The Presentation of Health-Related Search Results and Its Impact on Negative Emotional Outcomes

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ABSTRACT
Searching for health information online has become increasingly common, yet few studies have examined potential negative emotional effects of online health information search. We present results from an experiment manipulating the presentation of search results for common symptoms, which shows that the frequency and placement of serious illness mentions within results can influence perceptions of symptom severity and susceptibility of having the serious illness, respectively. The increase in severity and susceptibility can then lead to higher levels of negative emotional outcomes experienced–including feeling overwhelmed and frightened. Interestingly, health literacy can help reduce perceived symptom severity, and high online health experience actually increases the likelihood that individuals use a frequency-based heuristic. Technological implications and directions for future research are discussed.

Author Keywords
Online health information; negative effects; health literacy

ACM Classification Keywords
H.3.3. Information Search and Retrieval: (search process).

General Terms
Experimentation; Human Factors

INTRODUCTION
Health-related websites generate a significant amount of Internet traffic; Google [14] recently reported that, among the top 1000 websites worldwide, general health-related sites (e.g., nih.gov, webmd.com, medicinenet.com) together have an estimated 117.8 million unique monthly visitors. Separately, WebMD [31] has reported that they receive 111.8 million unique monthly visitors. These statistics corroborate with those found by Pew Internet stating that 80% of Internet users look online for health information, and that it is the third most popular online activity, after checking email and using a search engine [12]. Research has found that 66% of individuals looking for health information begin at a search engine [13], and one analysis of search logs found that about 250 thousand users (about one quarter of the total sample) engaged in a health-related search during an 11-month period [33]. Together, these findings suggest the importance of these tools in determining the content viewed by users.

Viewing online health information has been shown to be helpful for individuals in a variety of ways. Aside from the obvious benefit of providing knowledge, research has found online health information seeking to be associated with feeling more comfortable with information received from a health professional [20, 37], suggesting that it can serve a warranting purpose. Online health content has also had positive effects on medication adherence [24] and ability to make informed healthcare decisions [25]. Among caregivers, it has assisted with problem solving, coping, and communication with health professionals [17].

Yet, while there are clear benefits associated with online health information seeking, can there also be negative consequences of this behavior? A study of cancer patients found that one third felt more confused after reading online cancer information, and nearly one quarter felt more nervous, anxious, or upset [16]. In the general population, health-related Internet use has been found to be associated with increases in depression [4]. This is particularly an issue with college students—the subject population of our study—as about 44% felt confused the last time they searched for health information, 26% felt frustrated, 19% felt overwhelmed, and 15% felt frightened [5].

Due to the important implications associated with health issues and individuals' subsequent emotional involvement, it is not surprising that these effects occur, but it is unclear what makes them more likely to happen. Some research has suggested that the use of search engines may exacerbate these effects through the provision of potentially harmful information [30] or individuals' treating them as diagnostic devices to find medical causes for their symptoms [33]. Additionally, one study found that results from a web search, compared to general online content, give more weight to serious illnesses when individuals search for common symptoms. For example, when they performed a basic web crawl of 40 million pages listed in the Open Directory Project for the term "muscle twitches," the probability of ALS (Lou Gehrig's Disease) being associated with the symptom was 0.07. In contrast, when they did a web search using Microsoft's *Live Search* engine, the

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probability of ALS appearing among the results was 0.5 [33]. Clearly, search engine results are not a representative sampling of the wider population of content online.

To inform this study, the authors examined search results obtained for the common medical symptoms used in this experiment: headaches, abdominal pain, muscle twitches, and chest pain. Overall, there were several instances of serious illnesses being associated with the symptoms; heart attacks, for example, were mentioned in all of the first ten search results for chest pain. Additionally, appendicitis was mentioned in eight of ten results from an "abdominal pain" search. The frequency of these occurrences suggests that appendicitis is common, but only about 7% of Americans will get appendicitis in their lifetime [15]. Altogether, this brief analysis suggests that consumers are exposed to many instances in which serious illnesses are linked to common symptoms that often have benign causes. This could likely distort perceptions of the threat presented by the symptoms.

Therefore, this study examined how viewing online search results related to symptoms may affect perceptions and outcomes. Specifically, an experiment manipulated the presentation of results mentioning serious illnesses related to the symptoms and assessed effects on perceived symptom severity and susceptibility of experiencing the serious illness. In turn, the relationship of these perceptions to negative emotional outcomes was determined. Overall, the goal was to examine how simple changes in presentation, while keeping informational content consistent, changed outcomes. We found that manipulating the frequency and placement of search results that mention serious illnesses had effects on perceived severity and susceptibility, which both had effects on individuals feeling frightened and overwhelmed. Thus, even if basic information is kept consistent, the presentation of results can have significant effects on perceptions and emotional outcomes.

