Article

Google Medical Update: Why Is the Search Engine Decreasing Visibility of Health and Medical Information Websites?

Artur Strzelecki

Department of Informatics, University of Economics in Katowice, 40-287 Katowice, Poland;
artur.strzelecki@ue.katowice.pl

Received: 31 December 2019; Accepted: 11 February 2020; Published: 12 February 2020

Abstract: The Google search engine answers many health and medical information queries every day. People have become used to searching for this type of information. This paper presents a study which examined the visibility of health and medical information websites. The purpose of this study was to find out why Google is decreasing the visibility of such websites and how to measure this decrease. Since August 2018, Google has been more rigorously rating these websites, since they can potentially impact people’s health. The method of the study was to collect data about the visibility of health and medical information websites in sequential time snapshots. Visibility consists of combined data of unique keywords, positions, and URL results. The sample under study was made up of 21 websites selected from 10 European countries. The findings reveal that in sequential time snapshots, search visibility decreased. The decrease was not dependent on the country or the language. The main reason why Google is decreasing the visibility of such websites is that they do not meet high ranking criteria.

Keywords: Google; medical update; health information websites; search visibility; search engine

1. Introduction

Some types of websites could potentially impact people’s future happiness, health, financial stability, or safety. Google calls such pages “your money or your life” (YMYL) pages [1]. Google recognizes five types of YMYL pages. First are shopping or financial transaction pages. These webpages allow people to make purchases, transfer money, pay bills, and so on, online (such as online stores and banking) [1]. Second are financial information pages. These webpages provide advice or information about investments, taxes, retirement planning, home purchases, paying for college, buying insurance, and so on [1]. Third are medical information pages. These webpages provide advice or information about health, drugs, specific diseases or conditions, mental health, nutrition, and so on [1]. Fourth are legal information pages. These webpages provide legal advice or information on topics such as divorce, child custody, creating a will, becoming a citizen, and so on [1]. Fifth are news articles or public/official information pages that are important in order to have an informed citizenry. These webpages include information about local/state/national government processes, policies, people, and laws, disaster response services, and government programs and social services; as well as news about important topics such as international events, business, politics, science, and technology, and so on [1]. Of course, not all news articles are necessarily considered YMYL.

In past studies, authors observed three main areas in analyzing search data on health and medical information: medical and health information websites, search engine result pages with medical and health information results, and data collected from Google Trends and/or Google Flu Trends. The results of these studies reveal that YMYL websites are not necessarily the highest ranking websites on Google search results. The purpose of this study was to examine the YMYL websites and the visibility of their SEO results on Google search engine.
Trends and/or Google Cloud Healthcare application programming interface (API) (formerly Google Health).

In the years before Google Trends was released in 2010, a lot of research was done on medical and health information websites. Examples include searching for health information when studying focus groups [2], especially adolescents [3], young people [4], or parents [5], and types of health searches [6] and how they are readable [7], reliable [8], or evaluated [9]. In this period people used different search engines such as Yahoo! [10] and Google [11].

The quality of medical and health information websites is very important and has been measured by indicators such as authority, source, content, and so on [12]. The quality of health information websites can be checked by manual examination or automated tools. For manual checking, DISCERN questions and the Health on the Net Foundation Code of Conduct (HONcode) are used. DISCERN consists of 15 key questions plus an overall quality rating. Each question represents a separate quality criterion [13]. The 8-point HONcode assesses the following principles: authority, complementarity, privacy, attribution, justifiability, transparency, financial disclosure, and advertising policy [14]. One of its automated tools measures 18 technical quality criteria and measurable indicators. These criteria are in seven groups: author, source, currency, content, disclosure interactivity, and commercialization [13].

In terms of analyzing search engine results, this field is divided into two areas. First, researchers are evaluating organic results displayed by search engines with tools that are widely used today such as HONcode [13], the Journal of the American Medical Association (JAMA) benchmarks, and the DISCERN tool [14], and scales such as Flesch–Kincaid reading level and Flesch reading ease [14]. Results from Google are downloaded and evaluated [16] with regard to how they answer health questions [17], for example, from parents on neonatal intensive care [18], or on palliative care [19] or human papillomavirus vaccination [20]; and there are large systematic reviews of autoimmune diseases [21]. Some studies have examined data retrieved from the Google Planner tool [22], which contains information on the popularity and competitiveness of all queries used on Google in the last 12 months [23], or built their own Google-based search engine for mining radiology reports [24]. In addition, people are also using other search engines such as Yahoo! and Bing to search for information, especially to measure the popularity of online drug information on Bing and Yahoo! [25], to clarify medical queries on Bing [26], or to compare four search engines in terms of obtaining medical information [27]. Also, the Chinese search engine has been explored in terms of predicting the incidence of hand, foot, and mouth disease using search engine queries from Baidu [28]. Baidu is popular in China because of the general unavailability of Google in the country. In a few studies, researchers built [29], prepared [30], or used [31] specialized medical search engines and tested how the results were perceived by users.

Second, participants are invited to examine search queries and use them to find health and medical information. It has been shown that manipulating the presentation of search results for common symptoms, such as the frequency and placement of serious illness mentions within search results, can influence perceptions of symptom severity and susceptibility to having the serious illness [32]. Participants usually take part in interviews [33]. It has been observed that people without university education [34] and university freshmen [35] have to make evaluations when they are searching for health information on the Internet. Participants are observed with regard to how they solve complex health information tasks using a search engine and whether there is a difference in the amount of searches and time spent on searching among different age groups [36] or the use of specified medical search engines in comparison to Google [37]. Observed participants have a high tendency to use search engines in seeking health information, especially Google [38], however the information is not always complete and reliable [39]. Parents search for health and medical information before taking a child to the emergency department [40]. Many women play a key role in providing advice and health care for family members, by searching for health and medical information using search engines [41]. It looks like the same behaviors do not differ across different countries [42].
Finally, in recent years much research has been done using data collected from Google Trends (GT), Google Flu Trends, and Google Cloud Healthcare API. There is growing amount of research using GT [43]. Before GT was released, early studies were done on Google Flu Trends, a source for queries connected to diseases [44]. GT is a source of reverse-engineered data. It shows what was searched in Google, and the data are normalized in terms of search frequency and presented in relative search volumes. Data are segmented into years and months, and into geographical regions. Researchers can compare a maximum of five keywords using segments in one try. Studies on GT can be divided into four areas—infectious diseases, mental health, other diseases, and general population behavior [45]—and are mainly conducted to examine seasonality [46].

