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Twitter sentiment analysis of app based online food delivery companies

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Abstract

Purpose – There is a strong need for companies to monitor customer-generated content of social media, not only about themselves but also about competitors, to deal with competition and to assess competitive environment of the business. The purpose of this paper is to help companies with social media competitive analysis and transformation of social media data into knowledge creation for decision-makers, specifically for app-based food delivery companies.

Design/methodology/approach – Three online app-based food delivery companies, i.e. Swiggy, Zomato and UberEats, were considered in this study. Twitter was used as the data collection platform where customer's tweets related to all three companies are fetched using R-Studio and Lexicon-based sentiment analysis method is applied on the tweets fetched for the companies. A descriptive analytical method is used to compute the score of different sentiments. A negative and positive sentiment word list is created to match the word present on the tweets and based on the matching positive, negative and neutral sentiments score are decided. The sentiment analysis is a best method to analyze consumer's text sentiment. Lexicon-based sentiment classification is always preferable than machine learning or other model because it gives flexibility to make your own sentiment dictionary to classify emotions. To perform tweets sentiment analysis, lexicon-based classification method and text mining were performed on R-Studio platform.

Findings – Results suggest that Zomato (26% positive sentiments) has received more positive sentiments as compared to the other two companies (25% positive sentiments for Swiggy and 24% positive sentiments for UberEats). Negative sentiments for the Zomato was also low (12% negative sentiments) compared to Swiggy and UberEats (13% negative sentiments for both). Further, based on negative sentiments concerning all the three food delivery companies, tweets were analyzed and recommendations for business provided.

Research limitations/implications – The results of this study reveal the value of social media competitive analysis and show the power of text mining and sentiment analysis in extracting business value and competitive advantage. Suggestions, business and research implications are also provided to help companies in developing a social media competitive analysis strategy.

Originality/value – Twitter analysis of food-based companies has been performed.

Keywords Case studies, Communications technology, Sentiment analysis, Competitive strategy, App-based food companies, Lexicon-based sentiment analysis

Paper type Research paper

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1. Introduction

Advancement in mobile and internet technology has improved communication and freedom of speech in social networks, blogs and websites. Social media have significantly transformed our lives in a significant manner to connect with one another as well as with the general environment (Qualman, 2009; Brake, 2009). Latest researches demonstrate that online social interactive websites such as Facebook and Twitter have been used by groups of people having diverse motives such as finding new mates, connecting with old mates, acknowledging information and connecting with each other (Kaplan and Haenlein, 2010; Keckley and Hoffman, 2010; Park *et al.*, 2009; Raacke and Bonds-Raacke, 2008; Shih, 2009).

Accordingly, numerous organizations are embracing internet based social life to use this developing pattern so as to pick up business values, for example, driving client traffic, expanding loyalty of the customer and retention of the customer, expanding sales and incomes, enhancing satisfaction of the customer, creating awareness about the brand and building reputation of the organization (Culnan *et al.*, 2010; Kietzmann *et al.*, 2011; Azevedo *et al.*, 2011; Weber, 2009). Generally, interactive social websites incorporate concepts of marketing such as product development, price of products, brand promotion, client satisfaction, etc. (Di Gangi *et al.*, 2010; Culnan *et al.*, 2010). One such instance is that of numerous lodging places in the world, for example, Hyatt Hotels, Starwood Hotels, Marriott Hotels, etc. have been using the intensity of interactive social websites to stay connected with visitors, learn about criticism on their services offered to visitors, address complaints by clients, if any, and facilitate prospective visitors (Lanz *et al.*, 2010; Müller, 2011). Twitter is one of the most common and popular social media platforms that give freedom to people to present their views, thoughts and opinion to the world.

In 2013, Twitter stared its journey in India and swiftly caught on and gained popularity amongst Indian users. This was possible because of the growth of social media platforms in India. It is estimated that approximately 351 million people use social media in India, going by a 2019 report[1]. Twitter is a popular social media platform with close to 7.35 million users in India, with a diverse mix of users from celebrities to politicians. With popular leaders taking to twitter as a means of quick sharing of their thoughts, this has led to several companies taking to twitter with gusto to manage their online status, engage with users and build reputation. Starbucks is an example of leveraging Twitter to increase its sales by making their coffee a status symbol. Customizing drinks to customer's preferences, they encouraged people to share images of their cups on Twitter (Kwon and Sung, 2011). In this study, a detailed Twitter sentiment analysis has been done for three online food based companies with word-emotion lexicon-based methods, using the R-studio, including library "twitterR" (Gentry *et al.*, 2016) and "syuzhet" (Jockers, 2017).

Sentiment analysis is a method of contextual text mining to determine people's attitude and opinion toward a company, brand, people or events by extracting information from online sources (Alasmari and Dahab, 2017). Sentiment analysis helps companies to measure the results of ad campaigns, quality of products and services and help to correct issues before they become a liability to the companies, in short, it can help companies leverage and gain suitable competitive advantage over rivals. The sentiment analysis methods used in the previous studies computed sentiments of the people who post and write about mcommerce business in the food-tech industry.

The food-tech industry in India is estimated to be worth \$50bn as compared to \$600bn in the USA. According to studies, competitors of the food-tech industry are growing at a rapid rate, it is estimated that close to 1 million online deliveries are made every day, compared to China where close to 15 million deliveries are made every day. The present study looks at Swiggy, Zomato and Uber Eats, the three most prominent companies in the Indian sphere.