This paper offers multiple contributions. First, it demonstrates empirically that viewing severe health conditions in search results can indeed influence our negative emotions, such as fear. While this concern associated with using search engines has been speculated, it has never been experimentally demonstrated, to the authors' knowledge. Second, this paper extends research findings related to judgment heuristics and biases to the realm of health information seeking, and highlights the effects of placement and frequency on our perceived severity and susceptibility of severe conditions. Lastly, the findings suggest strategies for search engine developers and users that may help to avoid negative emotional outcomes.

SEARCH ENGINES AND HEURISTIC ASSESSMENTS

Although search engines are common and useful tools for finding health information, they are far from perfect sources. For example, a content analysis of search engine results related to complementary/alternative medicine found that links on the first page were most often commercial, led to pages containing content that could lead to physical harm, and were frequently trying to sell products [30]. Such results demonstrate that many of the highest-ranked pages may not come from unbiased, knowledgeable sources. In addition, search engine results can lead to negative effects by providing information that is inappropriate to the individual users' situation. Research studying "cyberchondria" has found that almost nine out of ten individuals have had experiences in which a web search for basic symptoms led to a review of information on serious illnesses, called an "escalation." In an observation of search logs, about 5% of online searches (about 600 occurrences) for health symptoms escalated into searches for more serious conditions—for example, people who began by searching for a headache eventually searched for brain tumor information [33]. The likelihood of a person having a brain tumor related to a headache is very low, so such an escalation is inappropriate to the situation.

Escalation has been found to occur more often when users see a serious explanation for their symptom before a benign explanation on a web page [34]. This suggests that people may be using cognitive shortcuts, or heuristics, when making judgments about online health information. This heuristic-based browsing has also been empirically demonstrated among women searching for menopausal information online [27]. Although such heuristics can be helpful in sorting through large amounts of information, they can also lead to biases or errors in judgment [28].

Anchoring and Availability Heuristics

In this paper we explore two types of heuristics that may play a role in evaluating results from health searches—*anchoring* and *availability*.

When individuals are operating under the anchoring heuristic, they make estimates of likelihood or probability by starting from an initial value and making subsequent adjustments until they decide on a final estimate. Often, the adjustments people make are inadequate, thus making their estimates biased toward the initial value [28]. In other words, individuals tend to stick with their first impressions, which is easier than thoroughly analyzing each new piece of information uncovered [23]. A study by Peters, Slovic, Hibbard, and Tusler [21, 33] found that different anchors (low vs. high) influenced individual's death estimates; for example, telling participants that 400 people die of appendicitis each year vs. 40,000 people dying of kidney disease led to lower death estimates for other conditions. Such studies suggest that this anchoring effect does indeed hold in the health realm. For this study, it is predicted that, if individuals first see a result mentioning a serious condition, they will form an initial impression that the symptom is severe, which will lead to a bias in their overall opinions of severity:

H1a: The placement of results discussing serious health conditions will have an effect on perceived symptom severity, such that when serious conditions are mentioned at the top of the results list, individuals will have higher perceptions of symptom severity.

Additionally, this study seeks to examine the role of online health information in bringing about negative emotional outcomes, as previous research has demonstrated can occur. It is suggested that, the more severe an individual perceives a symptom to be, the more threatening the symptom will be, which is a key premise of the extended parallel process model [35]. Because of a high level of threat, individuals will experience negative emotional outcomes (including feeling frightened and overwhelmed). The following hypothesis captures this prediction:

H1b: Perceptions of symptom severity will be positively related to reported negative emotional outcomes.

When individuals are operating under the availability heuristic, they are making judgments of the frequency, probability, or likelihood of an event based on how easy it is to recall instances or occurrences. The easier it is to think of examples of an event, the higher the perceived likelihood of the event occurring [28]. Researchers have discussed the role that this heuristic may play in medical decision-making. For example, Redelmeier [23] argues that, when doctors determine diagnoses, it is much more convenient (and often more appropriate) to make judgments based on one's past experiences with a given health condition than it is to memorize probabilities or epidemiological statistics. Among non-medical professionals, media mentions of cancer have been found to increase individuals' perceptions of risk and their subsequent cancer screenings [6, 11]. In these cases, it is likely that, because individuals heard about cancer more often and were thus able to think of more examples of diagnoses, their estimated likelihood of diagnosis increased.

Our hypothesis draws upon this availability heuristic, suggesting that the frequency of serious illness mentions within search results will provide more examples that a user can bring to mind, which will in turn affect their perceived likelihood of experiencing that serious illness. Specifically, it is predicted that the more often a serious illness associated with a given symptom is mentioned in the search results, the higher individuals' perceived susceptibility of experiencing the illness will be. This hypothesis is presented as follows:

H2a: The frequency of results discussing serious health conditions will have an effect on perceived susceptibility, such that serious conditions discussed frequently will lead to higher perceptions of susceptibility toward those conditions.

