DOI: 10.6911/WSRJ.202012\_6(12).0029

# The Attitudes of the Public Towards 'Sugar Tax Policy'

# -- Based on Twitter

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## **Abstract**

The UK government has published draft legislation for a tax on sugar-sweetened drinks, which is set to begin from April 2018". This legislation aims to address the already existing obesity problems, and many companies have already begun to reduce the sugar amount of beverages. According to statistics, there are twenty-eight countries that have imposed sugar tax on beverages till now such as America, Mexico, and France, while other countries are considering enacting similar policies. Previous research mainly focuses on the impact of the sugar tax, and there are few scholars concern about the public attitudes towards this policy. Due to these limitations of the previous research, in this report, the researcher decided to study the public's attitudes toward sugar tax. In order to investigate this topic, the researcher will collect more comprehensive data via Twitter to investigate the public attitudes toward the "sugary drink tax".

# **Keywords**

Social media, Twitter, sugar tax policy, Gephi, public attitudes.

#### 1. INTRODUCTION

On December 5th, 2016, according to BBC: "The UK government has published draft legislation for a tax on sugar-sweetened drinks, which is set to begin from April 2018". This legislation aims to address the already existing obesity problems, and many companies have already begun to reduce the sugar amount of the beverages. The government said it is expected that the tax will raise 520 million pounds in the first year (BBC, 2016). As soon as this news was published, it attracted the attention of the public quickly. In fact, The United Kingdom is not the only country that imposes a sugary drink tax. According to statistics, there are twenty-eight countries which have imposed sugar tax on beverages till now such as America, Mexico, and France, while other countries are considering enacting the similar policies (Bedi, 2018). Since the promulgation of the sugar tax policy, the UK has raised £153.8m by the end of October (BBC, 2018).

Social media platforms, such as twitter which is considered as a social media platform that has some functions of discussing democracy. (Montesinos et al., 2015). That means people could have chances to participate in democratic discussions via some social media platforms such as Twitter. Therefore, in this report, Twitter was used as a platform for data sources. By analyzing previous research on "sugar tax," it is noticed that almost research around "sugar tax" focused on the results and impacts of this tax, however lacking research on attitudes of people toward "sugar tax."

Hence, inspired by the previous investigations of scholars, this report will investigate the attitudes of people toward "sugar tax." In order to respond to this topic, the next section will be

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a literature review that is relevant to my research topic and problems, followed by the section of data and method, which will introduce the source of the survey data and some specific analytical techniques this report used, and then, there is a description of analytical results. Finally, the discussion and conclusions of these findings will be shown at the end of the report, which will answer the research questions about this topic.

## 2. LITERATURE REVIEW

Social media platform are considered as the essential tools for people to participate in discussions of social events. As previous research pointed out that since the end of the twentieth century, Internet users have proliferated around the world, at the same time, social media has become a non-negligible part of social life. These research also added that social media has the potential to support civil society (Majid, Fakhreldin and Zamli, 2016). What is more, Halpern and Gibbs (2013) state that by increasing social functions, the network can connect people through virtual social networks, which not only increases the diversity of information flow and opinions but also affects the government to make more professional and democratic decisions. Bertot et al. (2012) also argue that there is an increasing number of people who choose to connect with government through social media. Although this interaction between people and the government could lead to new problems such as the leakage of personal privacy, however, it is beneficial for government departments to establish these connections, which will make the government drawing on new ideas and recommendations to improve policy decision and problem-solving. Twitter, as a social media platform, is a microblog that many different topics will be discussed on this platform, and users write almost millions of short blogs on Twitter per day (Agarwal, 2011). Furthermore, Agarwal (2011) also states that Twitter is also a platform where people will express their political views and share emotions with others. In sum, Twitter is an appropriate data source for researchers to investigate the public attitudes toward some social events and government policies.

