CONFERENCE ARTICLE

NUTRITION INFORMATION POST COVID-19: A TWITTER CONTENT ANALYSIS

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ABSTRACT

Realizing social media's importance, many doctors, nutritionists, health coaches and general users have registered on social media and actively share health information. Users may easily access and exchange health information. It benefits both users and practitioners.

Qualitative data analysis is employed to study Twitter communication content to understand better the relationship between users' interest in healthy eating and information seeking on Twitter post COVID-19. The research examined Twitter nutrition health information using hashtags. The frequency of hashtags was ranked. The content analysis undertaken quantifies social media healthy diet hashtags. Theme modification and word and phrase recurrence analysis was used to identify two primary themes and significant sentiments relating to COVID-19 and nutrition. Python and NLP languages are used to analyze and interpret the data to help acquire in-depth information.

Twitter users linked nutrition to happiness and sadness post-pandemic, discussing health food, skincare, nutrition, and lifestyle. The research highlighted Twitter's nutrition education significance, including mental and physical health, diet, and natural remedies.

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KEYWORDS

twitter, content analysis, social media, nutrition-related information, python

INTRODUCTION

SOCIAL MEDIA AND HEALTH INFORMATION SHARING

Social media is becoming essential to communication. Social media may aid in disseminating preventive information and warnings and tracking the spread of viruses [1]. The Internet, particularly social networking sites (SNS), is a popular source of health information and assistance. Knowledge-sharing practices, knowledge-sharing culture, and improved communication are all things that may benefit from the use of social media and cross-platform apps [2]. This ensures that the content is shared widely and visible to a diverse population. Previous research suggests that individuals are likelier to pay close attention, trust, and act on various issues when the message is communicated via influencers and celebrities [3]. The COVID-19 outbreak has introduced unique challenges for public health practitioners and health communicators, which warrants an expansion of existing health communication guidelines to take into consideration the following: the new infodemic (or disinfodemic) challenge – particularly as treatment options and vaccines are being developed, communication of risk and uncertainty, health-information behaviours and the instantaneous nature of social media, as well as the relationship between media legitimacy and health-information dissemination [4]. Extensive research has been done on patients' and caregivers' use of websites, forum discussions, and SNS in the context of many health-related concerns, including social support, illness management and information sharing [5]. 50% of participants received replies to their health expert inquiries within a few hours, and 60% of health professionals agreed that social media would improve patient care [6]. According to the findings of another research, feelings not only indicated who would forward a message but also indirectly impacted how the communication was processed [7]. To build digital healthcare, artificial intelligence (AI) should be used early. It is crucial to combine developing technology to address a pandemic's massive hurdles [8], as social media sites may be manipulated by software-controlled personas called social bots.

COVID-19: SOCIAL MEDIA AND NUTRITION-RELATED INFORMATION SHARING

The global COVID-19 pandemic made healthy eating more complicated for most individuals. Lockdown affected eating, sleeping and exercise habits. Confinement enhances sedentary behaviours, primarily performed while sitting or lying down, requiring little energy expenditure [9]. The effects of COVID-19 on dietary intake and health have already spread beyond local communities and national borders [10]. Twitter and Facebook helped spread information during the COVID-19 epidemic. Some social media users "seed" misinformation, while others "spread" it to "receivers." Risk communication standards need the information to be accurate and credible, yet the initial COVID-19 pandemic's origin, consequences, and prevention were rapidly changing. In the wake of epidemics, people have begun to rely on social media to gather information about the sickness and communicate it in real time with their neighbours and friends [11]. In addition to being tedious, being subjected to constant media coverage of COVID-19 may be a source of anxiety. Overeating, particularly sugary "comfort foods," is correlated with increased stress levels in people. Furthermore, the risk of developing problematic eating habits may be elevated due to psychological and emotional reactions to the pandemic [12;13]. Overeating, or "emotional eating," is a typical response to negative emotions, as is well-documented [14].