Because a higher level of susceptibility toward a serious condition is likely to heighten perceptions of threat, it is also predicted that higher susceptibility will lead to more negative emotional outcomes [35]:

H2b: Perceived susceptibility of the serious health condition will be positively related to reported negative emotional outcomes.

In addition to heuristics, other personal factors may play a role in how people interpret search results. Two of these factors, health literacy and online health experience, were of special interest to this study and will be discussed in the following section.

Factors Impacting the Effects of Online Information Seeking

Conflicting results have been found about the role of online health information seeking experience on individuals' responses to online health information. Research has demonstrated that individuals who have a better understanding of online health information are more likely to use the Internet, over a doctor, as their primary source [18]. Additionally, individuals who have engaged in frequent health searches are less likely to judge search results for health topics as relevant to their initial queries, suggesting that they may be more critical of the results retrieved [19]. To explore the role of online health experience on individuals' responses to health-related search results, the following research question is posed:

RQ1: Does the extent of experience with online health information moderate the relationships between placement and severity and frequency and susceptibility?

Another quality that has been shown to have an effect on individuals' responses to health information is their overall health literacy, which has been defined as "a constellation of skills, including the ability to perform basic reading and numerical tasks required to function in the health care environment" [20]. Low health literacy has been linked to greater levels of distress [26], lower self-efficacy for screening behaviors, lower information seeking [29], lower knowledge regarding cancer, and more negative attitudes toward screening [8]. Given these effects, it seems likely that health literacy may have an impact on the way that people interpret health information from search engines, which is why the following research question was posed:

RQ2: Does health literacy moderate the relationships between placement and severity and frequency and susceptibility?

To test these hypotheses and research questions, a within-subjects experimental design was employed that explored individuals' perceptions of and reactions to search results about various symptoms. The details of this method are described in the following section.

METHOD

We conducted a 2x2 within-subjects experiment, in which we manipulated the presentation of health-related search results for four different symptoms: abdominal pain, chest pain, muscle twitches, and headaches. Manipulations changed the frequency (frequent vs. sparse) and placement (top vs. bottom) of serious illness mentions within the results list in order to study differential effects on outcomes.

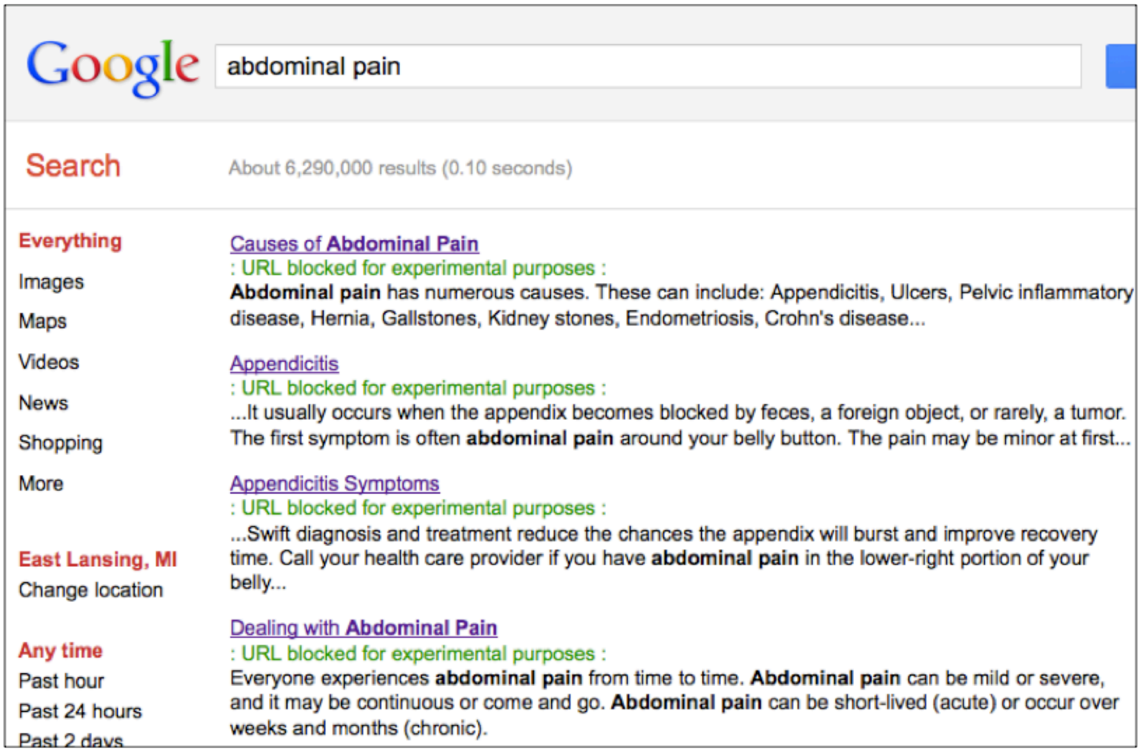


Figure 1. Example search results page

Recruitment and Participants

Participants were recruited from undergraduate communication courses at a large Midwestern university. In exchange for their participation, respondents were given course credit. 310 participants were recruited, but the final sample (N=274) contained only those who completed the entire experiment. The average age of respondents was 20, and 48.4% of respondents were female.

