Understanding the Impact of Marketing Outcomes from the Hashtags of the Wellness Industry: Twitter Perspective

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ABSTRACT

The study aims to find the surge in the interest in wellness that can be measured by the strength of the sentiment and find the hashtags that are playing a major trend in Twitter with the advent of the pandemic. To provide an original contribution to this research, around hundred core hashtags related to the wellness industry are collected by taking advantage of the Twitter API, an application that helps to mine the data of billions of users and tweets, through “Streaming API”. Findings highlight that few hashtags highlight positive sentiment as well as stronger negative sentiment due to various factors. The study has applications that would be useful to marketers as this research opens a new direction regarding the hashtag of the Wellness industry.

Keywords: Sentiment analysis, beauty and wellness industry, hashtag, tweets, social media marketing, digital marketing, data analytics and influencer marketing

1. Introduction

This microblogging platform Twitter has become instrumental in gauging the public mood in the later years. Millions of people share different perspectives on different topics every day (Patodkar & I.R, 2016). This information-gathering behaviour on Twitter helps find out the favourable as well as unfavourable opinions about the subject and is majorly employed in research to understand the negation words (Amalia et al., 2018; Dadvar et al., 2011). This is the reason why this platform is considered the fast and most effective way to analyse the various perspectives of the customers that are vital towards success in the marketplace (Chaudhary, 2016; Sarlan et al., 2014; Singh & Chaudhary, 2019). The sentiment analysis helps to analyse and deal with the massive volume of data that is highly unstructured, heterogeneous statements by categorising it into either positive, neutral, or negative (A. & Sonawane, 2016). The social network Twitter produces 1 billion tweets every two days, and this is considered the platform that is ideal for capturing the opinions on interesting topics related to brands, industries and perceptions. The novelty of the platform offers a vast horizon for further research in the wellness industry as there is no research conducted in this subject domain yet. Wellness discussions are taking a major trend online that is helping people become aware, making choices that are helping the audience on the social media platforms to support healthy and active lifestyles.

According to the FICCI’s latest estimates, the beauty and wellness sector in India have continuously been witnessing growth over the past few years, especially post Covid-19 pandemic. According to various estimates, the industry was valued at a around INR 490 billion. According to an Indian market research firm – Numb Research – the 443 million Indian millennials are spending an average of Rs. 4000 per month on health and wellness services and products. There are several fundamental reasons behind the fast growth of this sector. Some of the crucial factors and aspects are the increasing disposable incomes, increasing people's focus on "immunity, hygiene and health", specifically post-pandemic and foray of private-sector investors in the wellness domain etc. Besides that Government of India’s (GoI) initiative in inviting crucial players to invest in the wellness sector under the flagship program “Make in India” has been a significant contributor (Sharma & Gupta, 2021). GoI’s continuous impetus on establishing the Ministry of AYUSH has proved to boost the health, beauty and wellness market. (Bakhtiani, 2022; Gangrade, 2021). Globally, the size of the wellness industry was estimated to be around $4.2 trillion, and India still has a minute portion of it (Singhai, 2021).

This research study opens a new direction regarding the hashtag of a particular industry and understanding the behaviour of the market with the help of sentiment score and strength. This research could provide benefits to the research community by providing valuable insights into the perception of the users on Twitter regarding wellness. The document is structured as follows: In the following sections, the background and terminology regarding Twitter are explained, followed by the research's objectives and importance.

In the later sections, a literature review is established, followed by a brief research methodology, data, and analysis. In the last section, we summarized the conclusions. Lastly, the perspectives of the future work are briefly explained. The finding of the study is expected to be helpful in making decisions on who is in the field of the wellness industry to make the product or service reach more people through this social media platform.

2. Background and context:

2.1. Terminology

Today, the microblogging service Twitter is used by millions of users who tweet within the 140 character word limit. The trending information on any topic is likely to be retweeted, which is a particular case of instantly mentioned by the users, which signifies the fast diffusion of innovation (Kwak et al., 2010). Various researchers consider this as the electronic word of mouth concerning any situation or trending topics and brands (Jansen et al., 2009), which are characterised by a particular symbol before the topic called hash (Wang et al., 2011). For example, #fitnessfreak a hash before the topic is collectively called the hashtag. Users on Twitter connect with each other by following each other on the platform. If User X follows User Y, then User X receives in his or her timeline all the tweets from User Y. In this case, User X is a follower of User Y, and User Y is a follower of User X.

