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Association between Obesity and COVID-19: Insights from Social Media Content

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Abstract: The adoption of emerging technologies in healthcare systems plays a crucial part in anti-obesity initiatives. COVID-19 has intensified the Body Mass Index (BMI) discourses in AI (Artificial Intelligence)-powered social media. However, few studies have reported on the influence of digital content on obesity prevention policies. Understanding the nature and forums of obese metaphors in social media is the first step in policy intervention. The purpose of this paper is to understand the mutual influence between obesity and COVID-19 and determine its policy implications. This paper analyzes the public responses to obesity using Twitter data collected during the COVID-19 pandemic. The emotional nature of tweets is analyzed using the NRC lexicon. The results show that COVID-19 significantly influences perceptions of obesity; this indicates that existing public health policies must be revisited. The study findings delineate prerequisites for obese disease control programs. This paper provides policy recommendations for improving social media interventions in health service delivery in order to prevent obesity.

Keywords: obesity; COVID-19; Twitter; social media; pandemic; policy

Citation: Alotaibi, M.; Pai, R.R.; Alathur, S.; Chetty, N.; Alhmiedat, T.; Aborokbah, M.; Albalawi, U.; Marie, A.; Bushnag, A.; Kumar, V. Association between Obesity and COVID-19: Insights from Social Media Content. *Information* **2023**, *14*, 448. https://doi.org/10.3390/info14080448

Academic Editor: Arkaitz Zubiaga

Received: 20 June 2023
Revised: 4 August 2023
Accepted: 4 August 2023
Published: 8 August 2023

1. Introduction

Obesity has become one of the most common chronic diseases in the last two decades as people's lifestyles have changed worldwide. Obesity is measured using the BMI value, which considers an individual's mass (weight) and height. The BMI is defined as "the body mass divided by the square of the body height and is universally expressed in units of kg/m^2, resulting from mass in kilograms and height in meters" [1].

According to the World Health Organization (WHO) over 1.9 billion people aged 18 and above are overweight, with Asia contributing to around half of all overweight children [2]. Obesity affects over 650 million of these, and approximately 41 million children under the age of five are obese worldwide [2]. In 2016, Obesity Atlas reported that 33.4 percent of females and 24.1 percent of males were overweight or obese [3]. Furthermore, the obesity rate is also very high in some developing countries. For example, for children between the ages of 4 and 8, the prevalence of overweight and obesity in Saudi Arabia is approximately19.2 percent [3].

COVID-19 affects people with poor immune systems more than healthier people [4]. Several studies have found a link between obesity and other chronic conditions such as diabetes and hypertension [5–7]. According to these studies, obese children have a higher risk of developing diabetes at a young age. Modern lifestyle, eating habits and less physical activity contributes to obesity especially in children [8]. This implies the necessity of efforts to reduce obesity rates, particularly among children, by raising awareness in the early stages of their lives. As a result, modern technologies such as the Internet of Things, mobile health and social robotics offers excellent and cost-effective solutions to enhance societal understanding.

Modern technologies, intelligent mobile devices, robotics and social networks and the internet has accelerated the design and delivery of healthcare systems, aiding in managing and understanding chronic diseases like obesity and diabetes. This technological revolution established new virtual world with multilingual social networks allowing users to communicate with friends or individuals across geographical, political or economic boundaries. About 3.6 billion internet users use social networks, and these figures are expected to rise as mobile devices and social networks gain attraction [9].

AI technology uses large amounts of raw data as a new area of development and a valuable source of information about people's perceptions of political decisions or elections. Big data is a concept that describes the massive amount of structured and unstructured information that regularly floods a company [10]. In general, social networks are the most popular sources of big data. The attributes can be collected for each tweet, resulting in a massive volume of data in a short period, with the stream of data increasing sharply second by second. AI technologies help to analyze big data and they assist business decision-makers or governments with forming a picture about the population's opinions on a social, political or economic issue. The use of natural language processing to analyze healthcare data is prevalent [11]. Twitter data could be analyzed using deep learning techniques [12].