Swiggy was established in 2014 in Bengaluru and operates in 25 cities, having a delivery fleet of 120,000 and is estimated to be worth around $3bn. Zomato was established in 2008 as a review website but quickly moved to delivery, leveraging the relationships built with restaurants. Zomato operates globally in 25 counties. In India, it has a delivery fleet of 150,000 and is estimated to be with around $2.2bn. In India, Zomato started its journey from 2011. Uber Eats was launched in 2016 by the ride-sharing platform Uber. The company adds 4500 partners (i.e. what Uber calls it delivery fleet) every week. Uber CEO Dara Khosrowshahi claims that since 2016, the company has grown by 200% every year. All three companies are looking to raise capital this year with Swiggy and Zomato looking at Venture capitalists and Uber looking at an IPO. Sentiment analysis can offer a glimpse into how these companies are performing through social media, as they are service-based companies.

Social media instruments have produced an abundance of documentary information that may include concealed information, for business corporations to access for competitive advantage. Distinctively, marketing experts can probe into the massive volume of interactive social website information to distinguish and discover new information and mesmerizing examples, figure out the transforming business environment wherein competitors always want to score an edge against each other (Dey *et al.*, 2011). Marketing leaders of business organizations can likewise take strategic decisions to develop new products and services. It is accepted that competitive acumen can facilitate associations to recognize qualities and shortcomings, upgrade trade viability and develop consumer loyalty (Lau *et al.*, 2005).

In tune with the above discussion, this research tries to address following questions:

RQ1. How has social media become a powerful tool of expressing sentiments of users and impacting the business world?

RQ2. How do users expressing their sentiments differently for same type of companies?

RQ3. How do positive sentiments of a company bring opportunities for other companies to follow best practices?

RQ4. How do negative sentiments help a company to gain customer trust and help in managing good relations?

For getting answers of the above questions, this research conducted a Twitter-based sentiment analysis of three food delivery app companies (Zomato, Swiggy and UberEats). Further, comparison of customer sentiments is analyzed and presented. Based on positive and negative sentiments, recommendations are provided on different aspects of business.

Further, sections of this paper are arranged in the following pattern: Section 2 deals with related research. Section 3 explains the data collection followed by data preparation steps. Section 4 elaborates the description of sentiment analysis methods used in this study. Section 5 explores the results and analysis. Section 6 discusses the results, followed by business and research implications. Section 7 concludes the research.

2. Related work

A variety of work has been found in the literature where tweets sentiment analysis has been used on different social application domains. Because social media is a prominent medium to express sentiments about products, services and different events, the sentiment analysis of the tweets/comments of social media returns the valuable insights for organizations and policymakers. This section reflects the work done on the sentiment analysis of social media using tweets/comments/product and service reviews on various applications.

Table 1 summarizes the work done on twitter sentiment analysis. Perera *et al.*, 2010, clearly reveal the interlink between Twitter user location and patterns of user behavior in social networks. Their data collection technique is derived from a software architecture based on Twitter application program interface (API), to pull together tweets sent to specific users, which later are analyzed as per inter-arrival times between tweets and number of re-tweets. Stavrakas and Plachouras, 2012, exhibit a very significant aspect of data mining process related to social media platforms, especially Twitter, to explore people perception on various subjects. Their study emphasizes on selection of the relevant data set to derive trustworthy authentic results based on time, terms, users and their associations, combined in a single model. Walker, 2012, in another piece of research illustrates how Twitter can be used as an effective tool for teaching. Their studies through R statistics software program reveal how Twitter can be used effectively as a teaching tool through various new learning techniques by evaluating learner's data. This study by data visualization also aims to bridge the gap between student learning activities on Twitter and its usage as actual learning application for teaching practice.

Another piece of work done by Lee *et al.*, 2012, demonstrates the key role of user "session sequences", which can be used to address bulk shared enquiries related to application logs collection and data analysis. This study precisely illustrates Twitter's production logging infrastructure through which messages are now recorded in a well-formatted flexible thrift form as "client events" log format.

A study conducted by Gupta *et al.*, 2014, portrays data analytics research tasks for microblogging platforms, especially Twitter, which involves event detection mechanisms, event type, time span, credibility and user location forecast. Another research study carried out by Thom *et al.*, 2015a, 2015b, exemplifies the role of social media tools in monitoring crisis intelligence. In this research, they used Scatter Blogs visual analytics framework to create a customized system that measures the domain experts' individual performances with the system and predicts usefulness and applicability of social media for crisis intelligence.

Tao *et al.*, 2014, introduce Twitter Analytical Platform, a standard platform for steering analytical tasks with Twitter data, which includes a domain-specific Twitter Analysis Language as the interface to its functionality stack. This platform can be used for making customized analytical workflows to build relevant applications to resolve specific data issues. Another piece of research analysis done by Chae, 2015, describes the role of an analytical framework that uses three practices – descriptive analytics (DA), content analytics (CA) and network analytics (NA) – for examining supply chain tweets by network visualization and metrics. This study shows the probable role of Twitter in accurately forecasting supply chain practice, examination and its inferences for research.

Evidently illustrate in their study, the role of social media tools in monitoring public safety. In this research, they used Scatter Blogs visual analytics system to create a customized system along with additional tools explicitly catering to precise requirements as per their research results. Apart from the above work, sentiment analysis using social media analytics has been used in hospitality and tourism research also. In the work done by Bhardwaj *et al.*, 2017, a novel approach for sentiment analysis was established which extracts opinions from a given data source of travel industry. In this work, different sentiment emotions were extracted from reviews extracted from TripAdvisor in India. In another work done by Neidhardt *et al.*, 2017, user activities and interactions in the tourism domain were analyzed by extracting emotions of the users regarding forthcoming trips. Joseph *et al.*, 2017, aimed to examine the network, descriptive and content analysis of

