Close Encounters of the Digital Kind: Motivated Search, Selection and Decision-Making in an Interactive Digital Context

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Abstract

Interactive digital contexts have become ubiquitous and indispensable, capturing hours of attention and influencing everyday decision-making, content consumption, purchasing behaviors, and the formation and updating of attitudes in a variety of domains. These carefully designed environments interact with human motivation to influence behaviors and beliefs, including in impactful domains such as science and public policy. Digital information contexts such as the newly released AI ChatGPT and Google may or have become the de facto standard for information search and content delivery, however search results in these contexts arrive either devoid of editorial filtering or with limited procedural transparency, or both. The potential societal costs of "wild information" are immense, especially for areas such as scientific technology that can provide significant benefits with low and manageable risk (i.e. vaccines, or genetically modified foods (GM). Using GM foods as a focal topic, we designed and implemented a custom search engine and content delivery system to identify the stages at which human motivation operates and its effects on search and selection behavior, attitude updating and decision-making in the context of widely-used interactive digital technology. Results demonstrate Google format searching often reflects prior beliefs and background media sentiment about GM foods, while menu-style searching reflects only prior attitudes. Prior attitudes influence search and content selection and in turn, content selection influences both attitudes about GM foods and decision-making in a food selection task. These results demonstrate when and how motivation covertly operates during digital information search and selection, and how search-based interactive technology interacts with motivational and cognitive systems to influence belief and real-world decision-making.

-- HBO's Chernobyl Opening Monologue

"*It's not that we'll mistake them for the truth. The real danger is that if we hear enough lies, then we no longer recognize the truth at all. What can we do then? What else is left but to abandon even the hope of truth, and content ourselves instead... with stories*."

There are some people who, if they don't already know, you can't tell 'em.
-Yogi Berra

Introduction

Hume's dictum that "reason is and ought only to be the slave of the passions" has for centuries loomed large as one of the most enduring and appropriate descriptions of human cognition and behavior, highlighting the primary role of motivation in how we think and what we do. Equally important, however, is the question of how humans, knowingly or not, can become slaves to latent and explicit motivations, and how different environments can facilitate certain kinds of behaviors over others. In particular, habitual encounters with the current online media environment has laid bare how easily human cognition and behavioral tendencies can be coerced at the mercy of highly refined techniques (often referred to as persuasive technology) (Fogg, 2003) to mold and hold attitudes and behaviors (Hansen & Wänke, 2009; Stanovich, 2018), and even alter core cognitive processes such as attention and memory (Firth et al., 2019). Despite work demonstrating consistent patterns of online behaviors, and describing the ways in which the modern information environment influences information seeking behavior, memory, knowledge and attitudes (Fisher, Goddu, & Keil, 2015; Kammerer, Gottschling, & Bråten, 2021; Scheufele & Krause, 2019; Sparrow, Liu, & Wegner, 2011; Yi-Fan, Akin, Brossard, Scheufele, & Xenos, 2015), few attempts have been made to mechanistically understand the stages at which motivation operates and interacts with the digital information environment to shape specific online behaviors, attitudes, and decision-making. Naturalistic experimental platforms that faithfully mimic real-word online environments, such as a fully-functioning search engine with a content delivery system, can be used to construct a more complete and applicable understanding of the motivational and psychological processes involved in exchanges with interactive digital technology, from search engines to encounters with newer platforms such as TikTok and generative AI chatbots such as ChatGPT. The current work holistically assessed the digital information search, selection and consumption process, using a custom search engine and content delivery system to identify the stages at which human motivation influences these behaviors, how technological manipulation affects content decisions, and the concomitant effects on attitudes and decision-making about GMO foods, an important scientific topic and technology with the promise to reduce hunger, malnutrition, crop loss, among other benefits.

