JoCTEC: Journal of Communication Technology (ISSN: 2694-3883)

Published by the Communication Technology Division
of the Association for Education in Journalism and Mass Communication

OK, Google, Tell me about Birth Control: Sentiment Analysis of Anti- and Pro- Birth Control Headlines and Snippets

Anna Young[a], Kenneth A. Lachlan[a], and Robert C. Young

[a] University of Connecticut, Mansfield, Connecticut, USA
Correspondence: anna.2.young@uconn.edu

Abstract

Drawing on Language Expectancy Theory and Extended Parallel Process Model, the study aims to explore the difference between anti- and pro-birth control information available online by comparing word usage, sentiments and online popularity of anti- and pro-birth control headlines and snippets returned by Google Search engine. Findings indicated that anti-birth control entries used more emotional words, especially those communicating fear. Headlines and snippets with words communicating positive emotions were more popular on Facebook. In more than half of the cases, the headlines and snippets returned by Google were communicating conflicting messages about benefits and dangers of birth control. The implications of the results of this study for digital practitioners, healthcare workers and online consumers of health-related information are discussed.

Keywords: birth control, Google Search, sentiments analysis, text mining, well-being

Introduction

64.9% of women between 15-49 years of age reported having used birth control (Centers for Disease Control and Prevention, 2019). When it comes to finding information about a health-related issue in general, or more specifically, what contraceptive method to start with, the Internet has emerged as the most popular method given its immediacy and ease of access (Morahan-Martin, 2004). More than half of U.S. adults use the Internet as their main source of health-related information (National Cancer Institute, 2018). Yet, little is known about the framing of these online messages or what one can expect to find when searching using popular search engines. This is important for two reasons. First, understanding how the conversation on the birth control topic is framed through Google results can be the first step to finding effective strategies for communicating information fully and accurately, targeting people who are already looking for this information. Second, birth control is a rather controversial topic. Together with abortion, it has been used in political narratives to steer people to support one political party versus another. As a result, the Internet contains misinformation or scientifically inaccurate information on the topic. Such information online can mislead people's opinion about birth control. This can also lead to resistance to doctors' recommendations (Andaya, 2019).

The headlines and web-page snippets (Steiner, Troncy & Hausenblas, 2010) were chosen for the analysis because these two elements of Google Search results are the first things users see when they start their search for health-related information online to decide whether they should continue reading on the website. Headlines can affect existing knowledge or mindset about the issue and perhaps more importantly, the later recall of the details (Surber & Schroeder, 2006; Lewandowsky, Ecker, Seifert, Schwarz & Cook, 2012).

Overall, the current study hopes to address questions regarding the types of birth control related information in Google Search results, language bias and output characteristics of the search results that lead to Facebook interactions and thus help to spread the message further. Health professionals and educators who are trying to increase the accuracy of information about birth control will find this study especially useful.

Literature Review

Online Health Information about Birth Control

With the increasing use of the Internet for finding health information, there are more discussions about the scientific accuracy of the results returned by search engines (Lempert, 1995; Silberg, Lundberg & Mussacchio, 1997; Morahan-Martin and Anderson, 2000; Gilliam, Warden, Goldstein & Tapia, 2004; Morahan-Martin, 2004; de Freitas, Falls, Haque & Bursztajn, 2013). It might be troublesome considering that for adolescents Internet sources are the most common source of birth control and sex-related information (Borzekowski & Rickert, 2001).

Biased information can lead to hesitation and lower trust in recommendations given by medical professionals and interventions aimed to correct misperceptions have not been very successful (Moran, Lucas, Everhart, Morgan & Prickett, 2016). Once incorrect information is spread among the populous, it is very hard to correct it completely (Lewandowsky, Ecker, Seifert, Schwarz & Cook, 2012). It has been argued that manipulative and one-sided information about birth control is in abundance online (Pruitt & Mullen, 2005; Jaworski, 2009; Diamond-Smith, Campbell & Madan, 2012; Bryant, Narasimhan, Bryant-Comstock & Levi, 2014). Jaworski (2009) discovered a divisive and contradicting representation of birth control topics in popular media. Both in popular music and TV shows, negative and anti-birth control motives were emphasized. Women who chose to use birth control were portrayed negatively without much reasoning. The researchers also found misinformation about reproductive healthcare and reinforcement of negative stereotypes about women who used birth control (Jaworski, 2009).

In their analysis of the presentation of birth control topics on pregnancy resource center websites, Swartzendruber, Steiner, and Newton-Levinson (2018) found that most websites in their sample, “presented skewed information that could undermine confidence in the safety and efficacy of contraceptive methods and discourage the use” (p. 234). Using empirical methods, the authors demonstrated that webpages that talked about birth control emphasized risks and side effects. The authors concluded that they found a, “high degree of inaccurate and misleading information,” about birth control (Swartzendruber, Steiner & Newton-Levinson, 2018, p. 236).

Researchers looking at the quality and framing of birth control information in other languages found similar trends (Neumark, Flum, Lopez-Quintero & Shtarkshall, 2012). For example, Hebrew-language websites that contained birth control related information had a mean score of 50.9% for accuracy and completeness, as rated by the researchers, providing bias and inaccurate information on some aspects of birth control use. The authors noted that many of the websites in the sample were missing credible information like the source, citations, references or funding information (Neumark, Flum, Lopez-Quintero & Shtarkshall, 2012).

Marketing and advertising messages about birth control are a good example of how word choice and verbal presentation of information in general can impact attitudes about the products described (Knox et al., 2013). In their study, Knox and colleagues demonstrated how word choice in birth control related messages manipulated, “logically equivalent information,” (p. 71) as perceived by the readers.

This brings up an important question about the qualities of some information that makes the audience accept it without questioning. Emotions play a role in attitude development (Buck, Anderson, Chaudhuri & Ray, 2004). The researchers suggested that consideration of emotional factors may be useful in the promotion of different types of attitudes. Emotional language may lead to stronger emotional responses and behavioral intentions (Wolfe, Sharp & Lipsky, 2002). Also, if the topic discussed indicates a threat or hazard, relying on rational judgments may not produce the desired reaction (Buck, Anderson, Chaudhuri, and Ray, 2004). In fact, researchers looking at the persuasive features of inaccurate anti-vaccine messages have found that negative emotional narrative increases persuasive power of the message (Kata, 2010). For example, reading about kids dying after getting a vaccine leads to a strong emotional response among audiences and a decision not to study the subject further and not to vaccinate kids.

Language Expectancy Theory (LET)

LET describes how a message meeting or violating language patterns can influence the reader’s perception of the message (Burgoon, 1995). It relates to how the message features (e.g. word choice, intensity, negativity) can be used to support the stereotypical expressions of the issue. When expectations are violated, message persuasiveness either increases or decreases (Burgoon et. al, 2007).