Table 1. Summary of related work

S. no.	Citation	About the paper	Methodology	Findings
1	Saran *et al.* (2019)	Examined the collection of filtered information through Web-based geo-visual interface to forage and filter the place, time, theme, from Twitter for further geographical, temporal and thematic analysis	Sentiment analysis	This study empowers the Indian Bioresource Information Network (IBIN) project of India by web-based place-time-theme indexing application which promotes preservation and protection of bio-resources
2	Rathore and Ilavarasan (2020)	Demonstrate that accurate analysis of user generated content on social media in new product development process of three products like a car, pizza and a mobile phone	Sentiment analysis	The result shows the user's response in the pre and post launch of three products were asymmetrical
3	Pai and Alathur (2018)	Aimed to study customer perceptions regarding mobile health applications to make them more affordable, accessible and apt for the end user	The data extraction and evaluation process was conducted through a tool, R Studio, which uses twitter application programming interface for data mining	Results of data mining analysis help organizations to customize their applications as per users' penchants
4	Roji *et al.* (2018)	Revealed the significance of Twitter data to gauge public perception regarding political scenarios through research method using software reuse, which relies on reusable component-based software engineering (CBSE)	This research is based on methods such as requirement specification, component analysis, requirement modification, system design with reuse, development and integration and system validation	The importance of data mining analysis of Twitter data for companies' strategic decision making based on customers' opinions toward their products and services
5	Zhao *et al.* (2017)	To study about the significance of product reviews for the upcoming customers in taking a decision	A new framework for product review sentiment classification which uses generally available ratings	In this work, a novel deep learning model has been proposed for sentiment analysis and validated through 11,754 labeled review sentences from Amazon
6	Joseph *et al.* (2017)	Conducted a review of discussions on Internet of Things (IoT): insights from twitter analytics	Aimed to examine the network, descriptive and content analysis of hash tags and tweet through the tools R and NodeXL	Results of this study reveal the scope of applications, industrial influencers, business concerns, emerging smart technologies and manufacturing
7	Thom *et al.* (2015a, 2015b)	Exemplifies the role of social media tools in monitoring crisis intelligence	Scatter Blogs visual analytics framework	Concluded with a creation of a customized system that measures the domain experts' individual

(*continued*)

S. no.	Citation	About the paper	Methodology	Findings
				performances with the system and predicts usefulness and applicability of social media for crisis intelligence
8	Lee *et al.* (2012)	Explored the unified logging infrastructure for Data Analytics at Twitter	Twitter's production logging infrastructure through which messages are now recorded in a well-formatted flexible thrift form as "client events" log format	The development of this infrastructure has streamlined log collection and data analysis, thereby improving our ability to rapidly experiment and iterate on various aspects of the service
9	Walker (2012)	Illustrates how Twitter can be used as an effective tool for teaching	Their studies through R statistics software program reveal how Twitter can be used effectively as a teaching tool through various new learning techniques by evaluating learner's data	This study by data visualization also aims to bridge the gap between student learning activities on Twitter and its usage as actual learning application for teaching practice
10	Perera *et al.* (2010)	Reveal the interlink between Twitter user location and patterns of user behavior in social networks	Their data collection technique is derived from a software architecture based on Twitter application program interface (API), to pull together tweets sent to specific users, which later are analyzed as per inter-arrival times between tweets and number of re-tweets	The study indicated that the arrival process of new tweets to a user can be modeled as a Poisson Process while the number of re-tweets follows a geometric distribution. The results obtained in this research can be applied to study correlations between patterns of user behavior and their locations

Table 1.

hashtags and tweets, through the tools R and NodeXL. Results of this study reveal the scope of applications, industrial influencers, business concerns, emerging smart technologies and manufacturing.

In the research of Valera and Patel, 2018, consumers' reviews of top-rated products from the Amazon website were taken for sentiment analysis to measure positive and negative sentiments of users with top rating products. This work demonstrates a comparative analysis of top-rated products from Amazon website with competitor's products. In the work of Zhao *et al.*, 2017, sentiment classification of product reviews has been demonstrated. In this work, a novel deep learning model has been proposed for sentiment analysis and validated through 11,754 labeled review sentences from Amazon. Another work by Das *et al.*, 2018, shows real time sentiment analysis of Twitter streaming data for predicting stocks. In this work, a big data framework using spark streaming with Twitter API and Apache Flume, has been used for analysis. In the work of Singh and Srivastava, 2018, the Indian Government's decision of demonetization and its effect on the common person's sentiment were analyzed. Tweets from Twitter users discussing demonetization using popular hash tags and keywords, were extracted and analyzed.

In the research done by Jangid *et al.*, 2018, solution for FiQA 2018 subtask 1 has been identified using aspect-based sentiment analysis of microblogs and headlines of the financial domain. In this work, a multi-channel convolutional neural network for sentiment analysis and a recurrent neural network with bidirectional long short-term memory units have been used to extract and analyze aspect-based sentiments. Another work by Chen *et al.*, 2017, developed a microblog sentiment prediction model using weakly supervised deep learning model. In the work of Jianqiang *et al.*, 2018, a word embedding method obtained by unsupervised learning based on large Twitter corpora was introduced. In this method, latent contextual semantic relationships and co-occurrence statistical characteristics between words in tweets are used to build a sentiment model. Roji *et al.*, 2018, reveal the significance of Twitter data to gauge public perception regarding political scenarios through research method using Software Reuse, which relies on reusable component-based software engineering (CBSE). This research is based on methods such as requirement specification, component analysis, requirement modification, system design with reuse, development and integration and system validation. The importance of data mining analysis of Twitter data for companies' strategic decision-making based on customers' opinions toward their products and services (Halibas *et al.*, 2018) has been highlighted. The result of data mining analysis helps several organizations to derive actionable insights, based on which they customize advertising plans and promotions to fit users' inclinations.

