Seasonal Trends in Global Dieting Online: A Big Data Survey

Myung-Bae Park

Pai Chai University <https://orcid.org/0000-0002-1892-6632>

Jumee Wang (✉ jumeew@gmail.com)

The Korean Cardiac Research Foundation

Bernard E. Bulwer

Brigham and Women's Hospital

Chhabi Ranabhat

Health Science Foundation and Study Center

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Abstract

Background

We aimed to explore whether the massive amounts of data generated during online search interest in dieting and weight loss could be harnessed, using big data analysis, with a view to its potential incorporation in global health obesity prevention efforts.

Methods

We applied big data analysis to the major global health practice of dieting for weight management. Data was collected from Google and Naver search engines from January 2004 to January 2018 using the search term 'diet', in: A) selected six Northern and Southern Hemisphere countries, B) five primarily Arab and Muslim countries grouped as (i) conservative, (ii) semi-conservative, and (iii) liberal, and C) South Korea.

Results

Using cosinor analysis to evaluate the periodic flow of time series data, we found that global searches and interest in dieting and weight loss appeared to be seasonal (seasonality amplitude = 6.94, CI = 5.33 ~ 8.56, $P > 0.0000$), highest in April and the lowest in October for both Northern and Southern Hemisphere countries (seasonality amplitude for Northern Hemisphere = 6.68, CI = 5.13 ~ 8.22, $P > 0.0000$), with a different seasonal dieting trend generally seen in the Arab and Muslim countries (monthly seasonal seasonality (amplitude = 4.07, CI = 2.20 ~ 5.95, $P > 0.0000$).

Conclusions

Our findings indicate that big data analysis of social media can be harnessed as an adjunct tool for addressing important public health issues related to diet, weight loss, and obesity management including the optimal timing for healthy public interventions, and the avoidance of food fads and quackery.

Introduction

Big-Data in Public Health

Big-Data is defined as "data sets that are so voluminous and complex" that they overwhelm traditional data analytic methods¹. The "three Vs"—volume, velocity, and variety—is a popular concept used to describe big-data. This reflects not just the huge volumes of data, but also the speed at which such data is generated, and the wide range of data involved. Big-data analytic methods are better suited for analyzing massive datasets in a myriad of rapidly evolving scenarios^{2,3}.

One of the major advantages of big-data is that it can analyze global data cost-effectively, reliably, and accurately. The Pillbox project of the United States National Library of Medicine (NLM Pillbox) is an often cited example of how healthcare can be improved using big-data^{4,5}. This powerful public service tool is a massive database that provides information on a wide range of both prescription and over-the-counter (OTC) drugs. It was designed to help users to rapidly identify such drugs based on their ingredients and appearance. Pillbox simultaneously provides and collects information based on user queries, which can enhance convenience, save costs, and improve consumer safety, among other benefits. Big-data analysis by supercomputers such as IBM Watson that utilize machine learning and artificial intelligence algorithms, can improve diagnosis, minimizing errors, and improving care⁶.

Another example of Big-data application was Google's influenza forecast (Google Flu Trends). Massive amounts of data obtained from global online search patterns from dozens of countries, generating real-time insights and "nowcasts" about suspected influenza activity worldwide. In 2009, Google predicted the spread of the flu 7–10 days earlier than the U.S. Centers for Disease Control and Prevention, based on such online search data about the flu⁷. Several countries, including South Korea, India, and China have compared the predictive value of such data from online searches, compared to actual numbers using traditional public health approaches^{8–11}. Predictive analyses using social big-data can also reliably predict other global seasonal trends, for example, mental health issues like depression^{12,13}. Big-data analyses have limitations, but upgrades and improvements are constantly provided, with the aim of improving accuracy and precision^{14,15}.

Dieting

Dieting and weight loss efforts are global pursuits, considering the known health risks of obesity. Dieting mostly refers to a change in eating habits, but is also juxtaposed to increasing physical activity as part of a weight management regimen ^{16,17}. Obesity, especially central or visceral obesity, is an established risk factor for several diseases, especially cardiovascular disease, type II diabetes, musculoskeletal diseases, and cancer ^{18–20}. Obesity is also a factor in mental health disorders and depression ^{21–23}, with adverse effects on interpersonal relationships²⁴.

Global rates of obesity is on the rise, with an obesity epidemic observed in the Arab/Muslim world ²⁵, with seasonal trends observed in weight loss efforts in Western societies ^{26–28}. Therefore, global health efforts aimed toward the prevention of obesity are warranted ^{29,30}.

With the advent on the Internet and social media, there is a heavy profit-driven fad industry online ³¹. Much of this is wholly cosmetic, driven by a heavy emphasis on body image ^{32–34}. Such fads and food trends based on pseudo-science and quackery not only fail to deliver the results promised, but they also pose a real risk to health and well-being ^{32,35,36}.

