International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 07 | July 2020 www.irjet.net p-ISSN: 2395-0072

SOCIAL MEDIA ANALYSIS ON SUPPLY CHAIN MANAGEMENT IN FOOD INDUSTRY

Kaustubh A. Nale

University of Technology Sydney

ABSTRACT: *This paper proposes the importance of social media analysis in supply chain management in the food industry. In this analysis, the social media platform (Twitter) is used to obtain information. In this approach, two different software (Nodexl and Nvivo) are used to conduct data mining and text analysis. The outcome of this analysis will help researchers to make decisions based on customer feedback. This paper focuses on a case study in milk and grain supply chain on the bases of two weeks of data obtained from twitter*.

Keywords- *supply chain, Sentiment analysis, word cluster, data analysis, content analysis, network analysis.*

1. INTRODUCTION

In today's world, every business and all the research communities are using social media as a consumer feedback and development platform. Social media plays a very important role in the analysis. Businesses and various companies use these platforms as a marketing strategy and for brand management (Chae 2015a). The research committee from various fields has started investigating on how to utilises these platforms to collect information and how to use that information to identify the key areas for development such as prediction of a stock price, early event monitoring to maintain the stock.

Since there is a lot of research data and documents on how to use all the analytical capabilities for SCM, but still the generally the primary focus has been based on the traditional data resources and analytical techniques to calculate the various aspects which may impact the supply chain management (Chae & Olson 2013). There are a different small number of research data's that are published which discuss the potential role of supply chain management in the food industry (Casemore 2012).

This paper explains the importance of social media analysis and what are the different software and techniques used to conduct the study. Two different hashtags are used in this research they are #Milk, #Grains. All the tweets that are extracted from the twitter are based on these two hashtags (Ben Abdessalem Karaa et al. 2018).

The objective of this paper is to understand how we can use twitter as one of the platforms to conduct analysis in the context of SCM. The paper indicates the analytical framework (twitter analysis) for analysing the tweets based on supply chain management. As mentioned above, there are various research papers and case studies available on this topic. It is very crucial to understanding social media and their data with the SCM context (Cecere 2012). There is on any practical framework available to conduct this type of analysis. Thus, every annalist uses different frameworks.

The twitter analysis consists of three different types of research methods they are, descriptive analysis (DA), network analysis (NA), and content analysis (CA). These different types focus on different parameters of twitter analysis. The number of tweets used for the analysis is 17,946 tweets and metadata. The results are based on the following questionaries,

1) What are the characteristics of the supply chain tweets? Is there any structures of communication and distribution of information?
2) What are all the components of the supply chain circulated on social media? Have there been any related issues or contents?
3) What are the different sentiments obtained from the tweets?
4) What are the different characteristics of the users of Twitter discussing the topics of the supply chain?

Responding to these questions allows one to consider the future application of twitter in the supply chain (SCM), e.g. supply chain risk reduction, innovative product growth, stakeholder participation.

2. Data Mining & Twitter Background

Since past few years, there has been a substitutional increase in the use of social media around the world, which has led to an increase in searching for data from all parts of the world. Due to which a lot of big companies are focusing on social media as a platform to review, market, revise their products (Jensen, Panagiotou & Kouskoumvekaki 2014). Different companies and researchers use different type of frameworks to conduct their research. But the initial phase is typical in all frameworks, that is Data mining. In this phase, we use various means to extract the data from social media. Data mining or text mining is used as a big data analysis tool. Big data analysis is most used as it allows the user to manage a high volume of data and helps to convert them into useful means of format. Data mining is originated from a method called knowledge discovery from data (KDD) (Han, Pei & Kamber 2011).

A data mining consists of three different stages. The first stage consists of data pre-processing, i.e. to prepare a relevant target that is to be mined. The second stage consists of data pattern identification in which various patterns of data is identified. And in the third stage, pattern evolution and presentation take place. The various tools that are used are mentioned in Table 1. Big data is used for the optimisation of production, safety, and quality assurance purpose in the food supply chain (Godfray et al. 2010). In today's world, where the population is proliferating, it is becoming challenging to feed them all. Use of precision agriculture' and 'smart farming' are proposed to enhance agriculture production by continuous monitoring, modelling, and optimisation of operations. Due to ability to of handling such a huge data from various sources and able to store as well as analysis them, big data is rapidly used in the food industry(Klassen et al. 2018).

Software/programming language	Library/package
Python	Pandas (Python)
R Software	Scikit-learn (Python)
SAS Enterprise Miner	NLTK (Python)
IBM SPSS modeler	NetworkX (Python)
Oracle Data Mining	Numpy (Python)
Orange Data Mining	tm (R)
RapidMinder	Sympy (Python)
Weka Data Mining	Scipy (Python)
Anaconda	nlp (R)
GNU Octave	wordcloud (R)
Gephi	apriori (R)
STATISTICA	topicmodels (R)
NVIVO	textir (R)
BigML	network (R)

Figure 1 Different Software's

3. The data source of the text

The text can be obtained in various forms like in natural language text, which can be found on the web. Some of the text is obtained in the form of tweets, and some are obtained from the news, scientific data. This information is classified into three different parts, database data, social media data, Internet data fig 2. The database data consist of all the data that that is available on government and scientific database. Internet data consist of data that are available on the internet in the form of websites, blogs, news etc. And lastly the social media data includes all the information that is directly available on all the platforms such as Twitter, YouTube, Instagram (Jessica Einspänner-Pflock 2014). The information obtained in social media is generated by users. That can be published on any platforms. All the sources are discussed further below.