TWITTER AND NUTRITION RELATED INFORMATION SHARING

Since 2006, Twitter has functioned as an efficient and effective platform for communication, enabling users to share information in real-time and occasionally engage in a two-way discussion. More than 100,000 people working in healthcare throughout the globe tweet an average of roughly 300,000 times each day, reaching a total of more than 135 million subscribers. According to a review of various papers, Twitter is an efficient communication medium that medical professionals and health coaches often use to interact with the public [15]. Government agencies often use Twitter to disseminate information to the general public [16]. Twitter is the world's fourth most common platform for obtaining critical information during an emerging infectious disease (EID) [17]. There is a different level of vetting and quality control of health information through social media than in traditional public healthcare or commercial settings [18].

The population regularly consumes and distributes diet and nutrition information through social media. Users use Twitter for emotional contact with scheme information produced via podcasts and mobile phone apps [19]. Because an ever-increasing number of organizations are now using SNS to distribute information and create awareness connected to social concerns, it is essential to be attentive to the factors that predict shareability to guarantee the success of a campaign [20]. Many dietitians and nutritionists utilize social media, particularly Twitter, to communicate with their large and influential audience, which includes the general public, to influence their eating habits. Usage of social media by dietitians and nutritionists may also help them interact with peers and enhance public health while advancing their professions [21].

Food and nutrition research on social media has primarily employed manually coded tiny datasets. Twitter creates big data that is more extensive, varied, and faster than health monitoring and research data. The top 15 hashtags linked to diet and nutrition were identified and analyzed in the light of this information. The study will explore and answer the following research objectives.

1. To determine which nutrition-related search terms were most frequently used by Twitter users worldwide.
2. To determine the positive and negative feelings associated with tweets about specific diet and nutrition-related subjects posted soon after COVID-19.

3. To determine the significant theme of the post based on the content posted by different users.

RESEARCH METHOD

DATA COLLECTION

Hashtags are a social media tool for aggregating posts on a particular subject. Users may get a feed of information tagged with a specific hashtag by clicking on that hashtag or by searching for that subject in English. Initial data for this research included a list of 15 nutrition-related hashtags gleaned from a Twitter search of diet, nutrition, and weight-related material, with emphasis on the most popular and widely used hashtags. The 15 hashtags included in the study were Diet, Healthy Eating, Covid Diet, Immunity Diet, Immunity Food, Nutrients, Vitamin C, Clean Eating, Corona Diet, Corona Food, Covid Nutrition, Detox, Healthy Diet, Immunity and Food. The database has 36,792 tweets and 23,252 retweets for 60,281 entries (61.28% tweets and 38.72% retweets). In the study, we excluded hashtags like physical activity, fitness, obesity and dietary supplements.

Python has emerged as a complete programming solution searching for a solid programming language over which numerous data science applications may be constructed. Pandas let Python users analyze real-world datasets. Library construction began in 2008 [22]. Developers load, prepare, manipulate, model, and analyze data using it. The Natural Language Toolkit (NLTK) is a set of programs and libraries used in natural language processing [23]. Python-based English natural language processing (NLP) is used.

Tokenizing a word may be accomplished with the help of a fantastic collection of libraries. Nevertheless, NLTK, the Natural Language Tool Kit, is the most widely used Python package. With the help of the Python library, we can extract the most popular terms from tweets and retweets after removing the usual organizing words like articles and relational words and consolidating words like a, an, the, yet, and so on. Tokenization, word normalization, word segmentation (for dividing hashtags), and spelling corrections were performed using the software program Ekphrasis, a text preprocessing tool. Additionally, it helped separate hashtags. In addition, regex was used to strip out HTTP links, punctuation, and other potentially confusing elements [24].

