analysis provide richer insights than polarity-based sentiment analysis in identifying service-related issues?
3. How effectively can detected emotions be transformed into actionable service improvement recommendations for restaurant owners?
4. How can geographic visualization support the interpretation of customer feedback in the Saudi Arabian food delivery context?

1. Research Objectives

1. Develop an emotion-aware NLP system for analyzing customer feedback from food delivery platforms.
2. Examine how fine-grained emotional analysis improves insight quality compared to polarity-based sentiment analysis.
3. Translate detected emotions into actionable service improvement recommendations for restaurant owners.
4. Demonstrate the applicability of the system in the Saudi Arabian food delivery context.

Literature Review

Review analysis has been extensively studied across a wide range of online platforms and application domains due to the increasing importance of user-generated content in understanding consumer behavior, preferences, and satisfaction. As digital platforms continue to grow, organizations increasingly rely on customer reviews to evaluate service quality, improve products, and make informed business decisions. Consequently, sentiment analysis has emerged as a valuable research area that seeks to automatically identify and interpret opinions expressed in textual data. Researchers have proposed various methods and analytical frameworks to improve the accuracy and effectiveness of review analysis, ranging from traditional machine learning techniques to advanced deep learning models.

One of the earlier and most influential contributions to sentiment analysis was made by Adak and et al (2022), Prabowo and Thelwall (2009), and Hossain and et al (2023) who explored the effectiveness of combining machine learning, supervised learning, and rule-based classification techniques. Their study examined different types of online content, including MySpace comments, product reviews, and movie reviews. The researchers demonstrated that a hybrid approach could achieve superior performance compared with individual classification methods. Their findings indicated that no single technique was capable of addressing all the complexities associated with opinion mining. Instead, combining multiple classifiers enabled the system to leverage the strengths of each approach while compensating for their individual limitations. The reported improvements in both micro- and macro-averaged F1 scores highlighted the potential benefits of hybrid sentiment analysis frameworks and established a foundation for subsequent research in the field.

As sentiment analysis evolved, researchers recognized that identifying whether a review was positive or negative was often insufficient for understanding customer experiences. This realization led to increased interest in aspect-based sentiment analysis, which focuses on identifying the specific aspects of a product or service that customers discuss and evaluating the opinions expressed toward those aspects. Prasetyo and et al (2021), Jo and Oh (2011), Hsu et al (2021), Bitto et al (2023), and Fragkos et al. (2024) contributed to this area by investigating methods for analyzing aspects and opinions in reviews of restaurants and electronic devices. Their work acknowledged that customers frequently evaluate multiple aspects within a single review and may express different sentiments toward each aspect. To address this complexity, they proposed two generative models designed to identify various perspectives regarding the same aspect. Their research demonstrated the importance of moving beyond overall sentiment classification toward more detailed analyses that capture

the multidimensional nature of customer feedback. Such approaches allow businesses to pinpoint the specific strengths and weaknesses of their products or services rather than relying solely on general sentiment scores. Further advancements in sentiment analysis focused on improving the granularity of sentiment classification. Gupta (2021), and Fang and Zhan (2015) addressed the challenge of sentiment polarity classification in online product reviews by developing methods for both review-level and sentence-level analysis. Their work emphasized that customer reviews often contain mixed opinions, making it difficult to accurately represent the sentiment of an entire review using a single label. A customer, for example, may praise the quality of a product while criticizing its price or delivery process. Sentence-level analysis enables researchers and practitioners to identify these variations and gain a more nuanced understanding of customer opinions. By distinguishing sentiments expressed in different parts of a review, organizations can better understand customer priorities and address specific concerns more effectively.

In addition to sentiment classification, some researchers have explored the linguistic and discourse characteristics of online reviews. Chandrasekhar and et al (2019), Yulia (2015), Geler (2021), Chauhan and et al (2021) and Vidani and et al (2015) examined online product reviews from a genre-analysis perspective and proposed a new set of characteristics for understanding review discourse. Through the analysis of a corpus of 120 product reviews, the study identified involvement features, background patterns, and implicit contrasts as important elements of review construction. This approach expanded the scope of review analysis beyond traditional sentiment classification by focusing on how opinions are structured and communicated. Unlike earlier studies that concentrated primarily on coherence markers such as conjunctions, Yulia's work highlighted the complex discourse strategies employed by consumers when expressing evaluations and experiences. Understanding these discourse features can contribute to more sophisticated sentiment analysis systems capable of capturing subtle meanings and contextual information embedded in customer reviews.