Interactive technology platforms such as search engines and social media sites, among others, have become the defacto standard for information seeking, yet appear ethically indifferent to the side effects of opaque algorithms and engagement-oriented technological design elements. These technologies have effectively terraformed the information environment around human behavioral tendencies and motivation in order to produce increasingly consistent behavioral results, highlighting the pressing need to understand how encounters with these technologies interact with our motivational apparatus to condition our real-world search and sampling behaviors in a quickly evolving information landscape for which no precedent exists. Accumulated evidence indicates that the modern online media landscape has fundamentally changed our relationship with information, i.e. blurring the lines between editorialized content, advertising, and pure opinion (Brossard, 2013), and removing the cognitive friction involved in finding information and information sources congenial with one's predilections. Sans the dominance of editorial filters, the quality of online information now varies wildly, putting the onus of judgment regarding the credibility of sources and content squarely on users. Data across several studies indicates that most users make judgments about credibility based on cues and heuristics that are not related to information quality or accuracy, such as website design and user experience, as opposed to relevant factors such as information quality (Flanagin & Metzger, 2007; Weymann, Harter, & Dirmaier, 2015). Mixed source and non-delineated (i.e. editorialized vs. non-editorialized) content, coupled with recent research suggesting that people are poor at parsing article content from advertising (i.e. fake news (Wineburg, McGrew, Breakstone, & Ortega, 2016)), provide strong evidence that people struggle with assessing credibility for online content. Recent and upcoming research shows that spread of and engagement with misinformation, or fake content, exceeds that of accurate content, by on average as much as six (6) times (Edelson et al., 2021; Guess, Nyhan, & Reifler, 2020; Vosoughi, Roy, & Aral, 2018). Further, users do not appear to utilize metacognitive capacities to reflect on information seeking behaviors; self-reported information verification departs substantially from actual observed behavior (Flanagin & Metzger, 2007), and users are poor at assessing the relevance of content to a search goal (i.e. obtaining answers to a consumer health question (Coiera & Vickland, 2008)).

The societal implications related to the inability to assess credibility of information, unawareness of how one's own motivations and prior attitudes color algorithmically generated content, and complacency regarding the interaction and workings of digital technologies such as search engines, can be grave (Azzimonti & Fernandes, 2018; Tucker et al., 2018). For example, if one believes that GM Foods are dangerous to consume, a quick search in Google using keywords "GMOs dangerous" will return endless amounts of information from various sources relevant to the query. Search engines rank web pages based on a complex algorithm favoring relevance over veracity (Google, 2019), and enable web page owners to improve their standing through search engine optimization (SEO) techniques. Lack of scrutiny, or worse, lack of understanding regarding how search engines function, can easily lead to erroneous beliefs about scientific topics without any such intention. Other factors unrelated to the user, such as the fact that the catalog from which search engines select content departs dramatically from traditional library based searches, which catalogued editorialized content that survived a "meritocratic filtering" process (Metzger, Flanagin, & Medders, 2010), further hinder the probability of forming attitudes congruent with the best existing fact base. Inaccurate beliefs based on information retrieved online about technologies such as vaccines or GMO foods limit effectiveness of support campaigns and use, potentially prolonging events like pandemics or risking survival of viruses more generally (Dube et al., 2013); and delaying the ability to address hunger and malnutrition (Zilberman, Holland, & Trilnick, 2018). Thus, how and where people search for and retrieve information is of paramount importance, especially since, in many non-curated circumstances, the burden of content selection among an impossible volume of results, is placed on the user. In no place is this more apparent than search engines, which handle over a trillion searches daily and are used by over 90% of the population with internet access (Pew, 2012; Stats, 2021).