This study used Twitter data to investigate the polarity and emotions of people related to obesity issues during the COVID-19 pandemic. Twitter is a popular microblogging social network with a large number of active users worldwide [13]. It had 152 million monetizable daily active users (mDAU) globally as of the fourth quarter of 2019. The update feed allows registered users to read and publish tweets and follow others [9]. These tweets are significant because governments and decision-makers can use them to study people's behavior and, as a result, revise their strategies and action plans to meet their targets [14] through a process known as sentiment analysis. Sentiment analysis, also known as opinion mining, uses data mining techniques and methods to determine the opinions (positive or negative) and emotions of a text or message extracted from social media or surveys [15,16]. It helps a company to understand its brand, product, or service by tracking online conversations.

Previous research has found these techniques helpful in predicting and analyzing stock markets [17], elections [18], resource allocations [19] and new products and services [20,21]. Recently, the health domain has taken part in this virtual society. In addition to these fields, some patients post their experiences with a disease, and some physicians have social network accounts and use these to post clinical information to the public. Sentiment analysis has been used in the healthcare sector [22] to study people's behavior and sentiments towards a specific vaccination [23], lockdown, and the COVID-19 outbreak [24], as well as in social media games [25]. Obese people are more vulnerable to receiving obesity stigma [26]. The discourse referring to obesity/overweight could lead to mental health issues [27,28].

Social media platforms can be used to maintain privacy and self-disclose their physical condition and feelings about sensitive topics such as mental health, diabetes, cancer, heart disease, and HIV/AIDS [29–35]. Identifying people's and users' attitudes and emotions about obesity is critical, especially during the COVID-19 pandemic when nations are in lockdown and there are no regular fitness activities or regimes. The studies [36–38] conducted using social media during COVID-19 show that there is a relationship between obesity and COVID-19. As a result, this study aims to understand the mutual influence between obesity and COVID-19 and determine its policy implications using the Twitter platform.

Using Twitter data, AI can learn a great deal about obesity and people's perceptions of it. The large number of Twitter users worldwide, the high proportion of obese people worldwide, and the advanced AI technologies are sufficient motivations to conduct such a study. Moreover, most existing studies have shown the interrelationship between obesity and COVID-19 on medical grounds. With this motivation in mind, the objective of this study is to understand the mutual influence between obesity and COVID-19 from social media content and to determine the implications of this for policy.

The paper is structured as follows. Section 2 reviews the literature on the mutual influence between obesity and the COVID-19 pandemic, the methodology adopted is presented in Section 3, and in Section 4, the results are presented and discussed. Section 5 outlines the policy implications and Section 6 concludes the work.

2. Literature Review

Obesity and COVID-19 have mutual effects on individuals [39]. The emergence of COVID-19 worsened the health condition of people with obesity and vice versa. A separate review is presented of the impacts that each has on the other in the following sub-sections.

2.1. Impact of Obesity on Those with COVID-19

This section reviews the literature on the impact of obesity on an individual in terms of worsening the COVID-19 pandemic situation. Existing studies have shown that being obese increases the risks of respiratory diseases [39]. The experience with H1N1 influenza revealed that patients with obesity need utmost care in order to control H1N1 flu and similar diseases [40]. Table 1 shows the impact of overweight and obesity on people with the COVID-19 virus.

Table 1. The impact of obesity on COVID-19-associated risks.

