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Analyzing Customer Preferences in Food Companies and Food Technology with Artificial Intelligence[*]

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Abstract

The relationship between AI and consumer preferences is becoming a crucial area of study for both technology corporations and food industries in an increasingly digitalized environment. With the introduction of AI technologies, businesses can now monitor consumer behavior in novel ways and customize their products to appeal to their customers more intimately. The study of natural language processing aims to understand a language and enable machines to do meaningful tasks. This study emphasizes the use of sentiment analysis to improve service quality and gain a deeper understanding of costumer feedbacks. To find the favorable, negative, and neutral reviews about the policies the restaurant follows or violates, a real-time dataset was used. Following preprocessing, lexicon-based sentiment analyzers Textblob and Vader (valence aware dictionary for sentiment reasoning) are used to appropriately classify comments as either positive or negative. Oversampling is used to balance the data sets because there are more positive-labeled evaluations than negative ones. Training and test data for the feature extraction process are created using the count vectorizer and TF-IDF (Term Frequency Inverse Document Frequency). The results indicate that ease of use, product quality, and service effectiveness are strongly correlated with customer satisfaction. Businesses that put these factors first typically see an increase in client loyalty and favorable sentiment.

Keywords: Artificial Intelligence (AI), Lexicon-based sentiment analyzers, Textblob, VADER, TF-IDF.

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1. Introduction

Artificial intelligence (AI) integration theory strongly emphasizes on leveraging AI technology to enhance current systems or procedures. Artificial Intelligence is a system that uses pre-programmed algorithms to process data or information autonomously (Jiang *et al,* 2020; Kineber *et al.,* 2023). Because AI technology can offer many advantages for the growth of a system or process, knowing the philosophy of AI technology integration is essential. Systems and processes can function faster and more effectively using AI technology, improving their quality and productivity. Additionally, human mistakes are common occurrence in a variety of procedures, and AI technology can help reduce this risk (Sanchez-Franco *et al.,* 2019).

The relationship between AI and consumer preferences is becoming a crucial area of study for both technology corporations and food industries in an increasingly digitalized environment. With the introduction of AI technologies, businesses can now monitor consumer behavior in novel ways and customize their products to appeal to their customers more intimately. Food industries, for example, face difficult resource allocation problems as they use AI to streamline supply chains and enhance logistics. A recent study emphasized Food Bank Local's efforts, showing how AI may improve equitable food distribution by tackling allocation issues that are rarely examined in the literature (Walsh *et al.,* 2014). Additionally, analogous AI applications in food technology mirror patterns seen in other sectors, like hospitality, where executives recognize the operational difficulties as well as the possible advantages of incorporating AI systems into preexisting frameworks (Malone *et al.,* 2024). The way AI influences consumer preferences in the food industry is therefore a crucial topic for continued study and advancement.

Website and social network comments are now regarded as a valuable source of implicit knowledge (Walek & Fojtik, 2020). Thus, by processing these remarks and analyzing the underlying feelings, it is possible to determine the user's dietary preferences. This could be accomplished by using natural language processing techniques to process and uncover the implicit emotions concealed in user comments (Cambria *et al.,* 2017). Indeed, sentiment analysis methods could be used to infer the author's opinions on a wide range of subjects. However, because human language is complicated, people may communicate ideas using a variety of words. Consequently, a semantic approach to sentiment analysis makes sense.

Companies, governing bodies, and society at large have more opportunities to glean insightful, varied, and expressive knowledge from the content created by the social media community, especially in respects to the data source and how it is connected to contexts (Baumgarten *et al.,* 2013: 6). This is because social media constitutes many of the most abundant sources of the data regarding ideas as well as information. In order to improve the components that customers find lacking, decision makers must, in reality, understand how people feel about their services. Thus, using automated techniques to mine and analyze the data left on these sites is essential (Chiny *et al.,* 2021).

Sentiment analysis aims to extract from unstructured written text the subjectivity and opinion of people's critiques and attitudes toward things and their characteristics (Yıldırım *et al.,* 2020). Over the years, numerous techniques for sentiment vocabulary analysis have been put forth. To quantify phrase sentiment polarity, Turney (2002) employed a straightforward unsupervised categorization learning method to calculate pointwise mutual information based on the emotional qualities of words.

Understanding customer opinions about the items is highly helpful and aids in their continued improvement. If the restaurant industry ignores client feedback, it will be extremely difficult to establish a reputation in the marketplace. Lots of customers choose which restaurants to visit based on the online meal reviews of those establishments. Therefore, in order to attract customers, restaurants should take note of those reviews and work to enhance their offerings. Since reading through the countless evaluations left by different customers is an extremely difficult and time-consuming task for a human, sentiment analysis can handle this task with ease.

Three feature restaurants which include Mc Donalds, Pizza Hut and Starbucks and three of the techniques used for feature analysis, including Bow, Tf-Idf, and N-gram, were used in this research. To gain deeper insights into customer feedback, reviews were categorized into themes, CES NPS and CSAT were calculated. The research utilizes natural language processing (NLP) techniques, sentiment analysis (for both BOW and TF-IDF, several N-gram methods are used, as well as their combinations) and a structured classification approach to categorize customer feedback.

2. Literature Review

2.1. Food Industry

Nowadays, the food industry is a more demanding field in order to provide the wants of a vast global population. Certain people choose ready to eat dishes since they save precious hours in the kitchen in today's hurried lifestyle. But insufficient labor forces mean that technology must be used to supply the demand for food. A new technology in the food industry is artificial intelligence (AI), which enables different food types to be processed by machines or robots. In the business of food processing, hygiene is crucial. Personal hygiene and equipment hygiene are two crucial categories of hygiene. Individuals who work in the food sector or handle food goods are considered to have good personal hygiene. According to Addanki *et al.,* 2022, the primary causes of personal hygiene are wounds, oral infections, hair, and fingernails. Frequent sanitization of equipment is necessary to prevent contamination. Both cleaning in place (CIP) and cleaning out of place (COP) systems are frequently employed; small scale enterprises tend to favor COP systems because CIP systems are more expensive. CIP systems are preferred in large processing sectors to prevent greatest degree of contamination (Addanki *et al.,* 2022). According to Mariott (1999), best practices should be concentrated on topics like food innovation, preparation, and safety.

2.2.Overview of Artificial Intelligence in the Food Industry

The food sector is rapidly changing many operational areas, from production to customer engagement, due to the incorporation of AI. Machine learning as well as data analytics are two examples of AI technologies that help optimize supply chain management, increasing productivity and cutting waste. For example, businesses can use AI to analyze customer preferences and buying patterns, allowing for more personalized marketing campaigns that appeal to specific clients. Recent research shows that consumers are willing to pay for products with sustainability labels, both real and certified, influenced by AI-generated content. This shift is especially noticeable in the rising demand for sustainable products (Dubois *et al.,* 2024). The agri-food supply chain is also altering as a result of the growing popularity of veganism, forcing businesses to adjust to consumers' shifting preferences for ecologically friendly products (Hedayat *et al.,* 2021). Therefore, AI not only simplifies processes but also helps food companies adapt to changing consumer demands.