Looking at recent studies, GT has been used to track infectious disease data on chickenpox [47], Lyme disease [48], the Ebola epidemic [49], syphilis [50], conjunctivitis [51], and dengue fever [52]. Some researchers studied mental health [53] and depression [54] queries. Other topics studied using GT data are skin cancer [55], sunscreen use [56], sunburn [57], seasonality of bruxism [58], multiple sclerosis [59], cancer [60], stroke [61], HIV [62], lupus [63], norovirus [64], sepsis [65], pertussis [66], epistaxis [67], plague [68], rheumatoid arthritis [69], and prostate cancer [70]. In terms of general population behavior, research was done using GT data on pharmaceutical data [71], vaccinations [72], movement disorders [73], digital epidemiology [74], kidney stone surgery [75], foot and ankle pain [76], knee injuries [77], osteoarthritis [78], seasonality of cellulitis [79], tracking influenza epidemics using climate data [80], palliative care [81], cosmetic body procedures [82], and anaesthesia [83]. GT is also used for forecasting [84], real-time surveillance [85], or prevention [86] of diseases.

Basic search engine visibility is combined data of unique keywords, positions, and URL results. According to the concept of search engine visibility described in [87], the visibility of websites in search engines comes from algorithms that rank and order them according to calculated ranking positions. The original concept [88] of ranking for the Google search engine is named PageRank, after one of Google’s founders. PageRank was invented and published in 1998 [89]. This concept takes into account incoming links, and based on volume and quality, ranking positions for websites and corresponding keywords are estimated [90]. Currently, web search engines use different ranking factors for websites to determine their position on a results page.

Today this topic is attracting more attention [91] and can be divided into onsite and offsite factors [92]. Onsite factors are domain-, website-, and page-related [93]. Search engines take into account different elements found in the source code of a webpage such as title, headings, descriptions, time of last update, mobile design, and structured data for rich snippets [94]. Offsite factors are link-related [95], user action-related [96], special rules-related [97], brand-related [98], and spam-related [99].

The motivation behind the present study is to analyze what types of websites experience decreasing visibility on search engine results pages due to low-quality medical and health information content. There is no doubt that much research has been done on health and medical information websites and Google as a source of medical knowledge. However, there is little knowledge of the ways medical and health information websites are lowered or removed from search engine results pages due to low-quality content.

Thus, the current gap represents a lack of research on the decreasing visibility of medical and health information websites. There have been several studies on medical and health information presented on Google, conducted mainly by researching GT. Recognizing which websites are not considered to be proper sources of medical and health information by Google and why is a gap the author is trying to fill.

The objective of this study was to analyze data from an external service that monitors Google’s search engine results pages and collects data on websites’ visibility. By measuring increased or decreased visibility of health and medical information websites, it is possible to recognize the websites that are considered to have low-quality content. Based on the above discussion, the following research questions related to decreasing visibility of health and medical information websites in Google are proposed:

1. Why is the Google search engine decreasing the visibility of health and medical information websites?
2. How can we measure the decreased visibility of health and medical information websites?

The paper is organized as follows. Section 2 includes the method, search engine visibility concept, and material for data retrieval and processing. Section 3 contains the results, while Section 4 presents the discussion. In Section 5, the author highlights the contribution of the research, discusses its limitations, and, finally, draws conclusions about the results and proposes possible future research avenues.

2. Materials and Methods

This study used search engine visibility data on websites with health and medical information. The author selected European countries based on criteria using this list: https://en.wikipedia.org/wiki/List of European countries by population, including countries located in Europe, not in Asia (excluding Russia, Turkey, and Kazakhstan), and countries where Google operates. For the first to ninth positions on the list there was no doubt about population. For the tenth position, five countries had >10 million population, which was sufficient for choosing one of them. Greece was chosen, since this part of Europe was not yet represented in this study and French- and Dutch-speaking countries were already on the list, which is why Belgium was not chosen. Countries with higher populations have more Internet users, thus it is more likely that there are many health and medical websites. Ten countries were selected to check whether visibility in a search engine depends on the country or and language or is not influenced by either.

The author analyzed the top 20 results on a sequence of keywords: “google medical update site:.cc,” where “site” is a search operator that narrows the results, in this case to country domain name, and “.cc” means country-coded domain name. The author selected 10 countries with the highest populations in Europe: Germany, France, United Kingdom, Italy, Spain, Ukraine, Poland, Romania, the Netherlands, and Greece.

The term “Google medical update” refers to changes in Google’s algorithm starting on 1 August 2018 [100]. Results for these sequences of keywords allowed for collection of websites potentially affected by decreased visibility by the Google search engine. The new algorithm rewards websites with well-researched, accurate health and medical content and decreases the visibility of those whose content is lacking in terms of credibility [100].

The top 20 results returned by Google for the query “google medical update site:.cc” were examined and the author collected the list of websites as a convenient sample that could be the subject of further study. The steps for searching and examining results were repeated 10 times for each country, using the country-coded domain suffix. Table 1 shows a comprehensive list of found and selected websites for further examination.

In Table 1, Code refers to the country code used in the search query. Almost all of the websites collected use country-coded domain names; however, some websites use generic domain names such as “.com” or “.org” or others such as “.to,” which belongs to Tonga but in Polish means “.it.” Most websites use the official language; for example, Ukrainian websites are in Russian. Index size is the number of results displayed by the Google search engine for the search operator “site:website.” Although Google displays a maximum of 1000 results, this number is shown below the query and above the first results. It is a size indicator of the website and estimated number of pages that belong to one website. Index size was retrieved on 19 December 2019.

| Country       | Code | Website                          | Language | Index size |
|---------------|------|----------------------------------|----------|------------|
| Germany       | de   | bessergesundleben.de             | German   | 9260       |
| Germany       | de   | gesundheitsberater-berlin.de     | German   | 7730       |
| France        | fr   | docteurclic.com                  | French   | 8310       |
| France        | fr   | amelioretasante.com              | French   | 11,000     |
| United Kingdom| uk   | bmihealthcare.co.uk              | English  | 15,500     |
| United Kingdom| uk   | theprivateclinic.co.uk           | English  | 2790       |
| Italy         | it   | pazienti.it                      | Italian  | 85,400     |
Visibility in search engines is measured as the number of keywords, positions, and visible pages and can be used to compare competing organizations in one common area or industry [101,102]. The comparison will disclose the search market share of each compared organization [103]. Based on this comparison, further analysis of Internet strategies in marketing, sales, promotion, and publishing can be done. Visibility in search engines is always subject to algorithms that sort and set rankings of results based on type of content, metadata, and models of content creation [104–106].