LET has been successfully applied to health communication. More specifically, researchers started looking at not just if the content of the message violated expectations, but also whether the framing, language and other features of the message go against or are in-line with the established expectations when talking about a particular issue. Several studies have demonstrated the effect of the use of emotional language in health decision-making. The effect of emotional words usage, anticipated worry and regret are powerful predictors of changes in some health behaviors (Chapman & Coups, 2006; Lawton et. al., 2009). Language intensity has been found effective in enhancing the effect of sun protection messages delivered by a doctor (Buller, Borland & Burgoon, 1998). The researchers found that physicians who used words that conveyed stronger emotions when communicating to parents about the importance of applying sunscreen on their kids were more successful in achieving the desired effect. LET explains that people tend to use harsh language and exaggerate facts with the sole purpose to increase the emotional intensity of the message influencing readers' perception and decisions (Burgoon, Jones & Stewart, 1975). In an attempt to achieve positive violation and stronger persuasive effect as explained by LET, messages based on rumors are heavily skewed (bias), or bluntly false information contain, "more negative sentiments and adverse emotional words," (Ajao, O., Bhowmik, D. & Zargari, S., 2019, p. 2510) when compared to the reserved impassionate language of the fact-based informative messages (Zhou, Burgoon, Nunamaker & Twitchell, 2004). This adjustment in language was found to increase trust and persuasiveness of bias messages. More specifically, words communicating negative emotions are more often used in messages containing misinformation and manipulative content (van Kleef et. al., 2011; van Kleef, den Berg & Heerdink, 2015). Since anti-birth control content is likely manipulative and less likely to be based in fact, it follows logically that it will contain more emotional content. Thus, to extend previous research in the area, the following hypothesis and research question are proposed:

H1: Anti-birth control titles and snippets include more emotional words than pro-birth control titles and snippets.

RQ1: Is there a pattern of word usage for anti- and pro- birth control titles and snippets?

Extended Parallel Process Model

If pro- and anti-birth control content differs in its reliance on emotional content, this raises the question of the persuasive power of induced emotion and what specific emotions will most effectively elicit responses. A number of studies have looked at the effect of the induction of fear on the effectiveness of persuasive messages. Witte (1992) calls them "fear appeal" messages because their purpose is to scare people by describing awful things that will happen to them if they do or do not follow the warning in the message. Common birth control-related fear messages have been extensively used by some government officials to influence women's opinions about birth control. For example, Katy Talento appointed to the White House Domestic Policy Council in 2017 was actively spreading false claims that the pill was ruining female reproductive organs (Cohen, 2017). Another government official, Teresa Manning who was appointed to lead the Department of Health and Human Service in 2017, was trying to popularize a false claim that contraception does not work and permanently damages female organs (Cohen, 2017).

Fear is one of the primary message effects, along with happiness, sadness, anger and disgust (Tomkins, 1962; Izard, 1971; Ekman &

Friesen, 1972). Certain objects, as well as everything that is associated with them, can become fear stimuli according to Buck (2014). They can become negative incentives. When exposed to them, people respond with anxiety and avoidance. Festinger (1957) proposed that cognition about the self is stronger than about the environment. This suggests that our feelings and emotions may influence our attitude. If one feels scared about something, he/she will find elements in the environment to explain this fear even if it is not there (Buck, 2014).

Witte (1992) offers the Extended Parallel Process Model (EPPM) which includes the level of perceived efficacy by the consumer of the information (e.g. how likely it is that the reader will be able to follow the recommendations in the message to avoid the negative outcomes described). In brief, EPPM focuses on the perceived threat, which impacts the intensity of the reaction to the message and the degree of perceived efficacy which determines the nature of the reaction. Applying EPPM to the current research, the persuasiveness of the Google Search results might depend on the relation of the level of fear they are invoking (e.g. those taking birth control might have high chances of getting cancer) to their recommended actions to avoid the described outcome (e.g. not to take birth control). However, long before Witte (1992) developed EPPM, Janis (1967) proposed that the message was the most persuasive when the level of fear was moderate. Extreme levels of fear increase, “maladaptive responses, such as defensive avoidance” (Janis, 1967; Popova, 2012). This argument was embedded in EPPM through what Witte (1992) called a, “critical point,” (Witte, 1994; Witte, 1998) at which the level of fear becomes higher than the level of efficacy perception. In this case, the receivers of the message decide that there is nothing they can do to prevent the threat, and fear will dominate (Witte, 1992). This is when people will deny the threat and do exactly what the message is trying to scare them off from doing. Witte (1992) called this a boomerang effect. Taken together, a moderate level of fear is ideal for inducing attitude change (Popova, 2012). A meta-analysis, which examined fear appeal literature, suggests that strong fear appeals produce high levels of perceived severity, susceptibility and were found to be more effective than low or weak fear appeals (Witte & Allen, 2000).

Scholars point at conspiracy theories when talking about misleading messages that use fear appeal and have a significant effect on people's decision-making (Douglas et. al., 2019). A popular conspiracy theory about birth control is a claim that medical institutions try out new birth control methods on people without their consent and the government knows but does not tell accurate information about side effects. Another popular conspiracy theory is that the government uses birth control as a way to sterilize women and better control population among the poor and minorities (Thorburn & Bogart, 2005).

Applying these findings from fear appeal literature to the birth control headlines and snippets, we speculate that messages that are trying to create a negative attitude toward the topic in general or a particular birth control method will utilize fear language more often, in an effort to intensify threat perceptions and induce attitude change. To that end, the following hypothesis is proposed:

> **H2**: Anti-birth control headlines and snippets are more likely to use fear-related words than pro-birth control ones.

The Theory of Signals

Readers decide if a certain text is worth interacting with (e.g. reading, commenting, sharing on social networks) based on certain signals, according to the theory of signals (Zmud, Croes, Shaft & Zheng, 2010). Mayer (1975) originally defined signals as the elements of the text's organization which emphasize some of its aspects. Signaling devices in texts direct the reader's attention and guide the recall of some elements of text versus others (Lorch, 1989). In print, signals can be titles, cross-references, font size, type, emotional language, etc. (Lemarie, Lorch, Eyrolle & Virbell, 2008). There are even more signals in the online environment where it is easier to find and interpret them (e.g. likes, shares, comments, views). Words communicating emotions can be used as signals, too. The use of words with negative sentiments, especially those evoking anger, has been found to generate more web traffic (Berger, 2012). However, the specific impact of signaling devices on web traffic (e.g. "clicks-throughs") in health contexts has gone largely unstudied. In light of limited research in this area, the following research question is proposed:

> **RQ2**: What is the relationship between sentiments used and the number of interactions on Facebook of Google Search results?

Google Search Results

Initially, Google introduced rich snippet results to show the most important information related to the query to, "enrich the search results" (Steiner, Troncy & Hausenblas, 2010). Later, the system was modified, and now the user receives snippet results that are supposed to be a direct answer to the questions searched (Strzelecki & Rutecka, 2019). However, snippet results sometimes are not full sentences and other times are more of a combination of phrases from the website. This can be explained by how snippets are created. The search engine usually uses information provided by the developer of the website when formulating snippet results (Armano, Giuliani & Vargiu, 2012). However, if the information provided is not considered helpful by the search engine, it might replace it with its own description of the site to better match the search query (Armano, Giuliani & Vargiu, 2012). Based on this, we propose the following research question:

> **RQ3:** Is there a difference in the direction (pro- versus anti-) between titles and corresponding snippets of the entries about birth control returned Google Search results?