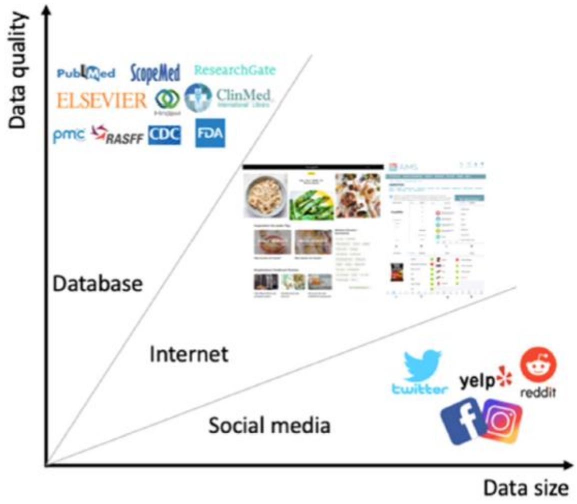

Figure 2 Source of text data

3.1 Database data

Many scientists have expressed interest in the mining of data from database data since last century (Chae 2015b; Hazen et al. 2014). A vast number of databases has been used to improve the understanding of food-related research and helped to identify the flaws and various scope of improvement. A fast Alert System database is used to obtain information on different hazards of food frauds. Various food manufacturing industries research different kinds of genes, an illness caused by the food with the help of the database. However, some of the industry based resources are private and often difficult to access and evaluate (Hazen et al. 2014). As of late, partial details such as the list of ingredients and the Food Products Nutrition Table are shared and can be obtained via government data.

3.2 Internet data

Internet is the most common source of information for food-related data. Because of a wide range of digital techniques and various news articles are published on the internet, which is readily available for researchers. All this data that are available on the internet are in the form of multisource data like news articles, government websites, blogs (Almutairi 2016). The labels and tags of each product are available on the internet and can be used to identify ingredients and use that information to create smart systems that can predict and provide relative remedies. These Internet-based data, released by official agencies or experts, are typically high in relevance and reputation.

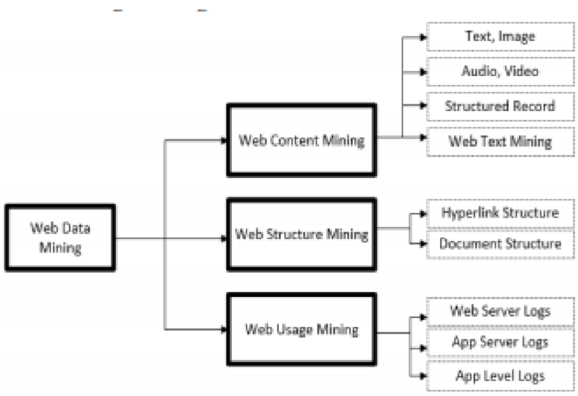

Figure 3 Internet data or web database

3.3 Social media data

Since the past few decades, there has been a subsequent growth in the use of social media platforms (Arias, Arratia & Xuriguera 2013). Due to the use of this platform, it is easy to obtain any information from any corner of the world. In today's world majority of the researchers use this database to research as they are more public-oriented than any other source. Social media platform consists of Twitter, YouTube, WhatsApp, Facebook, Instagram. This type of data source is continuously generating web-based microblogs that provide real-time data of sentiments, behaviour, various trends (Palen 2009; Singh, Shukla & Mishra 2018). Scientists use text data to obtain information regarding the dietary patterns, eating habits of people. This data is collected and maintained in the form of diaries, due to which regular surveys had to be conducted because of which there was a restricted scope of development.

Web mining, as well as social media research methods, are used to analyse data. However, because social media data are user-generated, there are still many challenges to the analysis of this text knowledge.

4. Background of twitter and its impact

Along with all other social media platforms, Twitter has shown rapid growth in the recent decade (Inauen & Schoeneborn 2014). After its launching in year 2006, this application has been one of the fastest-growing application in the entire world (Chae & Olson 2013). According to the survey conducted in 2011, around 75% of global fortune owns more than one twitter account. A tweet is a message which consists of 140 characters (Bruns & Stieglitz 2013). The tweets can be classified as, original tweets, replies, retweets. The original tweets appear on the homepage and timeline of the sender. Users of the twitter can take part any discussion using @replying to each other and retweeting. Both messages are traceable. Twitter provides every researcher and scientists with an API which helps them to access the data server of the twitter. This API allows them to collect the data using various queries, hashtags, keywords, etc. Unlike Facebook, Twitter is the only social media platform that provides 'open data' (Cecere 2012).

Also, Twitter has already impacted various fields in the research sector, which includes finance, health care, journalism, IT sector, politics.

Figure 4 Representation of a number of tweets on the world map

5. System for the Extraction of Information from Twitter Data

The first step towards the process is the identification of the keywords, hashtags, related to the topic. With the help of API, it is only possible to obtain 1% of the data from the database (Ghosh & Guha 2013). This data can also be obtained using various providers like DataSift they are also called as twitter firehose. These sources can provide 100% data from the twitter depending on the criteria. This is standard, but a very costly choice. Many social sites also have their API services like Facebook is offering the API Graph (Nikolaos Misirlis 2017).

The data that is obtained from twitter is enriched with various information like hashtags, user details. Due to which the data is less structured than any other corporate data that is obtained by surveys. The use of a broad range of metrics and research methods is essential to extract knowledge from deeply enriched and unorganised data on social media (Jensen, Panagiotou & Kouskoumvekaki 2014). Due to this factor, the rest of these sections are focused on developing an analytical framework which composes of various research methods and metrics for obtaining the vital information from twitter (Huang, Potter & Eyers 2019). The methodology is divided into three different sectors: Descriptive Analysis (DA), Content analysis (CA), and Network Analysis (NA).