To gather the data from Twitter, an open API is available to all the developers, making it accessible and easy for developers to pass the requests to Twitter to extract certain information (Makice, 2009). The request in this research is related to streaming API, which has access to the Global data stream. The specific data are obtained with the analysis of the core hashtags on the Wellness industry, and the data is extracted with a specific code.

2.2. Related Work

Various works by researchers involved identified the polarity of the sentiment and lexical resources by evaluating the expressions of the statement, which also involves identifying substantial clues of subjectivity (Ghiassi et al., 2016; Wiebe, 2000). The opinion question answering system was employed in the previous research at both document and sentence levels, which gave up to 91 per cent accuracy in the outcomes (Chen et al., 2017). The research works related to Twitter pertained to understanding the emotions and sentiments towards only a particular product and deployed in research that aided in comparative analysis of entities and products. For example, Camera X quality is better than Camera Y, which is utilised in extracting the key elements of the research and determining the sentiment through comparative analysis (Ganapathibhotla & Liu, 2008). With an unprecedented amount of user-generated data on Twitter, the advantage of Twitter API has been utilised by many researchers where one such research is done to even understand determining the stock prices in real-time streaming environment (Dickinson & Hu, 2015).

3. Problem Statement

Over the past few years, the wellness industry has been showing rapid growth and shows that it has a way ahead for all the potential companies toward a sustainable future. The reason for the industry's growth is due to the health consciousness in the people's mindset and acceptance and understanding of wellness. Wellness is the holistic approach toward the whole body, mind as well as soul. The significant transformation of the lifestyle of the people in the past few years in social media with respect to customized health services, transformations, fitness challenges, wellness and self-care routines has opened the doors in the social media sharing platform to express their opinions. The problem statement to be investigated here is regarding understanding the sentiment on Twitter by focusing on the strength of the core hashtags in the Wellness industry. This also helps to understand the major hashtags that the industry can utilize in offering the products and services in a manner that helps to identify the needs of the sector and also help in personalized targeting.(Eşiyok, 2018)

4. Research Questions

The overarching goal is to assess the surge of interest towards Wellness on Twitter which is addressed in heightened emotions, which are thereby measured in two ways:
Measuring the average sentiment of all the core hashtags in the wellness industry or by assessment of the most relevant hashtag, which is considered as the most important, is associated with the increased strength of the sentiment.

4.1 Main Research Question

Are the most tweeted hashtags on Twitter associated with the negative or positive sentiment strength having a scope to understand and implement different strategies by marketers in the wellness industry?

4.2 Sub Questions

- To what extent is the satisfaction affected by the use of sentiment of Wellness hashtags?
- Are there any core hashtags with a higher sentiment resulting from the pandemic? And why?

5. The Research Objectives:

- To understand the extent to which consumers are attracted to a campaign and trend in the wellness industry
- To study the consumer's reaction to hashtags related to wellness in the pandemic through sentiment analysis.
- To identify the hashtags in the wellness industry with a stronger sentiment score.

5.1 Relevance and Importance of the Research

This research gives implications to marketers in the Wellness industry to understand customers' perceptions regarding a specific topic from the analysis of the overall sentiment score. This sentiment analysis gives the inference to the industry to introduce new services or products (value additions in the product, line extensions) that can help increase customer satisfaction. The engagement of the topics regarding physical health and mental health is mainly understood with tweets and retweets, which gives inferences to focus on trending topics and helps to initiate a trend or a campaign. (Yeung et al., 2021)

6. Literature Review

In the context of current business scenario, millions of documents are online and social media are considered the prominent Big Data, while Twitter is one of the most popular and famous microblogging platforms where people express their views within 140 characters (Gupta & Hewett, 2017). Much research has attempted to identify and classify sentiment types of short texts. This paper takes into consideration of the sentiment types (happy, sad, grateful.) on Twitter with respect to the wellness industry. According to the paper on Enhanced Sentiment Analysis using hashtags and Smileys (Davidov et al., 2010; Hussein, 2018), sentiment can be defined as the “personal belief that is not discovered on proof or certainty”. Though the Wellness industry is expanding across different parts of the world, it is considered as the least researched area (Olof Lagrosen & Grundén, 2014), this industry has drastically changed with the advent of the pandemic, so this paper identifies especially to understand the wellness industry with the relevance of sentiment analysis on Twitter (Agarwal & Mewafarosh, 2021).