In this study, the data did not originate from Google, but from external services. Data regarding visibility was retrieved through the commercial online tool Ahrefs [107]. This tool is specialized in retrieving and saving data about website visibility in search engines. Ahrefs, except to preserve basic visibility, imports additional data and develops its own visibility metrics. These data were used to compare search engine visibility of websites on health and medical information before and after they were affected by Google’s new update.

The method of collecting data from a search engine is called scraping. Usually search engines, in their terms of service, do not allow data scraping. However, it is impossible for search engines to differentiate scraping, when done very gently, from normal user search behavior. Users use search engines dozens of times a day, and only if the search engine recognizes different traffic from the user’s network can it ask for a CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) to solve, to prove that entered queries are not automated. Google does not share any download or export methods for results or provide an API for exporting search results. The only way to obtain data is to scrape them directly from the results. Scraping Google is against the terms of service. Online tools such as Ahrefs allow subscribed users to use scraped data. These tools use scraping on a large scale to obtain data from Google. The next section shows results from the visibility of the websites examined.

3. Results

The first step of the study was to collect data on the visibility of health and medical information websites. The list contains 21 websites that are popular in the 10 most populated European countries. Using Ahrefs, four data snapshots were retrieved. Each snapshot has a 5- or 6-month time interval. The collected data were run through a search visibility metric developed by Ahrefs, built on the number of keywords and positions and estimated click-through ratio. Data snapshots were taken with the following timestamps:

- Snapshot S1: 30 July 2018
- Snapshot S2: 1 January 2019
- Snapshot S3: 1 June 2019
- Snapshot S4: 30 November 2019
The visibility metric estimates the total monthly search traffic to the target website from the organic search results. It is calculated as the sum of traffic from all keywords for which the target website ranks in the search engine results page. The data retrieved are presented in Table 2.

The data retrieved have very large scope, which strongly depends on the index size in the Google search engine. Websites with more indexed pages have more chances to be visible in search results, because more particular webpages can be displayed. Visibility strongly depends on keywords, resulting in webpages being shown in search results. The more pages indexed from one website, the more keywords will result in a search engine results page.

Table 2. Visibility data of 21 websites considered as decreased by Google medical update.

| Website                                      | S1     | S2     | S3     | S4     |
|----------------------------------------------|--------|--------|--------|--------|
| bessergesunde.de                             | 399,758| 140,437| 139,965| 14,760 |
| gesundheitsberater-berlin.de                 | 45,200 | 21,670 | 20,603 | 28,465 |
| docteurclic.com                              | 712,711| 711,744| 154,889| 568,476|
| amelioretasante.com                         | 1,215,983| 17,454 | 231,230| 84,006 |
| bmihealthcare.co.uk                         | 93,293 | 62,312 | 65,098 | 66,319 |
| theprivateclinic.co.uk                      | 31,597 | 10,882 | 24,845 | 9,584  |
| pazienti.it                                  | 1,515,014| 1,691,641| 867,826| 694,602|
| farmacoecura.it                              | 3,008,684| 3,608,904| 2,434,143| 2,967,836|
| reproduccionsasistida.org                   | 643,038| 55,762 | 62,037 | 12,390 |
| lavidalucida.com                             | 383,920| 40,333 | 74,143 | 6,100  |
| doc.ua                                       | 266,285| 80,954 | 182,940| 187,664|
| likarni.com                                  | 143,864| 143,138| 87,398 | 125,360|
| poradnikzdrowie.pl                           | 12,592,643| 13,130,013| 4,821,490| 9,730,085|
| portal.abczdrowie.pl                         | 6,110,596| 3,018,926| 3,588,311| 1,489,164|
| wylecz.to                                    | 1,990,617| 2,401,242| 1,337,807| 1,146,077|
| csid.ro                                      | 1,894,383| 3,205,719| 438,859 | 1,655,861|
| sfatulmedicului.ro                           | 1,709,594| 1,165,206| 516,015 | 954,856 |
| ziektevrileven.nl                            | 5669   | 4605   | 2960   | 2219   |
| boerenmedical.nl                             | 7718   | 7620   | 9544   | 6229   |
| healthyliving.gr                             | 183,773| 371,273| 134,460| 162,141|
| medlabgr.blogspot.com¹                       | 157,154| 110,688| 72,118 | 85,238 |

¹ Visibility is measured for a subdomain.

In the second step of the study, data were normalized in a similar way to data presented in Google Trends. In GT, the most frequent keyword is set to a score of 100 and is used as an indicator. Other keywords are relative to this indicator and have scores between 1 and 100. In this dataset, all results for snapshot S1 were normalized to 100 and were used as the starting visibility indicator. Then, results from the next three snapshots were relative to the starting indicator. Results from four snapshots are presented in Figure 1.

Figure 1 is a boxplot illustrating that visibility decreased in the following time snapshots. Snapshot S1 was taken two days before Google announced changes in its algorithm for health and medical information websites. The value for each website was normalized to 100, which is why all descriptive statistics in Table 3 for snapshot S1 equal 100. Data from the second snapshot reveal that changes in Google’s algorithm were observed. In snapshot S2, five websites had increased visibility, one had the same, and 15 websites had decreased visibility in Google search engine results.
Descriptive statistics for snapshot S2 show a median of 70 and mean of 77.57, whereas previously both were 100.