Methods

Text Mining and Sentiment Analysis

Content-analysis is a commonly used research method for analyzing the quality and potential effect of health information in media (Kruvand, 2012; Gurman & Clark, 2016; Oedingen, Scholz & Razum, 2018). It was noticed that in the cases when researchers were looking at messages on social media sites they relied on programs and services that could easily collect this kind of data for a minimal fee. However, when looking at other types of messages, like titles in newspapers or even newspaper articles, the search in most cases was performed manually. In these cases, the total N was much smaller. To avoid any potential human errors, and to maximize the collection of all data available for the specified time frame, the current study employed text mining and semantic analysis. This method will be utilized to see the difference between birth control results returned by Google Search in the form of headlines and snippets.

Text mining is the process of locating, collecting and identifying patterns and relationships in a large body of textual data (Feldman & Sanger, 2008; Mihalcea, 2008). It is an effective technique that helps to see word usage patterns (Younis, 2015). Text mining is closely connected with semantic analysis because computer algorithms detect semantic patterns of the words used or of the text in general. It helps to identify if, in general, the message is conveying a certain emotion (Silge & Robinson, 2017). Sentiment analysis has been widely used in marketing, political, crisis and health communication research (Sufian and Anantharaman, 2011; Taboada, et. al., 2011; Cambria et al., 2012). It is based on the categorization of words or phrases found within a bigger body of text, like a message or an article. Turner (2002) was among the first researchers who refined the application of sentiment analysis to online comments. Hopper and Uriyo (2013) could not find any papers on health-related topics that used sentiment analysis. Their prognosis was that the situation was going to change as more people would be discussing health topics online, and sentiment analysis was a good method to study and predict opinions on the Internet. Indeed, since then, more scholars have relied on this method (Graves et al., 2013; Mazzocut et al, 2016; Xu & Guo, 2018).

NRC Emotion Lexicon

Semantic analysis uses an existing emotion lexicon to identify emotions conveyed by the text. For the current research, we used the National Research Council of Canada (NRC) lexicon. Mohammad and Turney (2010) used Mechanical Turk to ensure that human coders were able to identify emotions communicated by words more accurately. The lexicon that they created contains more than 14,000 English words annotated according to Plutchik's wheel of emotions (Plutchik, 1980). The NRC lexicon focuses on eight emotions: joy, trust, sadness, anger, surprise, fear, anticipation and disgust. For the purpose of the current study, we used the NRC lexicon to detect the use of emotional language. Originally, NRC lexicon was developed for evaluating short online messages, like forum posts or tweets.

Identifying Search Words and Search Engines

Google.com was chosen because it is the most popular search engine in the world. In the United States, where the search was performed, Google has 87.3% of the market share (Capala, 2018). The scholars removed the search history and cookies before each search to ensure that previous searches did not affect the subsequent queries. Additionally, the researchers logged out of their Google accounts. A two-tiered approach was applied to determine the search terms. At first, a very general Google Search was performed using the terms "birth control" and "contraception" to determine what a general broad search would return. It is very representative since previous research on online health information searches indicates that people often start their search with broader terms especially when they are not sure about the details needed to narrow their search. After the initial search during which they learn a bit more on the topic, they refine their search using more specific words (Eysenbach & Kohler, 2002; Hansen, Derry, Resnick & Richardson, 2003; Morris, Teevan & Panovich, 2010). Google's PageRank procedure is also important for this first stage. The search engine ranks the results based on the number of links to the page (Facts about Google and competition, 2010). During the second stage of the research, we used the most popular words and phrases detected on the first stage in Google Trends to identify related popular search terms. Eventually, 12 most often used search queries on the topic were identified: "Birth control" danger, "Birth control" disorder, "Birth control" risk, "Birth control" hidden, "Birth control" disease, "Birth control" secret, "Birth control" effective, "Birth control" knowledge, "Birth control" fact, "Birth control" information, "Birth control" safe and "Birth control" benefit.

A Python (version 2.7) program was written and used to make programmatic requests to Google using Google's custom search JSON API. Searches were sent to Google as queries and results were returned in JSON format. These results were then parsed and organized as required for the analysis. Mimicking a general search using the Google Search engine from its main page, no limits or refinements were placed on the results returned. The search expressions themselves were the only parameters passed to the API. After the search was completed, results from each search expression were truncated to the first 100 results (if more than 100 results were returned). Duplicated search results were eliminated. The truncated results were compiled, and this became the dataset of this study. Due to the nature of data collection, it was limited to everything available through Google Search up until July 2018, the last day of data collection. The data was collected over the course of a week, July 15-22, 2018. The results were saved in an Excel spreadsheet. A custom written code in Python (version 2.7) was used to calculate 3-7-grams.

Sample

Despite a popular belief that Internet users go through only the first 10 web-pages (search-results) returned by the search engine (Eysenbach & Kohler, 2002), we decided to process all the results returned in response to our search. This way, we covered the readers who click on past the first 10 search results and address the issue of Google's algorithms frequently changing the top results for any given search term (Google Algorithm update history, 2019).

Initially, we obtained 836 results. Two undergraduate students were trained to check the entries, which met the following criteria were excluded: a) sites about animal birth control, b) sites in languages other than English, c) broken links and d) sites which required a password or additional software to view. However, we included links to open-access forums, blogs and online community discussions on the birth control topic. In the end, we eliminated a total of 31 titles with snippets that did not meet our criteria. The final sample ended up being 803 entries. After the titles were included in the final sample, two undergraduate coders assigned each title and snippet into one of the two categories (anti-birth control, pro-birth control).

Coding

Anti- and Pro-

Textual analysis programs count the frequency of words falling within theoretically derived psychological and linguistic categories (Pennebaker, Booth, Boyd and Francis, 2015). Due to its functionality, textual analysis cannot always detect hidden meanings of the entries, especially texts written as clickbait. Search engine results can communicate sarcasm, and snippets often contain unfinished sentences and selective alarm words with the purpose of attracting attention. Two undergraduate students were recruited and trained over a one-month period on a 10% subset of a sample to code whether the titles and snippets obtained were pro-, anti- or ambiguous about birth control. After training, each of them coded the whole sample. The coders indicated adequate levels of reliability for all variables (Scott's Pi >.70) (see Table 1).