College students frequently engage in online health information seeking; studies have found that about 75% of students have viewed health information online [10, 12]. Additionally, studies have shown that college students are susceptible to negative emotions arising from health information seeking [5]. These reactions, combined with the well-documented anxiety, depression, and stress experienced by college students [3], suggest that viewing online health information could exacerbate negative psychological states in an already-fragile population. Thus, they are an interesting population to study in this context.

Study Setup

Participants completed the study online. They were instructed to place themselves in the mindset of someone experiencing a symptom (headaches, chest pain, muscle twitches, and abdominal pain) who was looking for information as to the potential cause. Importantly, the majority of participants had, at some point, experienced each of the four symptoms of concern to this study: 89.7% had experienced a headache, 77.2% had experienced abdominal pain, 77.6% had experienced muscle twitches, and 65.4% had experienced chest pain. This suggests that they were likely able to place themselves in the correct mindset and adds to the validity of this experimental set-up. Participants were then presented with a search results page for the symptom. The results page looked exactly like a Google search with 10 links, but links to anything other than the results were disabled (see Figure 1). Additionally, though it was hosted on a non-Google domain, the results page was placed in a JavaScript frame within the survey that prevented participants from seeing the URL, thus maintaining some realism. Participants were encouraged to click on the search results and read the information carefully to diagnose their symptoms.

The search results and linked pages were created for the study. Content was paraphrased from trusted websites (e.g., nih.gov, mayoclinic.org). Additionally, the design of these pages was kept simple to avoid design effects, but varied slightly from page to page in order to preserve some realism. Figure 2 shows an example of one of these pages.

Study Manipulations

Each symptom scenario was randomly paired with one of our 2 x 2 conditions—varying the frequency and the placement of the results mentioning serious illnesses in its title or short description (see Figure 3). Each symptom was consistently associated with one serious illness or condition: chest pain with a heart attack, abdominal pain with appendicitis, muscle twitches with ALS (Lou Gehrig's disease), and headaches with brain tumors.

Importantly, the actual content of the linked pages was kept the same across conditions. For example, every page

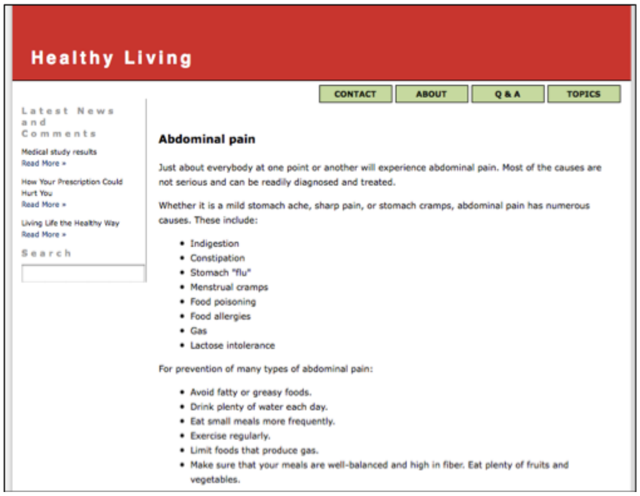


Figure 2. Example health content page

mentioning brain tumors said that they were rare, but some conditions presented such pages more often or at different places in the results list. Thus, if readers made judgments based solely on the information they read, they should arrive at the same conclusions regardless of condition.

Measures

After each symptom scenario, respondents were asked to what extent viewing the health information made them feel overwhelmed or frightened (7-point Likert scale from "not at all" to "very much"). These questions, chosen to ensure high face validity, have been used by in previous research [5, 13]. Additionally, participants were asked about their perceptions of severity and susceptibility using 6 items based on the Risk Behavior Diagnosis scale [36], listed in Table 1. The severity scale had high reliability (Cronbach's alpha=0.93), and the average of the three items was calculated to form a composite variable. The third item in the susceptibility scale was dropped due to poor reliability, which resulted in a scale with good reliability (Cronbach's alpha=0.76). These items were averaged to create a composite variable.

After all the conditions were viewed, respondents were asked about their history of viewing online health information (see Table 1), their health status, how often they experienced each of the four symptoms, and their demographic information. Last, their health literacy was assessed using the Newest Vital Sign (NVS) [22], a six-item tool (5 yes/no, 1 open-ended) that has been shown to have good reliability and validity [32]. The open- ended item in the NVS was dropped for this study to simplify analysis, and a composite health literacy score was created by adding up the number of correct answers (maximum score=5).