6.1 Key Concepts Theories and Studies:

The past researchers (Luke et al., 2011) identified different methods of analysing in this industry, such as demonstrating health mediating between groups. The main objective of every business is to understand each customer individually, which is possible through data mining techniques which can discover various patterns related to the industry (Ziafat & Shakeri, 2014). While few researchers state that it is essential to predict and understand the popularity of the hashtags to know the speed of the spread of information (Ma et al., 2013). In this research on the hashtags in the wellness industry, the author treats the hashtags as a functional means to structure the content on wellness. The reason being hashtags are becoming an integral part of social media communications (Rauschnabel et al., 2019); this research is guided to understanding the patterns of human behaviour with respect to human behaviour.

Nowadays, every individual’s daily activities are exponentially logged into every day and transformed into large-scale datasets, helping businesses analyse the algorithm to take decisions (Kim et al., 2018). This social media platform, Twitter, is a valuable source of data, which helps to delve into the mindset of millions of people, which helps to understand by mining through appropriate stream mining techniques (Bifet & Frank, 2010). As Twitter is overwhelmed with vast amounts of social data, which is noisy and unstructured, classification of the tweets plays a major role in the process (Belainine et al., 2016).

Different kinds of research questions related to social activities, such as #MeToo movement, were highlighted by examining the content from significant articles and newspapers through a textual analysis (Mishra, 2020). The main key concepts around hashtags used to revolve around hashtag commerce when users started using them in communications or to promote products that facilitated transactions in real-world scenarios (O’Leary, 2019). Creating hashtags as a form of expressing helps to decode the feeling of the audience on Twitter, and hence helps the companies gain customers, which in fact adds as additional value to managers to introduce new products based on the sentiment score. However, there are also controversies that few hashtags do not serve any meaning or extract information, according to a few researchers (Adamska, 2015).

6.2 Using Twitter for Wellness Industry

It is nowadays considered to responsibly utilise the social media that will help to model the current technologies in the health sector, which will empower these professionals by using the real-time data (George, 2011). In a new networked era, health professionals can take advantage by fostering inter-professional conversational skills by utilising opportunities in the rapidly emerging and evolving social world. This social media platform, Twitter, gives the advantage of utilising online microblogging to support real-world social groups by understanding the daily activities of the users studied through topological and geographical properties of Twitter by many researchers (Java et al., 2007). Twitter derived variables and sociodemographic characteristics were used to understand the level of happiness, food and physical activity with the analysis of geo-coordinates (Nguyen et al., 2016). The findings of a paper are confined towards the research of understanding the metadata in Twitter related to muscle strengthening, aerobic and associated physical activity tweets (Kendall et al., 2011). Association of Fitbits and Twitter were used among the participants in order to study the lifestyle changes with the descriptive statistics (Chung et al., 2017). Utilising the emerging form of unsolicited communication, patients who have turned to social media for peer to peer support were understood that promote good healthcare decisions (Naslund et al., 2016). Twitter data was used to analyse the characteristics of obesity and diabetes, which was leveraged to understand the health studies on the population (Nguyen et al., 2017). In addition, when it comes to self-branding, it is crucial to remember that through hashtags, companies can increase their visibility, and it can be an effective tool to remind about the brand to the customers which represents the fundamental value. Hashtags were widely utilised by all businesses, especially after Covid-19; almost all industries were much more likely to use them, with hashtag use ranging from 48.5 per cent in FMCG firms to 56 per cent in auto companies. Tweets containing hashtags were retweeted more frequently, similar to weblinks, especially the effect of hashtags across industries starting from FMCG up to brands achieved high follower numbers, which leads to revenue growth (Soboleva, 2018). Companies may use an abbreviation or a catchy combination of words that connect to their brand to attract new followers and consumers, as well as advertise their business on the Internet (Fedushko and Kolos, 2019).

We identified a high diversity of themes ranging from professional education in healthcare, to big data and sentiment analysis, social marketing and substance use, physical and emotional well-being of young adults, and public health and health communication. This diversity of themes and approaches warrants further broad and versatile use of Twitter for health-related research.