In 2012, Rivard et al. (2012) investigated 592 Americans about their attitudes toward sugary drink tax in America, and they aim to find how people interact with this legislation. The researching results show that majority of interviewers will reduce the consumption of sugar, and Thirty-seven percentage of interviewers said that they will still choose the soft drink, sugary drink tax has no impacts on them. Twenty percentage of them said that they would switch to duty-free drinks (such as soda and juice drinks) (Rivard et al., 2012). This research pointed out that majority of interviewers will not change their behaviors of consuming about soft drinks. However, this research only focus on 592 adults people and they just based on America, in other words, this survey has limitations that they did not include the opinions of other countries on sugar taxes and ignored the opinions of teens. Additionally, In the other previous sugar tax studies, some scholars investigated changes in the number of beverages purchased before and after the implementation of the sugar tax in Mexico. The results showed that the proportion of purchases of taxed beverages fell by 6%, while the proportion of purchases of untaxed soft drinks rose by 4%. (Colchero et al., 2016). Also, the researchers also predicted the impacts of the 20% sugar tax imposed by the UK. The results suggest that taxation of sugary drink may reduce the number of obese people in the UK, especially for young people. (Briggs et al., 2013). However, the previous research on sugar tax was mainly based on the impacts of the sugar tax on individuals, and they did not investigate the attitudes of the public toward this legislation. For example, after the implementation of the sugar tax, what is the attitude of people towards this policy? Whether people support this policy or they have no choices? Apart from some countries that have implemented sugar taxes, what are the attitudes of others toward sugar taxes? Due to these limitations of the previous research, in this report, the researcher decided to study the public's attitudes toward sugar tax. In order to investigate this topic, the researcher will collect more comprehensive data via Twitter to investigate the

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public attitudes toward "sugary drink tax", and this problem will be solved in the following sections.

Therefore, this topic will be divided into three survey questions in this research:

When talking about this issue, which aspect of this topic is most mentioned by people?

What is the emotional tendency of the public toward this issue?

Who are the most important gatekeepers in this issues on twitter platform?

In this report, Twitter will be chosen as the data source due to the specific function, as Lee (2016) mentioned that Twitter, as a social media platform, is essential for people to express their emotions and feelings, especially for some social issues. Besides, some social events such as "sugar tax" can easily attract widespread attention on Twitter. Furthermore, more details of analytical methods and tools will be introduced in the next section.

#### 3. DATA AND METHODS

In order to answer these research questions, the first step is to conduct "text mining." Hotho et al. (2005) argue that "text mining" has the same meaning as information extraction to some extent. Numerous social media platforms provide APIs (application programming interfaces) that allow third-party applications to access content and services (Bertot, Jaeger and Hansen, 2012). This report used Mozdeh, a third-party program, to collect tweets from twitter. Before using Mozdeh, it is important to enter the appropriate queries into this application, which ensures the most relevant tweets are obtained. According to the results of the search for related topics in Twitter and some news in the mainstream media platform, the queries are set to "sugar tax," "soda tax" and "sugar drink tax." The tweets crawled by Mozdeh are not just content, but also including relevant information such as usernames, the number of followers, and user URLs. Therefore, these raw data were saved as Excel and used by the following analysis methods. What is more, Mozdeh has a function that can identify the most frequent 1000 words, which is essential to find important things within a particular topic (Weller et al., 2014). This function could be used to answer the first question that which aspects mentioned much by people when talking about sugar tax.

The following step was analyzing sentiment levels of Twitter users toward sugar tax. As Liu (2012) pointed out that sentiment analysis, also known as opinion mining, is a researching area which focuses on analyzing public perspectives, emotions, attitudes, and evaluations through written language, and it is always used to analyze web data. The core of this method is using software to capture features to predict emotional content, such as words and emoticons people used (Weller et al., 2014). Furthermore, Liu (2012) also added that sentiment analysis had been widely applied to any aspects of society due to the importance of public opinions. Opinions are regarded as the core of human activities, which have huge impacts on behaviors and decision-making of people. This report used sentistrength, a software of sentiment analysis, to investigate the public emotional levels about sugar tax.

SentiStrengh is one software which designed for social networking data, which make it possible to study emotional levels on Twitter on a large-scale (Weller et al., 2014). What is more, SentiStrengh has clear and reasonable reasons for emotional classification, which are not available in other analysis software (Liu, 2012). Therefore although SentiStrengh is not the only software for studying social network data sentiment, it is one of the few software can be applied in social science surveys (Thelwall and Buckley, 2013). The results of values analyzed by SentiStrength represent the different levels of positive and negative emotions respectively: 1 to 5 represent positive emotions and -1 to -5 represent negative emotions. For example, one Twitter has both values of (1,5), that means this tweet has strong positive sentiment. In other

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words, one tweet analyzed by SentiStrengh has the scores of (-5, 1), which means this Twitter user has strong negative emotion in this tweet.

Moreover, it cannot be ignored that 1 and -1 both represent neutral sentiment. This report used this method to get the public emotions levels toward sugar tax; besides, the analyzed results not only include the sentiment scores, but other categories included such as usernames, user content and the number of favorite counts in tweets, etc. In this way, on the one hand, this report can get sentiment levels of people to answer the second question. On the other hand, the researcher can also get tweets with the most of favorite counts, that means based on the analysis of the most frequent words, the researcher can conduct a more comprehensive analysis to answer the first question: which aspects mentioned most by the public when talking about this issue.