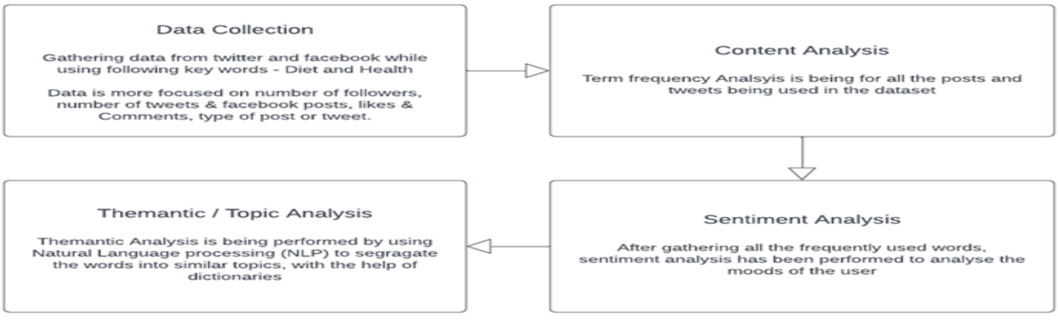
A theme analysis requires making choices to guarantee the study's validity and reliability; undoubtedly, these decisions must be identified [25]. We also conducted a sentiment analysis on the tweets using Python as well as the Vader Sentiment Analysis (SA) library [27] to compare the positivity as well as the negativity of tweets involving similar keywords to see if there were any differences in the way each keyword is typically used; this could provide insight into how the general public perceives these diets and issues.

RESULT AND DISCUSSION

GATHERING INFORMATION

This research aimed to analyze Twitter's healthy eating discussion by finding the most common themes and subjects. Twitter data is analyzed by time and person. Hyderabad and New Delhi in India have the most postings. Both cities had over 300,000 posters. As the dataset is imported from an Excel file, the programme also retrieves the necessary NLP libraries. OMW is a massive English wordnet library. Cognitive synonyms (synsets) are nouns, verbs, adjectives, and adverbs with the same meaning. Synsets work together due to conceptual-semantic and linguistic relationships. Synsets work together due to conceptual-semantic and linguistic relationships. Figure 1 depicts the process of gathering information from the following steps: Data Collection, Content Analysis, Thematic/ Topic Analysis and Sentiment Analysi

FIGURE 1: INFORMATION GATHERING APPROACH



Source: Author created

CONTENT ANALYSIS

The NLTK library cleaned data from posts and tweets. To make data-driven forecasts, stop words and punctuation marks were removed, and words were shrunk to their roots. Gensim analyses the data and visualizes it using pyLDAviz. The NLTK python package was used to analyze and clean data for a term frequency analysis (TFA) with above 70% accuracy. Each word was tokenized and isolated from dictionary terms to maximize dataset word occurrences. The dataset's word count affected the accuracy rate. The data businesses have 60,000 items, including 36,792 tweets and 23,252 retweets (61.28% tweets and 38.72% retweets).