Search engines are a primary and influential source of information, to which most users assign significant trust (Pan et al., 2007; Pew, 2012), yet possess poor understanding of the algorithmic methodology deployed and how their own motivations are used to generate search engine results (Brandverity, 2020; Schultheiß, Sünkler, & Lewandowski, 2018). Search terms are like the bait placed on the line of a fishing pole, which we cast into Google's (or other search engines or information gathering platform) vast seas of information. Specific kinds of bait reveal motivational influences, and importantly, attract search results relevant to those search terms. Importantly, search engine results carry no guarantee of truthfulness, providing primarily what we want, and not necessarily what we need in order to form opinions on the basis of fact. Preliminary research has assessed the effects of search engine technology on attitudes, suggesting that voting preferences can be altered to some degree based on interactions with search engines (Epstein & Robertson, 2015). In the health domain searches are often characterized by “positive hypothesis testing”, in which search and consumption behavior is skewed towards attempts to confirm a pre-existing association between symptoms and a specific condition (Kayhan, 2013). Computer-human interaction and communications research demonstrate that search engines including Google can influence belief and behavior (i.e. (Allam, Schulz, & Nakamoto, 2014) about vaccinations. Critically, offering a manipulated set of pro-vaccination results to participants both increased knowledge about vaccinations and attitudes towards them, however a control group that offered standard Google results showed a far more modest effect on knowledge and a negative effect on attitudes, with higher concern about vaccines. In an in depth study about the research process of journalists, search engines were found to have an outsized influence, but only careful, reflective construction of search terms yielded successful results (Machill & Beiler, 2009). Other work from the scientific communication field has examined how people select content, demonstrating the use of heuristics including cue use (i.e. cues that clarify ideological ramifications vis a vis the searcher promote broader sampling, while the absence of cues skews selection towards previously known sources) and confirmation bias in the content selection process (Yeo, Xenos, Brossard, & Scheufele, 2015). Such biases appear in online search environments, in which the number of search results can be staggering. When presented with significant amounts of information, as is the case in internet search, content selection is often biased towards preference-consistent information (Fisher et al., 2015), which can be exacerbated by relevance-focused search engines.

The relationship of online behaviors to attitudes and media use has also been studied in other online contexts. While providing valuable knowledge into various aspects of online behaviors and their relation to attitudes and understanding, to date most research examining effects of the interactive digital environment on news and scientific topics has been single component-oriented (i.e. evaluating content selection (Yeo et al., 2015)), at times contradictory (see (Iyengar & Hahn, 2009; Nelson & Webster, 2017) or correlational (Su, Akin, Brossard, Scheufele, & Xenos, 2015), limiting the translation of some of these results to real-world contexts. The current study enables bidirectional motivational influences (interactive content and the searcher) as they occur on real-world search engines, thus providing the full set of complex interactions and data necessary to assess the relation of search, selection and consumption processes as they naturally occur, to attitudes and decision-making. Further, we take into account a broad set of classic psychology phenomena to inform our hypotheses in the domain of the modern information environment. Specifically, memory research has shown that availability of information in memory is linked with attitudes (Hastie & Park, 1986), suggesting that attitudes commonly expressed across media platforms will be more available and potentially affect search behavior. Motivated cognition and attitude research consistently demonstrates that exposure is a powerful determinant of attitudes (Albarracín & Mitchell, 2004; Cappella, Kim, & Albarracín, 2015), and that people tend to gravitate to attitude-consistent information, especially when their values are at stake (Hart et al., 2009), in order to avoid dissonant emotions (Festinger, 1957) and validate their positions. These findings, together with 1) the way search algorithms work, prioritizing relevance, and making it extremely easy to find information congenial with one’s preexisting attitude; and 2) accumulated data demonstrating consistent online behaviors and misinformed beliefs, such as the overwhelming propensity of searchers to click on the first few search results (Chaffey, 2021), and mistaking access to information with knowledge (Sparrow et al., 2011), inform our hypotheses regarding how people search for, select, and consume content, and the effects these behaviors have on attitudes and decision-making.