Authors	Purpose	Methodology	Outcome	Remarks
Popkin et al. (2020) [41]	To identify the link between obesity and COVID-19 risk of infection and the medical consequences of infection	Meta-analysis of literature on COVID-19 in Chinese and English languages	Individuals with obesity are more prone to COVID-19 infection, hospitalization, requiring intensive care, and mortality	Obesity increases the risks of COVID-19
Busetto et al. (2020) [42]	To evaluate the relationship between the severity of COVID-19 infection and obesity	The statistical analysis method is used on hospitalized COVID-19 patients with different age groups and obesity	Overweight and obese patients suffering from COVID-19 requires the facilities of ventilation and the intensive care unit than the normal-weight patients	Obesity increases the severity of COVID-19 in patients
Gao et al. (2020) [43]	To understand whether obesity is a risk factor for COVID-19 severity or not	Statistical analysis of hospitalized COVID-19 patients (75 with obesity and 75 without obesity)	Obese individuals were classified as severe COVID-19 patients	Obesity increases the severity of COVID-19 in patients
Cai et al. (2020) [39]	To understand the association between obesity and severity of COVID-19	Statistical analysis was applied to data of consecutively hospitalized COVID-19 patients	The severity of COVID-19 in overweight patients was greater than in normal-weight patients The severity of COVID-19 in obese patients was greater than in overweight patients	Obesity increases the severity of COVID-19 patients
Nakeshbandi et al. (2020) [44]	To illustrate the association between obesity and COVID-19	A retrospective cohort study on hospitalized COVID-19 patients	Overweight and obese people had a higher mortality risk than normal-weight people. Overweight and obese people were more likely to require intubation than normal-weight people. Obesity raises the risk of mortality in males	Obesity increases COVID-19's associated risks
Nagy et al. (2023) [45]	To understand the impact of obesity on COVID-19 patients	Observational study on hospitalized COVID-19 infected	Obesity is found as the most significant risk factor for COVID-19 patients	Obesity increases COVID-19's associated risks
Guo et al. (2023) [46]	To identify the impact of obesity on respiratory tract immunity for COVID-19 infected	Examined the ventilated COVID-19 infected patients with obese and non-obese	The strength of the nasal immune cells of obese children is reduced	Blunted tissue immune responses in obese patients

People with obesity are more vulnerable to the consequences of COVID-19. The mortality rate of obese patients with COVID-19 was greater than that of those who had COVID-19 but were not obese [41]. COVID-19 attacks irrespective of the age of the target but its impact is most severe in older, overweight, and obese people than in young and normal-weight individuals [42,43]. COVID-19 also attacks irrespective of gender, but the mortality risks are greater for male patients than for female patients [44].

2.2. Impact of COVID-19 on Development of Obesity

The COVID-19 pandemic spread to most of the world by March 2020. The association between COVID-19 and obesity is not restricted to BMI but is rather a complex relationship with different levels of obesity [47]. Quarantine, isolation, lockdown, and border sealing are the standard measures adopted to contain the COVID-19 pandemic by the governing authorities of an individual nation. The COVID-19 control measures change an individual's lifestyle and eating habits and this can lead to overweight and obesity [48]. The availability of processed food lacking in nutrients was prevalent at the beginning of the pandemic as transportation and other facilities were blocked due to lockdowns in different counties [41,49]. High levels of consumption of non-nutrients and processed food could increase the risks of overweight and obesity [42,49]. Table 2 shows the relationship between COVID-19 and obesity development.

The COVID-19 control measures, such as lockdowns, disrupted individuals' activities [50]. This disruption of normal activities induced stress, anxiety, anger, and depression. Stress makes individuals eat more and it reduces physical activity, leading to increased overweight and obesity [35,48]. Specifically, the lockdowns resulted in lifestyle changes, mental health issues, and increased weight and obesity in people [47]. In general, the COVID-19 pandemic is increasing obesity by disturbing the normal activities of people.

Table 2. The impact of COVID-19 on obesity.

Authors	**Purpose**	**Results**
Abbas et al. (2020) [35]	To understand the mutual effects between COVID-19 and obesity	Obesity increased during the COVID-19 pandemic. Obesity is riskier for COVID-19 patients
Mattioli et al. (2020) [48]	To understand how the COVID-19 pandemic affected the risk of becoming obese	COVID-19 control measures induced stress, anxiety and anger. Stress changes lifestyle and results in obesity
Stavridou et al. (2021) [50]	To evaluate obesity among people of different ages during the COVID-19 pandemic	The emergence of COVID-19 disrupted the activities of individuals. Increased food intake and reduced physical work are leading to obesity
Dohet et al. (2021) [49]	To understand obesity during the COVID-19 pandemic	COVID-19-induced lockdown resulted in changes in lifestyle, mental health, and weight, leading to obesity

3. Methodology

A qualitative (i.e., user-generated content) methodology is followed in this study. The adopted method is a two-fold approach, with the first part supporting data extraction and the second part supporting data analysis. In the first part, the data were extracted from the Twitter social media platform by creating an application programming interface (API) using the RStudio tool. As the keyword 'obesity' is appropriate and generic, it was used for searching for relevant tweets on Twitter, following the approach described in the research of Bharti et al. (2016) [51]. While searching for 'obesity', the program extracted 52,077 posts from the Twitter website during the second wave of the COVID-19 pandemic (February 2021 to August 2021).