Table 1. Coded categories and associated reliability statistics

Category	Definition	Reliability
Pro birth control	The title contains an argument or consideration in favor of birth control.	.83
Anti birth control	The language of the title is not in support of birth control.	.81
Ambiguous	Can be either pro or anti, hard to say which way the article will go (but clearly it will go in either pro or anti direction).	.71

Pro-birth control titles and snippets were defined as those that contained arguments or consideration in favor of birth control. An example of a pro-birth control title was, "Little known benefits of the pill," and a snippet was, " the following is a list of the most common non-contraceptive benefits of birth control" (Stacey, 2019). Anti-birth control titles and snippets were defined as those against birth-control discouraging people from using it. An example of an anti-birth control title was, "Women are unaware Yaz, other birth control pills cause blood clots," and a snippet was, "newer birth control pills like Yaz are linked to increased risk of blood clots. Many of those taking Yaz are unaware of its dangerous side effects" (Llamas, 2013). A title or a snippet was considered ambiguous when it was hard to say whether the article was pro- or anti- but clearly it was leaning one way or another. An example of such a title was, "The real truth about birth control pill that NO ONE talks about...," (Papisova, 2015) and a snippet was, "It is a permanent birth control method produced by Conceptus Inc. How dangerous is it?" (Buttice, 2018).

Facebook popularity

The website SharedCount.com was used to obtain Facebook statistics of each entry based on its URL. SharedCount is a service that looks up and provides the total number of instances when a given URL has been shared on given social networks. The information is received through the program querying, the data directly from the social media services (SharedCount, 2020). Currently, the service works with Facebook, Pinterest and StumbledUpon data. For the purpose of the current study, we rely only on Facebook data. This decision was made purely based on the high popularity of Facebook. Facebook popularity was defined as a total number of interactions (reactions, shares and comments) with a post (Alhabash et al., 2013). Using the obtained data, we calculated the online popularity index for each article by adding the number of shares, reactions and comments of each article (Xu and Guo, 2018).

Sentiments

Positive sentiment was calculated by adding words with positive semantic orientation for each title and snippet using the results of the NRC categorization. We calculated the negative sentiment the same way, by adding words with the negative semantic orientation of each title and snippet as determined by the automated sentiment analysis using NRC categorization. The total number of emotional words used for each title and snippet was calculated by adding all the words communicating positive and negative emotions as it was programmatically determined using the NRC categorization. The researchers also calculated the number of words communicating "fear" as assigned by NRC for each title and snippet.

Analysis

To answer posted questions of the study of whether there is a difference in semantics used in pro- and anti-birth control articles returned by Google Search engine and how it impacts the popularity of these articles on Facebook, the final dataset was evaluated in the following steps. First, the whole dataset was examined and cleaned to the criteria above. To answer RQ1 and RQ3 about possible differences between pro- and anti-birth control results in titles and snippets, the researchers conducted a simple content analysis. Relying on human coders, titles and snippets were dummy coded (pro-, anti- and ambiguous). To better understand the patterns of words used in two groups, the authors explored word co-occurrence. To address H1 and H2, the dataset was subjected to semantic analysis using the NRC lexicon to examine general language trends in pro- and anti- results. The use of top sentiment words in each category was analyzed. Finally, this data was used to see how much the use of emotional lexicon contributed to Facebook interactions with the entries.

Results

The analyses began with an examination of the frequency of word usage. Ambiguous entries were included in this part of the analysis only to demonstrate a more general pattern of words used online when discussing birth control. Since the expression "birth control" was included in all Google Searches, it inevitably appeared in all search results. For this reason, it was not included in the frequency analysis and sentiment analysis. At first, we calculated frequencies of words. The most common word in pro-, anti- and ambiguous results was the same “pill” used with pretty much the same frequency in all three categories (4.34%, 5.03% and 5.91% respectively).

The final analysis included 2,368 words from headlines and snippets that were pro-birth control, 4,985 words from headlines and snippets that were anti- and 7,360 words from headlines and snippets that were classified as ambiguous in relation to birth control. The top 10 most frequently used words in search results that were pro-birth control were “pill” (4.34%), “male” (2.91%), “safe” (2.83%), “effective” (2.07%), “benefits” (1.35%), “study” (1.22%), “new” (.89%), “health” (.84%), “early” (.68%) and “women” (.68%). The top 10 words that were anti-birth control were “pill” (5.03%), “risk” (4.56%), “hormonal” (2.07%), “danger” (1.94%), “cancer” (1.86%), “effect” (1.82%), “breast” (1.6%), “side” (1.6%), “women” (1.56%) and “new” (1.22%). The top 10 words most frequently used in search results that were ambiguous in terms of birth control use were “pill” (5.91%), “women” (2.36%), “male” (1.86%), “safe” (1.73%), “use” (1.27%), “new” (1.22%), “disease” (1.10%), “effective” (1.06%), “methods” (1.06%) and “health” (1.06%). The word “pill” was the most frequent word in both pro- and anti- birth control entries returned by Google Search. However, anti- messages were much more likely to use words like “risk”, “danger” and “cancer” than the pro- group. For comparison, pro- birth control entries mentioned “danger” almost 8 times less and almost 6 times less frequently mentioned “cancer” as a potential side effect. Wordclouds were created to visualize words used most often in pro-, anti- and ambiguous search results (See figure 1, 2 and 3). The online program wordcloud.com was used to create the visualizations. When only sentiment words in each of the two groups were compared, the most popular in both groups still was the word “pill,” which according to NRC lexicon, has a trust sentiment. The rest of the most popular sentiment words were different for anti- and pro- entries. While the pro- titles and snippets relied more on words communicating joy (e.g. “safe”, “health”) and trust (e.g. “effective”, “real”), the most popular sentiment words in the anti-birth control group had predominant sentiments of fear and sadness (e.g. “danger”, “cancer”, “risk” and “disorder”).

Figure 1. Wordcloud of the most often used word in Google Search result talking positively about birth control.

Figure 2 . Wordcloud of the most often used word in Google Search result talking negatively about birth control.

Figure 3. Wordcloud of the most often used word in Google Search result talking ambiguously about birth control.

Research question one (RQ1) sought to explore how emotional word usage differed in pro- and anti-birth control search results. An independent t-test was conducted to see if there was a difference in the use of words related to negative emotions between pro- and anti-Google Search results talking about birth control. We found a significant difference between the two groups *t*(170)=-10.54, *p*=.001. Additionally, the examination of the mean scores, presented in Table 2, revealed that Google Search results that were pro-birth control were using almost three times less negative emotional words compared to anti-birth control results.

Table 2. Sample means for variables and t-statistics

	Mean	SD	*t* test		
			t	df	p
Negative emotions in pro-	1.13	3.09	-10.54	170	.001
Negative emotions in anti-	3.09	1.92			
Positive emotions in pro-	3.67	1.78	6.82	140	.001
Positive emotions in anti-	2.24	1.10			
Emotional words in pro-	4.33	2.08	-2.88	431	.004
Emotional words in anti-	4.99	2.58			
Fear words in pro-	1.03	.59	-8.01	425	.001
Fear words in anti-	1.63	.92			

To further explore the first research question, an independent t-test was conducted to see if there was a difference in the use of words related to positive emotions between pro- and anti- Google Search results talking about birth control. A significant difference was detected between the two groups $t(140)=6.82$, $p=.001$. Additionally, the examination of the mean scores provided in Table 2, revealed that Google Search results that were pro-birth control were using more words communicating positive emotions compared to anti-birth control results.