Variable Measured	Survey Items (7-pt Likert scale: from "not at all" to "very much")
Severity	[Symptom] is a serious symptom
	[Symptom] is harmful
	[Symptom] is a severe threat
Susceptibility	If I have [symptom], I am at risk for having [serious condition]
	It is likely that I have [serious condition] if I experience [symptom]
	[Symptom] is nothing to worry about. (reverse coded)
Online Health Experience	How often do you view health information online?

Table 1. Example survey questions

		Serious Illness Frequency	
		Sparse (3/10)	*Frequent (7/10)*
Serious Illness Placement	*End of search results*	Condition 1: 3 serious illness mentions, placed in the last 3 results on the page	Condition 2: 7 serious illness mentions, placed in the last 7 results on the page
	Beginning of search results	Condition 3: 3 serious illness mentions, placed in the first 3 results on the page	Condition 4: 7 serious illness mentions, placed in the first 7 results on the page

Figure 3. Explication of Study Conditions

Data Analysis

To analyze these data, mixed-model Analysis of Covariance (ANCOVA) was used. Before running any tests, variables that had non-normal distributions (i.e., susceptibility, frightened, and overwhelmed) were transformed by computing their square root values in order to correct for skewness. In all analyses, participant was treated as a random effect to account for potential correlation between responses due to the within-subjects design. The effects of anchoring and availability on severity and susceptibility (H1a and H2a) were tested with three predictors: placement and frequency, which were both binary variables reflecting the different manipulations, and their interaction. All of these variables were included in analyses to account for the non-independent nature of frequency and placement, which were both present in each condition.

These composite measures of susceptibility and severity were also used as predictors in the tests of H1b and H2b, testing their effects on potential negative outcomes (i.e.., frightened, overwhelmed). Similarly, participant was treated as a random effect due to repeated measures.

To test RQ1, the following predictors were used: frequency, placement, the interaction between frequency and placement, and experience with online health information (a binary variable, as a result of a median split). Additionally, the interaction between placement and online health experience was added to test effects on severity, and the interaction between frequency and online health experience was added to test effects on susceptibility. RQ2 was tested in the same manner, except a binary variable for health literacy was used (also as a result of a median split) instead of online health experience.

To explore the causal chain of the effects of placement and frequency on negative emotions, a path analysis, a statistical method of structural equation modeling, was used. The AMOS 20.0 program was employed to obtain maximum-likelihood estimates of the model parameters, and the model was edited until reasonable model fit was obtained. In these analyses, frequency and placement were treated as exogenous variables, while susceptibility, severity, and the two negative outcomes were endogenous variables. Additionally, two control variables, individual subjective health rating (ranging from "poor" to "excellent") and the order in which participants saw each condition, were added in as exogenous variables. Goodness-of-fit index (GFI) was used to assess model fit.

RESULTS

To assess the level of participation and adherence to the study directions, logs of participants' actions were collected. Overall, participants clicked on an average of 14 links (35% of all possible links) and spent an average of 101 seconds on each link. Though these data show that the participants typically did not view every line of text in the study, they do show a reasonable level of engagement.

Hypothesis 1: Placement, Severity, and Outcomes

H1a predicted that placement of results discussing serious illnesses would have an effect on perceived severity. Our analysis supported this hypothesis, as there was a significant effect of placement on perceived severity, $F(1, 813) = 20.94$, $p < .001$. Means are displayed in Table 2. H1b predicted that perceived severity would be associated with negative outcomes. Results also supported this hypothesis. Perceived severity was positively associated with feeling frightened ($F(1, 1059.08) = 201.62$, $p < .001$) and overwhelmed ($F(1, 1000.12)=47.68$, $p < .001$).

Hypothesis 2: Frequency, Susceptibility, and Outcomes

H2a predicted that frequency of results mentioning a serious illness would have an effect on perceived susceptibility. Our analysis supported this hypothesis, as frequency had a significant effect on susceptibility, $F(1, 813)=5.50$, $p = .02$. Means are displayed in Table 2. H2b predicted that perceived susceptibility would be positively related to negative outcomes. Overall, this hypothesis was supported. Perceived susceptibility was positively related to feeling frightened ($F(1, 1084.89) = 94.45$, $p < .001$) and overwhelmed ($F(1, 1036.55) = 23.08$, $p < .001$).