In snapshot S3, decreased visibility is still observable. Only one website had higher visibility compared with the starting date. Other websites measured had further decreased visibility in Google search engine results. Descriptive statistics for snapshot S3 show a median of 52 and mean of 51.43. In snapshot S5, visibility stayed on the same level as in the previous timestamp. Parts of websites have better visibility than in S3, but the dataset still had lower visibility compared with the starting date.

![Figure 1. Boxplot presenting relative visibility values for 21 websites in snapshots.](image)

**Table 3.** Boxplot statistics for Figure 1.

|                      | S1  | S2  | S3    | S4  |
|----------------------|-----|-----|-------|-----|
| Upper whisker        | 100 | 202 | 124   | 99  |
| 3rd quartile         | 100 | 104 | 69    | 80  |
| Median               | 100 | 70  | 52    | 58  |
| 1st quartile         | 100 | 35  | 30    | 30  |
| Lower whisker        | 100 | 1   | 10    | 2   |
| No. of data points   | 21  | 21  | 21    | 21  |
| Mean                 | 100 | 77.57 | 51.43 | 53.57 |

1 Snapshot S1 is normalized to 100.

Table 3 presents descriptive boxplot statistics for all snapshots. It shows that visibility in the observed periods changed, and in this dataset, visibility decreased in snapshots S2 and S3. The last snapshot, S4, is very similar to the previous one.

It was stressed in Section 2 that visibility over a long period of time depends on many factors. Search engines take into account different factors found inside and outside websites and treat them as ranking signals. All of these factors over a long period of time influence websites’ visibility. In a shorter period of time, large changes in visibility are the effects of changes in Google’s ranking algorithm. This proves that the studied websites had decreased visibility after Google rolled out its medical update.
4. Discussion

The main finding of this study is that websites that did not meet high ranking criteria in terms of health and medical information were lowered in ranking since 1 September 2018. According to Google’s general guidelines, the search engine considers three areas of a website when rating the quality of a page [1]. The first is webpage content, by identifying main content, supplementary content, and advertisements. The second is understanding the website by finding the homepage, who is responsible for the website, and who created the page content, and finding sections on the page such as “about us,” contact information, or customer service information. The third is evaluating the reputation of the website or the creator of the main content by identifying sources of information on reputation and customer reviews of businesses. Page quality rating is based on how well the page achieves its purpose.

According to the results of this paper, the websites studied have lower visibility in the Google search engine. Since the exact criteria used by Google are not generally known (e.g., the current ranking algorithm is considered confidential), it is assumed that the main reason for the lower visibility is low-quality content. Low-quality websites may have been intended to serve a beneficial purpose. However, they do not achieve their purpose well because they lack an important dimension, such as having an unsatisfactory amount of main content, or because the creator of the main content lacks expertise for the purpose of the website.

The observed change in Google’s algorithm is about health and medical information websites. Until this change, this topic was unregulated. As the answer to research question 1, the author found that anyone can create health and medical content and publish it online. It does not need to be checked and corrected by a medical professional. Many people search for health and medical information using Google, and researchers use data on this from GT. However, content created without any professional supervision can be misleading and ultimately dangerous. Inaccurate information can cause unforeseen consequences such not visiting a doctor or having a false sense of security. That is why the most accurate, respected, and thoroughly researched health and medical content is displayed at the top of the search engine results.

To measure decreased visibility, it is necessary to have a sample of websites. All websites need to be measured at the same time with the same visibility metric. In this study, the author used Ahrefs data as the source of visibility. When sequential data snapshots reveal that calculated metrics are decreasing in each timestamp, it proves that visibility is decreasing. This was observed for 21 websites collected as a convenient sample for this study. The results show also that visibility does not depend on the country or language of the website, thus answering research question 2 as well.

To the best of the author’s knowledge, this is the first study to use data on search visibility on Google to assess the fluctuation of health and medical information websites in search engine results. Moreover, this is one of the first studies to compare Google visibility data between multiple countries and languages.

5. Conclusions

Google has very high page quality rating standards for YMYL pages, because low-quality YMYL pages could potentially have a negative impact on users’ happiness, health, financial stability, or safety [1]. In terms of medical and health information websites, medical advice should be written or produced by people or organizations with appropriate medical expertise or accreditation. Medical advice or information should be written or produced in a professional style and should be edited, reviewed, and updated on a regular basis.

It is possible to have everyday expertise in YMYL topics. For example, there are forums and support pages for people with specific diseases. Sharing personal experience is a form of everyday expertise. If forum participants tell others how long their loved ones lived with liver cancer, this is an example of sharing personal experience (in which they are experts), not medical advice. Specific medical information and advice (rather than descriptions of life experiences) should come from doctors or other health professionals. Formal expertise is important for topics such as health and medicine.
The strength of this work is in pointing out that the dominant search engine has started to rate health and medical information websites more rigorously than before. This approach can be observed using the method proposed in this work. The weakness of this work is that low quality was only assumed in manually examining these websites. Most of them offer pseudo therapies or health tips not sustained by scientific evidence, and even cooperate to provide a platform for distributing fake health tips.

This study has several limitations. First is that the observation was conducted in only one area. It does not reflect other types of information-centred websites under higher page quality ratings, such as financial, legal, or government sites. Two health and information websites from each country were the subject of the study; however, this sample size cannot adequately represent the whole area. To make the conclusions more convincing, data from more websites will be collected in the future. Second, the observation was conducted only for 10 European countries. This observation does not reflect online health and information websites in other countries globally. Data reflecting more countries will be collected in order to further investigate the role of Google’s medical update in online health and information websites. Third, although each health and information website was observed in terms of the same factors, there are still unobservable factors such as brand recognition across online webpages, which might influence their search visibility. Further studies will retrieve more data to address this issue.

One avenue of future research is to study how health and information websites are reacting to decreased visibility and measures they take to counteract this decrease. Another direction for future research is to study health and information websites for which visibility has increased and analyze which factors influenced the increase.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The author declares no conflict of interest.