Pai and Alathur (2018) aimed to study customer perceptions regarding mobile health applications to make them more affordable, accessible and apt for the end user. The data extraction and evaluation process was conducted through a tool, R Studio, which uses Twitter Application Programming Interface for data mining. Results of data mining analysis help organizations to customize their applications as per users' penchants. Another piece of work by Pradyumn *et al.*, 2018, intended to classify, compare and evaluate various data mining methods and their applications, especially Twitter data analytics, by reviewing several papers from 20 journals on Twitter data analytics published from 2011 to 2017 which, in turn, will help to study trending patterns in data analytics domain. A study by Subramani *et al.*, 2018, clearly depicts the significance of machine learning algorithms which are used for Twitter real-time data analysis. Outcome of this data analysis substantiates the role of social media data extraction which empowers decision-makers to derive helpful insights through applications in healthcare, politics and social initiatives, etc.

A research study by El Bacha and Zin, 2018, emphases the comparative analysis of latest research techniques of data mining to use Twitter platform owing to its fast-moving timeline, which can be used by various applications for understanding latest trending subjects, finding influencers, understanding influence diffusion process and consumer perceptions. Additionally, Feng *et al.*, 2019, in their paper provide an all-inclusive approach toward big social data analytics and its related impact, from varied viewpoints. In this study, the foremost focus of big social data analytics is on monitoring public sentiment, tracking trending subjects and identifying human mobility patterns. In a recent work by Alaei *et al.*, 2019, different sentiment analysis approaches applied in tourism are reviewed and assessed in terms of the datasets used and performances on key evaluation metrics. Further, Rathore and Ilavarasan, 2020, demonstrate that accurate analysis of user generated content on social media such as tweets can be efficiently used to customize the new product development (NPD) process as per real-time feedback from users based on their anticipation and experience about any product via pre- and post-launch comparative assessment. Another work by Saran *et al.*, 2019, illustrates the collection of filtered information through Web-based geo-visual interface to forage and filter the place, time, theme, from Twitter for further geographical, temporal and thematic analysis. This study empowers the Indian Bioresource Information Network project of India by Web-based place-time-theme indexing application which promotes preservation and protection of bio-resources.

The present study aims to add significant information in tourism and hospitality research where sentiments of three food-tech m-commerce industries, namely, Swiggy, Zomato and UberEats, has been extracted and analyzed using Lexicon-based sentiment analysis using Twitter data. Different popular hash tags and keywords were incorporated to extract the tweets. Finally, interesting inferences are drawn after sentiment comparison of all three companies.

3. Data collection

A paper published by Chiasson and Davidson, 2005, shows that the food and restaurant industry is drawing more attention from researchers and developers and has a strong potential in Information Systems research. In India, online food order apps are gaining potential; people are paying attention and using such apps frequently and hence, we decided to conduct a social media competitive analysis with the three largest online food order app: Swiggy, Zomato and UberEats, as case study for this research. The rationale behind choosing these companies was their decent market share. In particular, Zomato makes up approximately 22.8%, Swiggy has approximately 20.87% and UberEats makes up 11.39% of the market. An extensive internet search also indicated that so far there is no academic article that investigates how large online food delivery companies are using social media to support their businesses. We conducted a sentiment analysis of tweets related to the three companies named above.

Tweets were extracted from Twitter using a Twitter app, which allows people to create applications for a wide variety of purposes including advertising, engagement, etc. The Twitter app was created and the access keys and tokens were extracted. "TwiiterR" library was used to extract information from Twitter and for processing the data. Keywords and hashtags related to the three companies (Swiggy, Zomato and Uber eats) such as (for Swiggy: "@swiggy_in","@SwiggyCares","#swiggy","swiggy", For Zomato: "@ZomatoIN", "#zomato", "#zomatoindia","@zomatocare","zomato" and for UberEats: "@UberEats_IND", "#EatsTweets", "#FoodieGyaan", "#FoodTalks","#UberEats", "#UberEatsIndia", "uber eats") were taken to extract relevant tweets and further convert into data-frames. A total of 5,000 tweets for each company were targeted. Finally, a total of

13,757 tweets were extracted through this method that included all three companies. Although there is a discrepancy in the number of Tweets extracted as the number of Tweets was not equal for all the companies, it should be noted that the companies serve in limited geographical locations and some companies are of more recent origin than others. Hence, a comparative analysis between the three companies was performed keeping the percentage tweets. Main focus of the analysis was to get the negative tweets and negative words that may be extracted to conduct more in-depth analysis to optimize service and quality of the companies. Because the analysis is based on words and the lexicon dictionary used in this research contains only English sentiment words, emoji's, slang words, etc. were removed during preprocessing. In addition, location and dates were not included in the data because of unavailability of tweets in particular locations. Comparative analysis may offer suggestions to the individual company to follow best practices from the other companies through positive sentiments of the users.

3.1 Pre-processing

Library "tm" was used for preprocessing along with the library "strinr" and "gsub", "sub" functions inbuilt in R (Pahwa *et al.*, 2018; Sreeja *et al.*, 2020). At first, the collected tweets were converted into a data frame and extracted words from the tweets then converted into lower case. Further, the tweets and words that were not important such as codes to indicate retweets, punctuations, URL links, symbols and numbers, were removed. The data frame was then converted into a corpus, i.e. a bag-of-words individual words were extracted to remove stop words that are frequently used in any language such as "The", "an", etc. In addition, "stemming" (reducing the word into a lower form like "eaten" to "eat"), "sparsity removal" (words with low frequency) were used to get only informative words in the tweets from the pool of the words extracted from all three companies. The corpus was then converted back to a data frame for analysis. Table 2 shows pre-processing of the tweets for all three companies, i.e. Swiggy, Zomato and UberEats.