5.1 Descriptive analysis (DA)

Twitter consists of a tremendous amount of data in the form of tweets and metadata. In the descriptive analysis, the primary focus is on various descriptive statics such as the number of tweets, various types of tweets, number of hashtags. Descriptive analysis is always conducted first, and every researcher gives the descriptive analysis as it helps to maintain the exact amount of metrics (Cornejo 2017). A small quantity of metrics is often used in survey data, due to this nature of Twitter data, it is possible to extract intelligence using a huge group of metrics for tweets, hashtags, URLs. A basic but vast perception of tweets data is prerequisite to conducting a detailed analysis. From the business value point of view, it is essential to know who tweets, retweets, and replies as this information will help them to identify kind of customers are using their product which indirectly gives the credibility of those tweets (Weiss et al. 2010). With the help of user metrics, it is possible to identify which user or group of users are active in terms of actives. The user information is more inclined towards the outcome of centrality analysis from the network analysis. Majority of the tweets contains one or more number of URLs, which could be news articles, reports and more. Due to URL analysis, it is possible to gather information on the most discussed topic on twitter (Fan & Gordon 2014).

Whereas only such three kinds of analysis are presented, other descriptive analysis and statistics are completely possible, which can be used for a variety of purposes. Nevertheless, using most of these criteria is likely to trigger duplication and misapprehension of information instead of knowledge.

5.2 Content analysis

The data obtained from the tweet is raw and unstructured; hence it is essential to conduct content Analysis (CA). The content analysis includes a diverse range of natural language processing (NLP) and various text mining techniques (Jessica Einspänner-Pflock 2014). A tweeter data is unorganised and consist of small words, URLs. Hence it is necessary to select proper text cleaning and processing techniques Machine learning and text mining techniques are critical components of CA Text mining transforms random text (or files) into encoded information (or documents) using methods such as tokenization, stopping, and deletion of stop words. Transformed text can be used for synthesis purposes, word frequency analysis, text cluster analysis. Although CA is obtained in supply chain research and practice, the method has been manual although CA is considered in supply chain research and experimentation, it has also been manual as well as semi-manual. Because of the immense complexity of Twitter data, CA at the TA Relays on digital document generation methods and algorithms or semi-manual, mainly through human understanding.

The starting of content analysis is word analysis. It consists of document summarization, clustering, and word frequency analysis. The (TF) is mostly considered in content analysis. The TF cab is merged with n-gram, which helps to identifies the keywords or phrases from documents which are vital for research. It helps researchers to recognise subjects of conversation, and often offer various uses of twitter as per the supply chain. Such demarcated topics are beneficial for document-level evaluation using unattended machine learning models (e.g. clustering). Text summarisation may characterise documents which will help to allow for a thorough review of certain documents in contexts of their classification. After that, the hashtag is another vital part of tweeting. Hashtags are equivalent to topics of research used for the categorisation of research journals. Clustering on mining unearths the relationship among all hashtags. Such kind of relationships illustrates various marketing strategies converge on Twitter.

Although word and hashtag analysis concentrate on discovering evidence in tweet text, sentiment analysis is mainly interested in obtaining subjective knowledge (e.g. opinions) from tweets. Sentiment analysis is carried out at two stages: (1) complete tweets, (2) multiple clusters of posts. The purpose behind this to categorise them into positive, neutral, negative tweets. It is possible to identify different types of clusters and sentiments can be conducted on these different clusters.

5.3 Network Analysis (NA)

Twitter users use @ reply, retweets; due to which, network data can be obtained from the twitter database with the help of metrics. There are two essential terms used in this theory, namely, Nodes and edges. The network topology consists of layouts of nodes and edges which are based on the data of tweets and replies. This kind of network analysis helps to uncover trends in user experiences. Different network metrics like average path length provide a comprehensive overview of the network. With the help of Twitter data, there are two types of topological network: @reply network friendship network. The friendship network is constructed based on the data obtained from the followers and following. Use of @reply indirectly creates an interpersonal link between the users.

Besides, this theory offers a centrality analysis using node-level metrics, that reveals the most influential people in the network. The primary metric describes who has large connections to those on social media (Wasserman, Faust & Faust 1994). While degree centrality relies on the nodes external to the focal point, "Beyond ness centrality" includes the distance paths of the focal node. Whereas the centrality analysis focuses primarily on individual nodes (or users on Twitter), the group analysis examines the features of the network. Modularity is a function of the degree to which the network is divided into the modules. Analysis of modularity defines different groups of visualisations from the network.

With analysis and metrics, there is true of a multitude of system definitions, evaluations, and metrics. A well-framed analysis query can, therefore, be useful in choosing a controllable set of analysis as well as metrics while using (DA) (Fathelrahman & Basarir 2018). Improvements in analytical methods, as well as metrics for all other social media data, should be made.

6. Research Method

The best approach to illustrate the established model and to educate Twitter regarding its usage and potential path in the supply chain network is to collect all Twitter data over a given period of time and also to acquire the related data. However, given a large percentage of Twitter data, all research using Twitter data requires data sampling techniques that depend on tweets and keywords to classify the necessary details. To gather Twitter tweets about issues and events related to supply chain, I initially carried out a series of keyword and hashtag, including SCM, beef, milk, grains. Due to which it has led to the finding of hashtags #milk and #Grains. The data collected in this research is dated from April to May 2020. The final data set consist of 17,496 tweets which also includes hashtags, retweets (Chae 2015b).

6.1 Descriptive analysis (DA)

This method of study is known to be one of the main fields of focus for companies and researchers. We use structured languages and various computational and data processing techniques to execute the DA. Script languages were needed to extract details as users and hashtags from the data collection of tweets.

6.1.1 Tweet statistics:

Among 17,596 tweets original tweets, retweets, and reply accounts for about 61% (10,571), 26% (4524) and 13% (2399) respectively. From the data around 2780 different hashtags ranging from popular SCM hashtags where obtained. Numerous tweets consist of two or more hashtags implying that most tweets are overlapping numerous different areas of interest.