7. Unravelling the Twitter Jargon

Table 1: The Common Twitter Jargons

Term	Explanation
Tweets	Twitter enables sharing of tweets which comprise 140 characters, which enables sharing of information, and additional blogs and hyperlink gives an extra source of information (C. R. Moorley & Chinn, 2014)
Follower	To subscribe to the tweets of the person, a user can choose to follow the accounts of the people that they are interested in receiving in their home feed (C. Moorley & Chinn, 2015)
Hashtags	Regardless of following each other or not, indexing in the form of a hashtag helps to organise information and exchange thoughts on a particular topic (Power, 2015).
Retweet	This permits them to share the information with their followers from the original source of information. Retweeting helps in knowledge sharing and also attracting attention from other professionals (O'Connor et al., 2014)
Favourite	If the users are interested in saving the tweet to keep a record of articles they favourite the tweet (O'Connor et al., 2014)
Bio	In order to encourage the followers, the users provide an interesting snapshot of the profile within 160 characters (C. Moorley & Chinn, 2015)

8. Role of Twitter for Professional Use in the Industry

Today's professionals across various fields on Twitter are exchanging credible and current information apart just from maintaining informal conversations and sharing daily leisure activities (Schnitzler et al., 2016). The major advantage of innovations, such as Twitter, is that they are expressed through economic gains (Archibald & Clark, 2014). This social media platform helps in enabling co-creation with consumers and helps in developing new products (Booth & Oudshoorn, 2014) to obtain structured information was deployed in research through semi-supervised recognition as well (Davidov et al., 2010).

9. Identified Research Gaps and Knowledge Contributions:

Researchers have worked on areas that proved the tracing of the data on Twitter, but there needs a depth exploration of finding the relevance of the hashtags in every particular industry (Arora et al., 2019). The main knowledge contribution towards this literature was identifying three core areas for analysing, namely analysing the user-generated content that is extracted by doing a descriptive, content and network analysis (Aswani et al., 2018). During the review of literature, it was observed that, seldom any study existed that highlights the engagement rate and sentiment analysis of the Wellness industry (Arora et al., 2019). A research study conducted by (Kalamatianos et al., 2015) mainly focused on developing automated methods that help in identifying sentiment intensity and also the past researchers most focus was on analysing the effect of one particular hashtag or a set of hashtags mainly to discover the use of the hashtag (Lal & Sharma, 2021). However, the research gap exists in the area where the research of hashtags and sentiment is utilised to infer the overall implications for the industry (Ahmad et al., 2019; T T, 2020; Timofeeva, 2019).

10. Key Debates and Controversies:

The debates include the difficulty of assessing the social media utterances, such as relying on a simple statement of fact can also have different communities and imagined publics which cannot be determined through the hashtag (Bonilla & Rosa, 2015). The major topic of discussion was raised as a result of online engagement through platforms like Twitter is the continuous user engagement as was evident in a study done on gambling brands on Twitter where 7 well-known gambling brands in the United Kingdom (UK), such as Bet 365, Betfair, Betfred, Coral, Ladbrokes, Paddy Power, William Hill posted between 89 and 202 tweets a day for continuous consumer engagement (Behnam et al., 2021).

The researchers are now upscaling the research as to appeal to the people from where the tweet was originated. Twitter is being used for the analysis of the brand image at different times, and locations through Support Vector Machine (SVM) was used to enhance accuracy, and it went up to 80% in feature selection, labelling tweet as positive, negative and neutral (Cho et al., 2014).

11. Research Methodology:
Many researchers have performed sentiment analysis on the data that is textual in nature, which helps to convert into an organised and structured manner of the data from the unstructured and unorganised data. This helps to find the opinion polarity, which is either negative, positive or neutral in nature. In this paper, a proper methodology has been proposed that will help to classify the sentiment polarity of the hashtags that are collected.

The proposed methodology facilitates us to carry out the analysis in an effective way. Researchers have explained briefly the idea about the vital components in the research methodology, along with a brief description of the tools used.