4. Research methods

Nowadays text mining and sentiment analysis is becoming popular among the business decision-makers, where a text written by a user is analyzed and recommendations are taken from there. Artificial intelligence (AI) and machine learning are popular in this domain. Because the requirements of the businesses are different and accordingly the interpretation of the sentiments are different, hence, rather AI and machine learning approach lexicon-based approaches are famous in the sentiment analysis domain where a specific dictionary is created for different kind of user's emotions and sentiments. Social media is the rich platform where people express their views about products and services of the different companies. Twitter is a popular social media platform where with a word limit peoples expresses their views. In this section two different tweet sentiment analysis methods based on lexicons are discussed that have been used in this research.

4.1 Lexicon-based sentiment classification using word-emotion association

Sentiment analysis is a study of extracted information to identify reactions, attitudes, context and emotions. Words are assigned polarities for example, "Happy, sweet, amazing" have positive connotations and "Boiling, alarming, clumsy" have negative connotations. The "syuzhet" package consists of five sentiment dictionaries which are "syuzhet", "bing", "nrc", "afinn" and "stanford" (Misuraca *et al.*, 2020). Sentiment analysis was done using the NRC and Nebraska Literary Lab dictionary. The NRC Emotion Lexicon method has a list of English words and associations with eight basic emotions (anger, fear, anticipation, trust,

S/N	Company	Tweets before pre-processing	Tweets after pre-processing
1	Swiggy	RT @swiggy_in: Got a lot on your mind? Let's give you something delicious to think about instead https://t.co/xyod0sjO8o	got lot mind let give something delicious think instead
2	Zomato	@Sanju94967396 @ZomatoIN @Zomato reached out to your email address. They say it's policy of your company to charge. . . https://t.co/YUQleBpSaN	reach out email address say policy company charge
3	UberEats	@UberEats_IND In my previous order i used the promo 50treat and got the wrong product now I am unable to use that code	previous order use promo treat got wrong product unable use code

Table 2.
Tweets (before/after) preprocessing

surprise, sadness, joy and disgust) and two sentiments (negative and positive). This method was developed by Mohammad and Turney, 2013, from the National Resource Council of Canada. The method was not based on a simple addition of sentiment values for each word but based on association with the words. Association of the words result in different types of emotions category such as anger, fear, disgust (negative emotion) and the word accomplished is related to joy(positive emotion).

In this research, different emotions of the users of all three companies were extracted and analyzed by using the method mentioned previously. Based on the analysis, the tweets were classified in different emotions category mentioned above. Conclusion and recommendations have been drawn on the basis of the analysis and classified tweets. Table 3 and Figure 1 depict tweets for different emotions of the users. These are mixed tweets received form all three food delivery companies. Figure 1 is the graphical representation of Table 3 which shows for all the companies positive emotions are more than other emotions. In contrast, users show more trust for UberEats than Swiggy and Zomato and users tweet joy-related sentiments for Zomato more than Swiggy and UberEats.

Emotion type	Tweet
Positive	"well deserved reward real hero and should inspire others who just prefer to stand around clicking"
Negative	"still no update in my case what a shameful company serve food which is bad and spoiled what a shame"
Anger	"someone please shutdown most terrible experiences delivery boy running away with the money to destroying"
Anticipation	"look at the expected time of delivery and time present"
Disgust	"you people are really shameless and ridiculous as well you think that customers are fool its b"
Fear	"do you add some anti-contagious agent with the food so as to prevent outbreak of epidemic"
Joy	"wish you a merry Christmas and may this festival bring abundant joy and happiness in your life spread happiness this"
Sadness	"unable to solve my issue had problem with this order no response only excuses poor pathetic servi"
Trust	"zomatomaking bank statement look like food diary since ever cheers"

Table 3.
Example of the tweets in different categories

4.2 Lexicon-based sentiment classification using sentiment polarity

This is also called dictionary-based approach (Kundi *et al.*, 2014) and relies on the lexicon or dictionary of words with pre-calculated sentiment polarity. This approach is different from machine learning approach. In this approach, classification performance depends on the quality of the lexicon extracted from the data. Further, a lexicon dictionary is used which contains the words, assigned with some sentiment polarity. After preprocessing, all the tweets data undergo sentiment score calculation by matching them against the words present in the lexicon dictionary. Finally, a sentiment score for the tweets is calculated. For example:

> A masterful [+0.92] film from a master [+1] filmmaker,unique [+1] in its deceptive grimness, compelling [+1] in its fatalist [−0.84] worldview.
>
> Sentiment of the above tweet is calculated as follows:
>
> Total sentiment score = +0.92 +1 +1 +1 −0.84 = 3.08, which means that the text expresses a positive opinion.

5. Results and analysis

5.1 Analysis with different emotions classifications

Different emotions classifications from the three different companies are mentioned in Table 4. From all the tweets extracted for the companies, percentage emotions have been calculated and a comparative analysis between the three companies was performed. More or less equal distribution for positive emotions and negative emotions was obtained, i.e. 24%, 26% and 25% positive emotions and 13%, 12% and 13% negative emotions for Swiggy, Zomato and UberEats, respectively. Comparison shows that Zomato is performing better than the other two companies in terms of consumer's perception.