**References**

1. Google General Guidelines; Google: Mountain View, CA, USA, 2019; pp. 1–166.
2. Toms, E.G.; Latter, C. How consumers search for health information. *Health Inform. J.* 2007, 13, 223–235.
3. Freeman, J.L.; Caldwell, P.H.Y.; Bennett, P.A.; Scott, K.M. How Adolescents Search for and Appraise Online Health Information: A Systematic Review. *J. Pediatr.* 2018, 195, 244–255.
4. Kim, H.; Park, S.-Y.; Bozeman, I. Online health information search and evaluation: Observations and semi-structured interviews with college students and maternal health experts. *Health Inf. Libr. J.* 2011, 28, 188–199.
5. Khoo, K.; Bolt, P.; Babil, F.E.; Jury, S.; Goldman, R.D. Health information seeking by parents in the Internet age. *J. Paediatr. Child Health* 2008, 44, 419–423.
6. Eysenbach, G.; Köhler, C. Health-related searches on the Internet. *JAMA* 2004, 291, 2946.
7. Mcinnes, N.; Haglund, B.J.A. Readability of online health information: Implications for health literacy. *Inform. Health Soc. Care* 2011, 36, 173–189.
8. Scullard, P.; Peacock, C.; Davies, P. Googling children’s health: Reliability of medical advice on the internet. *Arch. Dis. Child.* 2010, 95, 580–582.
9. Damman, O.C.; Hendriks, M.; Rademakers, J.; Delnoij, D.M.J.; Groenewegen, P.P. How do healthcare consumers process and evaluate comparative healthcare information? A qualitative study using cognitive interviews. *BMC Public Health* 2009, 9, 423.
10. Cooper, C.P.; Mallon, K.P.; Leadbetter, S.; Pollack, L.A.; Peipins, L.A. Cancer internet search activity on a major search engine, United States 2001–2003. *J. Med. Internet Res.* 2005, 7, 1–10.
11. Tang, H.; Ng, J.H.K. Googling for a diagnosis—Use of Google as a diagnostic aid: Internet based study. *BMJ* 2006, 333, 1143–1145.
12. Eysenbach, G. Infodemiology and Infoveillance: Framework for an Emerging Set of Public Health Inform. Methods to Analyze Search, Communication and Publication Behavior on the Internet. *J. Med. Internet Res.* 2009, 11, e11.
13. Chang, D.T.S.; Abouassaly, R.; Lawrentschuk, N. Quality of Health Information on the Internet for Urolithiasis on the Google Search Engine. *Adv. Urol.* 2016, 2016, 1–5.
14. Fahy, E.; Hardikar, R.; Fox, A.; Mackay, S. Quality of patient health information on the internet: Reviewing a complex and evolving landscape. *Australas. Med. J.* 2014, 7, 24–28.

15. Wang, Y.; Liu, Z. Automatic detecting indicators for quality of health information on the Web. *Internet J. Med. Inform.* 2007, 76, 575–582.

16. Dunne, S.; Cummins, N.M.; Hannigan, A.; Shannon, B.; Dunne, C.; Cullen, W. A Method for the Design and Development of Medical or Health Care Information Websites to Optimize Search Engine Results Page Rankings on Google. *J. Med. Internet Res.* 2013, 15, e183.

17. Kanthawala, S.; Vermeesch, A.; Given, B.; Huh, J. Answers to Health Questions: Internet Search Results Versus Online Health Community Responses. *J. Med. Internet Res.* 2016, 18, e95.

18. Dol, J.; Richardson, B.; Boates, T.; Campbell-Yeo, M. Learning to parent from Google? Evaluation of available online health evidence for parents of preterm infants requiring neonatal intensive care. *Health Inform. J.* 2019, 25, 1265–1277.

19. Prabhu, A.V.; Crihalmeanu, T.; Hansberry, D.R.; Agarwal, N.; Glaser, C.; Clump, D.A.; Heron, D.E.; Beriwal, S. Online palliative care and oncology patient education resources through Google: Do they meet national health literacy recommendations? *Pract. Radiat. Oncol.* 2017, 7, 306–310.

20. Fu, L.Y.; Zook, K.; Spoerh-Labutta, Z.; Hu, P.; Joseph, J.G. Search Engine Ranking, Quality, and Content of Web Pages That Are Critical Versus Noncritical of Human Papillomavirus Vaccine. *J. Adolesc. Health* 2016, 58, 33–39.

21. Ramos-Casals, M.; Brito-Zerón, P.; Kostov, B.; Sísó-Almirall, A.; Bosch, X.; Buss, D.; Trilla, A.; Stone, J.H.; Khamashta, M.A.; Shoenfeld, Y. Google-driven search for big data in autoimmune geoepidemiology: Analysis of 394,827 patients with systemic autoimmune diseases. *Autoimmun. Rev.* 2015, 14, 670–679.

22. Kamiński, M.; Loniewski, I.; Misera, A.; Mracic, W. Heartburn-Related Internet Searches and Trends of Interest across Six Western Countries: A Four-Year Retrospective Analysis Using Google Ads Keyword Planner. *Int. J. Environ. Res. Public Health* 2019, 16, 4591.

23. Abenhaim, H.A.; Baaazem, M. Google and Women’s Health-Related Issues: What Does the Search Engine Data Reveal? *Online J. Public Health Inform.* 2014, 6, e187.

24. Erinjeri, J.P.; Picus, D.; Prior, F.W.; Rubin, D.A.; Koppel, P. Development of a Google-Based Search Engine for Data Mining Radiology Reports. *J. Digit. Imaging* 2009, 22, 348–356.

25. Law, M.R.; Mintzes, B.; Morgan, S.G. The Sources and Popularity of Online Drug Information: An Analysis of Top Search Engine Results and Web Page Views. *Ann. Pharmacother.* 2011, 45, 350–356.

26. Soldaini, L.; Yates, A.; Yom-Tov, E.; Frieder, O.; Goharian, N. Enhancing web search in the medical domain via query clarification. *Inf. Retr.* 2016, 19, 149–173.

27. Wang, L.; Wang, J.; Wang, M.; Li, Y.; Liang, Y.; Xu, D. Using Internet Search Engines to Obtain Medical Information: A Comparative Study. *J. Med. Internet Res.* 2012, 14, e74.

28. Du, Z.; Xu, L.; Zhang, W.; Zhang, D.; Yu, S.; Hao, Y. Predicting the hand, foot, and mouth disease incidence using search engine query data and climate variables: An ecological study in Guangdong, China. *BMJ Open* 2017, 7, e016263.