2.3. The Role of AI in Understanding Customer Preferences

AI integration in food businesses offers a revolutionary method of comprehending client preferences and enables a sophisticated understanding of consumer behavior. Because large amounts of data can be analyzed by machine learning algorithms, firms can uncover previously hidden trends and preferences. For example, as the frameworks in Singh .K, 2024 demonstrate, AI not only automates data collecting but also provides profound insights into customer sentiments by micro-analyzing human emotions and interactions. This knowledge is crucial for marketing strategy, since AI helps with target audience segmentation and the creation of consumer-friendly, tailored marketing campaigns. Additionally, the application of AI at all work levels improves the customer experience; nevertheless, as mentioned in (Holthöwer & Van, 2021), it is crucial to resolve the reluctance of certain consumers to embrace such technologies. Food businesses can improve customer interactions and stimulate innovation in product offers that are suited to consumer demands by utilizing AI efficiently.

2.4. Related Work

Fast food establishments are now common in many kinds of societies because of the meal's appeal, accessibility, and diversity. Using machine learning alongside deep learning models, sentiment analysis as well as topic modeling was applied to the reviews of these eateries.

Pang *et al.,* 2002 used a typical bag of features technique to predict the sentiment class of film reviews in order to address sentiment classification. Their findings demonstrated that basic decision-making models that employed hand-picked feature words for sentiment classification were outperformed by machine learning techniques utilizing bag-of-words features. Turney 2002 created handwritten algorithms that can invert a word's semantic orientation when it is preceded by a negative word in order to get around the problems with bag-of-words techniques like negation. It can take a lot of work to create heuristically built rules that might not be able to manage the various instances present in human language, even though such algorithms represent a significant advancement to handle things like negation.

The researchers (Chen *et al.,* 2015) devised an algorithm that uses a bag of words to forecast product ratings based on comment content utilizing bigrams and unigrams. The study used a A set of Amazon video game reviews from UCSD users, Since average ratings varied little between years, months, along with days, time based analyses did not perform well. However, bigrams and unigrams produced accurate results, but unigrams came out successful. Unigrams that are popular have a higher variance, making them effective predictors. Unigrams surpassed bigrams by 15.89%. The paper (Shaikh & Deshpande 2016) employs several feature extraction or selection algorithms for sentiment analysis. Data was first acquired from Amazon, and then preprocessed to eliminate stop words and unusual characters. They use strategies for determining features or mining approaches, with naive bayes as the base algorithm, for single words or noun phrases. They discovered that Naive Bayes outperforms single-word analysis for phrases. The paper's main limitation is its reliance on the naive Bayes classifier technique, which may not yield sufficient results. As an extension of the experiment in the publication (Wang & Qiu 2015), TF-IDF is used here. It can predict ratings using a range of phrases. However, few classifiers are utilized in this case. The researchers used a root average square error model for linear regression.

2.5. Sentiment Reasoner and Valence Aware Dictionary Lexicon and Rule-based Sentiment Analysis

Because of the significant bias and nature of big data of social media information, sentiment analysis systems face significant obstacles (Pandey, 2018; Hutto & Gilbert, 2014). In fact, the primary focus of conventional textual sentiment analysis techniques is the analysis of lengthy texts, including news articles and entire documents. Short texts known as microblogs are frequently distinguished by loud noises, unusual terms, and acronyms. When used for processing small texts or microtexts, previous emotion classification techniques typically lack the ability to extract relevant features and have a poor classification effect (Xu *et al.,* 2020).

A sentiment analysis tool and rule-based lexicon designed especially for social media sentiments is called valence aware dictionary and sentiment reasoner (VADER). The sentiment lexicon used by

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VADER is a collection of lexicon properties that are often classified as either positively or negatively based on their semantics orientations.

The foundation of VADER is the wisdom of crowds (WotC) method Fleenor, 2006, which is used to obtain a reliable point estimate of each lexical feature's sentiment valence (intensity). A total of over 90,000 ratings were obtained from ten independent human raters who performed the VADER evaluation. As a result, 7,500 lexical features with valence values, which vary from -4 (highly positive) to +4 (highly negative) — were, adopted (Hutto & Gilbert, 2014). As demonstrated by this experiment, VADER performs better than even individual human raters. In addition to being responsive to the polarities and strength (positive as well as negative) of emotions, VADER can also be tailored towards the structure of networking sites that typically employ writing informally, which includes slang, abbreviations, multiple punctuation marks, and emoticon. The writing style on social networks does; in fact, VADER employs a number of text-based criteria to capture varied degrees of sentiment. These heuristics enable it to recognize that a capitalized word, when surrounded by non-capitalized terms, frequently has more emotional weight. Similarly, VADER interprets the presence of punctuation marks, such as exclamation points, as an increase in sentiment strength (Hutto & Gilbert, 2014).

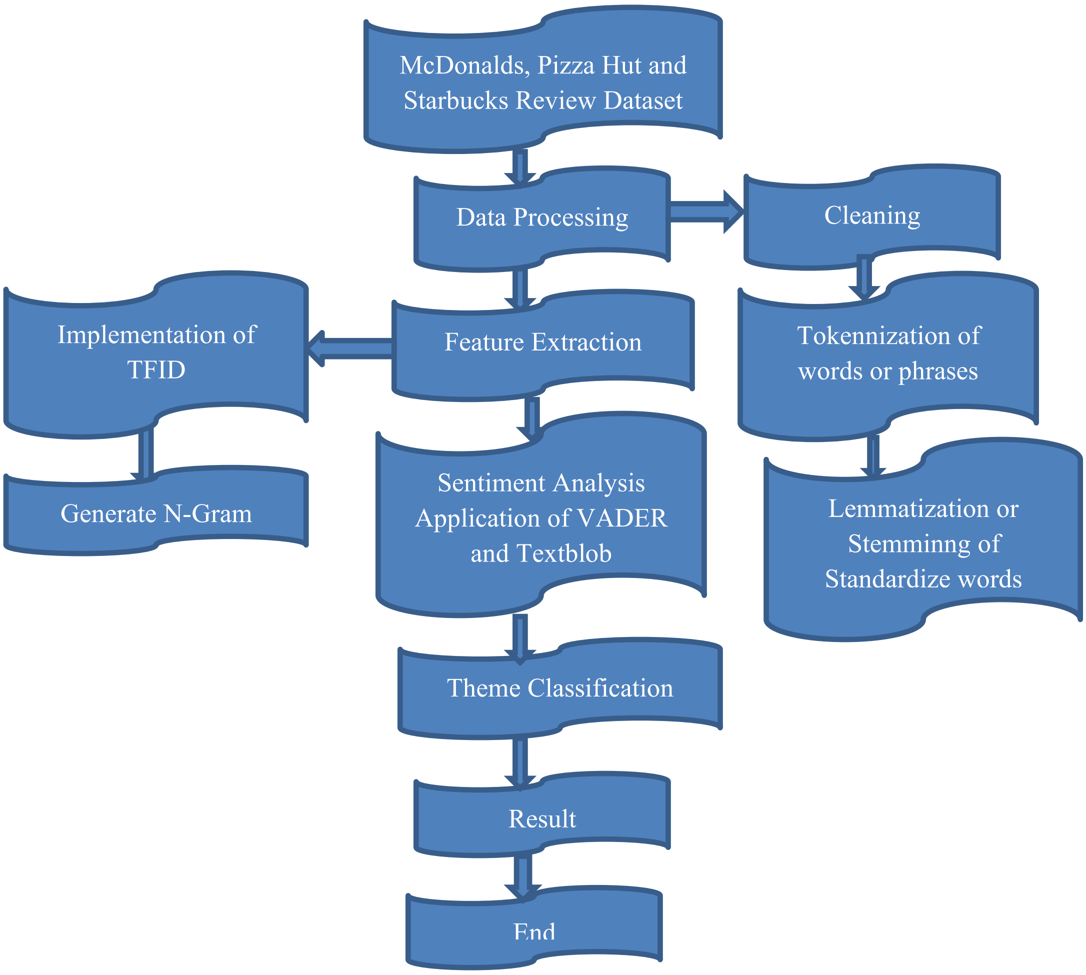
VADER provides a significant advantage because of its pre-trained status, especially when working with unlabeled data. This was used, for instance, by Borg & Boldt (2020) in their sentiment analysis of 168,010 emails from a Swedish telecom provider that did not have any initial sentiment data. Two Support Vector Machine models were trained for more thorough sentiment extraction and categorization after VADER and a Swedish sentiment lexicon supplied the required initial labels. In a different study, valdez *et al.,* 2020 used the VADER tool to examine the average daily sentiment of 86,581,237 U.S. time series tweet in order to identify themes in a corpus of COVID-19-related U.S. tweets and determine whether sentiment shifts in reaction to the pandemic. In Al Mansoori *et al.,* 2020 used sentiment analysis with the VADER model to evaluate criminal activity on facebook and twitter and successfully categorize the gathered data as negatively, positively or neutral in order to find suspects. In order to track the influx of tourists in Syria's Austrian region, Scholz *et al.,* 2020 also employed the VADER model to do a comprehensive semantic analysis that analyses the sentiment of tweets gathered from August 2008 and August 2018.