Finally, word association analysis was done based on word co-occurrence. Given the nature of the sample, it was noticed that the number of meaningful phrases was significantly decreasing past 4-grams. Because of this, the current study will focus on groups of three words appearing together in anti-and pro- titles and snippets. Table 3 presents the list of three word groups occurring the most frequently in anti- and pro- entries. Among those occurring more than four times there are only two word groups common for anti- and pro-titles: birth control pill and hormonal birth control. While “birth control pill” is the most frequently occurring phrase in both groups, it is followed by “male birth control” in the pro-group and “hormonal birth control” in the anti- group. “Breast cancer risk”, “link between birth”, “know about birth” and “dangers birth control” are the most frequently co-occurring unique words in the anti- group. “Male birth control”,

"control pill safe", "effective birth control" and "benefits birth control" are the next most often occurring three word phrases in the pro- group.

Table 3. Ten most frequent three words groups occurring in anti- and pro- birth control entries.

Anti-birth control	Pro-birth control
Birth control pill	Birth control pill
Hormonal birth control	Male birth control
Breast cancer risk	Hormonal birth control
Know about birth	Control pill safe
Link between birth	Effective birth control
Dangers birth control	Benefits birth control
Birth control blood	Birth control options
Dangers every woman	Study finds male
Control breast cancer	It's safe effective
Risk hormonal birth	Pill safe researchers

Hypothesis one proposed that anti-birth control Google Search results would include more emotional (sentiment) words than pro-. First, a simple bivariate correlation was conducted to explore the relation between pro- and anti- entries and the total number of emotional words used per entry. The results revealed that there was a significant positive relation between anti-birth control entries and the number of emotional words used (r=.18, p=.001) and no relation between pro- Google Search results and emotional words use (r=.026, p=.454, *n.s*).

A follow-up analysis checked the hypothesis that there was a difference between emotional word usage (both positive and negative emotions) in the two groups (pro- and anti-) of Google Search results. The results of an independent samples t-test, provided in Table 2, indicated that there was a significant difference between the use of emotional words in pro- and anti- headlines and snippets, $t(431)=-2.88$, p=.004. Further, an examination of the means for each group revealed that anti-birth control results used more emotional words than pro-. Hypothesis one was therefore supported.

An independent sample t-test was conducted to compare the use of fear words in the pro- and anti- Google Search results talking about birth control. There was a significant difference in scores for anti- and pro- results $t(425)=-8.01$, p=.001 (Table 2). More fear words were used in the anti-birth control headlines and snippets than pro-. These findings support the second hypothesis.

The second research question (RQ2) sought to see whether popularity on Facebook depended on the semantics of the words used. A simple bivariate correlation was conducted to explore the relationship between words communicating positive and negative emotion and the Facebook popularity of such titles and snippets. The correlation matrix (Table 4) demonstrates that there was a significant relation between search results with words communicating positive emotions and Facebook interactions (shares, comments and likes), r=.07, p=.04. The results with words communicating negative emotion did not significantly relate to Facebook interactions. This suggests that the results of the Google Search that had more words communicating positive emotions were shared more.

Interestingly, the result, which had the most interactions on Facebook (Total interactions=192016), was a positive article stating that male contraceptive pill is safe to use and does not harm sex drive, published by www.telegraph.co.uk and did not have reference to the source. The second most interacted with search results (with 60764 interactions) was a neutral post by LA Times about, “hidden horrors in the GOP’s new Obamacare discussions” (Hiltzik, 2017).

The third research question (RQ3) sought to explore whether there was a difference between the support direction (pro- or anti-) of the headlines and snippets. A frequency analysis revealed that there were 92 pro-birth control headlines and 210 pro-snippets, 127 anti-headlines and 154 anti-snippets, 249 ambiguous headlines and 213 ambiguous snippets. This demonstrates that in almost half of the cases where snippets were pro-birth control. Titles were not. The difference between anti- and ambiguous headlines and snippets was minimal.

Discussion

Online media narrative can have a strong effect on the attitudes toward health, science and politics-related information. It might be the case that the online resources returned by Google Search have an impact on the information seeker’s attitude toward an issue because of the difference in the content and its framing (e.g. Jiang, Anderton, Ronald & Barnett, 2018). The proposed research was the first to compare word usage, popularity and sentiments of headlines and snippets returned by Google Search when searching for birth control related information. Broadly, the study sought to explore how Google Search presents information on a birth control topic and how such entries spread further through Facebook. The findings are important because birth control has been an issue widely speculated on and misinterpreted by politicians, religious organizations and mainstream media (FioRito, 2019; Ramsey and Court, 2019). At the same time, young people often get their introduction to birth control from the media or by doing their own Google Search.

More precisely, the current research had its aim to better understand the sentiments used in pro- and anti-birth control headlines and snippets as well as the tools or signals their creators use to make sure they reach more people such as fear words and emotional language. For this, we borrowed insights about the effect of different sentiments from language expectancy theory and EPPM. Specifically, we drew on the prior discussion of the role of strong emotional language, especially fear, in message design and its potential effect on the reader. Carrying over the discussion about potential message effects into the online realm we looked at a specific impact of emotional language as a signaling device on web traffic (Facebook interactions) in health context.

Although previous research has looked into the framing of birth control issues by traditional media (Jaworski, 2009; Patton, Moniz, Hughes, Buis & Howell, 2015; Campo-Engelstein, Kaufman & Parker, 2017), to our knowledge, the current study is the first which took this question online and looked at it from the perspective of Google Search engine results. The current study also examined the full sample without any date restrictions. This is important especially for organizations trying to increase birth control awareness. Knowing what is already there, what people find when looking for information about birth control, can give a general idea about the knowledge on the topic spread online. Findings about which titles and snippets had the most interactions and how they were written can be used by professionals in the field trying to filter out bias entries and propagate correct information about birth control.

The first important finding of the current research is that emotional words are extensively used in titles and snippets that are anti-birth control. More specifically, fear words are much more common in anti-birth control titles and snippets than pro-. However, posts with words communicating positive emotions are the ones that were interacted with the most on Facebook. Among the top 10 mostly used sentiment words in the pro- and anti- headlines and snippets, there was only one shared word. The other nine differed. This demonstrates that anti- and pro- leaning entries differently present the birth control topic. They try to appeal to different emotions. For example, we found that pro-birth control titles and snippets are more forward-looking and unique in their discussion of male birth control as a great scientific development, relying on phrases like “male safe birth” and “safe effective male.” The anti-birth control entries appealed more to some sort of secrecy that they were encouraging the reader to find out about reading their online articles. They were more often using wording like “know about birth” and “need to know.” Such difference in representation of the topic becomes even more obvious when looking more closely at the emotions that each side is appealing to through word choices. While pro- birth control entries appealed to joy, trust, and anticipation, the anti- entries relied on fear, anger and sadness. Interestingly, the single, most common sentiment that both groups were appealing to was trust. The reason for this might be a desired outcome of trust to their content by the readers.