29. Hanauer, D.A.; Wu, D.T.Y.; Yang, L.; Mei, Q.; Murkowski-Steffy, K.B.; Vydiswaran, V.G.V.; Zheng, K. Development and empirical user-centered evaluation of semantically-based query recommendation for an electronic health record search engine. *J. Biomed. Inform.* 2017, 67, 1–10.

30. Myrick, J.G. The role of emotions and social cognitive variables in online health information seeking processes and effects. *Comput. Hum. Behav.* 2017, 68, 422–433.

31. Palotti, J.; Hanbury, A.; Müller, H.; Kahn, C.E. How users search and what they search for in the medical domain. *Inf. Retr.* 2016, 19, 189–224.

32. Lauckner, C.; Hsieh, G. The presentation of health-related search results and its impact on negative emotional outcomes. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems-CHI ’13*; ACM: New York, NY, USA, 2013; pp. 333–342.

33. Lee, K.; Hoti, K.; Hughes, J.D.; Emmerton, L. Dr Google and the Consumer: A Qualitative Study Exploring the Navigational Needs and Online Health Information-Seeking Behaviors of Consumers With Chronic Health Conditions. *J. Med. Internet Res.* 2014, 16, e262.

34. Kammerer, Y.; Amann, D.G.; Gerjets, P. When adults without university education search the Internet for health information: The roles of Internet-specific epistemic beliefs and a source evaluation intervention. *Comput. Hum. Behav.* 2015, 48, 297–309.
35. Kammerer, Y.; Gerjets, P. Effects of search interface and Internet-specific epistemic beliefs on source evaluations during Web search for medical information: An eye-tracking study. *Behav. Inf. Technol.* 2012, 31, 83–97.

36. Sharit, J.; Taha, J.; Berkowsky, R.W.; Profita, H.; Czaja, S.J. Online Information Search Performance and Search Strategies in a Health Problem-Solving Scenario. *J. Cogn. Eng. Decis. Mak.* 2015, 9, 211–228.

37. Hernández, M.A.; Sharit, J.; Pirolli, P.; Czaja, S.J. Adapting Information Search Tools for use by Health Consumers: Challenges and Lessons for Software Designers. *Int. J. Hum. Comput. Interact.* 2018, 34, 445–456.

38. Pang, P.C.-I.; Verspoor, K.; Chang, S.; Pearce, J. Conceptualising health seeking behaviours and exploratory search: Result of a qualitative study. *Health Technol.* 2015, 5, 45–53.

39. Kothari, M.; Moolani, S. Reliability of “Google” for obtaining medical information. *Indian J. Ophthalmol.* 2015, 63, 267.

40. Cocco, A.M.; Zordan, R.; Taylor, D.M.; Weiland, T.J.; Dilley, S.J.; Kant, J.; Dombagolla, M.; Hendarto, A.; Lai, F.; Hutton, J. Dr Google in the ED: Searching for online health information by adult emergency department patients. *Med. J. Aust.* 2018, 209, 342–347.

41. Lupton, D.; Maslen, S. How Women Use Digital Technologies for Health: Qualitative Interview and Focus Group Study. *J. Med. Internet Res.* 2019, 21, e11481.

42. Diviani, N.; Fredriksen, E.H.; Meppelink, C.S.; Mullan, J.; Rich, W.; Sudmann, T.T. Where else would I look for it? A five-country qualitative study on purposes, strategies, and consequences of online health information seeking. *J. Public Health Res.* 2019, 8, 33–39.

43. Arora, V.S.; McKee, M.; Stuckler, D. Google Trends: Opportunities and limitations in health and health policy research. *Health Policy (N. Y.)* 2019, 123, 338–341.

44. Ginsberg, J.; Mohebbi, M.H.; Patel, R.S.; Brammer, L.; Smolinski, M.S.; Brilliant, L. Detecting influenza epidemics using search engine query data. *Nature 2009*, 457, 1012–1014.

45. Nuti, S.V.; Wayda, B.; Ransasinghe, I.; Wang, S.; Dreyer, R.P.; Chen, S.J.; Murugiah, K. The Use of Google Trends in Health Care Research: A Systematic Review. *PLoS ONE* 2014, 9, e109583.

46. Mavragani, A.; Ochoa, G.; Tsagarakis, K.P. Assessing the Methods, Tools, and Statistical Approaches in Google Trends Research: Systematic Review. *J. Med. Internet Res.* 2018, 20, e270.

47. Pelat, C.; Turbelin, C.; Bar-Hen, A.; Flahault, A.; Valleron, A.-J. More Diseases Tracked by Using Google Trends. *Emerg. Infect. Dis.* 2009, 15, 1327–1328.

48. Seifert, A.; Schwarzwaldler, A.; Geis, K.; Aucott, J. The utility of “Google Trends” for epidemiological research: Lyme disease as an example. *Geospat. Health* 2010, 4, 135.

49. Alcino, C.; Bragazzi, N.L.; Faccio, V.; Amici, D.; Panatto, D.; Gasparini, R.; Icardi, G.; Orsi, A. Assessing Ebola-related web search behaviour: Insights and implications from an analytical study of Google Trends-based query volumes. *Infect. Dis. Poverty* 2015, 4, 54.

50. Young, S.D.; Torrone, E.A.; Urata, J.; Aral, S.O. Using Search Engine Data as a Tool to Predict Syphilis. *Epidemiology* 2018, 29, 574–578.

51. Deiner, M.S.; McLeod, S.D.; Wong, J.; Chodos, J.; Lietman, T.M.; Porco, T.C. Google Searches and Detection of Conjunctivitis Epidemics Worldwide. *Ophthalmolavim* 2019, 126, 1219–1229.

52. Husnayain, A.; Fuad, A.; Lazuardi, L. Correlation between Google Trends on dengue fever and national surveillance report in Indonesia. *Glob. Health Action* 2019, 12, 1552652.

53. Ayers, J.W.; Althouse, B.M.; Allem, J.-P.; Rosenquist, J.N.; Ford, D.E. Seasonality in Seeking Mental Health Information on Google. *Am. J. Prev. Med.* 2013, 44, 520–525.