5.2 Analysis with emotional valence

Figure 2 represents emotional valence of each food company for 100 tweets. Results show that performance of Zomato is better than the other two companies. Swiggy starts with negative valence till ten tweets; after that, from 11 to approximately 35 tweets, positive valence is seen; then, till 60 it is again negative. Hence, emotional valence pattern of Swiggy

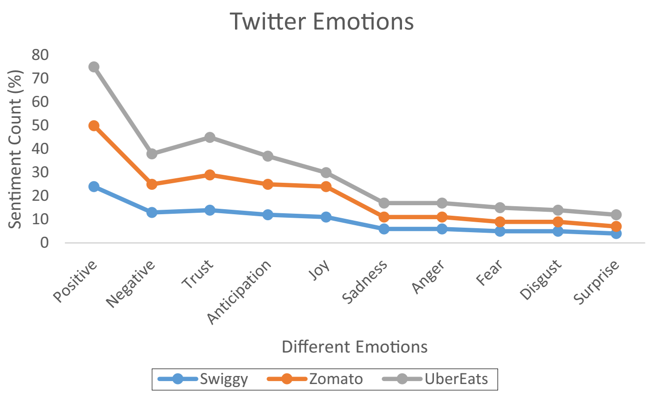

Figure 1.
Different emotions from tweets

is consistent. In UberEats, from 40 to approximately 80 tweets, positive valence is detected; however, for rest of the tweets, negative sentiment is found. The performance of Zomato is found better than other, as approximately from 10 to 25 tweets, positive sentiments are found and again, approximately from 38 to 92 tweets, positive valance is detected.

5.3 Analysis with polarity of the sentiment using Lexicon analysis

Figure 3 shows polarity values of the tweets for all three companies. The zero point of Figure 3 represents neutral sentiment of the tweet. Positive and negative values of Figure 3 represent positive and negative sentiments of the tweets and the value represents intensity of the tweets. After doing a comparative analysis of all the three companies, Zomato has shown good performance in terms of positive sentiments and also intensity of sentiment is found high and more than approximate +0.5. However, sentiments of Swiggy are found comparable. UberEats has shown more negative sentiments of users than positives. In this analysis, again Zomato has shown good performance in terms of positive word of mouth.

6. Discussion and implications

6.1 Discussion

Encouraging experience of customers is significant to make them vigorous brand supporters, enhancing brand loyalty and referrals and finally contributing to the company's revenues and profits (Sashi, 2011; Shen *et al.*, 2010). Empathica (2010), in a recent investigation found that "one out of three surveyed followed with recommendations received from their friends through Twitter or Facebook." Hence, it is rational to say that social media platforms have helped customers to become more powerful in this digital era (Constantinides and Fountain, 2008). Our study accords immediate evidence to support the assertion of Rosenthal (2010) and Rick, (2010), that the customer service landscape is changing with introduction of social media and more new firms such as food delivery apps, are trying to improve customer services.

For a comprehensive discussion, the tweets of all three companies (Swiggy, Zomato and Ubereats) were combined to do text mining. A few themes were identified which attracted more focus of consumers. Based on positive and negative sentiments of the consumers, a lot of recommendations may be taken. In the below part of the discussion, after analyzing tweets, different categories of recommendations have been formulated and discussed.

6.1.1 Order and delivery. Around 25%–30% customers expressed their emotions and sentiments for services offered by the companies related to online ordering and tracking. Both positive and negative sentiments were identified for all the three companies. Customers expressed their positive sentiments regarding timely delivery, clear tracking with

Table 4.
Different emotion percentage for swiggy, zomato and UberEats

S/N	Emotions	Swiggy (%)	Zomato (%)	UberEats (%)
1	Positive	24	26	25
2	Negative	13	12	13
3	Trust	14	15	16
4	Anticipation	12	13	12
5	Joy	11	13	6
6	Sadness	6	5	6
7	Anger	6	5	6
8	Fear	5	4	6
9	Disgust	5	4	5
10	Surprise	4	3	5