Finally, this report used Gephi to visualize the retweets network to find the gatekeepers of this topic sugar tax. Gepih, a visualization application, which can be used in various webs and graphs (Bastian and Heymann, 2009). The results of output in Gephi are nodes and edges, and these graphs can show users who have been retweeted most, and the larger the nodes, the much number of retweets. Furthermore, large nodes present the opinion leaders of the social network sites, and these opinion leaders, defined as gatekeepers, playing important roles in the social network (Myneni, Cobb and Cohen, 2013). Therefore, this report used Gephi to find the gatekeepers of the topic in sugar tax and then analyzed details about their backgrounds and tweets relevant to this topic.

There is no denying that when collecting the data from the internet, the researcher has to concern about the ethical problems. Although discussions and opinions generated by people can be defined as public information (Townsend and Wallace, 2016), however, the user is informed consent is still an ethical consideration. All collected data in this report will only be used for academic research, and other personal data which are irrelevant to my research questions will be erased such as user URLs.

## 4. FINDINGS

3 tax         100.00%         53.50%         1046         1837         25.9         668.8         ****           5 soft         28.00%         2.70%         293         333         18.5         342.7         ****           6 rink         35.10%         10.50%         367         522         15         226.2         ****           6 rink         35.10%         10.50%         367         522         15         226.2         ****           6 rink         35.10%         10.50%         367         522         15         226.2         ****           6 rink         35.10%         10.10%         384         677         10.4         10.7         ****           8 on         37.70%         19.10%         394         677         10.4         10.7         ****           10 forecast         5.60%         0.00%         59         59         9.2         85.4         ****           12 bbc         7.50%         0.70%         78         89         9         81.2         ****           12 bbc         7.50%         0.70%         74         84         8.8         78         ****           14 mount         7.10%	1	Word	Matches	NoMatch	Matches	Total	DiffPZ	Chisq	Sig (163 te
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5 soft	3	tax	100.00%	53.50%	1046	1837	25.9	668.8	***
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23 french     3.90%     0.10%     41     43     7.2     52.4     ****       24 tackle     4.30%     0.30%     45     49     7.2     52.3     ****       25 introduction     4.20%     0.30%     44     48     7.1     50.9     ****       26 opt     3.30%     0.00%     35     35     7.1     50.2     ****       26 worldobesity     3.30%     0.00%     35     35     7.1     50.2     ****       28 khildhoodobesity     3.80%     0.20%     40     43     6.9     48     ****       20 uk     8.70%     0.30%     39     43     6.6     43.8     ****       31 support     4.40%     0.50%     91     132     6.6     43.5     ****       2 fight     4.20%     0.50%     46     54     6.6     43.5     ****       33 revenue     5.00%     1.10%     52     69     5.8     33.7     ****       34 great     4.90%     1.10%     51     68     5.7     32.5     ****       36 industry     5.30%     1.60%     55     78     5.3     28.1     ****       37 coke     2.60%     0.30%     27     31	21	under	5.80%	0.70%	61	72	7.6	57.3	***
24 tackle	22	has	13.00%	4.80%	136	207	7.4	54.8	***
1.5   1.5	23	french	3.90%	0.10%	41	43	7.2	52.4	***
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3.30%   0.00%   35   35   7.1   50.2   ***	25	introduction	4.20%	0.30%	44	48	7.1	50.9	***
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29	27	@worldobesity	3.30%	0.00%	35	35	7.1	50.2	***
30 uk 8.70% 2.80% 91 132 6.6 43.5 ***  31 support 4.40% 0.50% 46 54 6.6 43.5 ***  32 fight 4.20% 0.50% 44 52 6.4 40.8 ***  33 revenue 5.00% 1.10% 52 69 5.8 33.7 ***  4 great 4.90% 1.10% 51 68 5.7 32.5 ***  55 @bbcbusiness 2.00% 0.00% 21 21 5.5 29.9 ***  61 industry 5.30% 1.60% 55 78 5.3 28.1 ***  37 coke 2.60% 0.30% 27 31 5.2 27 ***	28	#childhoodobesity	3.80%	0.20%	40	43	6.9	48	***
11 support 4.40% 0.50% 46 54 6.6 43.5 *** 12 fight 4.20% 0.50% 44 52 6.4 40.8 *** 13 revenue 5.00% 1.10% 52 69 5.8 33.7 *** 14 great 4.90% 1.10% 51 68 5.7 32.5 *** 15 @bbcbusiness 2.00% 0.00% 21 21 5.5 29.9 *** 16 industry 5.30% 1.60% 55 78 5.3 28.1 *** 17 coke 2.60% 0.30% 27 31 5.2 27 ***	29	childhood	3.70%	0.30%	39	43	6.6	43.8	
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34 great     4.90%     1.10%     51     68     5.7     32.5     ****       35 @bbcbusiness     2.00%     0.00%     21     21     5.5     29.9     ***       36 Industry     5.30%     1.60%     55     78     5.3     28.1     ***       37 coke     2.60%     0.30%     27     31     5.2     27     ***	32	fight	4.20%	0.50%	44	52	6.4	40.8	***
35 @bbcbusiness 2.00% 0.00% 21 21 5.5 29.9 *** 26 industry 5.30% 1.60% 55 78 5.3 28.1 *** 37 coke 2.60% 0.30% 27 31 5.2 27 ***	33		5.00%	1.10%	52	69	5.8	33.7	***
36 Industry 5.30% 1.60% 55 78 5.3 28.1 *** 37 coke 2.60% 0.30% 27 31 5.2 27 ***	34	great	4.90%	1.10%	51	68	5.7	32.5	***
36 Industry 5.30% 1.60% 55 78 5.3 28.1 *** 37 coke 2.60% 0.30% 27 31 5.2 27 ***	35	@bbcbusiness	2.00%	0.00%	21	21	5.5	29.9	***
37 coke 2.60% 0.30% 27 31 5.2 27 ***	36	industry	5.30%		55	78	5.3		
38 help 5.80% 2.00% 61 90 5.2 26.7 ***	37		2.60%	0.30%	27	31	5.2	27	***
	38	help	5.80%	2.00%	61	90	5.2	26.7	***