3. Methodology

3.1. Research Design

Figure 1 shows our suggested system's general layout. There are three steps in this section: sentiment analysis, clustering, and preprocessing. The general layout of the extraction preferences is displayed below. Data is first gathered from the designated domain, and then preprocessing is carried out by going through a number of procedures such stemming, tokenization, stop word removal, and lowercase conversion. Then, using various feature extraction algorithms, the text data was transformed into numerical data. Following conversion, the SVM supervised approach is used to try and determine if the reviews are good or negative. Lastly, a precision comparison of the performance is made.

Figure 1. The Research Design



3.1. Dataset

The "McDonalds Restaurant Reviews in USA, by **Nidula Elgiriyeithana**", "Starbucks review in USA by **Kanchana1990**" and "Pizza Hut review in USA by **Abhi Patel**" dataset was gathered from Kaggle. The collection includes reviews from various patrons of 33396 Mcdonalds, 851 Starbucks and 605 Pizza Hut eateries. All reviews were collected for the trial

3.2. Pre-Processing

Data preparation is the initial stage of data cleansing that makes the data easier for the algorithm to understand. Tokenization, part of speech tagging, stop word removal, stemming, noun extraction, and noun filtering are all included in the preprocessing. The following actions took place in this step:

- **URL Removal:** This procedure eliminates every URL from the text.

- **Lowercase Conversion:** This makes it much easier to identify the intended results when all text data is converted to lowercase. It is also among the most popular stages of text preprocessing in natural language processing.

3.2.1. Tokenization

The primary goal of tokenization is to identify words. A process called tokenization involves breaking a string of words up into smaller components called tokens. These tokens are comparable to words, which are units in sentences, and sentences, which are units in paragraphs. Subsequently, the words are classified according to their syntactic function the expression's verb, subject, adjective, etc. Stop words including "a," "an," "and," "but," "the," "that," "of," and "from" are removed (Vijayarani *et al.,* 2015). The stem of the words is then left intact while the prefix and suffix are removed. The tokenization technique is commonly used in sentiment analysis. For instance, "The food was absolutely wonderful" is transformed to (The, food, was, absolutely, wonderful).

3.2.2. Expression Removal

Generally speaking, expressions don't hold important data for sentiment analysis. Therefore, removing expressions is done as a preprocessing step and has little effect on the outcome.

3.2.3. Elimination of Punctuation

Eliminating punctuation is another typical pre-processing stage in natural language processing. Every punctuation character in the text is eliminated during this operation.

3.2.4. Elimination of Stop Words

Stop words are frequently words used in a language, which include "a," "is," "the," and so on. Eliminating stop-words from a text has no effect on its meaning because they don't convey any important information.

3.3. Stemming

A preprocessing technique called stemming involves reducing the altered words to their most basic or root form. According to Katariya *et al.,* (2015), stemming aids in condensing all of a word's derivatives that are semantically identical into a single idea. For instance, word such as "eating" and "eaten" can all be regarded as "eat" “cooked” can be “cooking”, “playing” can be “play”, and so on. It might not always be a word if they appear in a document. The terms that have been given the noun tag are retrieved because we are searching for user preferences, which are typically expressed as nouns. Unrelated nouns are filtered because there may be a lot of these nouns (Karasu *et al.,* 2020). Those nouns are searched up in the WordNet's food category for this purpose. A noun is removed if it is not present in the WordNet food vocabulary classifications and synonym.

3.4. Feature Extraction

3.4.1. Term Frequency-Inverse Document Frequency (TF-IDF):

TF–IDF is a weighing factor for characteristics that is computed on a per-term basis in text mining and machine learning. It is computed on a per-term basis. Whereas inverse document frequency gauges a term's significance based on its occurrence across a collection of documents, term frequency quantifies a phrase's frequency of occurrence appears in a document, indicating its relevance (Bengfort *et al.,* 2018). It can be inferred that a phrase is less informative about that text if it’s computed TF-IDF value is nearer 0. Conversely, a phrase is more informative if the score is nearer 1. The TF-IDF formula is as follows:

$$\text{tf idft} = \text{ft,d} \times \log \frac{N}{df\,t} \tag{1}$$

Where,

tfidft = weight of term t

ft,d = frequency of term t in document d

N = total number of documents

dft = number of documents containing the term t

3.4.2. N-Gram

Contiguous sequences of n items from a particular text or speech are called N-grams. The N-gram technique is a widely used method in natural language processing, where n denotes a continuous number of terms or words (Ahuja *et al.,* 2019). The level of analysis will determine whether these things are letters, phonemes, or words.

3.4.2.1. Types Of N-gram

1. Unigram: One item or word (n=1).
2. A Bigram is a pair of words or things (n=2).
3. A trigram is a group of three words or objects (n=3).
4. N-gram: An arrangement of n words or objects.

If we examine a sentence like the N-grams "The", "foods", "are", "really" and "tasty" are Unigrams. "The foods are really tasty" for example. Bigram's words include "the foods", "are" "are really" and "really tasty". Trigram says, "The foods are", "the foods are really" and they "are really tasty." The supervised learning model has been fitted using various N-gram schemes, TFIDF, and BOW feature extraction methods independently.