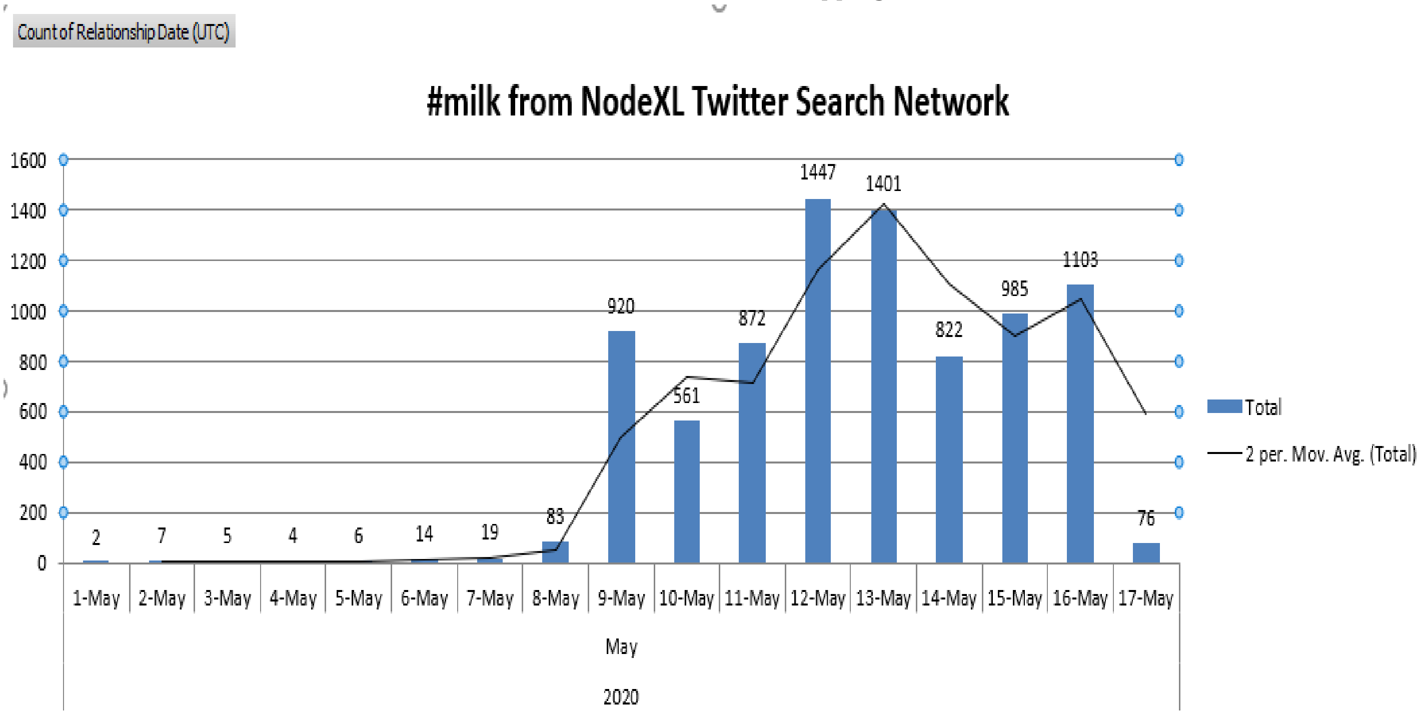

Figure 5 Data collection chart

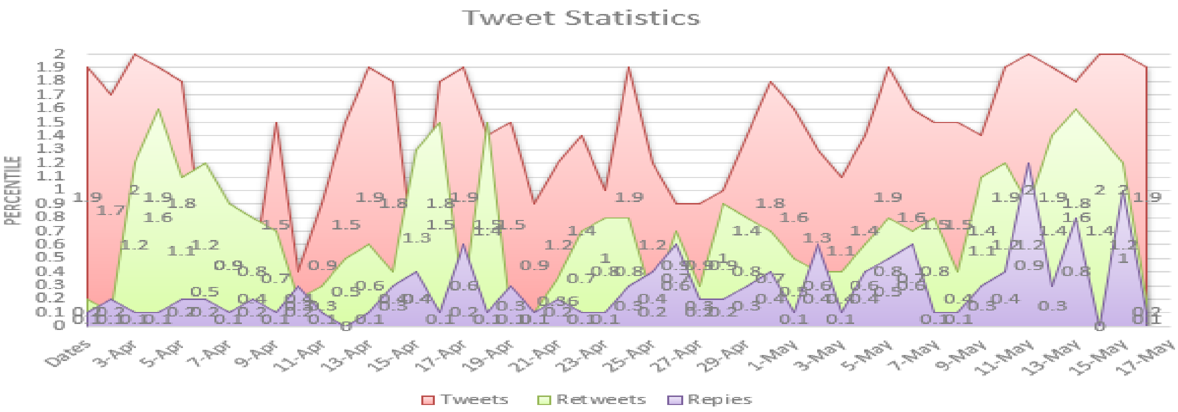

Figure 6 Tweet Statistics Chart

6.1.2 User analysis:

In this analysis, the focus was on the users that were posting tweets on twitter. During analysis, 6215 unidentical users were found in the entire database. This shows that every user has posted about 6.20 tweets, i.e. 4 actual tweets, 1.90 re - tweets and 0.30 @replies. The number of active users is determined based on the cumulative amount of posts (actual tweets, retweets, replies). Visibility of users is calculated based on the number of @replies received. We also visualised the activities of the most visible users. As a result, highly visible users appear to be involved users as well. Big logistics companies (e.g., UPS), manufacturers (e.g., Unilever) and retailers shave twitter accounts. They are identifiable but not active in our data, as most of their tweets may not contain the # supply chain.