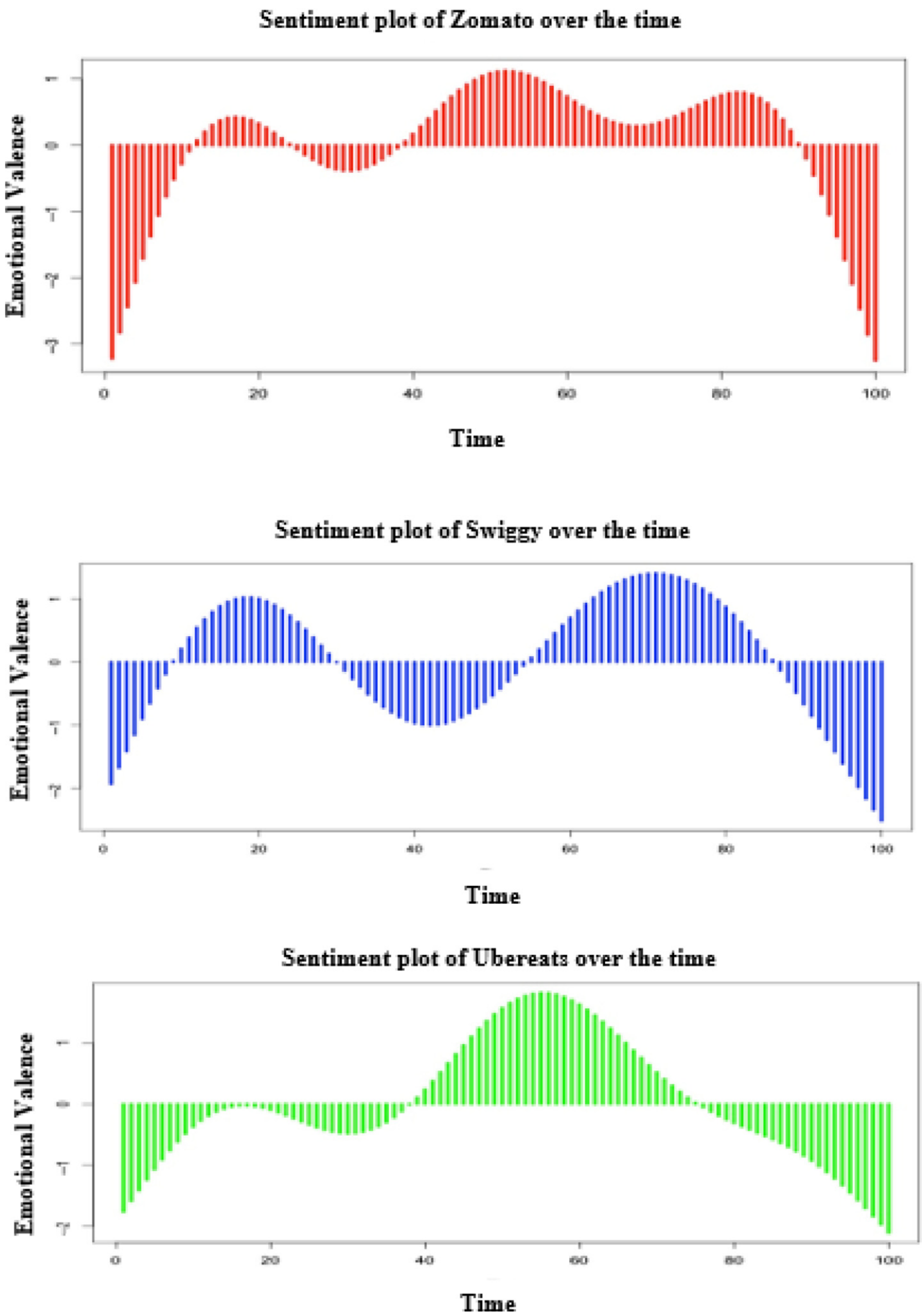

Figure 2.
Emotional valance of all three companies

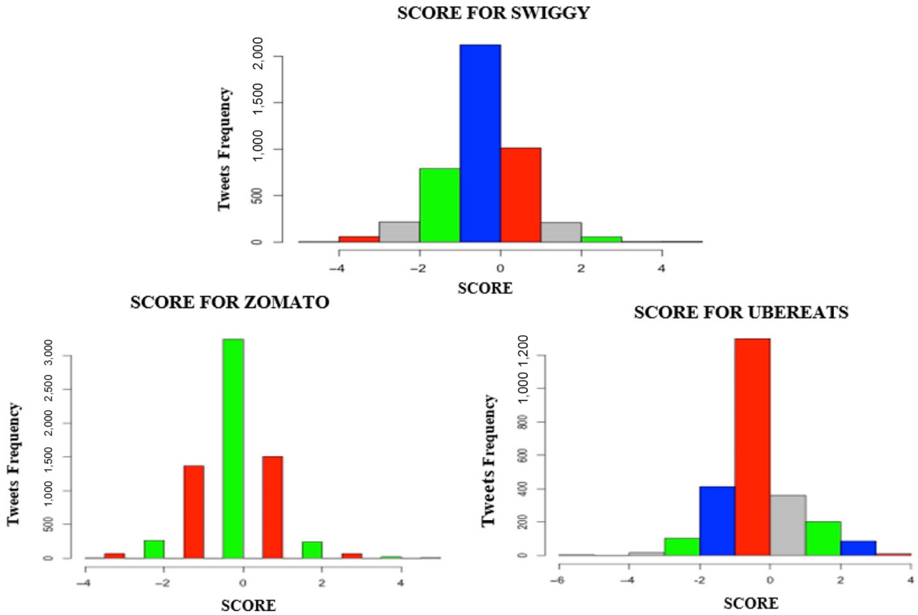

Figure 3.
Lexicon-based sentiment analysis

timestamp, delivery boy information correctly mentioned, etc. However, several complaints were found related to late delivery, wrong order delivery. Sometimes customers were unable to contact the delivery boy for current status. Such negative activity affects consumers repurchase behavior. Hence, companies are advised to create a flexible system and also a strong customer care system so that consumers' problems may be rectified fast. Also, even if some problem regarding timely delivery is happening, customer should be informed clearly so that trust of the customer with the company is maintained.

6.1.2 Quality of food. Apart from service satisfaction, many customers, around 20%–25%, were tweeting about food quality. In this theme, negative sentiments were more than positives, with customers complaining about smelly food, stale food and also some of them bringing up hygiene issue. The companies are suggested to ensure quality of food of the restaurants with a few minimum quality measures. They also should have the policy to black list a restaurant that has attracted a particular number of complaints regarding quality and unhygienic food.

6.1.3 Feedback of customers. Negative feedbacks are significant for online food delivery companies which provide learning to improve services and to maintain a good relationship. Companies should respond to the negative as well as positive tweets received from their customers. If companies appreciate the positive feedback, customers feel happy. It would also lead to increased loyalty of the customers. Response like "Thanks for feedback, enjoy the food" can add to positive sentiments.

6.1.4 Socialization tweets. It has been noticed that a number of tweets from the companies were casual and for building a good customer relationship. Tweets like "wish you a merry Christmas" and "may this festival bring abundant joy and happiness in your life spread happiness", create good socialization and would work in enhancing customer relationship.

6.1.5 Marketing tweets. After analysis, it has been seen than companies post replies to customers' queries and also post tweets to advertise promotional offers. Such marketing tweets accounted nearly 35%–50% of the total tweets posted by the companies. The analysis reflects that these proactive efforts are helpful in creating customer awareness and are effective strategies to engage Twitter audiences and help in gaining customer satisfactions.

6.2 Business implications

The analysis reveals that the three major app-based food delivery companies are aggressively active in social media, with committed significant resources for their efforts in social media. The data revealed that the companies were devoted to provide wonderful experience to their customers. For instance, if queries cannot be straightway addressed, their customer representatives swiftly apologize and give necessary directions by chat box facilities, the toll-free number or customer service, for additional help. Conversely, we also establish that the levels of commitment and engagement contrast across all food delivery companies and social media requests. Among the other two app-based food delivery companies, Zomato revealed a higher level of consumer engagement and commitment, through the larger number of comments and posts on social media. Zomato's social media efforts are more visible, bearing in mind that their market share (33.5%) is lesser than the market shares of Swiggy (nearly 50%). Specifically, we observed that Zomato's replied to user comments more speedily during the assessment period, which reflects their robust energies in monitoring and conducting activities on social media.