3.4.3. Bag Of Words (BOW)

Using a bag-of-words representation is the standard method for creating a single lexical context for each instance of a particular word or phrase (Indurkhya & Damerau, 2010). It is relatively straightforward to learn, simple to implement, and helpful for issues linked to natural language processing. By reporting the frequency of terms in a document, a bag of words is a text illustration that converts textual data into numerical format. It additionally generates a vocabulary for every term that was the same in every page in the training set. For instance, Texts 1 and 2 might say,

Text 1: "Best burger in town" and

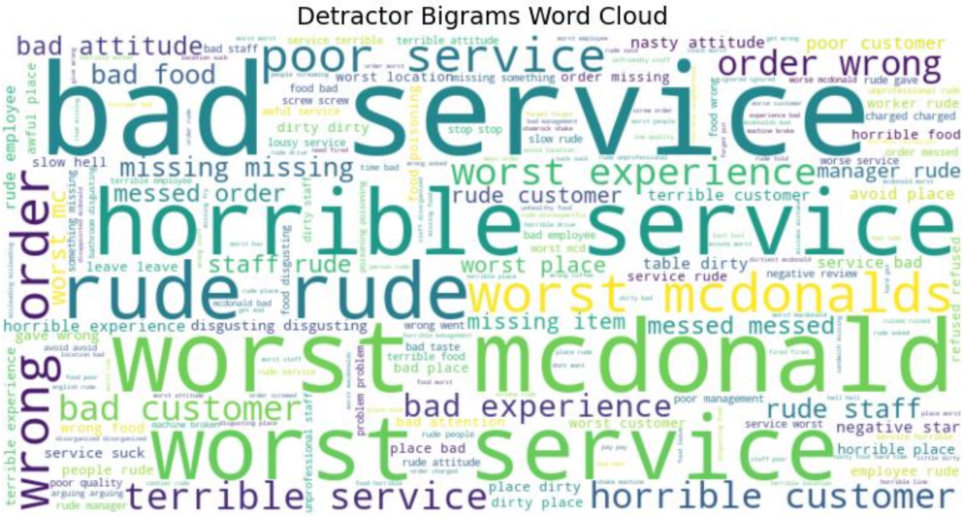
Text 2: "Best service ever."

“Best,” “burger,” “in,” “the”, “town,” “service,” and “ever” are the seven words that make up the vocabulary.

3.4.4. Word Cloud

Word clouds are a graphic aid for representing text that has grown in popularity. They are used to give a summary in a variety of circumstances by reducing the text to the terms that appear most frequently. This approach is typically used to summarize pure text (Heimerl *et al.,* 2014). The size of more common words is larger than that of less common ones. Word clouds are terms used in both positively and negatively evaluations were created independently. Certain neutral terms, such food, service, order, pricing, flavor, etc., are included in both of our word clouds. For both favorable and negative assessments, the word clouds are displayed in Figures 2.

Figure 2. Promoter and Detractor Word cloud



3.5. Sentiment Analysis

Sentences that contain any of a cluster's words are then moved to that cluster. It is important to remember that sentences can belong to multiple clusters because they usually contain multiple words. After that, the positive and negative attitudes in each statement are examined and extracted. At the document level, sentiment analysis is carried out since the sentiment scores of the entire cluster are determined after the score of each sentence have been determined. The SentiWordNet lexicon produced more accurate findings in this study after several sentimentanalysis techniques were applied. For sentiment analysis, the SentiWordNet lexicon is utilized in the manner described below. (Denecke 2008)

SentiWordNet assigns positive, negative, and objective polarity scores to each word's synonyms. The three scores should add up to one, and each score falls between 0 and 1. For instance, the word "good" has a triple score of (scorepos, scoreneg, scoreobj = 0.875, 0.0, 0.125) (Siersdorfer, *et al.,* 2010). SentiWordNet's sentiment analysis selects all phrases in phrases that has been given the tags "adjective", "verb" or "adverb" as attributes (Dang *et al.,* 2010). Next, using SentiWordNet, for each of these terms synonyms the triple score is defined.

The sum of the positive ratings of all of a word's synonyms divided by the total number of synonyms is the positive score for that term. The same formula is used to determine the objective and negative scores for each word A:

$$Score\ \mathrm{pos}\ (A) = \frac{1}{n}\sum_{i=0}^{n} Score_{\ \mathrm{pos}} \tag{2}$$

$$Score\ \mathrm{neg}\ (A) = \frac{1}{n}\sum_{i=0}^{n} Score_{\ \mathrm{neg}} \tag{3}$$

$$Score\ \mathrm{obj}\ (A) = \frac{1}{n}\sum_{i=0}^{n} Score_{\ \mathrm{obj}} \tag{4}$$

In this case, n is the number of synonyms. The phrase's score is determined in a similar manner once the triple polarity score for each feature in the sentence has been determined. In other words, the average positive score of every word in a sentence is equal to the positive score of each phrase. The same formula is used to determine objective and negative scores. Once each sentence's triple score has been calculated, the entire sentence is deemed positive if its positive score exceeds its negative score, and vice versa. The sentence is objective and is not taken into account when determining the cluster score if the positively and negatively ratings are equal. The following formula is then used to determine each cluster's sentiment analysis score:

$$S_c = \frac{\mathrm{Np+Nn}}{\mathrm{Np+Nn}} \tag{5}$$

The cluster's positive and negative sentence counts are denoted by Np and Nn, respectively. The user's food preferences cluster is determined by selecting the cluster with the highest score at the end of this phase. After combining the nouns from both clusters and returning the user's preferences, the second cluster is also chosen if its value is extremely near to the first cluster (below 0.1 differences).

3.6. Vader

VADER, an acronym for Valence Aware Dictionary and Sentiment Reasoner, is a sentiment analysis tool that uses a set of rules applied to its lexicon with an emphasis on social media emotion analysis. A set of lexical properties (words, for example) that are often classified as positive or negative based on their semantic orientation is combined with a sentiment lexicon in VADER. VADER uses these word evaluations to generate four sentiment metrics. The first three indicate the percentage of language that fits into the categories of positive, neutral, and negative. Combining all lexical scores that have been adjusted between -1 and 1 yields the composite score, the last metric.

Remember that capitalization and punctuation have an impact on the VADER model (Hutto & Gilbert, 2014). As a result, the sentiment has not been fully captured by filtering out special letters or changing the text to lowercase.

3.6.1. Textblob

For a given text, TextBlob provides three outputs: subjectivity, polarity, and more. The three sentiments that polarity offers are - 1 for negative sentiment, 1 for positive sentiment and 0 for neutrality attitude. Subjectivity is the presence of subjects or opinions.