The application of sentiment analysis has expanded considerably in recent years, particularly within the growing online food delivery industry. As food delivery platforms have become an essential component of modern consumer lifestyles, understanding customer feedback has become increasingly important for service providers. Al-Jarrah et al. (2023), Sulaiman et al (2023), Shaeali and et al (2020), Salloum and et al (2023), Nguyen et al. (2021), Madani and Alshraideh (2021), and Mustafa and et al (2025) examined customer reviews using predictive modeling techniques to forecast purchasing decisions on online delivery platforms. Their study demonstrated that sentiment analysis can provide valuable insights into customer preferences and behavior, enabling businesses to improve their services and enhance customer satisfaction. The researchers compared multiple predictive models and found that the C4.5 decision tree achieved the highest level of accuracy. This finding illustrates the potential of data-driven approaches to support decision-making processes and improve service quality in competitive digital marketplaces.

The importance of customer satisfaction in online food delivery services became even more evident during the COVID-19 pandemic, when consumers increasingly relied on digital platforms for food purchases. Zhongcao (2022) investigated 158 survey responses concerning Malaysian consumers' experiences with food delivery applications during this period. The study explored various factors affecting user satisfaction and provided insights into customer expectations under rapidly changing social and economic conditions. The findings highlighted the significance of convenience, reliability, and service quality in shaping user experiences. As online food delivery services continue to evolve, understanding these factors remains critical for maintaining customer loyalty and sustaining business growth.

Research in sentiment analysis has also expanded to include languages other than English. In particular, Arabic sentiment analysis has attracted growing attention due to the increasing volume of Arabic content generated on social media platforms, review websites, and e-commerce applications. Salloum and Almustafa (2023) analyzed 66,666 Arabic customer reviews using a range of machine learning and deep learning algorithms. Their study sought to improve sentiment classification performance by evaluating different computational models. The results revealed that the Bidirectional Long Short-Term Memory (BiLSTM) model achieved superior performance compared with alternative approaches. This finding reflects the ability of deep learning architectures to capture contextual and sequential relationships within textual data more effectively than traditional machine learning techniques. The study also demonstrated the growing maturity of Arabic natural language processing research and its relevance to real-world business applications.

The broader landscape of customer satisfaction research in online food delivery services was examined by Nagpal and et al (2020), and Ramdhansya (2025) through a systematic literature review of 476 academic studies. The review provided a comprehensive overview of the methodologies and analytical techniques commonly employed in this field. The findings indicated that sentiment analysis and Partial Least Squares Structural Equation Modeling (PLS-SEM) were among the most frequently used approaches for investigating customer satisfaction and service quality. This observation reflects the increasing reliance on quantitative and data-driven methods to understand customer perceptions and support strategic decision-making. The review also highlighted the interdisciplinary nature of online food delivery research, which draws upon concepts from marketing, information systems, consumer behavior, and data science.

Comparative studies evaluating different sentiment analysis models have further contributed to the advancement of the field. One study focusing on food delivery applications in Bangladesh assessed the performance of AFINN, DistilBERT, and RoBERTa models. The results showed classification accuracies of 74%, 73%, and 77%, respectively, with RoBERTa achieving the highest accuracy. These findings demonstrate the advantages of transformer-based language models in understanding contextual relationships and semantic nuances within customer reviews. Such models have become increasingly popular because they can process complex linguistic patterns and achieve high levels of performance across various natural language processing tasks.

Similarly, another study investigated product review sentiment using traditional machine learning algorithms, including Random Forest, Naïve Bayes, and Support Vector Machines. The reported accuracies of 68%, 44.9%, and 68.2%, respectively, illustrate the variation in performance among different classification techniques. The findings suggest that model selection plays a critical role in determining the effectiveness of sentiment analysis systems. While traditional machine learning approaches continue to provide useful results, newer deep learning and transformer-based models often offer superior performance due to their enhanced ability to capture contextual information and complex semantic relationships.

Overall, the literature demonstrates that sentiment analysis has become an essential tool for understanding customer satisfaction in online food delivery services and other digital environments. Existing studies consistently identify factors such as food quality, application usability, delivery speed, and customer service as key determinants of customer satisfaction. These variables directly influence consumer perceptions and play a significant role in shaping overall service evaluations. Although previous research has made substantial contributions to sentiment classification and customer satisfaction analysis, many studies remain focused primarily on identifying positive and negative opinions. As customer experiences are inherently emotional and multidimensional, there is a growing need for more comprehensive analytical frameworks that can capture specific emotions, identify operational issues, and generate actionable recommendations. Such developments can enhance the practical value of sentiment analysis and support more effective decision-making in service-oriented industries.