- Research Design – Using the primary data for the analysis, which is available on Twitter (scraping/mining of the data)
- Collection of Data – Using Twitter API and R programming, the collected tweets related to core hashtags on wellness are hundred (100) –71602 tweets.
- Models and Tools for Data Analysis – The reaction of the tweets will be studied through Sentimental Analysis Model, using tools like Microsoft Azure along with Excel, to interpret the data

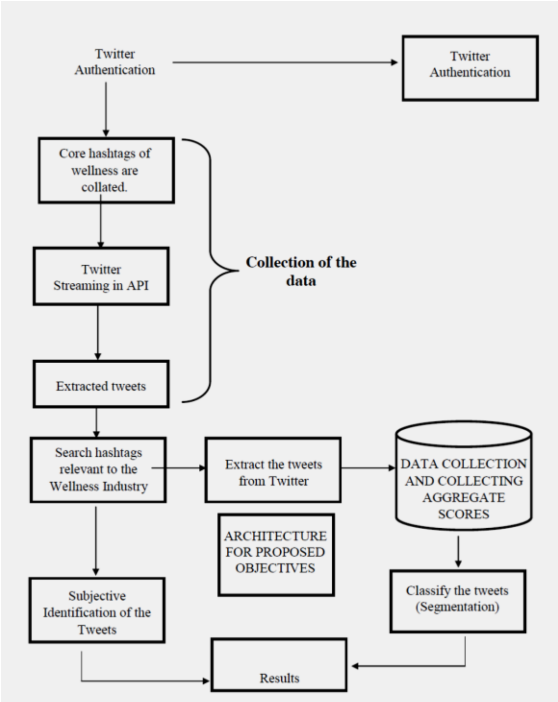

Figure 1: Architecture of the Proposed Framework

11.1 Data Collection:
The social media application Twitter is used in order to collect the data for the research. The tweets are collected based on core hashtags based on the wellness industry which covers a wide range of hashtags based on both physical health as well as mental health. This selection of the core hashtags makes it easier to categorise and search for the tweets. These tweets are extracted from the Twitter API. One of the constraints by Twitter API is that it allows a constrained number of tweets at a time, which sometimes is a time-consuming task. To access the Twitter API, authentication is required which is done by the researcher to access and collect the data. We can collect any hashtag related tweets through the Twitter streaming API. The data collection process is briefly shown in the figure as follows.

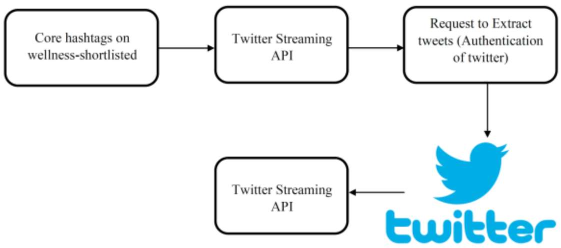

Figure 2: Process of Data Collection

11.2 Authentication of the Twitter Account:

The developer account access is one of the ways to get the authentication of Twitter API, which thereby enables the Streaming API with four components:

- API Secret
- API key
- Access token
- Access token secret

In this way we get the authentication by following process steps:
Step 1 – Creating developer account in Twitter
Step 2 – Connecting to Twitter API
Step 3 – Generating key and access tokens
Step 4 – Authentication of Twitter
Step 5 – Access to data in Twitter

11.3 Accessing the Data in Twitter:

With the authentication of Twitter API, we are given access to Streaming API that will enable us to search for the hashtags and tweets that we are looking forward to. A token is generated and made available to API for every Twitter server transaction data. By making use of this token, tweets are mined using the core hashtags in the wellness industry. Subsequently, data for all the hashtag are collected and stored as a dataset in csv (comma separated value) files.

11.4 Sentiment Classification and Analysis Technique:

In this phase to classify the sentiment polarity score, each data set is classified with negative, neutral and positive scores along with average of score and count of the tweet text.

- ► Input: Tweets of complete dataset – "Quantitative"
- ► Output: Group the tweet as positive, negative, neutral and Ascertain the score for each tweet – "Qualitative"

For each tweet, data pre-process is done to remove the stop words (Data cleaning), analysis of the POS (part of speech) for each tweet (by lemmatization) done followed by analysing that the word is either positive or negative or neutral by Microsoft Azure. By comparing it with two lists such as a positive and negative list the average score for each tweet is calculated.