**Figure 1.** The most frequent 1000 words associated with the topic

Firstly, by analyzing 2524 tweets collected by Mozdeh to find the most frequent words associated with sugar tax (see figure 1), the researcher found there are two words #childhoodobesity, childhood has strong significances. After searching these two words

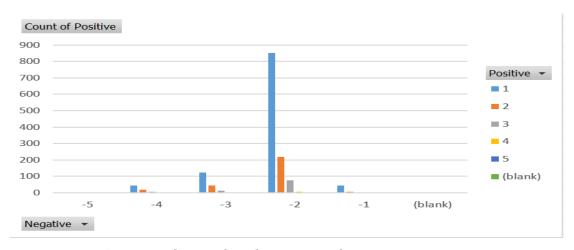
DOI: 10.6911/WSRJ.202012\_6(12).0029

separately via twitter, it was noticed that all tweets about these two words associated with links of an article, the content of this article are that the government has raised 150m pounds in "sugar tax" to help reduce the number of obese children in the UK.

Furthermore, after analyzing the most frequent words, the researcher entered the data into SentiStrengh to get the results of sentiment levels. Considering the accuracy of results, I filtered retweets from the raw data. According to the results (see Figure 2 below), the negative public emotions are higher than positive emotions, which mean that most people are not satisfied with this policy. After calculation, the content with negative emotions accounted for 96.38%. What is more, negative emotions are mainly concentrated in -2 (78.76%) and -3 (12.43%), which represent slightly negative and quite negative emotions separately (see Figure 2 and Figure 3). It is worth mentioning that although majority people have negative sentiment, there are still 27.25% tweets that have positive sentiment (the total of 2, 3, 4, 5), and 2.94% tweets with neutral sentiment (1, -1).

Count of Positive Column Labels 🔻													
Row Labels	1	2	3	4	5	(blank)	<b>Grand Total</b>						
-5	0.07%	0.07%	0.00%	0.00%	0.00%	0.00%	0.14%						
-4	3.07%	1.37%	0.48%	0.14%	0.00%	0.00%	5.05%						
-3	8.54%	3.01%	0.89%	0.00%	0.00%	0.00%	12.43%						
-2	58.13%	14.96%	5.12%	0.48%	0.07%	0.00%	78.76%						
-1	2.94%	0.41%	0.20%	0.07%	0.00%	0.00%	3.62%						
(blank)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%						
Grand Total	72.75%	19.81%	6.69%	0.68%	0.07%	0.00%	100.00%						