We selected a seemingly controversial topic, GM foods, as the conduit to examine the interaction of interactive digital technology with human motivation and cognitive tendencies. GM foods were selected as the focal topic based on 1) the frequent appearance of Non-GMO products in advertising campaigns and social media, often cast in a negative light; 2) a significant amount of misunderstanding about the science and safety of genetic modification, despite decades of independent research and assessments; and 3) GMs are typically encountered during every food shopping excursion, providing ecological validity to the subject matter investigated.

The current work sought to understand how an important widely-used area of the digital information environment interacts with human motivation and behaviors, specifically, how common cognitive and behavioral tendencies and motivation influence information search and selection, and the concomitant effects on attitudes and decision making. To address the lack of research examining the interactions of a realistic, everyday digital information environment and human motivational and cognitive tendencies, we developed a custom platform, Searchsci.org. Searchsci functioned as a stand-alone search engine and content delivery system, capable of hosting search tasks, clickable search page results, interactive content including infographics, comment areas and brief surveys. Importantly, these functionalities enable controlled investigation throughout the information search, selection, and consumption processes, providing the ability to probe motivational influences on these actions, how these actions relate to attitudes about GM foods, and within a real-world interactive digital context.

Hypotheses

Motivation in Search

Since the background valence about GMO in the media is decidedly negative (see (Cui & Shoemaker, 2018; Royzman, Cusimano, Metas, & Leeman, 2020; Ventura, Frisio, Ferrazzi, & Siletti, 2017) and information searchers are likely to default to search biased towards prior attitudes (Cappella et al., 2015), we predicted that generated sets of search terms would skew towards the media bias on account of enhanced availability of negative information, but still track with prior attitudes. We also predicted that when presented with a diverse menu of search terms, individuals would select terms that fit their prior predilections vis a vis GMs. However, in contrast with Google-style searching, we anticipated that menu-style searching would not reflect the negative availability bias since the information available with which to make search decisions expands beyond that which can be retrieved from memory. Specifically, we expected a significant difference in attitude sentiment between search methods to be driven by less negatively selected search terms (vs. generated search terms) across participants whose prior attitudes were not already aligned with the negative background media bias.

Motivation and Interaction with Digital Technology

Based on data regarding consistent behavioral tendencies on search results pages (i.e. (Chaffey, 2021; Joachims, Granka, Pan, Hembrooke, & Gay, 2005; Southern, 2020)), and the effect of the media backdrop on search generation, we predicted that attitudinal valence of generated search terms would not track with first clicks on the manipulated search results pages (see manipulation of search results in Methods). However, we expected our manipulation to affect first click behavior, such that, for example, participants assigned to the group shown Pro-GMO articles first would be more likely to first select Pro-GMO content vs. other content displayed further down in the search rankings.

While some recent work demonstrated a so-called “search engine manipulation” effect (Epstein & Robertson, 2015) in which search ranking persuades individuals towards attitudes expressed on popular, top ranked results, other work suggests this conclusion is unwarranted (Fortunato, Flammini, Menczer, & Vespignani, 2006). Reported effects relied on a manipulation in which the first few pages of search results favored a specific view. Even for political candidates we believe such a search result configuration is highly unlikely, as search results for names are likely to be less one-sided than explicitly motivated search. When searching for scientific topics such as GMOs, an analogous search term is “GMO”, which, similar to a name, returns a mixture of results (Google, 2021), some in support and some critical of the subject of search. As such, any realistic manipulation should include content sentiment that mirrors actual search results and reflects a more balanced set of content. When search results are manipulated in accordance with naturalistic scenarios, we predicted that manipulation group effects on attitudes reported previously (Epstein & Robertson, 2015) would wane in importance in favor of other factors. Specifically, in the current study, group assignment was not expected to produce attitude change, per se. However, to the extent the sentiment of first clicked content was congruent with prior attitudes, we expected first clicks to track more strongly with overall article sentiment bias (specifically, the average sentiment of all articles consumed) than when sentiment of first clicks was incongruent with prior attitudes. For participants holding neutral prior attitudes (uncertain participants), we predicted differences in overall article sentiment bias based on the sentiment of the first clicked content.