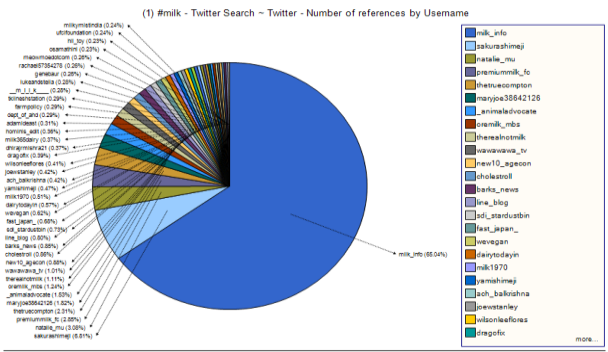

Figure 7 User Analysis

6.1.3 URL analysis:

URL is most common in tweets. Around 87% of tweets from the database consist of one or more URLs in them. According to the Analysis approx. 12.354 URLs where obtained. Particularly active and prominent users use URLs in their posts: almost all these users' tweets contain one URL. Leading URLs include Business Blogs, SCM web-based Newspapers, as well as industrial Leadership and data analysis posts. Top URLs that are obtained from the database are, www.youtube.com, www.atrdust-chjp.com, http://lineblog.me/sdmilk/archives/8441629.html. Fig.9 Shows the top URLs that are obtained from the network dataset.

Top URLs in Tweet in Entire Graph	Entire Graph Count
https://www.youtube.com/watch?v=7dbAqI	253
https://stardust-ch.jp/movie/category/784	184
https://fast-tokyo.com/harukana2-sono/	153
https://lineblog.me/sd_milk/archives/84416	142
https://lineblog.me/sd_milk/archives/84420	130
https://lineblog.me/sd_milk/archives/84418	130
https://www.youtube.com/watch?v=v1TH_g	122
https://natalie.mu/music/news/378766	118
https://lineblog.me/sd_milk/archives/84420	97
https://sd-milk.com/news/2739	92

Figure 8 Top URL in Tweets

6.2 Content Analysis (CA)

CA consists of three categories: word analysis, hashtag analysis, word analysis, sentiment analysis. Word evaluation is further divided into the analysis of the term frequency and cluster analysis. The hashtag research is focused on an overview of the hashtag frequency and interaction of various hashtags. CA is focused on NLP methods, synthetic algorithms, document clustering techniques, and opinion mining (Ben Abdessalem Karaa et al. 2018; Cornejo 2017; Fathelrahman & Basarir 2018).

6.2.1 Word analysis:

In word analysis, most words that are used in the dataset is obtained. Some of them are: diary (960), fakemotion (705), ebidan (1155), Http (10295), flowers (965), products (237), meat (164), #producemilk (1235), butter (1345), #diaryfarming (1999), prices (254), nutritional (614), slaughter (106), supply chain (2345), bread (105), milk powder (128), cream (55), tax (164), café (64), crops (276), lifespan (55), #diaryfree (61), #poultry (23), milk365 (23), taste (73), #livestock (46), #freshmilk (22), technology (37). Some other words are shown in fig.10. Further, all words were clustered to form a hierarchical chart, as mention in fig.11.

Top Words in Tweet in G1	G1 Count
#milk	652
milk	210
#grains	107
#food	60
more	43
m	37
#coffee	36
s	33
#breakfast	33
click	32

Figure 9 Top Word List And there counts

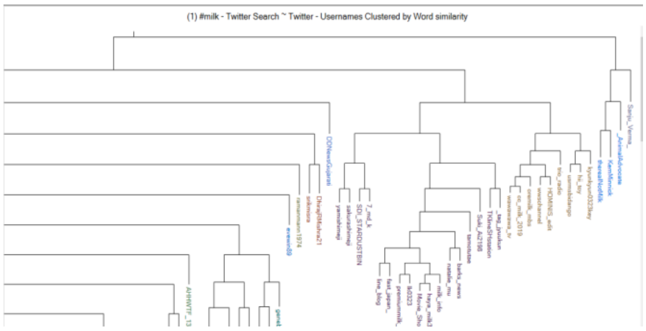

Figure 10 Cluster Analysis

6.2.2 Hashtag analysis:

In hashtag analysis, around 2973 hashtags were obtained from different tweets which appeared 34267 times. The most popular hashtags included where #supplychain, #milk, #freshMilk, #diaryfree, #poultry, #diaryfarming, #livestock, #beveragemilk, #freight, #sourcing, #distribution. According to the Analysis, there were on an average 2.14 hashtags per tweets. The two hashtags appeared multiple times (#milk and #supplychain). They appeared in almost 6.7% of tweets among the entire datasets.

Top Hashtags in Tweet in Entire Graph	Entire Graph Count
milk milk体操	922
佐野勇斗 milk stayhomeebidan	402
milk	366
ピンポン球チャレンジ milk stayhomeebi	253
さくらしめじ	235
milk 佐野勇斗 fakemotion 卓球の王将	174
fakemotion 卓球の王将 日本テレビ milk 1	173
曽野舜太 milk stayhomeebidan	169
yo fakemotion 卓球の王将 milk 山中柔太	145
fakemotion 卓球の王将 milk 山中柔太朗 1	134

Figure 11 Hashtag Analysis

6.2.3 Sentiment analysis:

Different types of tools are used to conduct sentiment analysis. The below table shows the sentiment of the entire database. Many of these tweets appeared to be neutral and are mentioned as non-categorised words (80%) in the table, and around 15% of remaining data are termed as positive and remaining (5%) accounted for the negative tweets. Some of these tweets showed a strong sentiment like angry and violent tweets. Fig 13 gives the graphical representation of the sentiment analysis of these tweets.

The fig.14 shows the head map of the sentiment analysis. The cells with dark red colour represent the highest frequency of tweets; as the colour changes from dark red to light red, light blue dark blue so does the frequency of tweets. The dark red colour indicates the highest number of tweets, and the dark blue colour indicates the lowest number of tweets.