Aims and goals

We aimed to explore whether the massive amounts of data generated during online search interest in dieting and weight loss could be harnessed, using Big-data analysis, with a view to its potential incorporation in global health obesity prevention efforts. We aimed to explore whether there were season trends, and perhaps an optimal time to potentially target people with online search interests in dieting? In this pursuit, we hypothesized that '*Interest or attempt to explore dieting online would be tend to be seasonal*'. Our study therefore (i) examined the time series and seasonality of dieting globally, using social big-data collected from online portals, and (ii) aimed to suggest timely healthy intervention strategy based on such findings.

Methods

Searching tools and keyword

Data was collected through Google web portal (Menlo Park, CA, USA), the most widely used global search engine, with its share of global search averaging 85–90 percent in most markets, except China³⁷. Since January 2004, Google has provided information on time-critical search terms through Google Trends; searches can be categorized as searches via the general web, or by images, or shopping, YouTube, etc. Searches were further categorized and analyzed according to global or individual country statistics. For South Korea, the search engine Naver was added, as its share of the South Korean market was 73.5% in February 2018, exceeding that of Google ³⁸.

This search terms 'diet', 'dieting', and 'weight loss' were used, and the monthly correlation coefficient between the three words was 0.946 ~ 0.980 (Table 1). Of these, the search volume for 'diet' was overwhelmingly high. Since the terms weight loss and weight control could convey other meanings, the search term 'diet', was finally selected.

Table 1
Correlation between search terms diet, dieting, and weight loss

	Diet	Dieting	Weight loss
Diet	1.000	0.980 < .0001	0.975 < .0001
Dieting	0.980 < .0001	1.000	0.946 < .0001
Weight loss	0.975 < .0001	0.946 < .0001	1.000

Study population and data

Three countries were selected from the Northern Hemisphere (United States [U.S.], Ireland, United Kingdom[U.K.]) and three from the Southern Hemisphere (South Africa, Australia, New Zealand) which had the highest search volumes for the search term "diet". In other words, the reference is based on the search volumes, which means that the interest in the six selected countries is the highest. As diet and weight loss are

also influenced by socioeconomic, cultural, and religious factors^{39,40}, we also selected five predominantly Arab and Muslim countries, excluding Iraq and Turkey, categorized as (i) conservative, (ii) semi-conservative, and (iii) liberal⁴¹. South Korea was also studied using the Naver search engine, due to its local dominance as aforementioned.

Theoretical model

Cosinor analysis is a method used to evaluate the periodic flow of time series data as a cosine function. This analysis has been frequently used to analyze body cycles (24 hours), such as circadian rhythm^{42,43}. It is also used to demonstrate the seasonality of differences in blood pressure, stroke incidence, and vitamin D concentration in the 12-month follow-up period^{44–46}. The model equation is $f(t) = M + A \cos(\omega t + \phi)$, M is midline estimating statistic of rhythm, A (amplitude) is the distance from the highest point, ω is the number of vibrations, ϕ (acrophase) is the time from the reference time to the first matching A, t is the time unit⁴⁷.

Statistical analyses

The data was analyzed by standardizing the number of periods with longest search period as 100 and the lowest as 0. In this study, we used web-search data from January 2004 to July 2018, and the time unit was one month. On the other hand, South Korea used data starting from October 2007 to March 2019, since no data from Naver was available prior to October 2007.

Results

Descriptive statistics

The combined results from the two Hemispheres was the highest in January (Mean: 72.2, S.D: 14.3) and the lowest in December (Mean: 43.9, S.D: 9.0). Both the Northern and the Southern Hemispheres were highest in January and the lowest in December. For the Arab/Muslim countries, April was the leading month (Mean: 40.4, S.D: 24.2), with August (Mean: 31.0, S.D: 19.2) and December (Mean: 31.0, S.D: 19.7) being the lowest. Based on socio-religious categories, the “conservative Arab/Muslim countries” (Mean: 46.4, S.D: 10.8) and the “semi-conservative countries” (Mean: 51.3, S.D: 22.2) were highest in April, and “liberal countries” (Mean: 31.6, S.D: 27.5) being highest in March. On the other hand, the lowest months were June (Conservative countries), August (semi-conservative countries), and December (liberal countries). For South Korea, the result based on Google searches was highest in July (Mean: 47.4, S.D: 31.8) and lowest in December (Mean: 35.6, S.D: 25.4). The results of Naver search were highest in February (Mean: 46.3, S.D: 15.4) and lowest in October (Mean: 30.5, S.D: 6.9) and November (Mean: 30.5, S.D: 6.8) (Table 2).