Motivation in Search, Selection, and Consumption Relating to Attitudes and Decision-Making

We predicted that overall article selection bias would be associated with prior attitudes, and hence also reflect the motivational valence of search behaviors. We also expected overall article selection behavior to predict attitude change after exposure to content, given exposure effects on attitudes (Albarracín & Vargas, 2010). Directionally, we expected search behaviors to be informed by prior attitudes, and in turn search behaviors would inform overall article selection bias, and this bias would be the primary factor producing effects on attitudes and decision-making about GM foods in post-task measurements.

We find that prior attitudes inform search behaviors for both search generation and search selection, and that these motivational predilections were reflected to a greater degree when participants selected search terms from among an extensive menu. Common behavioral tendencies on search results pages privilege the first few results, which receive an outsized number of clicks compared with lower ranked results, however, greater variance in attitude change was captured by overall article selection bias than first click behaviors. The sentiment of articles clicked on first did not match the tenor of Google-style or menu-style search results, demonstrating the power of online behavioral tendencies and trust in search engine technology. However, first clicks were found to track with prior attitudes, suggesting that while likely to click towards the top of the search results page, participants probably scrutinized among the top ranked search results. This finding highlights the potential importance of providing balanced search results. Using path analysis, we also found that prior attitudes inform search behaviors, that search sentiment is associated with content selection, and that content selection polarizes attitudes and decision-making. These experimental results have far reaching implications for many fields, including but not limited to education, science communication, medicine, and agriculture, for which getting accurate information to the public, and educating the public in regards to effective search, is paramount to inform and gain support for science-guided public policy.

Methods

Overview

The study consisted of two parts, completed on different days separated by a minimum of 24 hours. Part 1 probed participants' knowledge and attitudes towards GM foods, along with demographic and psychological variables identified to play a role in attitude formation. These survey measures were supplemented with a two-item forced-choice decision-making task from which we could infer the impact of beliefs about GM foods on real-world behavior. Search, selection and consumption was assessed in Part 2. Part 2 asked participants to provide different sets of search terms about GM foods, and in a separate search task, were also asked to select among experimenter provided terms. After performing the search task participants were shown a search results page containing over 20 articles, each with infographics, with which they could interact, share, and leave comments. To assess decision-making we provided participants with pairs of food items labeled either as conventional or Non-GMO and collected forced choices.

A Supplemental Study was conducted consisting of a single experimental session in which content was consumed and rated relating to perceived bias in order to validate the authors' assumptions about the perceived position supported or opposed in each piece of article content. Details regarding the Supplemental Study are included in the Supplementary Information accompanying this manuscript.

Materials

Platforms

Task and survey data were collected using two sources: 1) the Qualtrics online platform www.qualtrics.com was used to collect survey data for Part 1 and Part 2; and 2) a custom designed and coded online platform that functioned as a standalone website, hosted at searchsci.org ("SearchSci") for Part 2. SearchSci powered two search tasks, a fully interactable search results page, readable and visual clickable content, surveys, and an adaptive memory task which displayed questions based on specific content consumed by the individual participant. SearchSci received and tracked user data from Qualtrics, enabling flexible functionality based on group assignment.

SearchSci is a standalone platform utilizing a JSON-based API, with a Java servlets backend, MongoDB database, and a TypeScript with Knockout.js front end. SearchSci was implemented as a modern web application, with a TypeScript-based browser client interacting with a Java-based server using a bespoke JSON API. All client-server communications were encrypted on the wire with Transport Layer Security (TLS). Data was persisted to MongoDB as JSON documents and retrieved asynchronously for subsequent analyses. The server and database were deployed on a Linux virtual machine in the cloud.