Top Words in Tweet in Entire Graph	Entire Graph Count
Words in Sentiment List#1: Positive	3194
Words in Sentiment List#2: Negative	2563
Words in Sentiment List#3: Angry/Violent	4
Non-categorized Words	151318
Total Words	157076

Table 1 Sentiment analysis word count

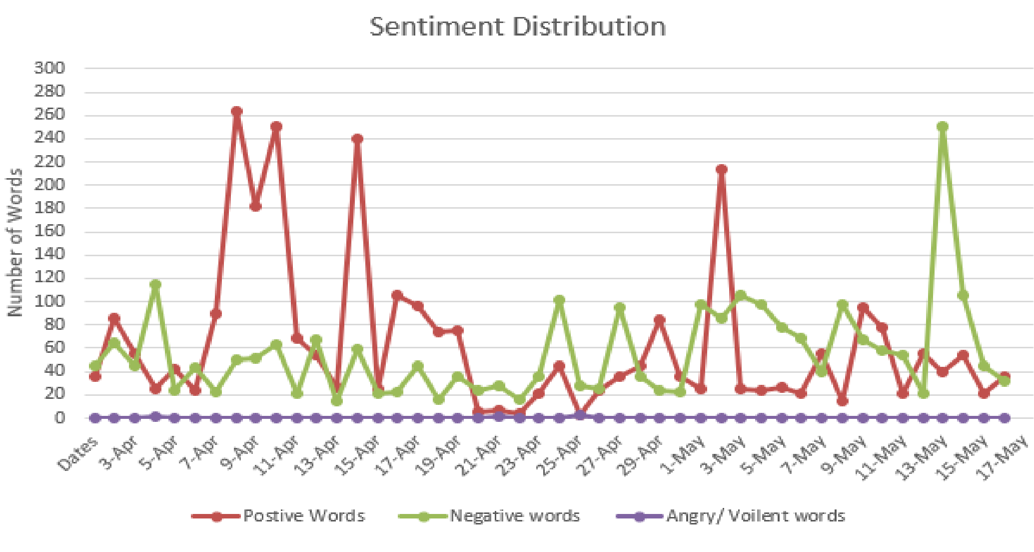

Figure 12 Sentiment Distribution

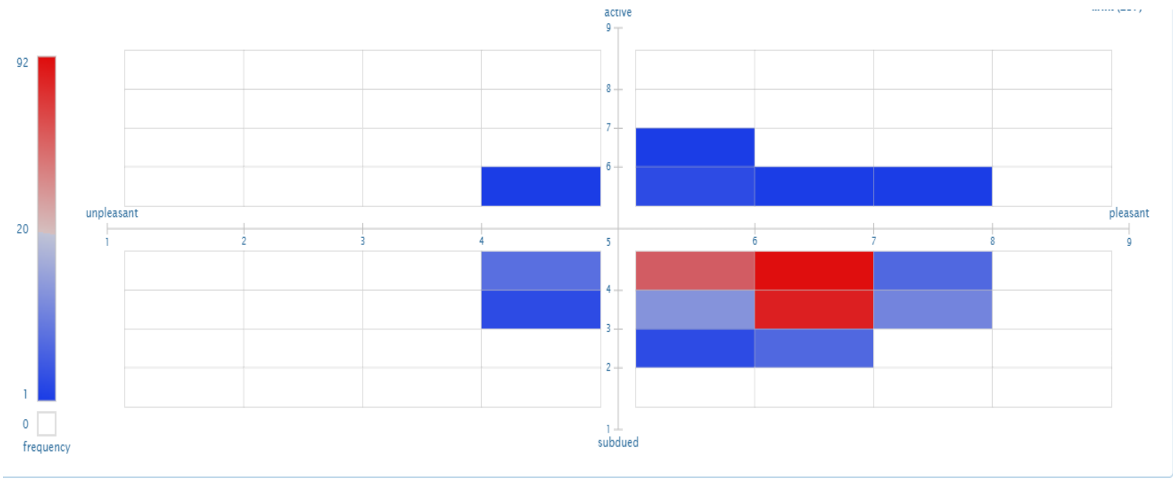

Figure 13 Sentiment Distribution (quadrant wise)

6.3 Network Analysis

6.3.1 Topology analysis:

A comprehensive social network was created with the aid of 6994 nodes and 51707 references. The modules in this network structure are some of the users that have either submitted or received @reply. The edges are also the relationships between these users via @reply. The length of the path of the majority of the nodes was around 2 to 7. The width of the network is 19, which is the maximum gap between both the two nodes on the network. Fig.15 shows the topology, which signifies that the network is significant and spare. Despite this, the mean length of the path is 6.21, signifying that each user is approximately seven nodes away from one another.

6.3.2 Centrality analysis:

Among a few node-level network metrics, in-degree is a basic feature of the nodes linked to each other and an indicator of the popularity of the consumer. Big companies like @toyota attract many posts or mentions, as they are high in-degree values. Similarly, few individuals are also noticeable. Many of those with strong links are seen to be in contact paths with other users. The centrality analysis is shown in fig16.

Vertex	Degree	In-Degree	Out-Degree
misharn	325	1	1
wearecsaw	316	1	1
greengrowth01	267	2	1
dhakalsaurav	245	0	1
lostinf00d	216	1	1
janditheis	168	1	1
wellnessmama	120	2	1
sjenterprises	98	0	1
indlandl	86	1	1
kellyalspals	62	0	2
eu_commission	48	5	0
menacommodities	39	10	4
fashnal_com	27	1	1
kncdaniels	21	0	1
youtube	16	19	0

Figure 14 Centrality Analysis

6.3.3 Community analysis:

Group research reveals that a very small graph density (0.001), suggesting that the complexity of the network is limited. The entire # supply chain network has been sparsely dispersed, as shown in fig17. It may mean that there are several scattered communities on the network; therefore, community detection approach implanted in Gephi, which is also an open-source graphics software is used. With this technique, we can uncover over 400-500 societies in the # supply-chain network. Any of such groups are low in scale in nature.