In the second part of the methodology, a pre-processing procedure was applied to the extracted tweets to smooth out or clean the data by eliminating content such as digits, punctuations, stop words, and website addresses. Stemming was applied to transform the different appearances of a phrase into its root. A sentiment analysis approach was used to assess the responses of Twitter users in the form of emotions. The emotional nature of tweets is analyzed using NRC (National Research Council) lexicon [52]. The wordcloud approach is used to group the words which depict different emotions. Topic modeling was applied to the pre-processed Twitter content to understand the interrelationship between obesity and COVID-19. To provide deeper insights into the data, a few tweets showing the relationship between obesity and COVID-19 are presented in the following section, and their purpose is interpreted. By making collective interpretations, inferences are drawn from the results to create policy suggestions.

4. Results and Discussion

The results obtained from the sentiment analysis, topic modeling and manual evaluation to identify specific themes concerned with obesity are discussed here. The analysis is carried out on 52,077 tweets.

4.1. Sentiment Analysis

Polarity and the emotions associated with obesity can be understood by applying sentiment analysis to the extracted posts. In this study, sentiment analysis was performed with Syuzhet and the sentiment analysis packages of RStudio. The results of the sentiment analysis of the posts, based on polarities and emotions, are calculated and depicted in Figure 1.

Figure 1 shows that the total negative sentiment count (72.44 K) is higher than the positive count (41.07 K, signifying that people have mainly negative opinions about obesity. In addition, people primarily expressed sadness (55.89 K), disgust (47.61 K), and fear (29.27 K) in their posts, among other emotional components. The expression of negative emotions may have been due to the pandemic-induced curfews and lockdowns across nations, resulting in the closure of sports centers, gyms, and other facilities, leading to food consumption for comfort.

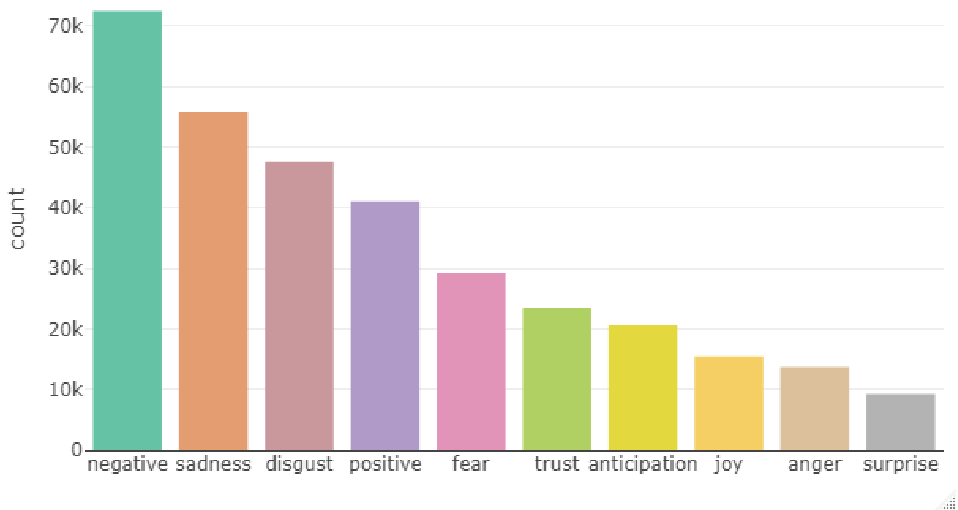

Figure 1. Polarity and emotions related to obesity.

A word cloud was drawn to depict the contents of the posts according to their emotional components, i.e., joy, sadness, surprise, anger, fear or disgust [53]. Figure 2 shows the word cloud for the retrieved Twitter content during the COVID-19 pandemic. The word cloud presents emotions and the words used to express them in different fonts and colors. The term “weight” has a high frequency, which reveals that individuals may have gained more weight during the pandemic and obesity increased.