Using data from human coders, this research demonstrated that there is a difference between how the reader interprets pro-birth control headlines and snippets. In almost half of cases with pro-birth control snippets, their related headlines were not seen as talking favorably about the topic. There were twice as many ambiguous headlines as anti- (as perceived by the reader) and were more than three times more ambiguous than pro- ones. This is important because if the reader just scans the headlines he/she might get a misleading idea about how birth control is portrayed through Google Search results.

Prior research on Internet use indicated that socio-demographic indicators (e.g. education, income, age), as well as social environment, impact how people consume and use Google platforms (Bucy, 2000; Park, 2015; Park, Jang, Lee & Yang, 2018). For example, Park (2015) analyzed data from the three waves of a survey conducted in the U.K. and demonstrated that the social background of users impact their Internet use. Those from underserved communities had lower access to the Internet and were significantly behind others in their use of the Internet for commerce. Carrying these findings over to the current research, we can speculate that demographic characteristics, prior medical experience, education about birth control, religion and social environment all together might be impacting how people process and react to information about birth control returned by Google Search engine. The current study does not account for these differences. To do so, the future studies should employ a survey or experimental design to determine how much socio-demographic indicators and sentiments used in the design of the titles and snippets account for the final effect.

Among other limitations of the current research is the possibility that we have failed to include in our list of key words other popular search terms due to constant changes in angles from which users are looking at the question. Another potential issue is the need to control for environmental factors that might be framing the popularity of the results returned by Google. A solution to both of these issues can be a repetitive measure design of the study. For example, collecting data every three months or so. One more limitation is that the NRC lexicon has its limitations and weaknesses. It focuses on eight emotions and semantic orientations but omits other emotions like guilt. Other studies can use other lexicons, which looks at a wider array of emotions.

Finally, future research can extend the analysis by breaking anti- and pro-birth control groups of titles and snippets into sub-categories. This will allow researchers to explore how Google Search results promote polarized opinions targeting different socio-demographic groups (e.g. Park, Jang, Lee & Yang, 2018).

Anna Young is a doctoral student in the Department of Communication at University of Connecticut. Her research interests include the influence and effects of new media technologies.

Kenneth A. Lachlan is Professor and Department Head in the Department of Communication at the University of Connecticut. His current research interests include the functions and effects of social media during crises and disasters, and the use of social robotics in delivering risk messages.

Robert C. Young (M.Eng. Rensselaer Polytechnic Institute) is an independent researcher. His research interest include big data analysis and new media technologies.

References

Ajao, O., Bhowmik, D. & Zargari, S.(2019). Sentiment aware fake news detection on online social networks. IEEE, 34(3), 2507-2511, 10.1109/ICASSP.2019.8683170

Alhabash, S., McAlister, A. R., Hagerstrom, A., Quilliam, E. T., Rifon, N. J. & Richards, J. I. (2013). Between likes and shares: Effects of emotional appeal and virality on the persuasiveness of anticyberbullying messages on Facebook. *Cyberpsychology, Behavior, and Social* Networking, 16(3), 175–182. doi:10.1089/cyber.2012.0265

Andaya, E. (2019). "I'm building a wall around my uterus": Abortion politics and the politics of pthering in Trump's America. *Cultural Anthropology, 34*(1). DOI: 10.14506/ca34.1.03

Armano, G., Giuliani, A. & Vargiu, E. (2012). Using snippets in text summarization: A comparative study and an application. *Proceedings of the Italian Information Retrieval Workshop*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.232.3639&rep=rep1&type=pdf#page=130

Berger, J. (2012). *Contagious: Why things catch on*. New York: NY, Simon & Schuster.

Borzekowski, D. L. & Rickert, V. I. (2001). Adolescent cybersurfing for health information: a New Resource that Crosses Barriers. *Archives of Pediatrics & Adolescent Medicine, 155*, 813–817.

Bryant, A., Narasimhan, S., Bryant-Comstock, K. & Levi, E. (2014). Crisis pregnancy center website: Information, misinformation and disinformation. *Contraception, 90*, 601-605.

Buck, R. (2014). *Emotion. A biosocial synthesis*. Cambridge University Press. ISBN 978-0-521-81316-7

Buck, R., Anderson, E., Chaudhuri, A. & Ray, I. (2004). Emotion and reason in persuasion: Applying the ARI Model and the CASC Scale. *Journal of Business Research, 57*(6), 647-656.

Bucy, E. (2000). Social access to the Internet. T*he Harvard International Journal of Press/Politics, 5*(1), 50-61.

Buller, D. B., Borland, R. L. & Burgoon, M. (1998). Impact of behavioral intention on effectiveness of message features: Evidence from the Family Sun Safety Project. *Human Communication Research, 24*(3), 433–453.

Burgoon, M. (1995). Language Expectancy Theory: Elaboration, explication, and extension. In C. R. Berger & M. Burgoon (Eds.), *Communication and social influence processes* (pp. 29–52). Michigan State University Press.

Burgoon, J. K., Jensen, M. L., Kruse, J., Meservy, T. O. & Nunamaker, J. (2007). Deception and intention detection. In H. Chen, T. S. Raghu, R. Ramesh, A. Vinze & D. Zeng (Eds.), *Handbooks in information systems* (Vol. 2, pp. 193–214). Amsterdam: Elsevier.

Burgoon, M., Jones, B. & Stewart, D. (1975). Toward a message-centered theory of persuasion: Three empirical investigations of language intensity. *Human Communication Research, 1*(3), 240–256.

Buttice, C. (2018). Essure - Safe Birth control or dangerous medical device? *Med news*. Retrieved from https://www.medsnews.com/health/essure-safe-or-dangerous-device/

Cambria, E., Havasi, C. & Hussain, A. (2012), "SenticNet 2: A semantic and affective resource for opinion mining and sentiment analysis". Retrieved from www.aaai.com

Campo-Engelstein, L., Kaufman, S. & Parker, W. (2017). Where is the pill for the "Reproductive Man?" A content analysis of contemporary US newspaper articles. *Men and Masculinity, 22*(2), 360-379.

Capala, M. (2018). Global search engine market share for 2018 in the top 15 gap national. Medium. Retrieved from https://medium.com/@SearchDecoder/global-search-engine-market-share-for-2018-in-the-top-15-gdp-nations-2cf65c11e5f5

Centers for Disease Control and Prevention. (2018). Contraception. Retrieved from https://www.cdc.gov/reproductivehealth/contraception/index.htm

Centers for Disease Control and Prevention. (2019). Contraceptive Use. Retrieved from https://www.cdc.gov/nchs/fastats/contraceptive.htm.

Chapman, G. B. & Coups, E. J. (2006). Emotions and preventive health behavior: Worry, regret, and influenza vaccination. *Health Psychology, 25*, 82–90.

Cohen, P. (2017, March 10). Sean Spicer's quick Twitter reaction to jobs report may break a rule. *The New York Times*. Retrieved from https://www.nytimes.com/2017/03/10/business/february-jobs-reporttrump-white-house.html

Diamond-Smith, N., Campbell, M. & Madan, S. (2012). Misinformation and fear of side-effects of family planning. *Culture, Health & Sexuality, 14*(4), 421-433.