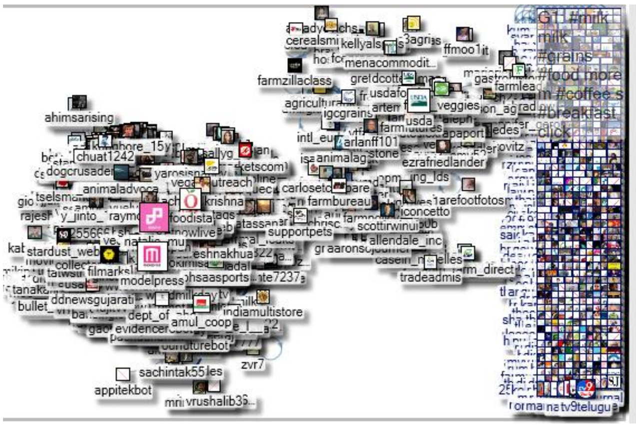

Figure 15 Community Analysis

7. Discussion

This section will answer those questions mentioned in the introduction. This section also discusses the limitations and further research.

What are the characteristics of the supply chain tweets? Is there any structures of communication and distribution of information?

There are various explanations for the tweeting of human and corporate people (Godfray et al. 2010). Twitter users convey information through URL, talk about everyday lives, involved in a various conversation using @reply, and share news about any new or previous events (Almutairi 2016). In the survey of sample tweets, the rate of retweets is about 5% were as 25% tweets consist of URL. On the other hand, 89 per cent of # supply chain tweets include URLs, and 28 per cent are retweeted. All in all, it proves that supply chain tweets occur to be more communicative and participating than spontaneous tweet samples. A lot of supply chain professional use tweeter as a primary platform to share news and information. About 14% of random tweets consist of conversations (@reply). This rate is much slower than that of #supply chain, which is about 19%. This shows that #supply chain tweets have most appeared that conventional tweets.

The use of hashtags also draws attention. Many users add a hashtag in their tweets to indicate that the tweet is topic-oriented so that other people with similar interest can join. According to the report, 15% - 19% of tweets consist of at least one hashtag. On average, every tweet consists of about 2-3 hashtags. I found that there are two factors which play a crucial role in deciding the delivery of supply chain tweet information. Firstly, tweets regarding timely problems and concerns tend to become more prevalent than others. The result shows that such tweets widely spread via retweets generally contain six hashtags on avg, twice that of many other quasi-popular tweets.

What are all the components of the supply chain circulated on social media? Have there been any related issues or contents?

The supply chain topic is vast and diverse, as proved by many hashtags. Most popular topics have similar hashtags. Some of these topics are #poultry farming, #logistics, #risks, #distribution, #sourcing. After closer examination, we realised that the most used topics are much broader than anticipated. Some of them are #climate change, #bigdata, #corona, #Social Media, #analysis. Amount these hashtags there is one most common hashtag (#Corona) that has been used in the past few months. On December 2019 there was a huge outbreak of deadly virus called corona / COVID – 19 in China. Due to this pandemic, there was a global shutdown, which had a huge impact on the supply chain of food products. This has led to an increase in discussion regarding the SCM on twitter with some topics such as #safety, #availability, #transportation, # ethics. Any of these tweets remind people about the recent pandemic (swing flu) that had a major effect on the financial economy and supply chain. Term research reveals that the content of both messages is close to that of hashtags (Klassen et al. 2018). However, term research of clustered texts suggests that there are unique terms used in clustered twitter posts. Common URL directories seem to have been suited to the study of a hashtag as well as terms. The variability of supply chain articles is also apparent in the research results of more than 400 network analysis societies.

Top Domains in Tweet in Entire Graph	Entire Graph Count
lineblog.me	874
youtube.com	525
sd-milk.com	246
instagram.com	197
fast-tokyo.com	197
stardust-ch.jp	185
natalie.mu	128
twitter.com	100
milk-inc.com	56
lnk.to	52

Figure 16 Top Domain

What are the different sentiments obtained from the tweets?

The #supplychain tweets contain comparatively low feelings. This is demonstrated using descriptive analysis and content analysis. Including those posts, either pro or against any of the other major groups and videos, much of the # supply chain posts were also about things, SCM updates and papers, work, and advertising. Several other twitter posts have shown a high amount of dissatisfaction at the company's courier service, sales figures, and logical standards, as well as risks and disruptions in the distribution chain. Some of the tweets are mention in the table. In the analysis, three different kinds of sentiments, namely, positive, neutral, and negative, are obtained. Majority of the tweets were found to be neutral, and next to that were positive tweets and lastly negative tweets. The research also revealed that there were few tweets which showed a strong sentiment like anger and violence.

What are the different characteristics of the users of Twitter discussing the topics of the supply chain?

The analysis has revealed more critical information about who are the most active users on twitter. Majority of the active users are job and career consultancies. Majority of the tweets from this data are regarding the announcement of jobs for supply chain and logistics companies (LI 2009; Makrehchi, Shah & Liao 2013). The study also reveals that a minor number of users contributes to a significant proportion of tweets. For e.g. in a study of about 9 lakh tweets, it was found that only 7% of tweets accounted for 95% of tweets. This type of pattern appears in #supplychain tweets. That is more apparent in the ratio of users to the initial tweets. The highest 10% of users account between 52% to 33% of the initial messages. Even so, the remaining 90 per cent of users compensate for a large portion (50 per cent) of retweets, suggesting that this community of users continues to be supporters of certain most prominent accounts on the platform.

8. Limitations and further scope

Supply chain analysts will allow good use of social networking networks and social network resources for creation and review purposes. However, the field of SCM is relatively slower in the identification of the real potential role and uses of all the social media platforms. This study reacted to the most current scenario by utilising an empirical method for twitter data based on a wide variety of information such as emotions, contact habits.