Table 2
The Diet search results by cosinor analysis

Month	Six countries with highest search volume			Arab and Muslim countries				South Korea	
	Overall	Northern Hemisphere	Southern Hemisphere	Overall	Conservative	Semi-Conservative	Liberal	Google	Naver
1	72.2(14.3)	70.9(15.9)	73.6(12.5)	33.7(21.2)	41.2(7.4)	43.2(19.0)	24.9(22.1)	47.3(30.1)	42.9(10.7)
2	59.5(11.4)	58.0(12.1)	61.1(10.6)	36.0(23.2)	43.3(15.3)	43.6(17.6)	28.5(26.4)	38.8(30.3)	46.3(15.4)
3	57.9(10.4)	57.2(10.7)	58.7(10.2)	39.6(24.3)	44.9(13.2)	49.0(19.3)	31.6(27.5)	41.6(31.8)	42.2(12.7)
4	58.5(10.7)	58.8(10.9)	58.3(10.5)	40.4(24.2)	46.4(10.8)	51.3(22.2)	31.0(25.3)	45.2(33.3)	43.3(11.9)
5	59.2(11.4)	59.4(12.0)	59.1(10.9)	38.5(24.2)	44.5(9.0)	49.4(21.5)	29.2(25.9)	46.6(34.2)	42.9(12.6)
6	57.5(11.2)	57.5(11.1)	57.4(11.5)	33.7(20.5)	38.6(7.3)	43.6(19.9)	25.5(20.7)	45.5(32.8)	43.5(12.7)
7	57.3(10.8)	55.9(11.4)	58.8(10.2)	31.4(19.7)	41.1(14.7)	40.0(18.0)	22.5(18.4)	47.4(31.8)	40.6(10.9)
8	58.3(11.8)	53.4(10.9)	63.1(10.7)	31.0(19.2)	37.6(14.8)	39.4(17.2)	23.3(18.8)	39.7(27.9)	36.6(8.6)
9	57.8(12.7)	50.6(10.2)	64.9(10.8)	31.3(19.8)	39.9(11.2)	43.4(19.0)	20.4(16.5)	39.1(28.6)	31.9(7.4)
10	55.0(11.8)	47.3(7.7)	62.6(10.2)	31.4(19.6)	39.6(8.2)	41.3(17.2)	22.2(19.6)	42.1(28.6)	30.5(6.9)
11	52.7(11.3)	46.3(8.3)	59.1(10.3)	34.3(21.3)	43.5(9.0)	43.2(17.9)	25.3(22.7)	35.9(25.6)	30.5(6.8)
12	43.9(9.0)	39.0(7.2)	48.9(8.0)	31.0(19.7)	42.4(17.5)	41.4(17.3)	20.2(16.0)	35.6(25.4)	31.3(8.5)
Red: Highest month, Blue: Lowest month									

Cosinor analysis

As a result of cosinor analysis of the Northern and Southern Hemispheres, there was seasonality (amplitude = 6.94, C.I = 5.33 ~ 8.56, $P > 0.0000$); searches were the highest in April and the lowest in October. As a result of analyzing only the Northern Hemisphere, seasonality (amplitude = 6.68, C.I = 5.13 ~ 8.22, $P > 0.0000$) was highest in April and lowest was in early October. In the Southern Hemisphere, seasonal variation of the curve was not statistically significant (amplitude = 1.21, C.I = -0.26 ~ 2.67, $P > 0.1058$) (Fig. 1).

When the five Arab/Muslim countries were integrated, monthly seasonal periodicity was observed (amplitude = 4.07, C.I = 2.20 ~ 5.95, $P > 0.0000$). Conservative countries like Saudi Arabia (amplitude = 2.75, C.I = 0.24 ~ 5.27, $P > 0.0316$), semi-conservative countries (amplitude = 3.99, C.I = 1.15 ~ 6.83, $P > 0.0059$), liberal countries (amplitude = 4.66, C.I = 1.95 ~ 7.36, $P > 0.0000$) showed seasonal periodicity on a monthly basis. The trends for the monthly curve of these three groups were similar (Fig. 2).

For South Korea, the seasonal periodicity of monthly data was not seen (amplitude = 3.71, C.I = -1.43 ~ 8.85, $P > 0.1574$), in the Google data, but seasonal periodicity was statistically significant in data using Naver (amplitude = 7.45, C.I = 6.48 ~ 8.42, $P > .00000$)(Fig. 3).

Discussion

Obesity is an important global public health challenge, as it is a major risk factor for cardiovascular and chronic diseases, with major impact on morbidity, mortality, and health care costs. Effective management of obesity includes prevention of premature death and disability, reducing the economic burden of disease, and the promotion of healthy diets and lifestyles^{29,48}.