Douglas, K., Uscinski, J., Sutton, R., Cichocka, A., Nefes, T., Ang, S. and Deravi, F. (2019). Understanding Conspiracy Theories. *Political Psychology*. https://doi.org/10.1111/pops.12568

Ekman, P., Friesen, W. V. & Ellsworth, P. (1972). *Emotion in the human face*. New York: Pergamon.

Eysenbach, G. & Kohler, C. (2002). How do consumers search for and appraise health information on the World Wide Web? Qualitative study using focus groups, usability, and in-depth interviews. *British Medical Journal, 324*, 573-577.

Facts about Google and Competition. (2010). Retrieved from https://web.archive.org/web/20111104131332/https://www.google.com/competition/how googlesearchworks.html

Feldman, R. & Sanger, J. (2008). The text mining handbook: Advanced approaches to analyzing unstructured data. Cambridge, England: Cambridge University Press, 125–127.

Festinger, L. (1957). Informal social communication. *Psychological Review, 57*, 271–82.

FioRito, M. (2019). Melinda gates is wrong: Birth control isn't poverty control. *National Catholic Register*. Retrieved from http://www.ncregister.com/daily-news/melinda-gates-is-wrong-birth-control-isnt-poverty-control

de Freitas, J., Falls, B., Haque, O. & Bursztajn, H. (2013). Vulnerabilities to misinformation in online pharmaceutical marketing. *Journal of Royal Society of Medicine, 106*(5), 184-189.

Gilliam, M., Warden, M., Goldstein, C. & Tapia, B. (2004). Concerns about contraceptive side effects among young Latinas: A focus-group approach. *Contraception, 70*, 299-305.

Google Algorithm Update History. (2019). A history of major Google algorithm updates from 2000-present. Retrieved from https://moz.com/google-algorithm-change

Greaves, F., Ramirez-Cano, D., Millett, C., Darzi, A. & Donaldson, L. (2013). Use of sentiment analysis for capturing patient experience from free-text comments posted online. *Journal of Medical Internet Research, 15*(11). doi:10.2196/jmir.2721

Gurman, T. & Clark, T. (2016). #EC: Findings and implications from a qualitative content analysis of Tweets about emergency contraception. *Digital Health, 0*(0), 1-16.

Hansen, D., Derry, H., Resnick, P. & Richardson, C. (2003). Adolescent searching for health information on the Internet: An observational study. *Journal of Medical Internet Research, 5*(4), 1-10.

Hiltzik, M. (2017, July 14). Column: Here are the hidden horrors in the Senate GOP's new Obamacare Repeal Bill. *Los Angeles Times*. https://www.latimes.com/business/hiltzik/la-fi-hiltzik-bcra-20170714-story.html

Hopper, A. & Uriyo, M. (2013). Using sentiment analysis to review patient satisfaction data located on the Internet. *Journal of Health Organization and Management, 29*(2), 221-233.

Izard, C. E. (1971). *The face of emotion*. New York, NY: Appleton Century Crofts.

Janis, L. (1967). Effects of fear arousal on attitude change: Recent developments in theory and experimental research. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 3, 166-225). New York: Academic Press.

Jaworski, B. (2009). Reproductive justice and media framing: A case-study analysis of problematic frames in the popular media. *Sex Education,* 9(1), 105-121.

Jiang, K., Anderton, B., Ronald, P. & Barnett, G. (2018). Semantic network analysis reveals opposing online representations of search term "GMO". *Global Challenges, 2*(1). DOI: 10.1002/gch2.201700082

Kata, A. (2010). A postmodern Pandora's box: Anti-vaccination misinformation on the Internet. *Vaccine, 28*(7), 1709–1716.

Knox, S., Viney, R., Gu, Y., Hole, A., Fiebig, D.,Street, D., Haas, M., Weisberg, E. & Bateson, D. (2013). The effect of adverse information and positive promotion on women's preferences for prescribed contraceptive products. *Social Science and Medicine, 83*, 70-80.

Kruvand, M. (2012). The pill at fifty: how the New York Times covered the Birth Control Pill, 1960-2010. *American Journalism Historian Association, 29*(4), 34-67.

Lawton, R., Conner, M. & McEachan, R. (2009). Desire or reason: Predicting health behaviors from affective and cognitive attitudes. *Health Psychology, 28*, 56–65.

Lemarié, J., Lorch, R. F., Jr., Eyrolle, H. & Virbel, J. (2008). SARA: A text-based and reader-based theory of signaling. *Educational Psychologist, 43*(1), 27–48.

Lempert, L. (1995). Electronic support groups. *Technology Review, 98*, 14-15.

Lewandowsky, S., Ecker, U. K. H., Seifert, C. M., Schwarz, N. & Cook, J. (2012). Misinformation and its correction: Continued influence and successful debiasing. *Psychological Science in the Public Interest, 13*(3), 106–131.

Llamas, M. (2013). Millions of women in the US don't know of blood clot risk in birth control pills. *Drug Watch*. Retrieved from https://www.drugwatch.com/news/2013/09/20/birth-control-pills-blood-clot-risk/

Lorch, R. F. (1989). Text-signaling devices and their effects on reading and memory processes. *Educational Psychology Review, 1*(3), 209–234.

Mayer, R. E. (1975). Different problem-solving competencies established in learning computer programming with and without meaningful models. *Journal of Educational Psychology, 67*(6), 725–734.

Mazzocut, M., Truccolo, I., Antonini, M., Rinaldi, F., Omero, P., Ferrarin, E. & Tasso, C. (2016). Web conversations about complementary and alternative medicines and cancer: Content and sentiment analysis. *Journal Of Medical Internet Research, 18*(6), doi:10.2196/jmir.5521

Mihalcea, R. (Eds.) (2008). Learning to identify emotions in text. *Proceedings Of The ACM Symposium on Applied Computing*. doi.org/10.1145/1363686.1364052

Mohammad, S. & Turney, P. (2010). Emotions evoked by common words and phrases: Using Mechanical Turk to create an emotion lexicon. In *Proceedings of the NAACLHLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*. LA, California.

Morahan-Martin, J. & Anderson, C. (2000). Information and misinformation online: Recommendations for facilitating accurate mental health information retrieval and evaluation. *CyberPsyhology & Behavior, 3*(5), 731-746.

Morahan-Martin, J. M. (2004). How Internet users find, evaluate, and use online health information: A cross-cultural review. *CyberPsychology & Behavior, 7*(5), 497–510.

Moran, M., Lucas, M., Everhart, K., Morgan, A. & Prickett. (2016). What makes anti-vaccine website persuasive? A content analysis of techniques used by anti vaccine websites to engender anti-vaccine sentiment. *Journal of Communication in Healthcare, 9*(3), 151-163.

Morris, M., Teevan, J. & Panovich, K. (2010). A comparison of information seeking using search engine and social networks. *International AAAI Conference on Web and Social Media*. Washington, DC.