	Susceptibility Mean (SE)
Frequency	
Low	3.17(.06)
High	3.32 (.06)
Health Literacy	
Low	3.44 (.08)
High	3.16 (.05)
	Severity Mean (SE)
Placement	
Last	3.66 (.06)
First	4.00 (.07)
Health Literacy	
Low	4.05 (.08)
High	3.73 (.05)

Table 2. Means and Standard Errors

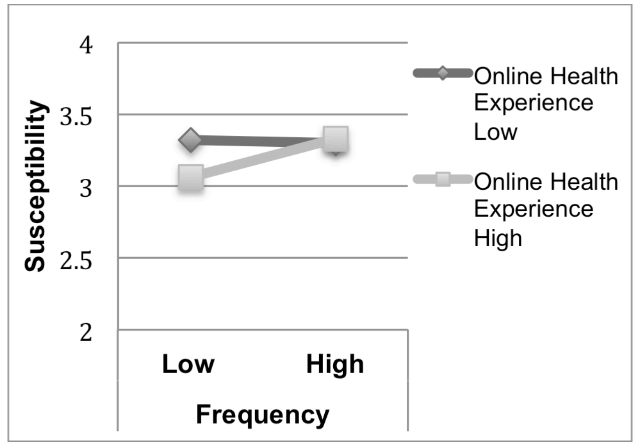


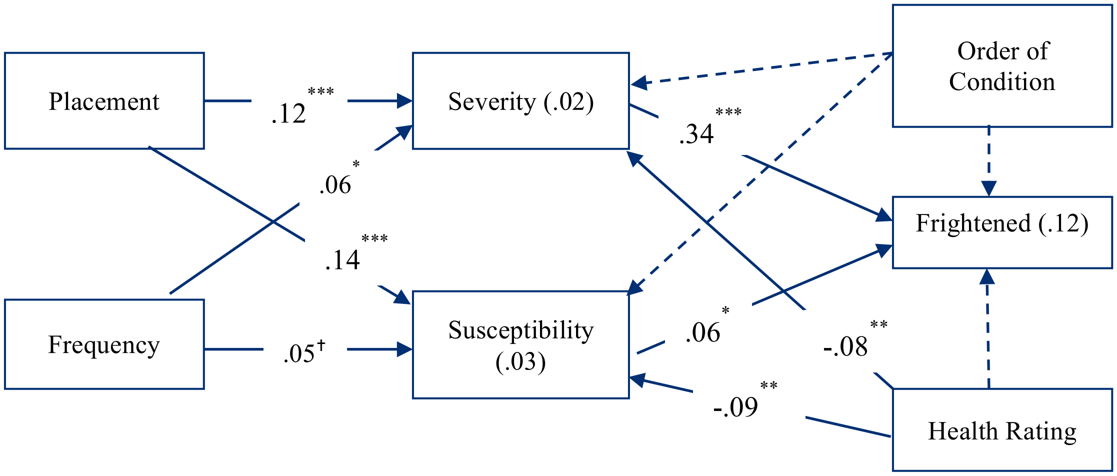
Figure 4. Moderating effect of online health experience

RQ1: Online Health Experience as a Moderator

RQ1 explored the moderating effects of online health experience on the relationships between placement and severity and between frequency and susceptibility. Online health experience did not have a statistically significant effect on severity, and the interaction between placement and online health experience was not significant. In the relationship between frequency and susceptibility, experience with online health information did not have a significant main effect on susceptibility. However, the interaction between frequency and online health experience was significant, $F(1, 813) = 4.39$, $p < .04$. For those with low experience in viewing online health information, frequency of serious illness mentions had little to no effect. Among those with high online health experience, however, frequency had an effect in the predicted direction: the more serious illness mentions, the higher the perceived susceptibility. This relationship is illustrated in Figure 4.

RQ2: Health Literacy as a Moderator

RQ2 explored the moderating effect of health literacy on the relationship between placement and severity and frequency and susceptibility. Health literacy had a statistically significant effect on severity, $F(1, 270) = 6.01$, $p < .02$. The interaction between placement and health literacy was not significant, however. Health literacy did not have a statistically significant effect on susceptibility, nor was the interaction between frequency and health literacy significant. Means are displayed in Table 2.



Note: Only significant coefficients are presented. All the coefficients are standardized. R^2 for each endogenous variable is reported in the parentheses. † < .10, *p < .05, ** p < .01, *** p <.001

Figure 5. Exploratory Path Analysis: Standardized Coefficients and Multiple Correlations

Exploratory Analysis: Path Model

Up to this point, we have shown that frequency and placement can affect severity and susceptibility and that severity and susceptibility correlate with negative emotions. In order to further examine the causal chain from frequency and placement to negative emotions, as well as to address the small *F* values associated with several variables (e.g., frequency), multiple iterations of a path model were tested. The model presented here has an acceptable fit, with GFI=0.90 (Figure 5). Overall, this model explained 12% of the variance in individuals' levels of fright. Results showed that frequency has a small, weakly-significant effect on both severity and susceptibility. Comparatively, placement had much stronger effects on both severity and susceptibility. An individual's subjective health rating had a significant negative effect on both susceptibility and severity, but not on their level of fright. The order in which an individual saw a given condition was not found to be significantly associated with any of the variables.