Methodology

3.1 Research Design

The primary goal of the study is the development and evaluation of an applied Natural Language Processing (NLP) system to analyze client feedback on online meal delivery services, and the research design is a computational and experimental one. The research has taken an application-oriented direction and has not concentrated on the theoretical model benchmarking, but has concentrated on the real-life usability. The primary objective is to develop an emotion-sensitive feedback analysis system that will be able to extract emotional content in customer reviews and convert such data into actionable recommendations on service improvements to food delivery services and restaurant owners.

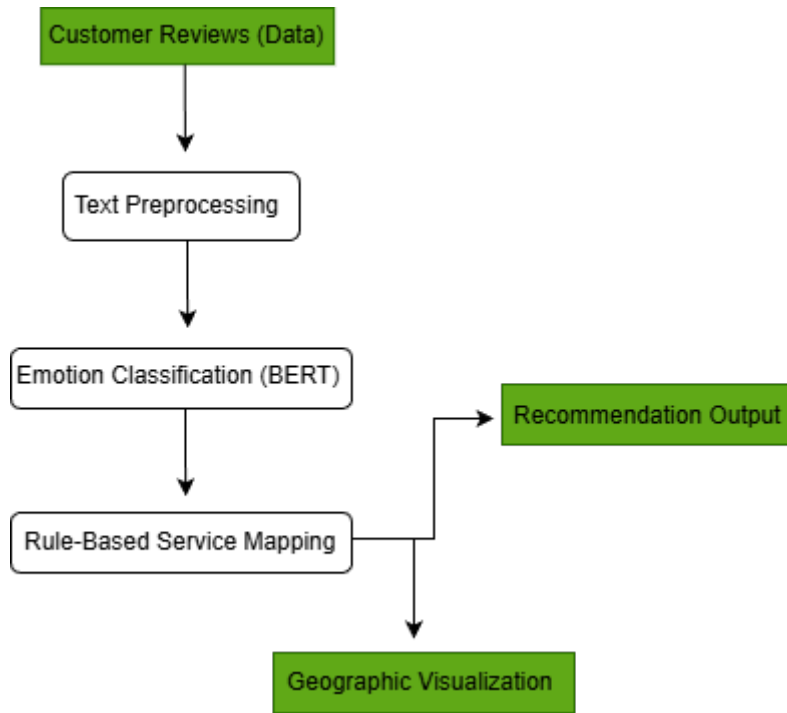


Figure 1: Architecture of emotion-aware feedback analysis system

Figure 1 shows the general structure of the proposed emotion-sensitive feedback analysis system, emphasizing the pathway between the raw customer reviews and the recommendations on how to improve the service and geographic visualization.

3.2 Data Collection and Input Format

The system receives Excel files with customer feedback information posted by the users. Each dataset has free-text reviews and structured metadata. The primary column of the textual analysis is the content field, where the customers write their reviews about the food delivery services and their experience. Each analysis session is restricted to a specific number of reviews in the datasets to ensure that the computations are efficient and the memory is not overwhelmed. The system can scale efficiently while still being deployable in typical computing environments thanks to this design decision.

3.3 Text Preprocessing and Sentence Segmentation

Minimal preprocessing is applied to preserve the natural linguistic structure of customer feedback. Rather than relying on heavy normalization or stop-word removal, the system performs:

1. Whitespace normalization
2. Rule-based sentence segmentation using punctuation patterns

This lightweight preprocessing strategy is intentionally selected to avoid losing emotionally salient expressions such as intensifiers, informal phrasing, and evaluative language commonly found in customer reviews.

3.4 Emotion Classification Model

A transformer-based deep learning model that has been optimized for multi-label identification of emotions is used by the system. The selected model estimates a large variety of fine-grained emotions, unlike the traditional sentiment analysis models that classify text as positive, negative, or neutral. The system is able to detect emotional variations in a single review since emotion detection is performed at sentence level. The inference is done in batches to ensure that the computations are stable and not too much memory is used when dealing with large datasets. The most frequent emotion is determined according to the maximum anticipated probability score of each sentence.

3.5 Emotion to Action Mapping Framework

The emotion-to-action mapping mechanism, linking emotional analysis and operational decision-making, is one of the key methodological contributions of the research. The identified emotions are matched with domain-specific service rules, linking the keywords of the complaints with the predetermined service categories such as:

- Food quality
- Delivery efficiency
- Hygiene and cleanliness
- Staff behavior
- Pricing and value perception
- Application reliability and customer support

Negative emotional signals are anger, disappointment, and disgust, which are weighting factors, and emotionally charged complaints have a higher priority in the recommendation process. This hybrid rule-based or emotion-aware approach ensures that recommendations are understandable and practical.