4. Results And Discussions

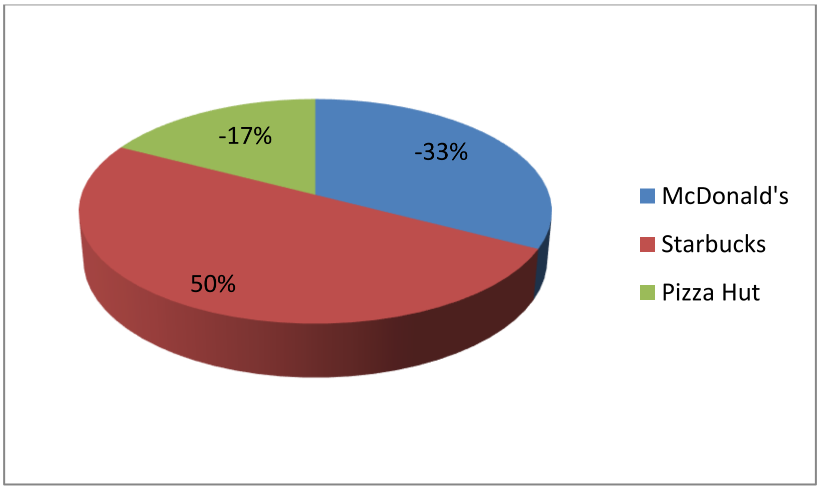
The results of the experiment on how customers feel about food restaurants are presented and discussed in this section. Reviews are taken in order to assess customer experiences and pinpoint areas that need improvement. The following lists the outcomes of the lexicon-based method to sentiment analysis on the subjects that were covered.

4.1. Overall Sentiment Analysis

A hybrid approach incorporating VADER and TextBlob was used to conduct sentiment analysis; Figure 3 below showed sentiment ratings with a range of -1 (negatively) to +1 (positively). In general, sentiment scores are interpreted according to a standard: scores between 0.5 and 1 denote strong positivity, scores between -0.5 and 0.5 imply neutrality, and ratings between -1 and -0.5 indicate extreme negative. A more organized discussion of consumer sentiment trends is made possible by this framework.

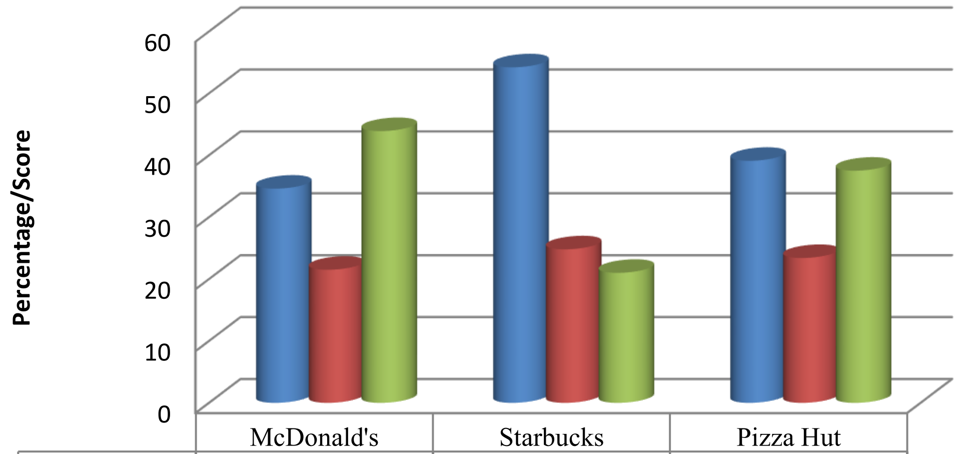
From the pie chart representation results showed below that the most positive feedback was given to Starbucks which indicated 50% suggesting a more favorable opinion among its consumers. Pizza Hut -17% and McDonald's -33% got lower average scores, indicating a greater proportion of unhappy consumers. With an average sentiment score of -0.08 as opposed to McDonald's -0.15, Pizza Hut did marginally better than McDonald's. This implies that although there is a great deal of discontent with both businesses, Pizza Hut's condition is more neutral, suggesting a comparatively better customer experience than McDonald's, but it is still below the range of 0.5 to 1 for overall favorable sentiment. Therefore, this shows a higher percentage of dis-satisfied customers from both restaurants. Strong consumer satisfaction was demonstrated by Starbucks, which had the highest percentage of favorable evaluations (54.2%). Pizza Hut was ranked between Starbucks and McDonald's in terms of consumer perception, with 39.1% of evaluations being positive. Although it fell short of Starbucks' satisfaction ratings, it outperformed McDonald's by a significant margin.

Figure 3. Average Sentiment Score



The most unfavorable sentiment (43.9%)was expressed about McDonald's, suggesting discontent with the food, service, or delivery. Although Pizza Hut had a higher percentage of negative attitudes (37.5%) than McDonald's, it was marginally better, indicating that although consumers still had problems, they were not as bad as those at McDonald's. Both Pizza Hut and McDonald's are in the negative sentiment category (below -0.5 to 0), whereas Starbucks is in the positive sentiment range (above 0.5). This suggests that both firms generally need to enhance their customer service.

Figure 4. Sentiment Score Range



	McDonald's	Starbucks	Pizza Hut
Positive (%)	34.6	54.2	39.1
Neutral (%)	21.5	24.8	23.4
Negative (%)	43.9	21	37.5

4.2. Customer Satisfaction Scores (CSAT)

The percentage of positive evaluations, which represents total customer satisfaction, is measured by CSAT.

Figure 5 shows the diagrammatic representation of Starbucks having the highest CSAT (54.2%), which indicates that more than half of its customers had a satisfying experience. Following with 39.1%, Pizza Hut which had a moderate level of satisfaction. The CSAT for McDonald's had the lowest at 34.6%, meaning that almost 65% of its customers are either neutral or unhappy. Starbucks clearly at the top of the list for consumer happiness. Although it is still in need of improvement, Pizza Hut is doing marginally better than McDonald's. The worst customer satisfaction ratings are probably caused by bad experiences with delivery, meal quality, and service at McDonald's.

4.3. Net Promoter Scores (NPS)

When assessing client loyalty, NPS takes into account both advocates and critics. Figure 5 below represents Starbucks having more promotors than detractors, as evidenced by its highest NPS (+21.9). Pizza Hut has nearly equal numbers of promotors and detractors, as indicated by its slightly negative NPS of -2.7. With the lowest NPS (-10.6), McDonald's has a lot more detractors than promoters. Starbucks' high NPS indicates a high level of brand preference and consumer loyalty. Although Pizza Hut's NPS is close to zero, it indicates that its consumers are not very excited, suggesting that it is reasonably balanced. Given that more customers are unhappy than satisfied, McDonald's low NPS indicates that company has a significant problem with client retention.