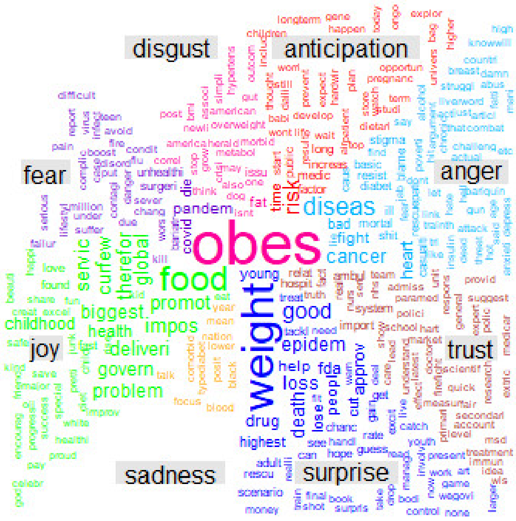

Figure 2. Emotion word cloud for obesity.

Table 3 shows the association between the most frequent words found in the tweets. The cell values of the adjacency matrix indicate the co-occurring frequency of the terms. These values reveal that obesity is most closely associated with food, health, people and COVID-19. Obesity could have been increased due to the unhealthy eating habits of an individual and the emergence of COVID-19. The weight of a person co-appeared most with the terms 'obesity' and 'people' in the discussions. Similarly, the word 'risk' was used alongside the terms 'obesity', 'diabetes', and 'COVID'. The life of an individual is more at risk with diseases such as obesity, diabetes, and COVID-19.

Table 3. The adjacency matrix of associated terms.

Terms	Obesity	Food	Health	People	Can	Problem	Weight	Risk	Diabetes	COVID
Obesity	31,451	2280	3472	2784	1444	2093	1640	1629	1936	2253
Food	2280	3031	1479	141	102	1418	56	32	79	57
Health	3472	1479	4737	253	191	1465	173	198	191	199
People	2784	141	253	4634	283	84	534	179	181	496
Can	1444	102	191	283	2435	27	206	150	162	126
Problem	2093	1418	1465	84	27	2235	28	18	22	64
Weight	1640	56	173	534	206	28	2768	111	60	61
Risk	1629	32	198	179	150	18	111	2267	270	341
Diabetes	1936	79	191	181	162	22	60	270	2461	213
COVID	2253	57	199	496	126	64	61	341	213	3464

The graphical representation of the adjacency matrix or the association among the frequent terms used to discuss obesity during the COVID-19 pandemic is depicted in Figure 3. The nodes represent the terms, and the edges represent the relationship strength between the words. Obesity is the central topic of discussion because it occurred most time, and the node labeled 'obesity' is centered in the graph. The obesity and COVID-19 nodes are connected, and the distance between the two is average. The connection and the average distance between both diseases indicate that they influence each other.

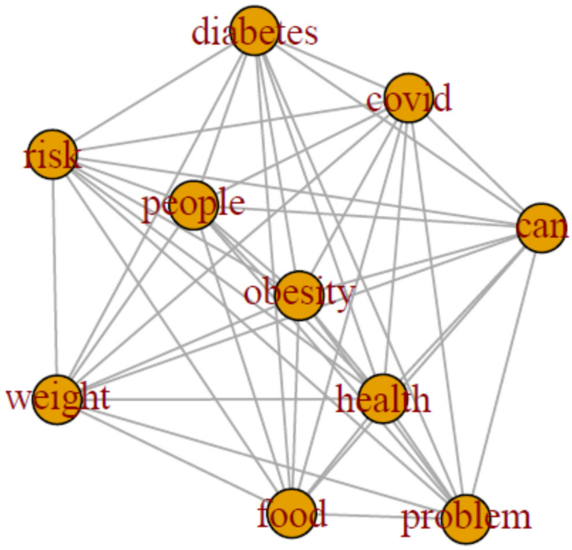

Figure 3. Adjacency graph of associated terms.

4.2. Evaluation of Selected Tweets

In this section, a few of the tweets showing the interrelationship between obesity and COVID-19 are selected and their meaning interpreted. The selected tweets representing the influence of obesity on COVID-19 are categorized as risk, hospitalization, mortality, and future possibility, as shown in Table 4. The tweets numbered 1 to 6 reveal the dangers of COVID-19 for persons with obesity. That is, those with obesity are more vulnerable to COVID-19 infection. The hospitalization possibilities of obese individuals are presented through tweets 7 and 8. In these tweets, obesity is viewed as one of the most significant causes of hospitalization in COVID-19 patients.