With respect to the promotion of healthy diet and lifestyle, our aim was to analyze global dieting and weight loss trends, being cognizant that sociocultural, societal, and traditional practices could potentially play a role. Since dieting and weight loss pursuits are a global enterprise, with the Internet a major portal for disseminating information and advertisements, we considered Big data analysis ideal for studying this vast amount of data on global dieting practices and trends^{49–51}. No attempt was made to exclude fad diets and weight loss programs, even though these also have potential health risks, including increased risks of eating disorders, mental health problems, including stress, anxiety, and depression.^{52–54 32,55–60}.

In this study, we found that the search volume for the Northern and Southern Hemisphere diets was the highest in January, which coincides with the New Year, where people traditionally make New Year's resolutions following the Christmas holidays and festivities. On the other hand,

for the predominantly Arab and Muslim countries, the highest search volumes were in April. For South Korea, the highest search volume was in February.

On cosinor analysis, which analyzes periodic trends, online search interest in dieting in the Northern Hemisphere was statistically significantly seasonal, but for the Southern Hemisphere, it was not.

Studies using cosinor analysis tend to show opposite dieting trends of Southern compared to Northern Hemisphere countries^{46,61}, probably reflecting the divergent seasons. The data on global seasonal trends in dieting is apparently limited, but studies on weight changes in three major countries, including Japan, the United States, and Germany, showed a sharp increase from December, with the greatest increase in weight in early January, just after the Christmas holiday festivities^{62,63}.

In this study, the search volumes of both Northern and Southern Hemispheres were the highest in January. Overall, search interest reached its peak before summer (April) in the Northern Hemisphere, and November in the Southern Hemisphere^{64–66}. For predominantly Arab and Muslim countries, seasonality was not striking, and the magnitude was smaller than that observed for the Northern Hemisphere, with April being the highest point in the periodic rate. Seasonality tended to be a bit more pronounced in the liberal Arab and Muslim countries, compared to their more conservative counterparts.

Finally, in South Korea, data from Naver showed seasonality, with April being the peak month for online diet searches, with the trend of rhythm being similar to that of the Northern Hemisphere. However, there was no statistically significant seasonality in the data from Google, which may be a reflection of the lower percentage of Google searches on this topic in South Korea. Because of this skew, such Google searchers on the subject was most likely unrepresentative.

Although our study is exploratory, our Big-data analyses could suggest the potential for seasonal emphasis on weight control programs. More-cost effective health awareness and prevention weight loss strategies could harness the power of online Big-data analyses and real-time “nowcasting”, for optimal timing of public health interventions for obesity. In the same way that marketing strategists use such Big data to target consumers, so too could public health authorities utilize Big data for optimal timing of public education and intervention programs.

Strengths and limitations

The authors are unaware of any previous studies to analyze the global seasonality of diets using social big-data. Big-data analysis of seasonal dieting trends is rather easy to access and analyze, and therefore potentially more cost-effective. This approach can also hold relevance to other areas of public health.

Our study has clear limitations. Firstly, we conducted the keywords search terms in English only, which is less representative for countries that do not use English as their primary search language, such as in South Korea and in the Arab and Muslim -majority countries we studied. It may therefore be more accurate to include searches using the preferred language of such countries. Secondly, it is difficult or near impossible to examine the individual characteristics of each person who performed each search, without breaching social media confidentiality or other agreements. Thirdly, we could not accurately predict the actual figures by analyzing the search volume using web-based methods only.

Conclusion

Big-data analysis can reliably analyze the huge metadata trends such as global seasonal patterns such as search interests in dieting and weight loss. In our study, some degree of seasonal patterns emerged, e.g. the highest search volume during the summer months in the Northern Hemisphere countries. Weight management and weight loss strategies could take such trends into account for optimal timing of their health promotion and intervention strategies. Big-data analytics, including artificial intelligence algorithms, can be harnessed to provide cost-effective insights and optimal approaches for global health promotion and intervention programs.

Declarations

Authors' contributions

M-B Park designed the study model and analyzed data. J Wang reviewed related literature and suggested the scope. BE Bulwer involved designing the study and interpreting the data. C. Ranabhat checked statistical method and framework.

Ethical Approval and Consent to participate

Not applicable.

Availability of data and material

All data can be used and analyzed through "https://trends.google.com/" and "https://datalab.naver.com/"

Competing interests

The authors declare that they have no competing interests.

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Figures

Figure 1

Northern-Southern search volume and cycle by month Search volume of (a) six countries with highest search volume, (b) three southern, and (c) three northern countries. Cycle by cosinor analysis of (d) six countries with highest search volume, (e) three southern, and (f) three northern countries.

Figure 2

Five Arab and Muslim countries' search volume and cycle by month Search volumes of (a) the five primarily Arab and Muslim countries in our study and the subcategories (b) conservative (c) semi-conservative, and (d) liberal. Cycle by cosinor analysis of (e) five Arab and Muslim countries search volume, (f) conservative countries, (g) semi-conservative countries, (h) liberal countries