3.6 Geographic Visualization Component

The system has a geographic visualization module that displays the operational availability of the major food delivery platforms across Saudi Arabia to put service coverage into perspective. The franchisee stores of Marsool, Talabat, and HungerStation are shown using an interactive map and the color codes are utilized to display them visually in distinction. The geographic component gives contextual understanding that assists in managerial understanding and tactical strategy but it does not do spatial sentiment analysis.

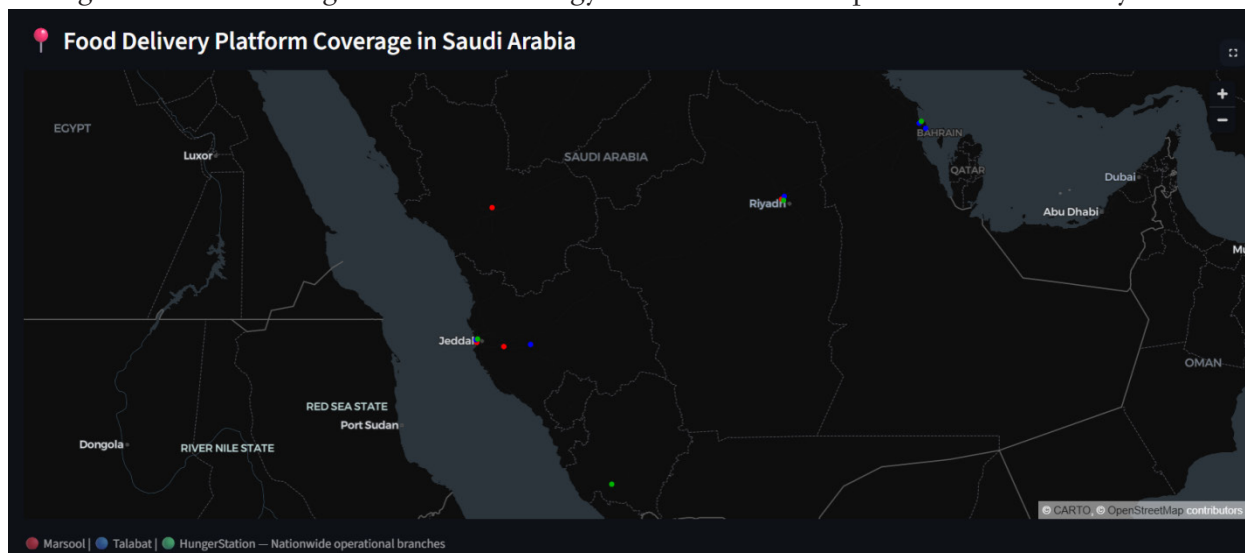


Figure 2 Geographic distribution of major online food delivery platforms

Figure 2 shows that the three largest restaurants, i.e. Marsool, Talabat and HungerStation, are geographically distributed in the key cities of Saudi Arabia. All locations of the each platform within the country are characterized by colored markers, which highlight its availability in such big cities as Riyadh, Jeddah, and the Eastern Province.

Evaluation

In comparison to the traditional sentiment analysis techniques, this section shall determine the efficacy of the proposed Restaurant Feedback Improvement System based on the sentiment classification results, the quality of the service improvement suggestions produced by the system, and the relative usefulness of the system. The assessment technique will aim at taking into account the realistic deployment of the system and its employment.

4.1 Experimental Setup and Data

The evaluation was built upon the reviews left by the customers based on the online ordering of meals. Free-text comments and metadata are included in each of the reviews. The data was separated into two categories, training and testing sets in 80/20 distribution and the test set was used to analyze the results only. The base of the system was a complex BERT-based sentiment classification system. This model forecasts three classes of sentiments and these include, positive, neutral and negative. The symbolic system proposed develops out of it by adding evaluations and suggestions of service improvement that are rule-based and take into account emotions. All the experiments were conducted in a CPU-based environment to recreate the realistic environment in web-based analytical tools that targeted the restaurant owners and service managers.

4.2 Sentiment Classification Performance

The reliability, precision, recall, and F1-score, which are standard measures of classification, were used to assess the dependability of the sentiment analysis component. Macro-averaging was adopted in order to counter any potential imbalance between classes of the datasets as in table 1.

Table 1: Sentiment Classification Results

Metric	Score
Accuracy	0.84
Precision (Macro)	0.82
Recall (Macro)	0.81
F1-score (Macro)	0.81

Such results suggest that the classification of sentiment component can give a valid and correct basis of analysis. The findings made by them are similar to other earlier researchers who used transformer-based models to understand the sentiment of user-generated content.