This study validates that the three app-based food delivery companies have increased interaction with customers and build brands through significant efforts in social media. Specially trained employees have been assigned to involve customers and observe the content that customers suggest in social media submissions. For gaining insight into customers' behavior, concerns, needs and wants, to serve them better, they have used "social media" as an additional communication and customer service tool. Perhaps, they used social media for surveying their customers and listen to their opinions and feedback, both positives and negative, for providing better services and experience to the customers (Rosenthal, 2010). A few of the suggestions and ideas suggested by customers have been incorporated to improve taste and quality of food. Because of social media, the customers can post their views or messages through social media forums publicly and the message content is not private. Communications between food delivery companies and customers can attract the interest of other users of social media, who are currently not customers of that particular food app. Thus, social media applications become tools which enable customers to talk with one another, and these conversations are out of directly control of the managers (Mangold & Faulds, 2009). The present study also reveals the social media impact on customer service. To some extent, social media applications like Twitter work as "a giant word of mouth catalyzer and information accelerator" (Dellarocas, 2003; Godes and Mayzlin, 2004; Kumar *et al.*, 2007). Consequently, it is necessary for the app-based food delivery companies to monitor and track customer conversations on social media to resolve customer concerns/complaints proactively.

6.3 Research implications

Competitive analysis in social media permits a business firm to have competitive advantage over others by analyzing the social media data of its competitors, which is available publicly through internet. To improve performance, business firms can compare and contrast its social media data with that of its competitors, which will ultimately help the business to identify its weaknesses, new opportunities and alter their existing social media strategy. Social media competitive analysis is a key technique in text mining, which analyzes a large amount of complex social media textual data. Customarily, text mining mainly emphasizes on the business's internal textual data analysis. As social media and other Web applications become more prevalent, the use of text mining for analyzing textual data befits an acute business need, which is expected to better support and facilitate richer analysis for decision-makers. Big data also reveals a trend regarding significance for business firms to develop competence in collecting, keeping and analyzing internal as well as external data, to generate information for decision-making and planning.

Nowadays, it has become necessary for firms to track and monitor their presence/activities as well as of their competitors, on social media. Therefore, there is a need for the firms to create a social media competitive analysis and monitoring strategy, to steadily and systematically analyze and manage social media data regarding their competitors. The social media competitive analysis strategy and monitoring helps a firm to define how its products and services are acknowledged by its customers and also gives a better understanding of its competitors' products and services, in addition to market knowledge. Web services and tools, both commercial and free, are available, which can be helpful in monitoring social media by searching specific keywords. In recent years, text and data mining techniques have been applied to analyze social media data, as manual coding of social media data is time consuming (Barbier and Liu, 2011). It is significant for a business firm to accumulate their own as well as their competitor's social media data and apply mining on this large textual data to assess insights, trends, pattern and unseen relationships. A modern trend is to carry out opinion analysis on social media for identifying consumer opinions, sentiments and feelings on specific issues and to find out possible reasons for an opinion change (Chiang *et al.*, 2011; Pang and Lee, 2008).

Social media impact findings should be examined by organizations for achieving real competitive advantage. There is a need to examine the correlation between events of price changes, social media opinions and sentiments, competitors' promotional behavior and sales data, for providing exact information for taking important strategic decisions by business firms (Dey *et al.*, 2011).

7. Conclusion and future research

Social media is nowadays drawing attention of many industries. It is significant to comprehend how social media data is useful for taking important strategic decisions at the industry level. Recently, many studies on social media focus on individual organizations; however, a few studies have performed systematic competitive analysis on social media data of leading business organizations. This study, as an exploratory study, contributes to perform competitive analysis by applying text mining for user data generated on Twitter on three main app-based food delivery companies "Swiggy", "Zomato" and "UberEats." A comparative sentiment analysis was done using two different Lexicon-based sentiment classification methods on the three food delivery app companies and different sentiments were captured. The comparative study suggested that overall performance of the companies was toward the positive emotions of users; however, Zomato received more positive sentiments compared to the other two companies; results of Swiggy were comparable with Zomato. UberEats received more negative tweets than positive but with less negative intensity. Results reveal that all the three companies were actively engaging their customers through social media. They not only used social media to promote their products and services but also to develop bond with their customers. Through negative tweets, what customers think negative about the food delivery companies' apps has been fetched and recommendations have been given based on analysis. The study also suggests that social media plays a significant role in sustaining a healthy relationship with customers.

Later on, the overall recommendations have been given to the companies which are doing online businesses and provide products and services to the customers. At first, all the positive and negative tweets from all three companies were collated and then five categories were observed for giving recommendations. All the given recommendations suggest to the companies on following aspects: how to build a strong customer relationship by using social media; how social media plays important role in marketing of the product and services; how quality of the product and services influences the customers; and how consumer's feedbacks and review can help to the businesses to improve their product and services.

This research only deals with Twitter as a data source for this analysis; however, other social media platforms such as Facebook, Instagram, etc., may be incorporated in the analysis. Another limitation of this study is the location which has not been taken care of in this study. In further research, location wise social media data may be fetched for location specific implications. Another factor is date and time, which may be taken care of in future research. It can give more in-depth analysis and suggestions may be refined more precisely. In this study, only tweets written in English language have been considered. However, in future studies, other languages may also be considered. The information may also be improved by considering opinion carriers such as emoticons, emoji's and slangs.

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