54. Tana, J.C.; Kettunen, J.; Iirola, E.; Paakkonen, H. Diurnal Variations of Depression-Related Health Information Seeking: Case Study in Finland Using Google Trends Data. *JMIR Ment. Health* 2018, 5, e43.

55. Bloom, R.; Amber, K.T.; Hu, S.; Kirsner, R. Google Search Trends and Skin Cancer: Evaluating the US Population’s Interest in Skin Cancer and Its Association With Melanoma Outcomes. *JAMA Dermatol.* 2015, 151, 903–905.

56. Hopkins, Z.H.; Secrest, A.M. Public Health Implications of Google Searches for Sunscreen, Sunburn, Skin Cancer, and Melanoma in the United States. *Am. J. Health Promot.* 2019, 33, 611–615.

57. Hopkins, Z.H.; Secrest, A.M. An international comparison of Google searches for sunscreen, sunburn, skin cancer, and melanoma: Current trends and public health implications. *Photodermatol. Photoimmunol. Photomed.* 2019, 35, 87–92.

58. Kardeş, S.; Kardeş, E. Seasonality of bruxism: Evidence from Google Trends. *Sleep Breath.* 2019, 23, 695–701.
59. Moccia, M.; Palladino, R.; Falco, A.; Saccà, F.; Lanzillo, R.; Brescia Morra, V. Google Trends: New evidence for seasonality of multiple sclerosis. *J. Neurol. Neurosurg. Psychiatry* **2016**, *87*, 1028–1029.

60. Foroughi, F.; Lam, A.K.-Y.; Lim, M.S.; Saremi, N.; Ahmadvand, A. “Googling” for Cancer: An Infodemiological Assessment of Online Search Interests in Australia, Canada, New Zealand, the United Kingdom, and the United States. *JMIR Cancer* **2016**, *2*, e5.

61. Ling, R.; Lee, J. Disease Monitoring and Health Campaign Evaluation Using Google Search Activities for HIV and AIDS, Stroke, Colorectal Cancer, and Marijuana Use in Canada: A Retrospective Observational Study. *JMIR Public Health Surveill.* **2016**, *2*, e156.

62. Young, S.D.; Zhang, Q. Using search engine big data for predicting new HIV diagnoses. *PLoS ONE* **2018**, *13*, e0199527.

63. Radin, M.; Sciascia, S. Infodemiology of systemic lupus erythematosus using Google Trends. *Lupus* **2017**, *26*, 886–889.

64. Osaka, H.; Hall, A.J.; Wikswo, M.E.; Baker, J.M.; Lopman, B.A. Temporal Relationship Between Healthcare-Associated and Nonhealthcare-Associated Norovirus Outbreaks and Google Trends Data in the United States. *Infect. Control Hosp. Epidemiol.* **2018**, *39*, 355–358.

65. Jabaley, C.S.; Blum, J.M.; Groth, R.F.; O’Reilly-Shah, V.N. Global trends in the awareness of sepsis: Insights from search engine data between 2012 and 2017. *Crit. Care* **2018**, *22*, 7.

66. Gianfredi, V.; Bragazzi, N.L.; Mahamid, M.; Bisharat, B.; Mahroum, N.; Amital, H.; Adawi, M. Monitoring public interest toward pertussis outbreaks: an extensive Google Trends–based analysis. *Public Health* **2018**, *165*, 9–15.

67. Urfal, A.A.; Dubal, P.M.; Pfaff, J.A.; Friedel, M.E.; Eloy, J.A.; Kountakis, S.E. Doctor Google: Correlating internet search trends for epistaxis with metropolitan climates. *Am. J. Otolaryngol.* **2019**, *40*, 358–363.

68. Bragazzi, N.L.; Mahroum, N. Google Trends Predicts Present and Future Plague Cases During the Plague Outbreak in Madagascar: Infodemiological Study. *JMIR Public Health Surveill.* **2019**, *5*, e13142.

69. Wu, G.-C.; Tao, S.-S.; Zhao, C.-N.; Mao, Y.-M.; Wu, Q.; Dan, Y.-L.; Pan, H.-F. Leveraging Google Trends to investigate the global public interest in rheumatoid arthritis. *Rheumatol. Int.* **2019**, *39*, 1439–1444.

70. Cacciamani, G.E.; Bassi, S.; Sebben, M.; Marcer, A.; Russo, G.L.; Cocci, A.; Dell’Oglio, P.; Medina, L.G.; Nassiri, N.; Tafuri, A.; et al. Consulting “Dr. Google” for Prostate Cancer Treatment Options: A Contemporary Worldwide Trend Analysis. *Eur. Urol. Onkol.* **2019**, doi:10.1016/j.euo.2019.07.002.

71. Schuster, N.M.; Rogers, M.A.M.; McMahon, L.F. Using search engine query data to track pharmaceutical utilization: A study of statins. *Am. J. Manag. Care* **2010**, *16*, e215–e219.

72. Berlinberg, E.J.; Deiner, M.S.; Porco, T.C.; Acharya, N.R. Monitoring Interest in Herpes Zoster Vaccination: Analysis of Google Search Data. *JMIR Public Health Surveill.* **2018**, *4*, e10810.

73. Brigo, F.; Erro, R. Why do people google movement disorders? An infodemiological study of information seeking behaviors. *Neurol. Sci.* **2016**, *37*, 781–787.

74. Cervellin, G.; Comelli, L.; Lippi, G. Is Google Trends a reliable tool for digital epidemiology? Insights from different clinical settings. *J. Epidemiol. Glob. Health* **2017**, *7*, 185–189.

75. Dreher, P.C.; Tong, C.; Ghiraldi, E.; Friedlander, J.I. Use of Google Trends to Track Online Behavior and Interest in Kidney Stone Surgery. *Urology* **2018**, *121*, 74–78.

76. Telfer, S.; Woodburn, J. Let me Google that for you: A time series analysis of seasonality in internet search trends for terms related to foot and ankle pain. *J. Foot Ankle Res.* **2015**, *8*, 27.

77. Dewan, V.; Sur, H. Using google trends to assess for seasonal variation in knee injuries. *J. Arthrosc. Jt. Surg.* **2018**, *5*, 175–178.