4.4. Comparison of Net Promoter Scores (NPS)

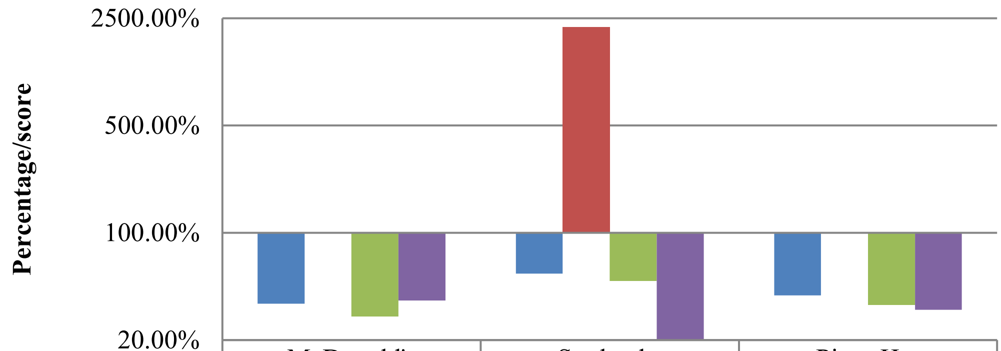
When assessing client loyalty, NPS takes into account both advocates and critics. Figure 5 above shows Starbucks has more promoters than detractors, as evidenced by its highest NPS (+21.9). Pizza Hut has nearly equal numbers of promoters and detractors, as indicated by its slightly negative NPS of (-2.7). With the lowest NPS (-10.6), McDonald's has a lot more detractors than promoters. Starbucks' high NPS indicates a high level of brand preference and consumer loyalty. Although Pizza Hut's NPS is close to zero, it indicates that its consumers are not very excited, suggesting that it is reasonably balanced. Given that more customers are unhappy than satisfied, McDonald's low NPS indicates that the company has a significant problem with client retention.

4.5. Theme-Based Sentiment Analysis

Four major themes emerged from the customer reviews:

- Customer Service
- Product Quality
- Delivery/Timeliness
- Ease of Use

Figure 5. Customer Experience Across Companies

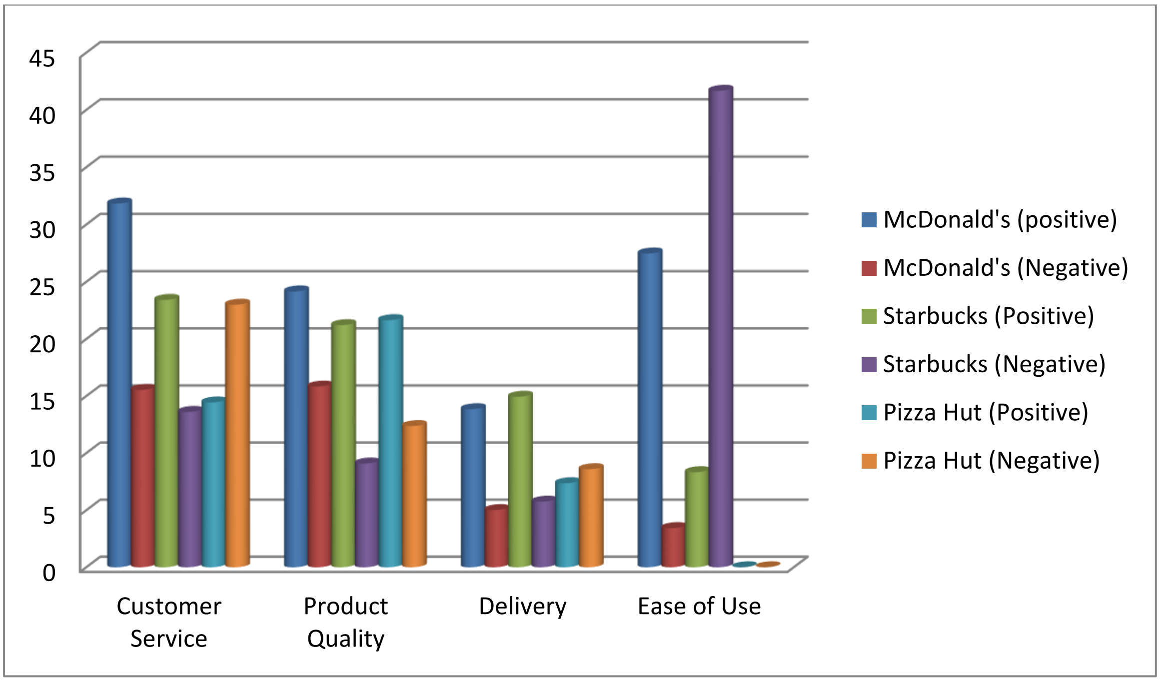


	McDonald's	Starbucks	Pizza Hut
CSAT (%)	34.60%	54.20%	39.10%
NPS SCORE	-10.6	21.9	-2.7
Low Effort (%)	28.50%	48.60%	33.80%
High Effort (%)	36.30%	20.30%	31.50%

4.5.1. Customer service

From the bar chart above in figure 6, The Company that exhibits the highest negative sentiment (23%) and the lowest positive sentiment (14.44%) is Pizza Hut. This implies serious problems with customer service. Inaccurate orders, lengthier wait times, or trouble fixing problems are some possible causes. The company with the highest positive sentiment (31.83%) and the moderate negative sentiment (15.54%) is McDonald's. McDonald's still has some effort-related problems, but it probably benefits from frequent customer encounters and efficient operations. With a respectable positive sentiment (23.42%) and a moderate negative sentiment (13.61%), Starbucks is in the middle. The more balanced outcomes may be attributed to Starbucks' emphasis on the customer experience. Often brought up in the analysis evaluations, this suggests that people are talking about how good the service was there. The term "staff friendly" draws attention to remarks about how approachable and kind the employees are. While consumer reviews of Pizza Hut, Starbucks, and McDonald's are examined, a number of recurring unfavorable bigrams—two-word phrases—appear across important topics. The following five negative bigrams are common and are arranged under Customer Service which includes: "rude staff", "poor service", "unfriendly employees", "slow service" and "bad experience".

Figure 6 Theme Based Sentiments



Therefore, in the fast-food industry, recognizing consumers' demands for high-quality service and matching delivery to those needs is the key to achieving customer satisfaction (Frost & Kumar, 2000; Sharkey *et al.,* 2009; Quyet *et al.,* 2015). A client's evaluation of a product or service based on whether it has fulfilled their expectations is known as customer satisfaction, according to Zeithaml *et al.,* 2009: 59. According to Gronroos (1984), a fast-food restaurant, for instance, can maximize customer satisfaction by making sure that its offerings are tailored to the requirements and desires of its customers. Achieving customer happiness requires that service delivery and customer needs be aligned, according to Kotler and Keller (2016). It should be mentioned that when a service does not meet the expectations of the consumer, the client becomes unhappy. However, surpassing consumer expectations result in a higher degree of customer satisfaction.

4.5.2. Product Quality

For product quality, McDonald's had a moderate positive sentiment (24.16%) and the greatest negative sentiment (15.83%) This suggests possible problems with quality control or product uniformity while Pizza Hut displayed a decent positive sentiment (21.65%) and a moderate negative sentiment (12.37%). Customer service and delivery may be more important than product quality. For Starbucks had a moderate positive sentiment (21.21%) and the lowest negative sentiment (9.09%). This implies that Starbucks typically produces high-quality goods.

A number of typical bigrams (two-word combinations) appear in customer reviews for Pizza Hut, Starbucks, and McDonald's. These bigrams fall under particular categories that are pertinent to my analysis. "Food quality" reflects what consumers think about the quality and flavor of the meal served. "Coffee taste" especially pertinent to Starbucks, but also brought up in conversations on McDonald's and Pizza Hut's "awful taste". Quality of the Product "cold food", "poor quality", "stale bread", "undercooked meat" and "bad taste" under negative themes.