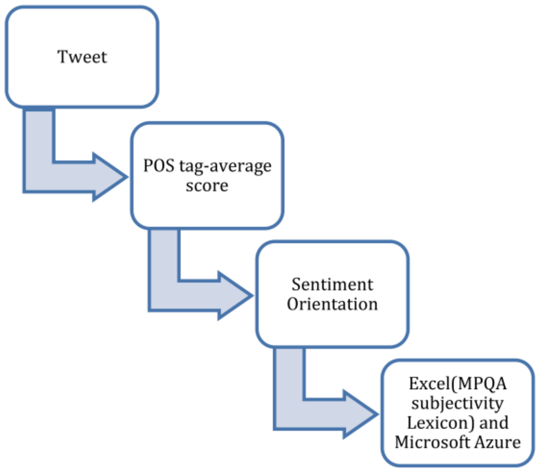

Figure 3: Process of Classification of tweets

11.4.1 Pre-processing of the Data:

The data mined on Twitter with the help of relevant hashtags through Twitter API, are unstructured and unorganised because they are expressed in various languages, and vocabulary. So this process specifically includes Data cleaning. The duplicated data and noisy data are removed during this stage for effective analysis.

11.4.2 Experiment and Result:

The data is collected from the Twitter API, analysing the popular and the core hashtags in the wellness industry. In this experimental research, the tweets analysed for all the 100 hashtags are stored in csv files, which are later analysed in the database to identify the sentiment of every particular hashtag. The hashtags are extracted from 25 July 2020 to 26 January 2021.

The Microsoft Azure was used as an add on in Excel application that helped to carry out the sentimental analysis for every data set, there was data cleaning required when the tweets for the particular hashtag were repeated.

Table 4: Data Collection

Particulars	Number collected
The Overall Number of Hashtags	100
The Overall Number of Tweets	71602
The Overall Number Positive Tweets	33,487
The Overall Number Negative Tweets	22,111
The Overall Number Neutral Tweets	16,004

The detailed analysis of tweets is into mainly three categories: Neutral, Positive, and Negative tweets. Dataset of the hashtag "health" contained about 4832 tweets, which had the highest number of tweets from the hashtags collected, and also shows a positive trend of 36 per cent tweets, which might many external factors affecting the trend, COVID 19, also might be one of the reason for a positive perception of people towards health.

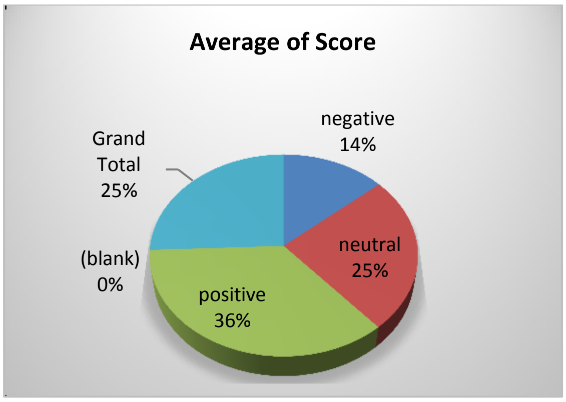

Figure 4: Analysis of the Tweets

According to the pie chart depicted above, on the hashtag #health it was observed that 36 per cent of the tweets are positive, 25 per cent of the tweets are neutral and 14 per cent of the tweets are negative.

The trend towards hashtags such as #mindfulness, #organic, #healthchange, #therapy, #wellbeing, #selfcare shows a higher percentage of positive tweets as well more number of tweets, which are around 2000, so a comparison of the positive tweets was made.

These results show that there is a majority of positive sentiment towards #wellbeing as well as #organic, because of the health consciousness of people towards both physical as well as mental health.

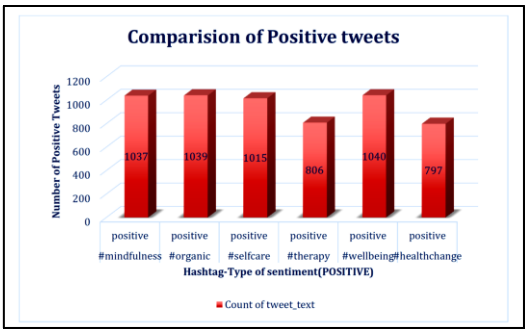

Figure 5: Comparison of Positive Tweets

It is also observed, that there is a more negative tweet count than a positive count in the hashtags specifically, #cleanfoods, #naturallyfit and #immunity, the reasons can be the consumers not trusting the quality of the food available and shifting behaviour towards wellness companies who are offering different trustworthy products, so if out of various external factors that could be reason for this trend, the wellness companies can take the advantage of using the real time data in twitter to take necessary actions by understanding the mindset and the current needs of consumers and introducing products or services.