Surveys

Part 1 collected the Public Perception of Scientific Uncertainty Scale ("Science Uncertainty Scale") (Broomell & Kane, 2017), a 14-item scale designed to assess 1) perceptions regarding the precision of a given research field; 2) perceptions of uncertainty associated with each research field; and 3) perceptions of uncertainty due to the distant past and future. All studies collected GM knowledge and position scales ("GM Knowledge and Position Scales"), designed to assess the basic understanding of GM science and the current state of policy and availability, and subjective beliefs about GM foods (McFadden & Lusk, 2016). Based on research suggesting a moral dimension to GM opposition (Scott, Inbar, & Rozin, 2016), Study 1 also included a Moral Purity Scale based on Moral Foundations Theory (Graham et al., 2013). These data are not reported, but are available upon request

Part 2 included a reassessment of the position portion of the GM Knowledge and Position Scale; the Need for Closure Scale (Kruglanski et al., 1997); and the Need for Cognition Scale (Cacioppo & Petty, 1982); and a selected subset of the General Social Survey (GSS) in order to quantify political orientation (see Supplemental Materials for selection). Data pertaining to the Need for Cognition and Need for Closure Scale are not reported, but are available upon request.

Search Tasks

Two search tasks were designed to assess the ability of participants to effortfully generate search terms related to GM foods, and how participants select among information presented to them, much like a news or social media feed. Since these tasks require and demand a different cognitive repertoire (i.e. generating search terms requires effortful cognition and memory retrieval, while selecting among provided options does not) and level of effort, the extent to which motivation affects search behavior in distinct contexts could be elucidated. The search generation task was presented first to avoid the impact of viewing a set of highly specific search terms.

Search Generation Task

The search generation task was identical to the entry of search terms into a search engine such as Google or Bing (Figure 1, Panel A), except that instead of one set of search terms, five sets were required. Participants were provided five (5) minutes to generate and enter the five search terms. Search terms were rated by three (3) independent raters, who provided values of -1, 0, or 1 to each search term, indicating Anti-GMO, neutral, or Pro-GMO, respectively. Ratings for each participant were summed across the five search terms, and then compared across raters, generating an acceptable value of Krippendorf's alpha (alpha = 0.71, n = 345). Krippendorf's alpha was selected based on its flexibility with respect to handling interval data and generating unbiased estimates for missing values. The three (3) ratings per participant were then averaged to create one search generation value used in statistical analyses.