Flavors, taste quality, and characteristics that appeal to the participants' gustatory senses are all represented in the descriptions. On the other hand, the statements' expressions reveal a viewpoint or remark regarding the product's quality (taste). Comments are statements that indicate one's opinions, according to Cambridge University Press and Assessment (2012). The fact that the statements are based on the participants' own personal expressions as a result of their product-tasting experiences supports the idea that they are themes that reflect tasting comments. According to Medrano *et al.,* (2023), taste and flavor are crucial components of eating enjoyment. The fact that the majority of the data collected discusses the product's flavor is then a trustworthy indication. Thus, it might be regarded as having an effect on a company's success. Furthermore, Suchánek *et al.,* 2015 suggest that a customer's happiness is a result of their perception of a product that meets their needs.

4.5.3. Delivery/Timeliness

With the highest negative sentiment (8.59%) and the lowest positive sentiment (7.36%), Pizza Hut is the obvious choice. Considering how dependent Pizza Hut is on delivery, this is alarming. Online ordering problems, erroneous projected times, and delivery delays are some possible causes. The company with the lowest negative sentiment (5.01%) and the highest neutral sentiment (81.14%) is McDonald's. Though delivery and punctuality might yet be improved, McDonald's probably has effective procedures. Starbucks' negative sentiment is marginally higher than McDonald's (5.75%), while it’s positive sentiment is moderate (14.94%). Wait times may lead to more effort, but Starbucks' dependence on in-store experiences may help to alleviate delivery concerns.

Fast-food restaurants' responsiveness is demonstrated by their capacity to fulfill consumer orders quickly (Kotler & Keller, 2016). A number of typical bigrams (two-word combinations) appear in customer reviews for Pizza Hut, Starbucks, and McDonald's. These bigrams fall under particular categories that are pertinent to the analysis. "Delivery time" which relates to consumer opinions of how quickly food delivery services are delivered and "Order accuracy" refers to the question of whether the delivered order is what was ordered. When examining customer reviews for Pizza Hut, Starbucks, and McDonald's, a number of recurring unfavorable bigrams—two-word phrases—appear across important topics. The following list of five common negative bigrams is organized by theme: "late delivery", "long wait", "order missing”, "slow response" or "delayed order"

A well-planned operational strategy is what creates such a situation. Customers should have their needs and desires met as soon as possible, and a fast-food establishment is said to be reliable if it can deliver on its commitments (Tahir & Abu-Bakar, 2007; Kotler & Keller, 2016). This factor pertains to the kitchen crew's ability to prepare meals in a way that produces the flavor that is promised on the menu. This makes it crucial for the fast food establishment to take all reasonable steps to guarantee that the consumer receives their order as planned. In order to increase client satisfaction, prompt delivery services are essential.

4.5.4. Ease of Use

For ease of use, Pizza Hut had the odd outcome of 100% "Neutral" and 0% negative and 0% positive. This may suggest a highly specialized, dependable, and possibly rigid user experience, which could be connected to their ordering system or procedures. Additionally, it may indicate that user experience is not varied enough. Negative sentiment is the lowest at McDonald's (3.43%), while positive sentiment is the most at 27.47%. This implies an experience that is easy to use, probably as a result of user-friendly interfaces and effective support. With the highest negative sentiment (41.67%) and the lowest positive sentiment (8.33%), Starbucks is the most notable. This is a serious problem since it suggests that there might be usability problems with their app, online ordering, or in-store procedures.

A number of typical bigrams (two-word combinations) appear in customer reviews for Pizza Hut, Starbucks, and McDonald's. These bigrams fall under a few categories that are relevant to my analysis: "mobile app" references to the businesses' mobile ordering applications' usability and functionality. "Online ordering" discusses the effectiveness and simplicity of placing orders using internet channels. Several recurring negative bigrams (two-word phrases) surface across major topics when examining customer evaluations for Pizza Hut, Starbucks, and McDonald's. Five common negative bigrams are listed below, arranged by theme: "app crashes", "difficult navigation", "payment issues", "login problems" as well as "website errors". According to the framework for the technology acceptance model (Kaasinen, 2005), the target audience's willingness to adopt and use new technology is greatly influenced by factors like utility and convenience of use. According to thematic research, Africans are not an exception in this instance, as they valued mobile e-commerce apps due to their practicality and user-friendliness. But in this context, ease of use can be summed up as the simplicity of creating a profile, navigating the app, and checking out although the usability complaints were made in PizzaHut and McDonald's.

4.6. N-Gram

The feedback from our most loyal customers (Promoters) was subjected to an n-gram analysis in order to better comprehend the language they use. In particular, we looked at bigrams, which are two-word sequences, to find the expressions that best reflect positive attitude and raise Net Promoter Scores. The relevance of each bigram in the promoter comments was assessed using the Term Frequency-Inverse Document Frequency (TF-IDF) score, which highlights phrases that are both common in this group and quite distinct from the rest of the dataset.

The top promoter bigrams reveal several important motifs, as shown in Figure 7. Phrases like 'happy place' (TF-IDF score: X) strongly imply that their facility, service, or product arouses favorable feelings and makes the experience enjoyable for promoters. This suggests that they have a close emotional connection, which fuels their loyalty which shows Strong Emotional Bond. Bigram words such as "take care" (TF-IDF score: Y), "good customer" (TF-IDF score: Z), "help help" (TF-IDF score: A), and "help asking" (TF-IDF score: B) are present, highlighting the significance of encouraging and helpful customer encounters in fostering promoter sentiment. These expressions imply that clients are treated with respect and provided helpful support which shows a Superb Customer Support. Positive Staff Attitude shows the bigram 'large attitude' (TF-IDF score: C) is especially notable, possibly suggesting that the lively and upbeat attitude of employees greatly enhances customer satisfaction and encourages advocacy. In a similar vein, "happy job" (TF-IDF score: D) can imply that contented workers result in happy clients.

Overall favorable experience shows the terms that are generally positive, such as "great experience" (TF-IDF score: E) and "good experience" (TF-IDF score: F), support the idea that promoters are regularly having favorable overall experiences with the brand or item.