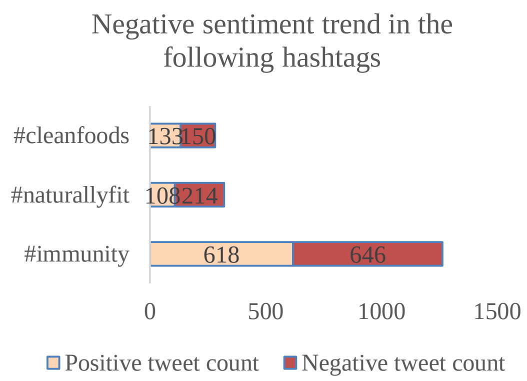

Figure 6: Analysis of Negative sentiment

12. Word Cloud:

This type of data visualisation is done to give more insights into the research that helps the readers to understand the text-based insights. As this is one of the measurable analytics that helps to understand the frequency of the hashtag used that appears in bigger font size, it can be used in a simple way to market any product based on the audience usage of the hashtag on Twitter. From different hashtags that are collected, these act as a powerful tool, if utilised in a proper way such as:

- Helps us to understand the pain points of the customer-This analysis and gives us the opportunities to connect with the audience on Twitter, such as current opinions regarding wellness, and convenience in services.
- Identification of hashtags to target-This can be specifically used to attract the target audience because this research helps to identify the potential keywords on Twitter, especially in the wellness industry.

Word cloud of the hashtag with most numbers of tweets is generated through RStudio (R programming), after the mining of the data from Twitter API.

13. Findings:

It can be observed fitness, bodybuilding, motivation, and workout are all also frequently used hashtags in the tweets. The hashtag #health, which consisted of tweets above 4000 has a different type of terminology that is not frequently used, but the most popular terminology during the data collection period is health and wellness. After examining all the hashtags related to Twitter, we can understand from the positive tweet count that mental wellness is of considerate importance as the hashtags like #therapy, #mindfulness and #wellbeing. The findings of the research also include that there are more positive tweets which are identified in a few hashtags, which indicates that there is a strong sentiment. The weaker sentiment is associated with the hashtags that might impact the overall industry of wellness and hence require measures that should be taken by the marketers by understanding the level of service and needs that the customers are expecting. The most popular terminology associated with hashtags can be utilised effectively by marketers. Potential hashtags for the wellness industry have been identified with a strong sentiment polarity. These results show that there is a majority of positive sentiment towards #wellbeing as well as #organic, because of the health consciousness of people towards both physical as well as mental health. From these findings, it is understood that wellness companies can take advantage of using the real-time data on Twitter to take necessary actions and steps to improve the polarity of the positive sentiments of a particular product.

Researchers observed that there are definitely useful in identifying and categorising the different forces in the Wellness industry. It is revealed that Twitter is far more effective for businesses than it was in previous years ago. Despite tweeting less than a year ago, most businesses have seen the most growth in their Twitter audiences it is evidence that Twitter is swiftly becoming one of the favoured channels for expressing the opinions, views and brand communication because of its popularity among masses. As can be seen, the most efficient technique to call attention to information is with hashtags. Posts with at least one hashtag have a 12.6 per cent greater engagement rate than posts without hashtags. Hashtags play a significant role in allowing companies to reach out to specialised audiences and particular areas of interest. Twitter accounts also demonstrate a positive impact on the research study, which thereby has a wider range of aspects that has a stronger effect on the research. This research endeavours to contribute to the wellness industry and literature on Twitter. (Ariestya et al., 2020; Shakeel et al., 2020)

14. Practical Implications:

In the virtual utterances of emotions, it is of paramount importance to interpret these cues for sentiment because the consumers are giving the data to use different emotions like sarcasm, anxiety and anger regarding a particular product on this social media platform, Twitter.

The main challenging aspects faced are dealing with negative expressions, understanding the product features, and decoding complex sentences. The popular hashtags identified from the analysis with a higher number of positive tweets can be a very good opportunity on Twitter in order to promote a particular product or service related to wellness.