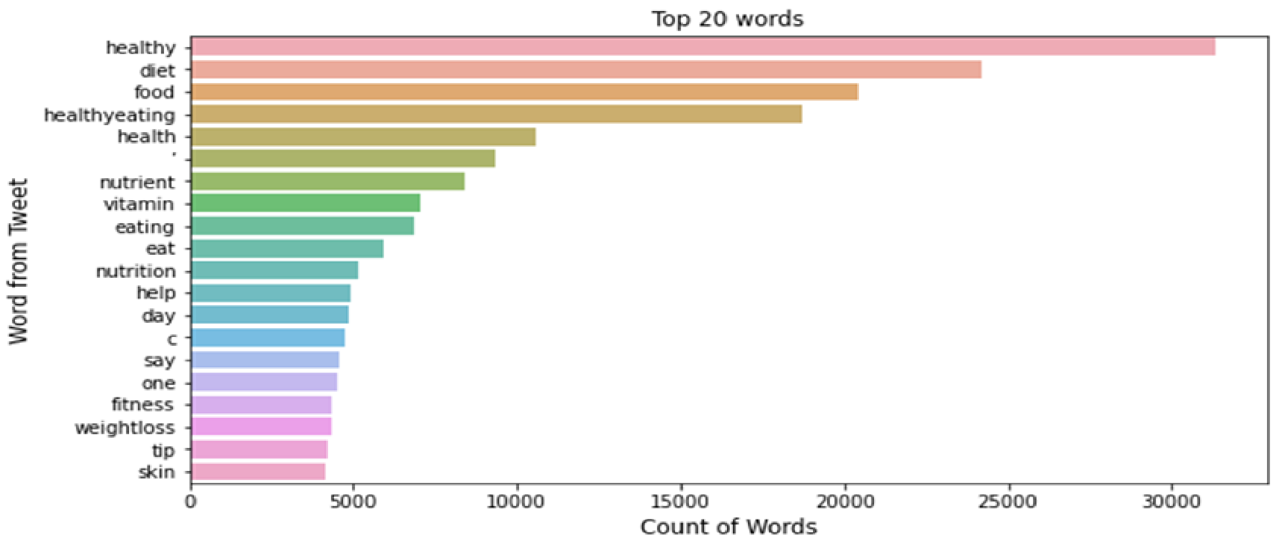
TFA (TERM FREQUENCY ANALYSIS)

Excluding unnecessary columns cleans the data. For further study, we did a frequent-terms analysis on the cleaned tweets. The code following removes punctuation as we did not need it for analysis. Tokenizing words prevent repetition. We add terms to a list to justify each phrase, counting only the unique values (because certain words, like "good," "better," and "best," may be expressed in several ways)—dataset word count. Seeing the phrases makes it easy to count them. Twitter users typically tweet and retweet about healthy food items, daily routine hacks, skincare routines, eating habits, health recommendations, and other subjects linked to a healthy lifestyle (Figure 2). After attending several recent events, people are arguing about health, diet, vitamins, and weight loss. After eating a lot, they write about weight loss.

SENTIMENT ANALYSIS

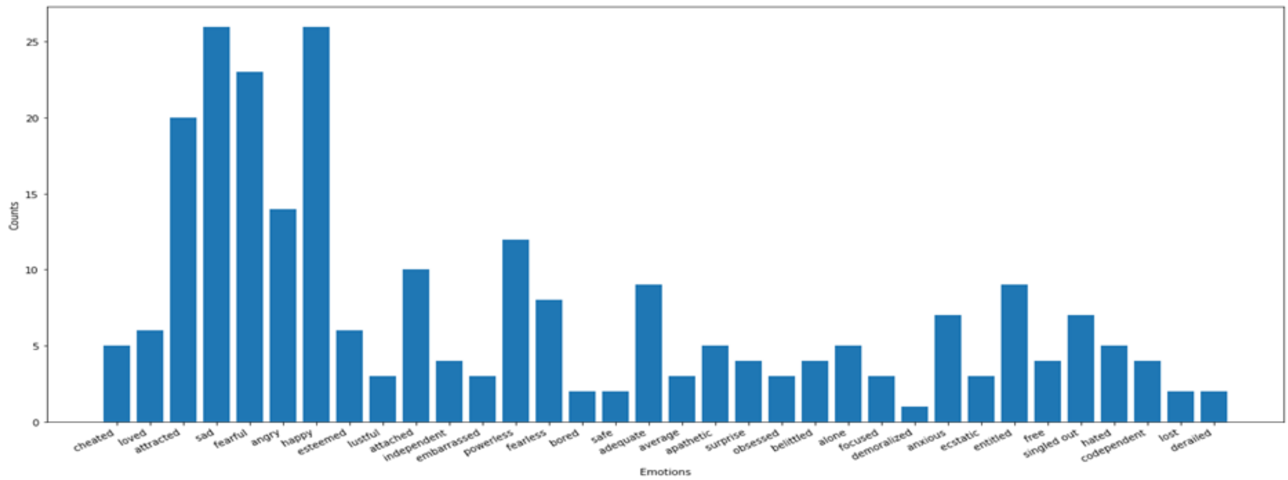
After sorting lemmatized words into emotional categories, the terms linked with each emotion are recorded and shown in a bar chart. The cleaned text is shown in an LDA model. We also count nutrition-related phrases to assess tweets' emotional content. Every tweet term that communicates an emotion was found and evaluated using sentiment vocabulary. Standardizing the amount of positive (or negative) sentiment words relative to the tweet's overall word count calculates positive and negative sentiment ratings. The graphic shows the findings (Figure 3). People are optimistic yet worried. The second most prevalent feeling was "fearful," which was linked to worries about one's lifestyle, health, family, and powerlessness. "Happy" and "sad" also accompanied nutrition-related tweets after COVID-19.