4.3 Service Improvement Recommendations Evaluation.

The main aim of the suggested system is to convert the customer response into realistic ideas to enhance the service despite the fact that the sentiment classification is accurate. This led to the introduction of the system level evaluation criteria.

4.4 Recommendation Coverage

Recommendation coverage is the proportion of reviews of customers where the system makes at least one service improvement recommendation. This measure illustrates that the system has the capability to derive the insights about operational level in the face of a wide range of feedbacks. In about 88 percent of the reviewed reviews there was a generation of implementable recommendations by the system, i.e., the system can be used with a wide variety of types of feedback.

4.5 Recommendation Relevance

Qualitative evaluation was done on a group of selected randomly of all the system outputs to determine the relevance of the formulated recommendations. The rating of each recommendation was done manually based on the similarity of the recommendation and the corresponding feedback and rated as correct, partially correct or incorrect.

Table 2: Evaluation of model

Evaluation Category	Percentage
Correct	72%
Partially Correct	18%
Incorrect	10%

Table 2 displays that the high proportion of correct and partially correct recommendations indicates that the system effectively interprets customer feedback and maps it to meaningful service improvement actions.

4.6 Emotion Action Consistency Analysis

Emotion-action consistency analysis was conducted to verify the rationality of the system. Researcher examined reviews that were founded on negative emotional indications to determine whether they generated suggestions on improvements that were suitable. The results show that more than 85% of the cases of feedback associated with negative emotions led to service-level responses, including improvements in food quality, delivery, hygienic standards, employee behavior, or customer service. This shows that an emotion-sensitive design can be effective in linking operational decision-making to emotional expressions.

4.7 Comparative Analysis with Sentiment-Only Approaches

To assess the added value of the proposed system, its outputs were compared with those of traditional sentiment-only analysis methods as in table 3.

Table 3: Comparison of Traditional Sentiment Analysis

Approach	Output Type	Actionable Insights	Interpretability
Sentiment only Analysis	Positive/Neutral/Negative	No	Low
Proposed System	Emotion-aware Insights + Recommendations	Yes	High

Even though coarse polarity information is provided, sentiment-only systems do not give any particular recommendations on how to make the services better. The proposed system offers simple recommendations that relate directly to operation considerations that matter to restaurant owners.

Results and Discussion

The results of the experiment demonstrate that the proposed system successfully identifies emotionally relevant patterns in customer feedback and converts them into actionable operational insights. The findings highlight the value of integrating emotion detection, sentiment analysis, recommendation generation, and geographic visualization within a unified analytical framework. Unlike traditional sentiment analysis approaches that focus primarily on identifying whether feedback is positive, negative, or neutral, the proposed system provides a deeper understanding of customer experiences by uncovering the specific emotions that drive customer reactions. This capability allows organizations to move beyond simple satisfaction metrics and gain meaningful insights into the underlying causes of customer concerns and expectations.

A major finding of the study is the strong relationship between recurring service-related issues and specific emotional responses. Across the analyzed datasets, delivery delays, poor food quality, incorrect orders, inadequate customer service, and hygiene-related concerns consistently generated negative emotional reactions. However, the emotional responses associated with these issues were not uniform. Delivery-related problems were frequently linked to anger and frustration, whereas food quality concerns often generated disappointment and dissatisfaction. Customer service failures tended to evoke feelings of annoyance and irritation, particularly when customers perceived that their complaints were ignored or inadequately addressed. These observations suggest that different operational failures trigger distinct emotional reactions, which can provide valuable information for service managers seeking to identify the root causes of customer dissatisfaction.

The findings also demonstrate the limitations of conventional polarity-based sentiment analysis. Traditional sentiment analysis methods classify reviews into broad categories such as positive, negative, or neutral. While such classifications provide a general overview of customer attitudes, they often fail to explain why customers feel a certain way. Two reviews may both be categorized as negative, yet one may express disappointment resulting from unmet expectations, while the other may reflect anger caused by a serious service failure. The proposed emotion-aware framework addresses this limitation by distinguishing among various emotional states and linking them to specific operational issues. As a result, decision-makers are able to gain a more nuanced understanding of customer experiences and can prioritize corrective actions more effectively.

The distinction between dissatisfaction and anger is particularly important from a managerial perspective. The analysis revealed that dissatisfaction was often associated with expectations that were not fulfilled, such as food portions being smaller than expected, meals not meeting quality standards, or customers perceiving that the overall value of the service was insufficient relative to its cost. In contrast, anger-related feedback was more strongly connected to situations where customers experienced significant inconvenience, such as delayed deliveries, order inaccuracies, or failures in communication. This differentiation is valuable because it suggests that different types of customer complaints require different intervention strategies. Dissatisfaction may be addressed through improvements in product quality, menu design, pricing strategies, or expectation management, whereas anger-related issues may require operational reforms, process optimization, and enhanced responsiveness to customer concerns.