**Figure 2.** The results of positive and negative sentiment



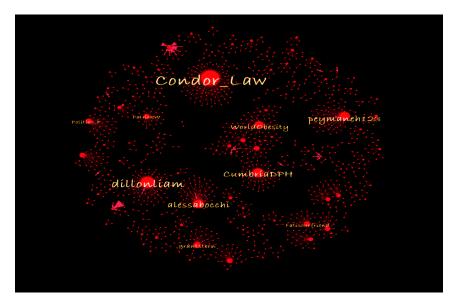
**Figure 3.** The results of positive and negative sentiment

In addition, the scores of -5 (extremely negative) and the scores of 5(extremely positive) accounted for 0.14% and 0.07%, which represent that minority people have extreme sentiments toward this legislation. In order to investigate further public attitudes toward this policy, I used the "filter" function to find the tweets with extreme scores. The tweet with the most negative score (-5, 1) described an event that people who lived in Cook County rejected to accept the restore of the "sugar tax." The most positive tweet with the score of (5, -2) praising the sugar tax which was enacted to reduce obese people is a huge success.

DOI: 10.6911/WSRJ.202012\_6(12).0029

Then, the researcher used the filter in excel to find the tweets with the most "favorite count," in this way it is easier to find the most concerned aspects when people are discussing sugar tax. The tweet with 416532 "Favorite Count" is one of the most favorite tweets on this topic. The content is that according to the estimation of scholars, by 2030, Mexico's sugar tax policy will prevent 134,000 people from diabetes. What is more, based on the searching results of the most frequent words people used such as #obesity, childhood obesity, and the favorite tweets, people concern more on the impacts of sugar tax in public health.

Finally, this report used Gephi to visualize the content, which could generate a retweet network. In this way, it was easy to find these Twitter users whose tweets have been retweeted the most times, in other words, the gatekeepers of this topic. Myneni et al. (2013) mentioned that the nodes represent the retweeted times. Meanwhile, users, who have the biggest nodes, are considered as opinion leaders in the social network. From the results of Figure 4, people can notice that there are four largest nodes, then when searching these users via Twitter, the researcher found that they are the Olympic swimmer, politics writer, freelance journalist, and a non-profit organization. Majority of them have more than 11.8k followers, which represent that influential people have dominated this topic about "sugar tax." It is worth mentioning that according to their introductions, there is only the writer among those who has ever researched the government policies in-depth.



**Figure 4.** The results of gatekeepers via Gephi

## 5. DISCUSSION AND CONCLUSION

This report used three methods and relevant tools to answer the three research questions such as sentiment analysis, text mining and some software such as Gephi, Mozedh, and SentiStrength. According to the results, when discussing the "sugar tax," people are more concerned about the impacts of this legislation. For example, the content associated with the most frequent words mainly focused on the impacts of "sugar tax" in reducing the obese children, and the most favorite tweets showed that "sugar tax" can prevent people from getting diabetes. Compared with the previous research, these findings strongly explained the searching results of Rivard et al., (2012), which indicated that the majority of people would choose to reduce the consumption of sugar.

From the results of sentiment analysis, there are more negative emotions than positive in this event although the prediction of scholars shows that "sugar tax" will have benefits in reducing the number of obese individuals. However, Majority still have slightly negative sentiment with

DOI: 10.6911/WSRJ.202012\_6(12).0029

the score of -2. However, emotions are unstable, due to the limitation of Mozdeh, which can only collect data about one week, the results may have some deviation. On the other hand, public emotions can be influenced by opinion leaders.

According to the results of Gephi, this report found six gatekeepers of this topic, and after searching the backgrounds of these people via Twitter, it is noticed that only one is a nonprofit organization, and just one politics writer who familiar with the relevant field of government policy. Furthermore, the rest are influential personal accounts, which show the content of their tweets is subjective views. As Myneni et al. (2013) mentioned that opinion leaders are significant in social media networks. Therefore, it is possible that these opinions of influential personal accounts will mislead the public to some extent

In sum, this report answered the research questions surround the topic. However, there are still many aspects could be improved. Firstly, although there are 2524 tweets, however, all data collected via Mozdeh are within one week due to the time limitation of this software. Secondly, when analyzing the sentiment levels via SentiStrengh, some complicated emotion icons cannot be analyzed by this application. Moreover, Compared with other countries, the United Kingdom began to impose a "sugar tax" in April 2018, resulting in many data concentrated on the "sugar tax" in the UK. Further research could spend more time collecting data to get many comprehensive data. Also, comparing the sentiment results analyzed by different tools could improve the accuracy of sentiment analysis.

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