This study provides synergies to provide guidelines to the digital marketing practitioners in the Wellness industry. The intertextual potential of the hashtags makes it possible to link one particular topic and thus gives many perspectives. The major practical implications include gaining insights on the hashtags sentiment that can be further deployed in the development of new services and implementing them in line with the expectations of the consumers and trends. Further, the potential for investments in Artificial Intelligence (AI), Data Analytics and Machine Learning for this industry is tremendous, and it could be a way forward to overcome the technology-related challenges.

15. Theoretical Implications:

The insights derived from this study are expected to contribute to the sentiment analysis and social media content analysis for a specific industry. It is observed that both researchers and practitioners will benefit from this research which contributes from multiple perspectives. This study acknowledged the importance of hashtags and considered as one of Twitter's key purposes, which will lead academics to propose the most significant impact on information usefulness. The findings add to the growing body of evidence that hashtags function as a secondary trigger in message processing. As a result, hashtag scalability must be viewed as a fundamental element in users' information processing on social media platforms.

This study also gives a fresh literary perspective on the Wellness industry and the potential of understanding sentiment in Twitter. There are no studies that critically addressed the studies of the wellness industry. This study utilises the current and relevant literature in order to discuss the opportunities and contextualise that will help in aiding the research impact in the Wellness sector.

16. Managerial Implications:

The findings of this study have managerial relevance. To begin with, many businesses, especially FMCG have been interested in using social media to engage with both current and new consumers. One of the key characteristics impacting evaluations of the utility of brand awareness, according to this study, is the hashtag.

As a result of internet interaction, users' perceptions of advertising shift, this study makes managerial recommendations on how advertisers may use hashtags to better identify keywords and enhance ad perception. A precise technique for employing a specified quantity of hashtags for the most successful branding was devised depending on the social network. As a result, hashtags are likely to be utilised as a method of categorising and storing material for quick searches on a certain topic. As it seen, companies might be able to reach their target audience more successfully by classifying social media material under a certain hashtag. Findings revealed that Twitter hashtags are a strong tool for increasing brand awareness and success and building an effective hashtag strategy which is one of the greatest ways to get posts noticed by new Twitter audiences, followers, and even customers.

17. Scope for the Future Work:

The findings point to a number of areas where further studies can be conducted. The streaming data on Twitter has the potential to enable and discover the recent trends happening at any point time in the world. Diverse information in this microblogging website makes it feasible for opinion mining and sentiment analysis. The results portrayed in this research on the Wellness industry can be extended to get results on the basis of geographical place, which can be helpful for marketers to target services and products in an efficient way. A similar type of analysis could help in future research to apply in other industries which will help to apply the solutions in real life scenarios. Future work can also be applied in comparing the type of preferences amongst the consumers through comparative sentiment analysis. The low performance of the particular hashtags may be the result of the lack of awareness amongst the users, which can be further researched for this reason, of the process of social diffusion among the users regarding a particular health trend. As the sentiment analysis of the wellness hashtags reflects the popularity of a particular trend, this can be utilised to understand the relation between the research of behaviour and language usage on Twitter which would be helpful in improving understanding of the users and the particular trends the researcher is looking for. There exists scope for more studies for other industries, product categories and/or even comparing different product categories.

18. Conclusion:

The strategic use of Twitter helps to generate professional networks and helps to understand the consumer perceptions towards existing products and services can be clearly understood from the tweets and sentiment polarity and also provide the opportunity for the development of new products in the marketplace. To achieve conscious adaptation in this sector, all the areas need to be critically addressed, which shows that there is relatively a future work that can be done in this area. Analysis of the hashtags through the sentiment analysis approach has a response to different trending topics on wellness. Twitter as a social technology platform helps to identify the inherent culture, etiquette and evolving opinions about different products and services all around the world. This provides an array of situations to understand the users' needs and interests by understanding the dynamics of Twitter and then taking necessary actions according to the analysis. Lastly, without any ambiguity, we can conclude that Twitter did play a major role in globalising the opinions regarding wellness and has a wonderful potential to research any particular industry to understand the sentiment of any research area. Organizations may influence and develop brand recognition on Twitter, as evidenced by this study, as well as form strong networks. This study found that taking a strategic approach to communicating with customers and stakeholders on Twitter can lead to increased engagement with both customers and other businesses, which can help businesses, reach a larger audience, build their brand, and ultimately help them achieve their objectives.

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