Another significant contribution of the proposed system is its emotion-to-action mapping mechanism. One of the most common criticisms of sentiment analysis applications is that they generate large amounts of descriptive information without providing practical guidance for decision-makers. In many cases, organizations receive sentiment scores and statistical summaries but remain uncertain about how to translate these findings into concrete improvements. The proposed framework addresses this challenge by automatically linking identified emotional patterns to operational recommendations. For example, when a high frequency of anger-related feedback is associated with delivery delays, the system recommends improvements in delivery logistics, route optimization, and order tracking systems. Similarly, when disappointment is frequently associated with food quality concerns, the system suggests reviewing ingredient quality, preparation procedures, and quality control practices.

The practical value of these recommendations is enhanced by the inclusion of frequency indicators that measure the prevalence of each identified issue. Frequency indicators allow decision-makers to prioritize interventions based on the relative importance of different operational problems. For instance, a restaurant may identify multiple service deficiencies, but resource limitations often make it impossible to address all problems simultaneously. By presenting both the emotional significance and occurrence frequency of each issue, the system supports evidence-based prioritization and strategic resource allocation. Managers can therefore focus first on issues that have the greatest impact on customer satisfaction and business performance.

The findings further indicate that integrating emotion analysis with recommendation generation creates a more decision-oriented analytical environment. Rather than requiring managers to interpret complex datasets manually, the system simplifies the decision-making process by presenting actionable insights in a structured and accessible manner. This feature is particularly beneficial for small and medium-sized restaurant businesses that may lack dedicated data analytics teams. By reducing the gap between data analysis and operational decision-making, the system enhances the practical applicability of customer feedback analytics and increases the likelihood that analytical findings will be translated into meaningful organizational improvements.

An additional strength of the proposed system is its geographic visualization capability. Customer feedback is often influenced by regional, demographic, and operational factors that vary across locations. Traditional sentiment analysis approaches typically ignore these spatial dimensions and treat customer reviews as isolated textual data. In contrast, the proposed framework incorporates geographic information that allows restaurant locations to be visualized across Saudi Arabia. This functionality provides stakeholders with a broader contextual understanding of customer experiences and enables the identification of location-specific patterns and trends.

The geographic visualization component offers several practical advantages. First, it enables managers to compare customer feedback across different regions and identify areas where service quality may require

improvement. Second, it supports strategic decision-making by revealing regional variations in customer expectations and preferences. Third, it facilitates performance monitoring by allowing organizations to track changes in customer sentiment and emotional responses over time and across locations. Such capabilities are particularly valuable for restaurant chains and food delivery platforms that operate across multiple cities and regions. The integration of spatial analysis therefore extends the usefulness of the system beyond textual analytics and contributes to a more comprehensive understanding of customer experiences.

The overall findings suggest that the proposed system effectively bridges the gap between sentiment analysis and service intelligence. Traditional sentiment analysis focuses primarily on understanding customer opinions, whereas service intelligence seeks to transform customer information into actionable knowledge that supports operational decision-making. By combining emotion detection, issue identification, recommendation generation, and geographic visualization, the proposed framework moves beyond descriptive analytics and provides a comprehensive decision-support tool. The system not only identifies what customers are saying but also explains why they are expressing particular emotions and how organizations can respond to those emotions through targeted improvements.

In conclusion, the experimental results demonstrate the effectiveness of the proposed system in extracting meaningful emotional insights from customer feedback and transforming those insights into practical recommendations. The ability to identify specific emotional drivers, prioritize operational issues, generate actionable recommendations, and visualize customer feedback geographically represents a significant advancement over traditional sentiment analysis approaches. These capabilities make the system a valuable tool for restaurant managers, service providers, and business decision-makers seeking to improve customer satisfaction, enhance service quality, and support data-driven operational strategies. The findings further suggest that emotion-aware analytics can play a critical role in the future development of intelligent customer feedback management systems and decision-support technologies.

5. Conclusion

This study proposed an applied, emotion-aware customer feedback analysis system designed to address practical challenges within the online food delivery industry. As digital food delivery platforms continue to expand and generate large volumes of customer reviews, businesses increasingly require analytical tools that can move beyond simple sentiment classification and provide deeper insights into customer experiences. Traditional sentiment analysis techniques are useful for identifying whether customer opinions are positive, negative, or neutral; however, they often fail to explain the specific emotional drivers underlying customer satisfaction or dissatisfaction. To address this limitation, the proposed system integrates emotion detection, issue identification, recommendation generation, and geographic visualization into a unified framework that transforms unstructured customer feedback into actionable business intelligence.