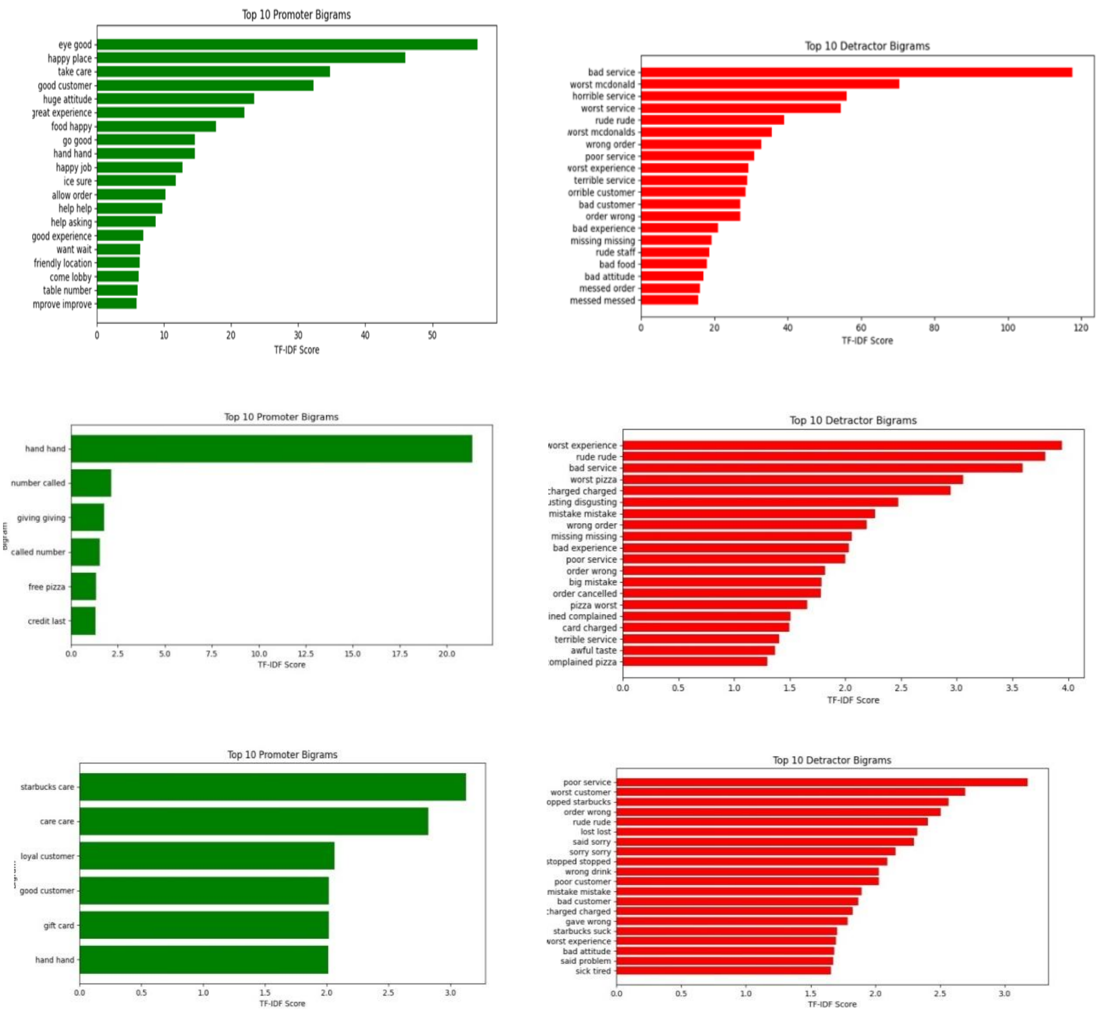
Notably, some bigrams need further contextual analysis, including "want wait", "Hand hand", and "table number". To ascertain the precise sentiment and context, it is crucial to look at the original customer comments that contain these phrases. For example, the phrase "want wait" could be used to indicate efficiency in a positive remark like "didn't want to wait long," while "hand hand" could be used to indicate hand in hand or holding hands of a customer whereas "table number" might be associated with favorable service experiences at a particular table. "Bad service": This is an obvious sign that you're not happy with the level of service you received. The term "horrible service" is comparable to "bad service," but it carries a more negative connotation. "worst service": Another potent sign of unhappiness with the service. Words like "rude rude" or "rude staff" indicate unpleasant encounters with employees who are disrespectful or rude.

"Wrong order" or "order wrong" or "messed order" or "messed messed" are all signs of order accuracy issues, which are a major source of annoyance for clients. The phrase "messed messed" could allude to a series of mistakes or a seriously off order. "Poor service": An additional general word emphasizing subpar service. The terms "worst experience" and "bad experience" imply that the critics' interactions were often inherently unpleasant. The phrase "terrible service" describes the quality of the service that was provided. "Bad customer" or "horrible customers" are alarming terms that may refer to unfavorable experiences with consumers, sometimes as reported by employees, or they may be complaints by customers who felt mistreated. Here, more background information from the initial remarks is essential. The phrase "missing missing staff" alludes to problems with personnel levels, which could cause delays or subpar service. "Bad food": A straightforward statement expressing discontent with the food's flavor or quality. "Bad attitude": Like "rude staff," this term refers to unfavorable encounters with staff conduct.

In each n-gram range (bigram), the top 10 words or phrases are displayed in the charts below. In each gram range, the frequency of positive grams is significantly larger than the frequency of negative grams because of the unbalanced dataset. Furthermore, the words in unigrams appeared in word cloud which is more general than those in bigrams, which contain more precise terms and expressions for every product category. These factors suggest that the models' assessment variables that will be developed for trigrams will be modest.

With the N-gram chart this may recommend focused changes to improve the overall customer experience and lessen negative sentiment by examining these top detractor bigrams, which give you important insights into the main causes of consumer dissatisfaction as well as promoter feedback which provides useful information for highlighting favorable elements of the customer journey, figuring out which food firms' strongest points and comprehending the language of food brands.

Figure 7. N-gram of McDonalds, PizzaHut and Starbucks



5. Conclusion

This study emphasizes the use of sentiment analysis to gain insight into customer attitudes and enhance the quality of services. By putting these suggestions into practice, fast-food businesses may improve consumer loyalty, satisfaction, and brand recognition. Customer service and delivery/timeliness were the most criticized features of all three organizations, according to a more thorough examination of theme-based sentiment analysis. In order to offer insights that help improve customer satisfaction and service quality, this study sought to assess consumer sentiment in the food business with a particular focus on McDonald's, Pizza Hut, and Starbucks. In order to do this, customer evaluations were processed and examined using natural language processing (NLP) techniques. A number of crucial phases were included in the methodology: a real-time dataset was first collected for customer reviews and preprocessing the text data with methods including stemming, tokenization, and stop word removal. Then lexicon-based sentiment analyzers was used—TextBlob and VADER, in particular—to categorize evaluations as neutral, negative, or positive. To find important themes in customer feedback, TF-IDF was also employed and count vectorizer for feature extraction and N-gram analysis.

Several important conclusions emerged from our analysis. While McDonald's and Pizza Hut displayed a higher percentage of disgruntled consumers, Starbucks overall displayed the highest levels of customer satisfaction and favorable sentiment. Theme-based research also revealed that all three businesses need to enhance their customer service and delivery/timeliness, while McDonald's is also facing challenges with product quality and ease of use. These results highlight the close relationship among consumer satisfaction, product quality, service effectiveness and ease of use.

The outcomes of this research are substantial for food firms looking to boost customer loyalty and brand impression. Businesses can take data-driven steps to enhance the customer experience by giving priority to the elements that were found to be essential for customer satisfaction and addressing the particular areas of weakness that the study revealed. Subsequent studies may examine the use of increasingly sophisticated AI methods to forecast consumer preferences or look at how particular service interventions affect customer satisfaction. To sum up, this study offers insightful information about consumer sentiment in the food sector and a road map for companies looking to increase loyalty and customer satisfaction through focused enhancements.

Competing Interests

The authors declare that they have no competing interests.

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Ethical Statement

It is declared that scientific and ethical principles have been followed while carrying out and writing this study and that all the sources used have been properly cited.

Authors' contributions

The authors have contributed equally to the study.

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