78. Jellison, S.S.; Bibens, M.; Checketts, J.; Vassar, M. Using Google Trends to assess global public interest in osteoarthritis. *Rheumatol. Int.* **2018**, *38*, 2133–2136.

79. Zhang, X.; Dang, S.; Ji, F.; Shi, J.; Li, Y.; Li, M.; Jia, X.; Wan, Y.; Bao, X.; Wang, W. Seasonality of cellulitis: Evidence from Google Trends. *Infect. Drug Resist.* **2018**, *11*, 689–693.

80. Zhang, Y.; Bambrick, H.; Mengersen, K.; Tong, S.; Hu, W. Using Google Trends and ambient temperature to predict seasonal influenza outbreaks. *Environ. Int.* **2018**, *117*, 284–291.

81. McLean, S.; Lennon, P.; Glare, P. Internet search query analysis can be used to demonstrate the rapidly increasing public awareness of palliative care in the USA. *BMJ Support. Palliat. Care* **2019**, *9*, 40–44.

82. Tijerina, J.D.; Morrison, S.D.; Nolan, I.T.; Vail, D.G.; Lee, G.K.; Nazerali, R. Analysis and Interpretation of Google Trends Data on Public Interest in Cosmetic Body Procedures. *Aesthet. Surg. J.* **2019**, *40*, 1–10.
83. Niforatos, J.D.; Feinstein, M.M.; Pescatore, R.M. Search engine queries as a metric of public interest in anesthesia. *Anaesth. Intensive Care* 2019, 47, 302–304.

84. Kandula, S.; Pei, S.; Shaman, J. Improved forecasts of influenza-associated hospitalization rates with Google Search Trends. *J. R. Soc. Interface* 2019, 16, 20190080. doi: /10.1098/rsif.2019.0080

85. Clemente, L.; Lu, F.; Santillana, M. Improved Real-Time Influenza Surveillance: Using Internet Search Data in Eight Latin American Countries. *JMIIR Public Health Surveill.* 2019, 5, e12214.

86. Hao, Z.; Liu, M.; Ge, X. Evaluating the impact of health awareness events on Google search frequency. *Prev. Med. Rep.* 2019, 15, 100887.

87. Strzalecki, A. Google Web and Image Search Visibility Data for Online Store. *Data* 2019, 4, 125.

88. Brin, S.; Page, L. The Anatomy of a Large-Scale Hypertextual Web Search Engine The Anatomy of a Search Engine. *Comput. Netw. ISDN Syst.* 1998, 30, 107–117.

89. Page, L.; Brin, S.; Motwani, R.; Winograd, T. *The PageRank Citation Ranking: Bringing Order to the Web*; World Wide Web Internet Web Information System; Stanford InfoLab.: Stanford, CA, USA, 1998.

90. Kleinberg, J.M. Authoritative sources in a hyperlinked environment. *J. ACM* 1999, 46, 604–632.

91. Serrano, W. Neural Networks in Big Data and Web Search. *Data* 2019, 4, 7.

92. Ziakis, C.; Vlachopoulou, M.; Kyrkoudis, T.; Karagkiozidou, M. Important factors for improving Google search rank. *Futur. Internet* 2019, 11, 32.

93. Evans, M.P. Analysing Google rankings through search engine optimization data. *Internet Res. 2007, 17*, 21–37.

94. Strzalecki, A.; Rutecka, P. The Snippets Taxonomy in Web Search Engines. In *Perspectives in Business Informatics Research*; Parikowska, M., Sandkuhl, K., Eds.; Springer: Champagne, IL, USA, 2019; Volume 365, pp. 177–188, ISBN 978-3-030-31143-8.

95. Bifet, A.; Castillo, C.; Chirita, P.-A.; Weber, I. An analysis of factors used in search engine ranking. In Proceedings of the 4th International World Wide Web Conference, Chiba, Japan, 10–14 May 2005.

96. Agichtein, E.; Brill, E.; Dumais, S. Improving Web Search Ranking by Incorporating User Behavior Information. *ACM SIGIR Forum* 2019, 52, 11–18.

97. Strzalecki, A. Website removal from search engines due to copyright violation. *Aslib J. Inf. Manag.* 2019, 71, 54–71.

98. Dotson, J.P.; Fan, R.R.; Feit, E.M.; Oldham, J.D.; Yeh, Y.-H. Brand Attitudes and Search Engine Queries. *J. Interact. Mark.* 2017, 37, 105–116.

99. Gyöngyi, Z.; Garcia-Molina, H.; Pedersen, J. Combating Web Spam with TrustRank. In *Proceedings 2004 VLDB Conference*; Elsevier: Amsterdam, The Netherlands, 2004; pp. 576–587.

100. Sullivan, D. Google Core Update. Available online: https://twitter.com/searchliaison/status/102469187202533472 (accessed on 1 December 2019).

101. Dickinson, Z.; Smit, M. Canadian public libraries and search engines: Barriers to visibility. *Aslib J. Inf. Manag.* 2016, 68, 589–606.

102. Baye, M.R.; De los Santos, B.; Wildenbeest, M.R. Search Engine Optimization: What Drives Organic Traffic to Retail Sites? *J. Econ. Manag. Strateg.* 2016, 25, 6–31.

103. French, R.B.; Fagan, J.C. The Visibility of Authority Records, Researcher Identifiers, Academic Social Networking Profiles, and Related Faculty Publications in Search Engine Results. *J. Web Librariansh.* 2019, 13, 156–197.

104. Zhang, J.; Dimitroff, A. The impact of webpage content characteristics on webpage visibility in search engine results (Part I). *Inf. Process. Manag.* 2005, 41, 665–690.

105. Killoran, J.B. How to Use Search Engine Optimization Techniques to Increase Website Visibility. *IEEE Trans. Prof. Commun.* 2013, 56, 50–66.

106. Miklosik, A.; Evans, N.; Zak, S.; Lipianska, J. A framework for constructing optimisation models to increase the visibility of organisations’ information in search engines. *Inf. Res.* 2019, 24, 808.

107. Ahrefs-SEO Tools & Resources to Grow Your Search Traffic. Available online: https://ahrefs.com/ (accessed on 2 December 2019).

© 2020 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).