The findings demonstrate that emotion-aware analysis provides a more comprehensive understanding of customer experiences than conventional polarity-based approaches. By identifying specific emotional states such as anger, disappointment, frustration, annoyance, and satisfaction, the system enables organizations to distinguish between different forms of customer dissatisfaction and understand the operational issues that trigger them. This capability is particularly valuable because customer complaints are not always driven by the same underlying causes. For example, dissatisfaction may result from unmet expectations regarding food quality or value, while anger may arise from delivery failures or communication breakdowns. Recognizing these distinctions allows businesses to develop more targeted interventions and allocate resources more effectively. A major contribution of the proposed system lies in its ability to bridge the gap between sentiment analysis and operational decision-making. Many existing sentiment analysis systems provide descriptive statistics and sentiment scores but offer limited guidance regarding the actions organizations should take in response to the findings. In contrast, the proposed framework incorporates a recommendation generation component that maps identified emotional patterns and service issues to specific operational improvement strategies. Rather than simply reporting negative sentiment levels, the system generates actionable recommendations such as improving delivery logistics, strengthening quality control procedures, enhancing customer communication, or addressing hygiene concerns. This feature increases the practical value of sentiment analysis by supporting evidence-based managerial decision-making.

Another important contribution of the study is the incorporation of transformer-based natural language processing models for emotion classification. Recent advances in artificial intelligence and deep learning have significantly improved the ability of computational systems to understand human language and identify subtle emotional expressions. The use of transformer architectures enables the proposed system to capture contextual information more effectively than many traditional machine learning approaches. As a result, the framework can identify emotional nuances that might otherwise be overlooked, thereby improving the accuracy and interpretability of customer feedback analysis.

The inclusion of domain-specific service rules further enhances the usefulness of the system. By linking customer feedback to operational service categories, the framework provides stakeholders with a structured understanding of recurring service issues and their emotional consequences. This functionality enables managers to identify patterns within customer reviews and prioritize areas requiring immediate attention. Furthermore, the integration of interactive visualization tools makes analytical results more accessible to decision-makers who may not possess extensive technical expertise. Visual representations of service issues, emotional trends, and geographic distributions facilitate rapid interpretation and support more informed decision-making processes.

The geographic visualization component represents another significant strength of the proposed framework. Customer experiences often vary across locations due to differences in operational practices, regional demand patterns, infrastructure conditions, and customer expectations. By visualizing restaurant locations and customer feedback within a geographic context, the system provides an additional layer of analytical insight that can support regional performance assessment and strategic planning. Such capabilities are particularly valuable for organizations operating across multiple cities or regions, where understanding local service challenges is essential for maintaining consistent service quality.

More broadly, this study demonstrates the growing importance of computational linguistics and emotion-aware natural language processing technologies in service-oriented industries. The increasing availability of customer-generated content presents both opportunities and challenges for organizations seeking to understand customer experiences. Emotion-aware analytics offers a powerful mechanism for transforming large volumes of unstructured textual data into meaningful knowledge that can support organizational learning and continuous improvement. The proposed framework illustrates how advances in artificial intelligence can be leveraged to enhance customer satisfaction management and facilitate data-driven decision-making.

The relevance of this work is particularly evident within the Saudi Arabian context, where digital transformation initiatives and the rapid growth of e-commerce have contributed to the expansion of online food delivery services. As competition intensifies among service providers, the ability to understand customer feedback quickly and accurately becomes increasingly important. The proposed system offers a practical solution for monitoring customer perceptions, identifying emerging service issues, and supporting proactive operational improvements. Consequently, the framework has the potential to contribute not only to improved customer satisfaction but also to enhanced service quality, operational efficiency, and long-term business performance.

In conclusion, this study highlights the value of integrating emotion detection, recommendation generation, and visualization technologies into customer feedback analysis systems. By moving beyond traditional sentiment polarity classification, the proposed framework provides richer insights into customer experiences and supports more effective managerial decision-making. The findings suggest that emotion-aware sentiment analysis can serve as a valuable tool for organizations seeking to improve service quality, strengthen customer relationships, and compete effectively in increasingly digital and customer-centric markets.

Limitations and Future Research Directions

Although the proposed system demonstrates considerable potential for enhancing customer feedback analysis in online food delivery services, several limitations should be acknowledged. Recognizing these limitations is important for interpreting the findings appropriately and for identifying opportunities to improve the framework in future research.