FIGURE 2: TERM FREQUENCY ANALYSIS



Source: Author created

FIGURE 3: SENTIMENT ANALYSIS



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THEMATIC ANALYSIS

The cleaned text is shown in an LDA model. This utilizes cleaned texts to construct a vocabulary the model can search, then uses the dictionary to classify words into a terms matrix that can be used to extract each user's chosen topic from their comments. The next cell shows the two main themes, and the training model is run fifty times over the material.

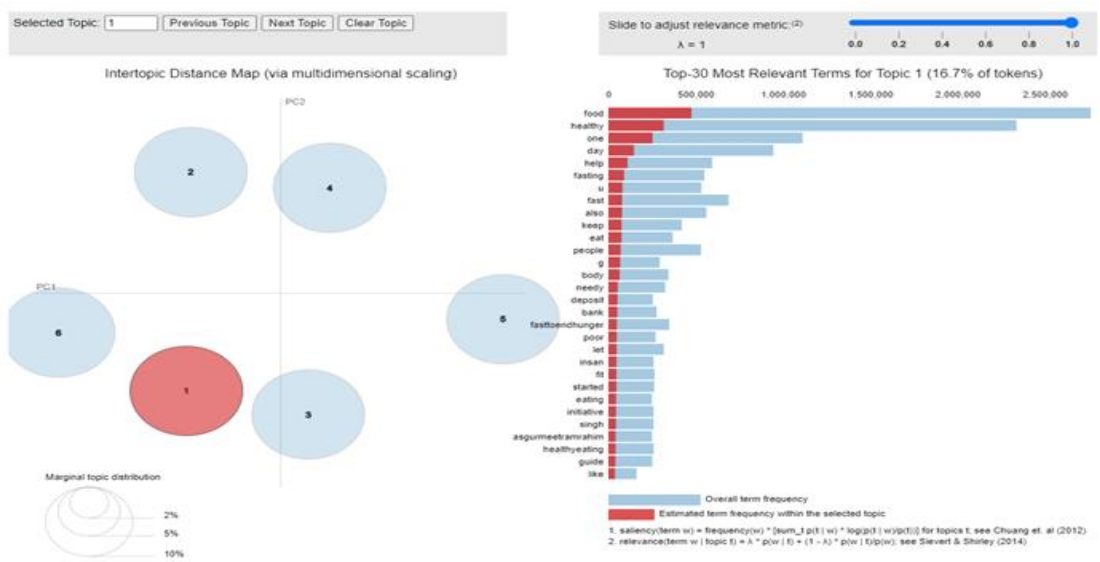
Central Theme – Health Food

During the research, one of the themes emerged: "Healthy Food"(Figure 4). Social media can effectively spread nutrition information. People are tweeting how to enhance mental and physical health, food intake, and impunity. People are also posting about nutrition and children's health. Ayurvedic and herbal therapies are sought during the epidemic. People post on social media about their struggles or how they began their fitness journey to inspire lazy people. This conversation is about how to stay healthy or become fit rapidly.