Table 4. The text of the selected tweets.

Number	Tweet	Category
1	#COVID19: #obesity and Excess Weight Increase Severe Illness Risk; Racial and Ethnic Disparities Persist. . .	Risk
2	@MidwestHedgie Obesity arguably worse than COVID wrt health impacts & cost. There should be more attention here. Si. . .	
3	Fat shaming, BMI and alienation: COVID-19 brought new stigma to large-sized people by @marialaganga for the. . .	
4	Obesity increases the risk of covid19 as the body is more prone to infections and immunity may not be able to fight. . .	
5	@nytimes Obesity = #1 risk factor for Covid	
6	Next there will be a link between obesity, a sedentary lifestyle and dying of COVID	
7	Main reason for Covid hospitalization was obesity	Hospitalization
8	@TuckerCarlson @damonroberts 78 percent of people hospitalized for COVID-19 were obese. Obesity caused by bad food. . .	
9	Risk of death from Covid increased by 90% in all people with a BMI over 40	Mortality
10	Biggest contributors to covid deaths, age, obesity and heart conditions	
11	@DrTomFrieden 94% of all covid deaths were a result of comorbidities preventing the immune system from working a fu. . .	
12	@nytimes COVID-19 has a higher mortality rate among the morbidly obese	
13	@_Simonian Misleading headline, very few healthy people die of COVID, most of the people who die have another co-mo. . .	
14	@ABC If you don't succumb to Covid, obesity is next in line	Caution

The tweets numbered 9 to 13 show the mortality/death rate of COVID-19 patients with obesity. That is, there is a greater possibility of dying from COVID-19 for patients who are obese. The last tweet, number 14, alerts and cautions people about the future by saying that if you survive COVID-19, you may be at risk of obesity in the future. Twitter users believed that obese people are more vulnerable to the risks associated with COVID-19 in one way or another. Some users tweeted about the causes of obesity also. For brevity, only the tweets that expressly mention the relationship between obesity and COVID-19 are presented.

The selected tweets that discussed the influence of COVID-19 on obesity are briefly described here. One tweet saying "Coronavirus lockdown has been shown to worsen child obesity worldwide; reports have shown children have LESS physic..." reveals the impact of COVID-19 on children in terms of developing obesity. Another tweet, "Health Risks of Obesity. More people have become obese with all of @thedemocrats' China-pandemic bailouts & welfar..." states that more people developed obesity during the COVID-19 pandemic than before it. Similarly, the following tweet, "No question that prolonged school closure has led to a spike in Pediatric obesity," highlights the influence of COVID-19 on children in terms of increased obesity.

One tweet commented on the influence of physical activity and the intake of high-calorie foods: "#Obesity is a result of several factors, like reduced #physicalactivity, increased availability of #highcalorie...". It concluded that reduced physical activity and the consumption of high-calorie foods resulted in increased obesity. The tweet saying "During #COVID-19 pandemic and lockdowns there have been huge rises in stress, depression, anxiety, alcoholism, suici..." indicates the development of stress, depression, anxiety, consumption of alcohol and suicide attempts during the COVID-19 pandemic. Both tweets reveal the indirect influence of the COVID-19 pandemic on obesity development.

5. Policy Implications

The policy implications are derived from the results of the analysis and they are discussed below. For collective suggestions of policies to contain the emergence and impact of COVID-19, this study's outcome is synthesized from literature, sentiment analysis, and the manual evaluation of tweets.

Vaccination is one of the essential measures employed to contain COVID-19 and similar infectious diseases [54]. Providing vaccination to all the world's citizens quickly is difficult, as it requires financial investment and a strategic plan to schedule the manufacturing. Until the completion of the vaccination program for all citizens, there will be the appreciable implementation of non-pharmaceutical measures such as lockdowns, social distancing, quarantine, and isolation to control COVID-19. Therefore, the primary effort of each nation should be focused on the vaccination of everyone while also adopting non-pharmaceutical measures. As the vaccine is less effective in persons who are obese or overweight [54], the emphasis could be extended to specific cases (obese) rather than concentrating only on general cases during the testing and development of vaccines.