This research has some limitations. Due to the access issues, it becomes difficult to obtain the dataset from twitter as it has firewalls that allow the researcher to obtain an only specific number of tweets (Pearson & Perera 2018). The data that is obtained from the tweeter is limited to a few months. That is, we can obtain data for only past three to four months, not more than that. Another way to obtain multiple data is by using various keywords that are related to the topic. This approach will help researchers to obtain a large quantity of data related to the supply chain.

REFERENCES

1. Almutairi, N. 2016, 'A Review of Social Media Marketing: Examples of Food and Drink Product.'.
2. Arias, M., Arratia, A. & Xuriguera, R. 2013, 'Forecasting with twitter data', ACM Transactions on Intelligent Systems and Technology, vol. 5, no. 1, pp. 1-24.
3. Ben Abdessalem Karaa, W., Mannai, M., Dey, N., Ashour, A.S. & Olariu, I. 2018, 'Gene-Disease-Food Relation Extraction from Biomedical Database', Soft Computing Applications, pp. 394-407.
4. Bruns, A. & Stieglitz, S. 2013, 'Towards more systematicTwitteranalysis: metrics for tweeting activities', International Journal of Social Research Methodology, vol. 16, no. 2, pp. 91-108.
5. Casemore, S. 2012, 'Social media and the coming supply-chain revolution', CFO. February, vol. 29, p. 2012.
6. Cecere, L. 2012, 'Big Data: Go big or go home', Supply Chain Insights LLC.
7. Chae, B. & Olson, D.L. 2013, 'Business Analytics for Supply Chain: A Dynamic-Capabilities Framework', International Journal of Information Technology & Decision Making, vol. 12, no. 01, pp. 9-26.
8. Chae, B.K. 2015a, Insights from hashtag #supplychain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research, Int. J. Production Economics.
9. Chae, B.K. 2015b, 'Insights from hashtag# supplychain and Twitter Analytics: Considering Twitter and Twitter data for supply chain practice and research', International Journal of Production Economics, vol. 165, pp. 247-59.
10. Cornejo, A.d.O. 2017, 'Social media impact on consumer's food choice', no. Universität Kassel.
11. Fan, W. & Gordon, M.D. 2014, 'The power of social media analytics', Communications of the ACM, vol. 57, no. 6, pp. 74-81.
12. Fathelrahman, E. & Basarir, A. 2018, 'Use of Social Media to Enhance Consumers' Options for Food Quality in the United Arab Emirates (UAE)', Urban Science, vol. 2, no. 3.
13. Ghosh, D. & Guha, R. 2013, 'What are we 'tweeting'about obesity? Mapping tweets with topic modeling and Geographic Information System', Cartography and geographic information science, vol. 40, no. 2, pp. 90-102.
14. Godfray, H.C., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M. & Toulmin, C. 2010, 'Food security: the challenge of feeding 9 billion people', Science, vol. 327, no. 5967, pp. 812-8.
15. Han, J., Pei, J. & Kamber, M. 2011, Data mining: concepts and techniques, Elsevier.
16. Hazen, B.T., Boone, C.A., Ezell, J.D. & Jones-Farmer, L.A. 2014, 'Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications', International Journal of Production Economics, vol. 154, pp. 72-80.
17. Huang, S., Potter, A. & Eyers, D. 2019, 'Social media in operations and supply chain management: State-of-the-Art and research directions', International Journal of Production Research, vol. 58, no. 6, pp. 1893-925.

18. Inauen, S. & Schoeneborn, D. 2014, 'Twitter and its usage for dialogic stakeholder communication by MNCs and NGOs', Communicating corporate social responsibility: Perspectives and practice, Emerald Group Publishing Limited.
19. Jensen, K., Panagiotou, G. & Kouskoumvekaki, I. 2014, 'Integrated text mining and chemoinformatics analysis associates diet to health benefit at molecular level', PLoS Comput Biol, vol. 10, no. 1, p. e1003432.
20. Jessica Einspänner-Pflock, M.D.-A. 2014, 'Computer-assisted content analysis of Twitter data'.
21. Klassen, K.M., Borleis, E.S., Brennan, L., Reid, M., McCaffrey, T.A. & Lim, M.S. 2018, 'What People "Like": Analysis of Social Media Strategies Used by Food Industry Brands, Lifestyle Brands, and Health Promotion Organizations on Facebook and Instagram', J Med Internet Res, vol. 20, no. 6, p. e10227.
22. LI, S.P.B.a.X. 2009, 'ON SOCIAL NETWORK ANALYSIS IN A SUPPLY CHAIN CONTEXT', University of Kentucky.
23. Makrehchi, M., Shah, S. & Liao, W. 2013, 'Stock Prediction Using Event-Based Sentiment Analysis', paper presented to the 2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT).
24. Nikolaos Misirlis, I.N. 2017, 'A Roadmap to Social Media Analytics', <https://www.researchgate.net/publication/317645396>.
25. Palen, A.L.H.a.L. 2009, 'Twitter adoption and use in mass convergence and emergency events', Int. J. Emergency Management, vol. 6, no. University of Colorado at Boulder, USA.
26. Pearson, D. & Perera, A. 2018, 'Reducing Food Waste', Social Marketing Quarterly, vol. 24, no. 1, pp. 45-57.
27. Singh, A., Shukla, N. & Mishra, N. 2018, 'Social media data analytics to improve supply chain management in food industries', Transportation Research Part E: Logistics and Transportation Review, vol. 114, pp. 398-415.
28. Wasserman, S., Faust, K. & Faust, K. 1994, 'Social Network Analysis. Structural Analysis in the Social Sciences', Cambridge University Press, Cambridge UK.
29. Weiss, S.M., Indurkhya, N., Zhang, T. & Damerau, F. 2010, Text mining: predictive methods for analyzing unstructured information, Springer Science & Business Media.