Central Theme – Immunity

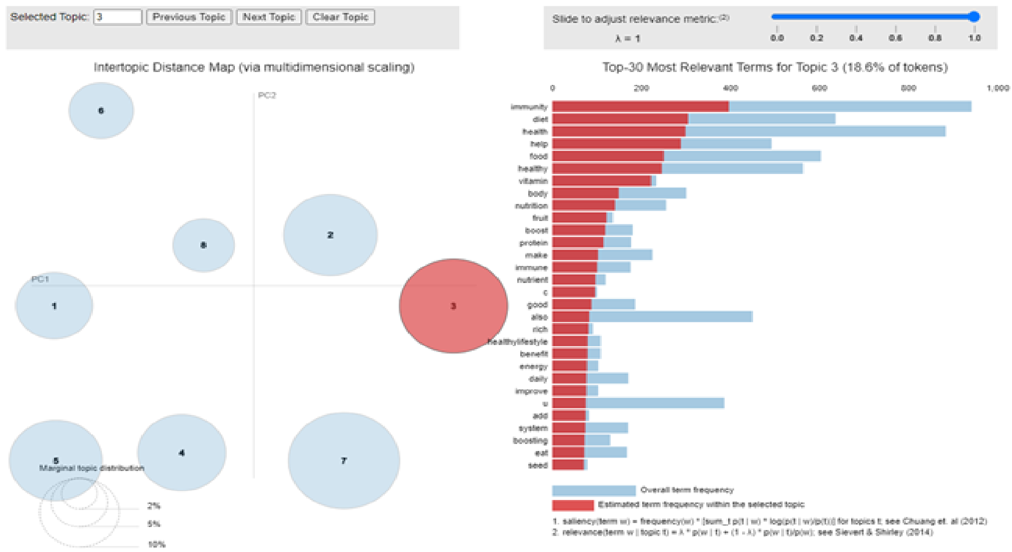
An "infodemic" driven by unrestrained COVID-19 news, propaganda, and misinformation provoked widespread anxiety and unscientific reactions. India, the world's most connected nation, has many Twitter users seeking COVID-19 information. "Immunity-boosting foods" were popular during the epidemic to avoid COVID-19, a second central theme (Figure5). Many people are discussing and exchanging knowledge about foods that may boost the immune system, such as seeds, fruits, and diets.

FIGURE 4: THEME 1



Source: Author created

FIGURE 5: THEME 2



Source: Author created

Topics related to nutritious eating on Twitter were analysed. People on Twitter spoke about anything from healthy eating to beauty advice to their daily routines. Lemmatized words were sorted into emotional categories via Sentiment Analysis. More people were upbeat than worried. The second most prevalent feeling was "fearful," which was linked to worries about one's own lifestyle, health, family, and feelings of powerlessness. There were both "happy" and "sad" tweets on nutrition after COVID-19. Thematic analysis using LDA yielded the subjects. There were two major considerations. In the first forum, titled "Health Food," participants spoke about the psychological and physiological effects of their diets. The effects of diet, physical activity, and Ayurvedic and herbal treatments for the pandemic were investigated. The second was "immunity," which was spurred by the COVID-19 pandemic. Seeds, fruits, and diets that may help prevent COVID-19 were topics of conversation. The COVID-19 epidemic brought to light the value of social media in the fields of nutrition and health.

LIMITATIONS

Few studies combine enormous social media datasets and machine learning tools to analyze nutrition and food concerns, but a new methodology should be studied. This study has limitations, but they suggest future research directions. First, the dataset checked comprises much data, but it's just a small sample of social media's nutrition, diet, and food topic. It also has a limited group of terms used for search. Second, we gather data from one social media site, Twitter only, and language was English only. In the future, further research should examine food, fitness, obesity, and dietary supplements.

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