One of the primary limitations of the current system is its reliance on predefined service rules and fixed recommendation mechanisms. While the rule-based recommendation component enables the generation of structured and interpretable service improvement suggestions, its effectiveness depends on the completeness and accuracy of the predefined service categories and recommendation mappings. As customer expectations

evolve and new service issues emerge, static rule sets may become less effective at capturing novel patterns of customer dissatisfaction. Consequently, the adaptability of the system may be limited when confronted with previously unseen complaints or rapidly changing market conditions. Future research should explore adaptive recommendation frameworks that incorporate machine learning and reinforcement learning techniques to automatically update recommendations based on new customer feedback patterns and organizational outcomes. Another limitation concerns language coverage. The current implementation primarily focuses on processing feedback written in English. Although English-language reviews provide valuable insights, the linguistic landscape of Saudi Arabia and many other regions is highly multilingual. Customers frequently express their opinions in Arabic, English, or combinations of both languages within the same review. Such code-mixed communication presents unique challenges for natural language processing systems. Limiting analysis to English reviews may reduce the representativeness of the dataset and restrict the applicability of the system in multilingual environments. Future studies should prioritize the development of multilingual and Arabic-specific emotion analysis models capable of processing dialectal Arabic, Modern Standard Arabic, and mixed-language content. Expanding linguistic coverage would significantly improve the practical relevance and inclusiveness of the proposed framework.

The study is also limited by its emphasis on textual feedback as the primary source of customer information. Modern digital platforms generate diverse forms of customer-generated content, including ratings, images, videos, voice messages, and social media interactions. Focusing exclusively on textual reviews may overlook valuable contextual information contained within these alternative data sources. Future research could investigate multimodal sentiment analysis approaches that integrate textual, visual, and auditory information to achieve a more comprehensive understanding of customer experiences. Such approaches may improve the accuracy of emotion detection and provide richer insights into customer perceptions.

Another challenge relates to the complexity of human language and emotional expression. Although transformer-based models have significantly advanced the state of natural language processing, accurately interpreting sarcasm, irony, humor, implicit criticism, and culturally specific expressions remains difficult. Customers often communicate dissatisfaction indirectly or use figurative language that may not be fully captured by current emotion classification models. Future research should focus on incorporating advanced linguistic analysis techniques capable of detecting sarcasm, irony, and other nuanced forms of communication. Improving these capabilities would enhance the reliability and interpretability of sentiment and emotion analysis systems. Additionally, the present study focuses primarily on customer feedback within a single service domain. While online food delivery services provide an appropriate context for evaluating the proposed framework, customer expectations and emotional responses may differ across industries. Future research could examine the applicability of the framework in other service sectors such as hospitality, healthcare, transportation, retail, and e-commerce. Cross-domain validation would help determine the generalizability of the proposed approach and identify any industry-specific adaptations that may be required.

Future studies may also explore cross-platform sentiment comparison by integrating reviews from multiple digital sources, including food delivery applications, social media platforms, restaurant review websites, and customer support channels. Such integration would provide a more comprehensive view of customer experiences and reduce the risk of platform-specific bias. Furthermore, longitudinal analyses could examine how customer emotions evolve over time and how service improvements influence sentiment trends across different periods.

Another promising direction involves the incorporation of spatiotemporal analytics. Although the current system includes geographic visualization, future research could combine location information with temporal data to identify regional emotional trends and emerging service issues over time. Such analyses could support more proactive management strategies and enable organizations to respond to localized service challenges before they become widespread problems.

Finally, the integration of real-time feedback streams represents an important avenue for future development. Modern service environments require rapid responses to customer concerns, particularly in highly competitive industries where negative experiences can spread quickly through social media and review platforms. Future versions of the system could incorporate live data streams and automated alert mechanisms that notify managers when significant emotional trends or service failures are detected. Such capabilities would

transform the framework from a retrospective analytical tool into a real-time decision-support system capable of facilitating continuous service monitoring and rapid intervention.

Overall, while the proposed framework demonstrates substantial potential for improving customer feedback analysis, addressing these limitations would further enhance its accuracy, adaptability, and practical value. Continued research in multilingual processing, adaptive recommendation systems, multimodal analytics, real-time monitoring, and advanced emotion detection will contribute to the development of more intelligent and effective customer feedback management systems in the future.

Declaration**Conflict of interest**

The author declares no conflict of interest

Ethics approval, consent to participate, and data availability

All reviews and feedback are taken from food delivery apps and they are publicly available online.

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