The consumption of quality food, and daily physical activity could keep an individual healthy. As the frequent consumption of processed food develops overweight/obesity in an individual [49], people may be motivated to use better quality food products, or policy makers should regulate the food processing system to meet current requirements. The collective impact of processed food and the lack of physical activity is to increase the risk of contracting COVID-19. Therefore, the governance authorities could improve the infrastructure to make physical exercise accessible to everyone.

The sentiment analysis of Twitter users' responses reveals that most expressed their views through negative emotions such as sadness, disgust, and fear during the COVID-19 pandemic. A frequent expression of negative emotions may result in depression, stress, and anxiety in an individual. Reducing negative emotions and their impact on individuals could be achieved through intervention policies using intermediaries such as social media platforms. Social media platforms should intervene positively to counter negative feelings and nullify the panic that people feel. The countering emotions of an individual may be expressed through discussions that aim to persuade and shape behavior.

The word cloud and adjacency graph show the interrelationships between the different issues associated with people and COVID-19. The larger font size of the words COVID, food, weight, and obesity in the word cloud reveals that consuming low-quality food leads to increased weight, which causes obesity and then increases the severity of a COVID-19 infection in an individual. The connection between COVID, diabetes, obesity, and weight in the adjacency graph shows that people with high weight, diabetes, and obesity are most prone to the risks of the COVID-19 pandemic. The manual evaluation of the selected tweets also shows a mutual influence between obesity and the COVID-19 pandemic. Hence, the analysis of different sections such as literature, sentiments, adjacency matrix, and tweets reveals the stigma of obesity. Therefore, policy makers could emphasize associated diseases rather than concentrating only on the control of COVID-19.

6. Conclusions

Social media acts as an enabler for maintaining privacy and disclosing people's feelings about highly sensitized topics such as obesity, mental health, and diabetes. The study presented in this paper emphasizes obesity and COVID-19. This study aimed to analyze Twitter content to understand the mutual influences between obesity and the COVID-19 pandemic. The analysis of the Twitter content was carried out through sentiment analysis, a word cloud and adjacency graph, and the manual evaluation of tweets.

The sentiment analysis results show that there were more negative opinions than positive opinions and this demonstrates that people have negative feelings about the situation during the pandemic. In addition, people primarily expressed feelings of sadness, disgust, and fear in their posts, among other emotional components. The terms included in the word cloud reveal that the consumption of unhealthy food leads to people becoming overweight, leading to obesity and higher risks associated with COVID-19.

The adjacency graph analysis shows the interrelationship between different issues, i.e., obesity, weight, diabetes, and COVID-19. Moreover, the selected responses from Twitter users reveal that obesity and COVID-19 have a mutual influence on each other; a mutual association exists between both pandemics, and the control of both is required to reduce their impact on human beings. With the results and the existing research, this study can be generalized to provide the relationship between disasters and health issues.

This study considered only the Twitter social media content to understand the relationship between COVID-19 and obesity. The outcome can be strengthened by considering the use of other social media content during the pandemic and robust machine learning techniques.

Author Contributions: Conceptualization, M.A. (Mohammed Alotaibi), R.R.P., A.B. and N.C.; methodology, S.A., T.A., M.A. (Majed Aborokbah) and U.A.; software, M.A. (Mohammed Alotaibi), N.C., R.R.P., V.K. and A.M.; validation, S.A., A.M., A.B., T.A. and M.A. (Majed Aborokbah); formal analysis, M.A., V.K. and A.M.; investigation, N.C., M.A (Mohammed Alotaibi) and R.R.P.; resources, M.A. (Mohammed Alotaibi), T.A. and A.M.; data curation, A.B., M.A. (Majed Aborokbah) and U.A.; writing—original draft preparation, M.A. (Mohammed Alotaibi), R.R.P. and N.C.; writing—review and editing, S.A., A.M., V.K. and A.B.; visualization, N.C., U.A. and M.A. (Mohammed Alotaibi); supervision, S.A., M.A. and A.B.; project administration, M.A. (Mohammed Alotaibi); funding acquisition, M.A. (Mohammed Alotaibi). All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Deanship of Scientific Research (DSR) University of Tabuk, Tabuk, Saudi Arabia, grant number 1440-258 and The APC was funded by 1440-258.

Data Availability Statement: Data is unavailable due to privacy or ethical restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

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