National Cancer Institute (2018). Health information national trends survey 5 cycle 2. Retrieved from: https://hints.cancer.gov/viewquestions-topics/question-details.aspx?PK_Cycle=11&qid=688

Neumark, Y., Flum, L., Lopez-Quintero, C. & Shtarkshall, R. (2012). Quality of online health information about oral contraceptive from Herbrew-language websites. Israel *Journal of Health Policy Research, 1*(1), 1-10.

Oedingen, C., Scholz, S. & Razum, O. (2018). Systematic Review and meta-analysis of the association of combined oral contraceptives on the risk of venous thromboembolism: The role of the progestogen type and estrogen dose. *Thrombosis Research, 165*, 68-78.

Papisova, V. (2015). 5 benefits of the pill no one ever tells you about. *Teen Vogue*. Retrieved from https://www.teenvogue.com/story/beneficial-side-effects-of-birth-control-pills

Park, Y. J. (2015). Explicating net diversity in trend assessment. *Communication Research, 45*(5), 783-809.

Park, Y. J., Jang, M., Lee, H. & Yang, G. (2018). Divide in Ferguson: social media, social context, and division. Social Media and Society, 4(3). doi.org/10.1177/2056305118789630

Patton, E., Moniz, M., Hughes, L.,Buis, L. & Howell, J. (2015). National network television news coverage of contraception in the era of the Affordable Care Act. Obstetrics and *Gynecology, 125*, 74S.

Plutchik, R. (1980). *Emotion: Theory, research, and experience*. New York, NY:

Academic Press.

Popova, L. (2012). The extended parallel process modal: Illuminating the gaps in research. *Health Education and Behavior, 39*(4), 455-473.

Pruitt, S. & Mullen, D. (2005). Contraception or abortion? Inaccurate Descriptions Of Emergency Contraception In Newspaper Articles, 1992-2002. *Contraception, 71*, 14-21.

Ramsey, L. & Court, E. (2019). The strange tale of how a battle between 2 healthcare companies morphed into a viral twitter backlash against CVS. *Business Insider*. Retrieved from https://www.businessinsider.com/pill-club-fight-with-cvs-caremark-over-reimbursement-for-birth-control-2019-8

SharedCount. (2020). Frequently asked questions. Retrieved from https://www.sharedcount.com/faq

Silberg, W., Lundberg, G. & Mussacchio, R. (1997). Assessing, controlling, and assuring the quality of medical information on the Internet. *The Journal of the American Medical Association, 277*, 1244–1245.

Silge, J. & Robinson, D. (2017). *Text mining with R: A tidy approach*. Boston, MA: O'Reilly Media.

Stacey, D. (2019). The little known benefits of the pill. *Very Well Health*. Retrieved from https://www.verywellhealth.com/noncontraceptive-benefits-of-birth-control-906748

Steiner, T., Troncy, R. & Hausenblas, M. (2010). How Google is using linked data today and vision for tomorrow. *Google Germany*. Retrieved from https://storage.googleapis.com/pub-tools-public-publication-data/pdf/37430.pdf

Strzelecki, A., & Rutecka, P. (2019, September). The snippets taxonomy in web search engines. In *International Conference on Business Informatics Research* (pp. 177-188). Springer, Cham.

Sufian, A. & Anantharaman, R. (2011). *Social media data mining and inference system based on sentiment analysis*. Master's thesis, Chalmers' Publication Library, Gothenburg. http://publications.lib.chalmers.se/records/fulltext/155907.pdf

Surber, J. & Schroeder, M. (2006). Effect of prior domain knowledge and headings on processing of information text. Contemporary Educational Psychology, 32(3), 485-498.

Swartzendruber, A., Steiner, R. & Newton-Levinson, A. (2018). Contraceptive information on pregnancy resource center websites: A statewide content analysis. *Contraception, 98*(2), 158-162.

Taboada, M., Brooke, J., Tolifoski, M., Voll, K. & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics, 37*(2), 267-307.

Thorburn, S. & Bogart, L. M. (2005). Conspiracy beliefs about birth control: Barriers to pregnancy prevention among African Americans of reproductive age. *Health Education & Behavior, 32*(4), 474–487.

Tomkins, S. (1962). Affect, imagery, consciousness. Springer. (1982). Affect theory. In P. Ekman (ed.), *Emotion in the Human Face* (pp. 353–95). Cambridge University Press.

Turner, A., Altemus,M., Yip, N., Kupferman, E., Fletcher, D. & Bostrom, A. (2002). Effects of emotion on oxytocin, prolactin and ACTH In women. *Stress, 5*, 269–276.

Van Kleef, G. A., Van Doorn, E. A., Heerdink, M. W. & Koning, L. F. (2011). Emotion is for influence. *European Review of Social Psychology, 22*, 114–163.

Van Kleef, Gerben, den Berg, Helma & Heerdink, Marc. (2015). The persuasive power of emotions: Effects of emotional expressions on attitude formation and change. *Journal of Applied Psychology, 100(*4), 1124-1142.

Witte, K. (1992). Putting the fear back in to fear appeals: The Extended Parallel Process Model. *Communication Monographs, 59*, 329–349.

Witte, K. (1994). Fear control and danger control: A test of the Extended Parallel Process Model (EPPM). *Communication Monographs, 61*,113–134.

Witte, K. (1998). Fear as motivator, fear as inhibitor: Using the Extended Parallel Process Model to explain fear appeal successes and failures. In P. A. Andersen & L. K. Guerrero (Eds.), *Handbook of Communication and Emotion. Research, Theory, Applications and Contexts*. San Diego, CA: Academic Press.

Witte, K. & Allen, M. (2000). A meta-analysis of fear appeals: Implications for effective public health campaigns. *Health Education & Behavior, 27*, 591–615.

Wolfe, R. M., Sharp, L. K. & Lipsky, M. S. (2002). Content and design attributes of antivaccination web sites. *JAMA, 287*(24), 3245–3248.

Xu, Z. and Guo, H. (2018). Using text mining to compare online pro- and anti-vaccine headlines: Word usage, sentiments, and online popularity. *Communication Studies, 69* (1), 103-122.

Younis, G. (2015). Sentiment analysis and text mining for social media microblogs using open source tools: An empirical study. *International Journal of Computer Applications, 112*(5), 44–48.

Zhou, L., Burgoon, J. K., Nunamaker, J. F. & Twitchell, D. (2004). Automating linguistics-based cues for detecting deception in text-based asynchronous computer-mediated communications. *Group Decision and Negotiation, 13*(1), 81–106.

Zmud, R., Croes, H., Shaft, T. & Zheng, W. (2010). Systematic differences in firm's information technology signaling: Implications for research design. *Journal of the Association for Information Systems, 11*(3), 149–181.

To cite this article:

Young, A., Lachlan, K. A., & Young, R. C. (2021). OK, Google, Tell me about birth control: Sentiment analysis of anti- and pro- birth control headlines and snippets. *Journal of Communication Technology, 4*(1), 1-27. DOI: 10.51548/joctec-2021-002.