DISCUSSION

Heuristic-Based Browsing and its Effects

This study examined the effects that the presentation of search results for medical symptoms has on individuals' perceptions and their reactions. Results indicated that, even when informational content is kept consistent, the frequency and placement of serious illness mentions on a search results page can have an effect on perceived susceptibility and severity. Additionally, perceived severity and susceptibility were positively associated with feeling frightened and overwhelmed after viewing the search results.

The hypothesized mechanisms behind these negative responses are anchoring and availability heuristics, and the results lend support to research that has found that users rely on heuristic processing when viewing search results [27]. Users are not attending to the content enough to make judgments based on the information alone. Instead, they are relying on cues provided in the link titles and page text. This is concerning, as our pre-study analyses of Google's search results, as well as previous research [33], have shown that serious illnesses are over-represented within search results, especially those found on the first page. Based on the findings of this study, one could extrapolate that individuals viewing *actual* search results for their own symptoms are forming perceptions of symptom severity and susceptibility of having a serious illness that are more inflated than the actual incidence rates would suggest. These perceptual effects alone are significant, as they demonstrate the potential cognitive inaccuracies resulting from viewing search results. This could lead to persisting beliefs about the associated symptoms that may resurface every time they are encountered by the individual. These perceptions of severity and susceptibility, as we found in our study, would then likely lead to negative emotions for these individuals. This is in line with previous research on threat, which is composed of perceived severity and susceptibility and has been shown to lead to fear arousal [35].

It is important to note that the statistical results showed relatively small effects, but this is likely the result of the subtle nature of the experimental manipulations. Overall, placement of serious illness mentions accounted for 12% of the variance in severity and 14% of the variance in susceptibility. Considering the increasing frequency with which individuals search for online health information, even just 12% of variance explained translates to large groups of individuals. Additionally, although negative outcomes were present to a certain degree in this study, respondents did not report strong feelings in response to the search results. In general, respondents were not highly frightened (*M*=3.16, *SD*=1.71) or overwhelmed (*M*=3.38, *SD*=1.72). It is likely that this was also a product of the experimental design, as individuals were simply asked to place themselves in the mindset of someone who had experienced the symptom at hand. Low involvement and relevance may have led to the weak reactions. However, observation studies using participants with high involvement in the health topic have found that such users still use heuristic processing [27]. Thus, it is likely that the findings from this study would be replicated in such populations and individuals would experience even stronger negative emotions due to the real-life implications of the content they encounter. Our findings highlight the need for additional research examining negative emotional outcomes stemming from online health information behaviors.

Investigating the Causal Chain

Our path analysis revealed that, after controlling for an individual's health status and the order in which they saw the various conditions, the tested variables explained about 12% of the variance in levels of fright. Additionally, the path analysis showed that the placement of serious illness mentions had a much stronger effect than frequency. A potential explanation is that study participants mainly looked at links above the fold of the results page. This is consistent with the logs from this study, which showed that individuals clicked on approximately four links per condition—which is about how many were visible above the fold. Thus, the effects of frequency were limited because, by not attending to all the links, the manipulations were not fully apparent. However, the placement manipulations of serious illnesses were always visible, even if they did not look at all the links on the page. This interpretation is in line with previous research, which has found that users focus much more attention on the first few links in a search results page than on links further down the list [7]. Overall, these results demonstrate that placement of serious illness mentions within search results is a much more important factor when it comes to influencing individual perceptions.

Effects of Health Literacy and Online Health Experience

Another interesting finding of this research is the interaction between experience with online health information and frequency of serious illness mentions. When serious illnesses were mentioned sparingly, individuals with high levels of online health experience had lower perceptions of susceptibility than when mentions were frequent. This suggests that they were more sensitive to the cues we manipulated within the results. The reasons why this occurred are unclear, particularly because we anticipated that individuals with more experience would be *less* susceptible to the experimental manipulations, simply due to more exposure to online health content. It may be the case that these individuals have had to develop tactics over time for sorting through the immense amount of health information online. In other words, they have grown to rely on heuristic cues as a means of saving time during their browsing sessions.

Interestingly, individuals with low levels of online health experience had virtually the same scores on perceived susceptibility across conditions. The mean scores show that, on average, individuals with low experience had higher scores of perceived susceptibility (M=3.32, SD=1.40) than individuals with high levels of experience (M=3.20, SD=1.40). Perhaps individuals with low online health experience are simply alarmed by *any* mention of serious illnesses, as they are not accustomed to the presence of such content in relation to seemingly innocuous symptoms. Conversely, individuals with more experience in online health may have trained themselves to be more skeptical of online content. Further research should explore the mechanisms by which experienced vs. inexperienced online health users form perceptions of online content, as this could help to target websites toward specific users.

Although health literacy did not have a moderating effect, it did have a significant and negative relationship to severity. Regardless of condition, individuals with low health literacy had higher perceptions of symptom severity. As previous research has demonstrated that low health literacy is associated with lower knowledge [8] and information seeking [29] regarding health issues, it may be the case that these individuals did not have contextual knowledge regarding the likelihood of serious illnesses being related to common symptoms. Thus, overall, their perceptions of the severity of a given symptom may have been inflated. Conversely, individuals with high health literacy likely had an increased ability to assess likelihood based on the information they read, as well as more general knowledge regarding the health issues at hand. This, in turn, helped them to see past the heuristic cues and "correct" for potentially inflated perceptions of the likelihood of the serious illnesses occurring. Such findings highlight the importance of educating individuals to develop their health literacy skills so that they may better interpret health information both online and offline.

Technological Implications

These findings have important implications for the presentation of health-related search results. Developers of search engines may, in the future, develop algorithms to determine when users are searching for health information, and tailor the results page to help educate the users about search results. For example, a simple warning could be placed alongside the results telling users to read content carefully and contact a health provider with any concerns. Or, Google could direct users to their custom search engine for health topics, which searches only the 50 most reliable websites to ensure that search results are trustworthy [1]. This may not mitigate all negative effects, but can help to avoid users encountering results that inaccurately portray risk information.

Interestingly, since this study was conducted, Google has started providing "related searches" at the top of the results page for some health symptoms. For example, Figure 6 shows the related searches for one of the symptoms used in this study, muscle twitches. Many muscle twitches are benign, and can be caused by diet deficiencies, caffeine, stress, or exercise [9]—however, this is not reflected in

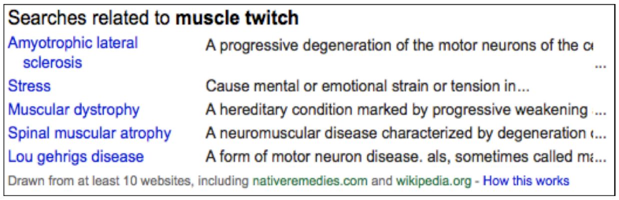


Figure 6. Current display of Google search results

these related searches. These suggest that twitches are associated with serious conditions, including ALS (Lou Gehrig's disease) and muscular dystrophy. Based on our results, because these are placed at the top of the page, this may lead to more negative effects among users. Thus, this strategy may need to be re-considered if optimal outcomes are to be achieved and negative reactions are to be avoided.

Some website developers have sought to accommodate individuals with low health literacy levels when developing content [2], which, based on our study, could help mitigate some negative emotional outcomes. In addition, search engines may consider including educational support in interpreting the search results page in order to offset some of the more popular judgment heuristics, such as availability and anchoring. However, health information search is a complex process and our findings have highlighted the need for additional research to better improve existing search engines to support our various health-related needs.

LIMITATIONS AND GENERALIZABILITY

The use of the college student population for this study raises concerns of generalizability because young people tend to have fewer health problems than older populations. This was especially apparent as related to the symptom of chest pain, which only around 60% of the participants had actually experienced. Research with more diverse individuals is needed for studying this topic and will help to better reflect the experiences of the average online health information seeker.. Additionally, while our experimental approach allowed us to specifically test the effects of placement and frequency, it did come at the cost of realism. Future studies should build on this research to confirm our findings in less controlled but more realistic field settings and with different population groups. It is important, however, to consider the ethical implications of such research: manipulating information related to symptoms in order to induce specific emotional effects is potentially problematic if individuals are actually experiencing the symptom. For example, if a person with a headache reads that it may be a sign of a brain tumor, they may experience significant emotional trauma or distress. Future studies should consider the consequences of such research and seek creative ways of examining this phenomenon without causing harm to participants. Last, the measures used to assess emotions were simplistic, with only one question included for each emotion. This was done in order to reduce participant burnout and to increase face validity, but it may have limited the robustness of our analysis. The measures of severity and susceptibility were validated, however, and represent significant results in and of themselves.

CONCLUSION

This experimental research has demonstrated that the presentation of search results related to health symptoms can affect individuals' impressions. This study has furthered research in this area by not only examining negative effects, which are often overlooked in research, but by also examining specific features of search results that can affect perceptions. The presence of serious illnesses at the beginning of a search results page for a common symptom, as well as a high frequency of serious illness mentions, can lead to increased perceptions of threat. In turn, this leads to negative emotional responses. In many cases, these perceptions are inflated and the reactions are unfounded if one considers the actual incidence rates of serious conditions. This study, and future research, can help to eliminate factors that cause fear and other negative outcomes when they are inappropriate, with the ultimate goal of making online health information viewing as helpful as possible.

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