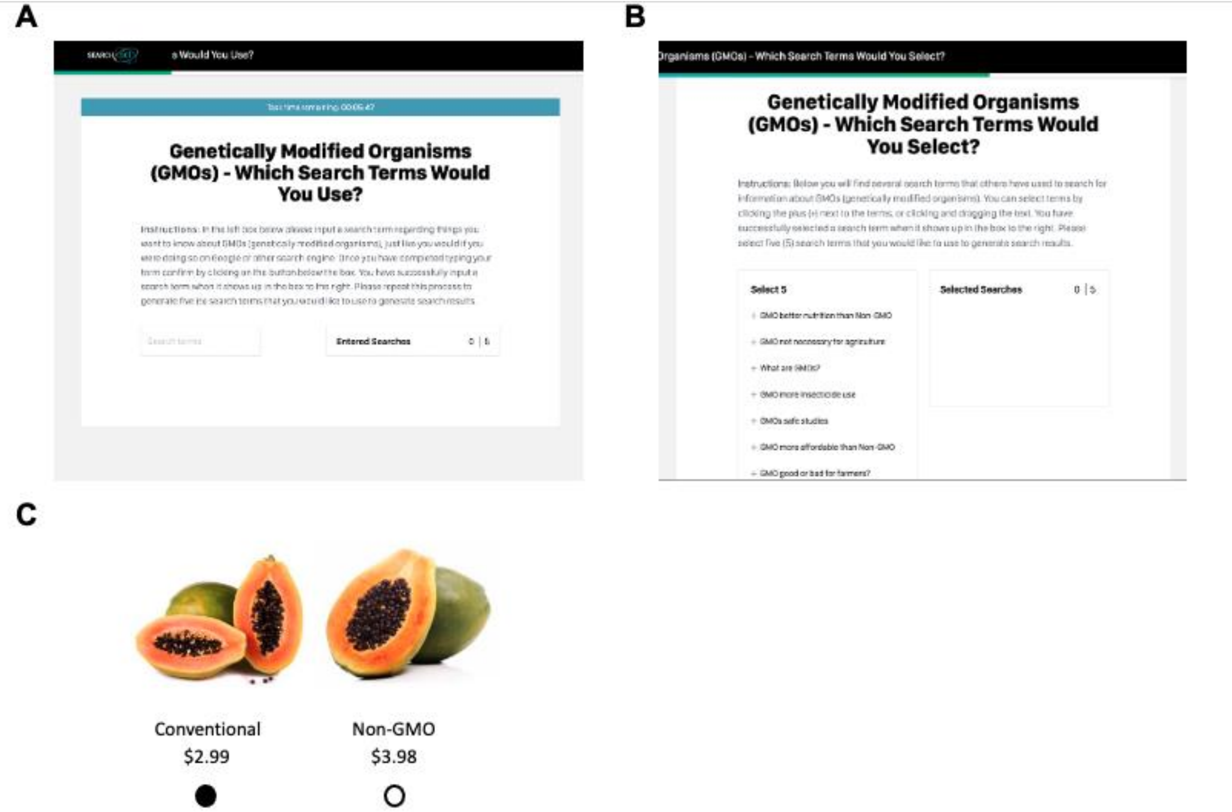


Figure 1

Depiction of Search and Decision-Making Tasks. A. The Google-style search generation task provided instructions that the participant enter five (5) sets of search terms. Each set of terms was displayed on the right-hand side of the screen. B. The menu-style search selection task provided a set of 33 search terms from which the participant was asked to select five (5). C. The decision-making task displayed a pair of food items, one Non-GMO and one conventional item, that varied in price. The price differential reflected market conditions and was fixed at 33%.

Search Selection Task

The researchers created a set of 33 search terms (see Supplementary Information for complete list), composed of an equal number of Pro GMO, Anti GMO and neutral (Neither Pro-GMO nor Anti-GMO) search terms. These terms were displayed in random order to each participant

(Figure 1, Panel B). Using a mouse or trackpad, the participant was asked to select any five (5) search terms and were given five (5) minutes to do so. Each search term was classified as Anti-GMO, neutral, or Pro-GMO (see Supplementary Information for details) and coded -1, 0, or 1, respectively. Ratings were summed across the five search terms to generate a single search selection score. The single value score was used for statistical analyses.

Content and Content Task

A set of 23 articles (10 Pro-GMO; 9 Anti-GMO; 4 neutral) was collected from sources on the internet. Average word count of the selected articles was 1043 words. Original sources were maintained for articles obtained through copyrights, while the remaining articles were assigned a source from among seven (7) sources including: 1) Scientific American; 2) National Geographic; 3) The Genetic Literacy Project; 4) Natural News; 5) GMO Awareness; 6) Fox News; and 7) MSNBC. Copyrighted articles were sourced from Scientific American and National Geographic. Three (3) articles were assigned to each source except Scientific American and Natural News, which appeared as sources for four (4) articles. Some articles not subject to copyrights were edited for length. Individual article content is available upon request.

The Content Task followed the search tasks, and consisted of an information foraging and consumption period of 35 minutes (Figure 2). Participants viewed search results on the searchsci.org search engine (Figure 2, Panel A), similar to any popular search engine. All content was clickable, and participants could spend as long as they wished reading any selected article content and engaging with the functionality. All article content contained source information, a title, shareable links, author, an opening image, article text, comments, an infographic, and a custom notepad (Figure 2, Panel B, C and D). Article content was supplemented with custom designed and clickable infographics to improve engagement. Participants could highlight text deemed important and insert it into a custom notepad.

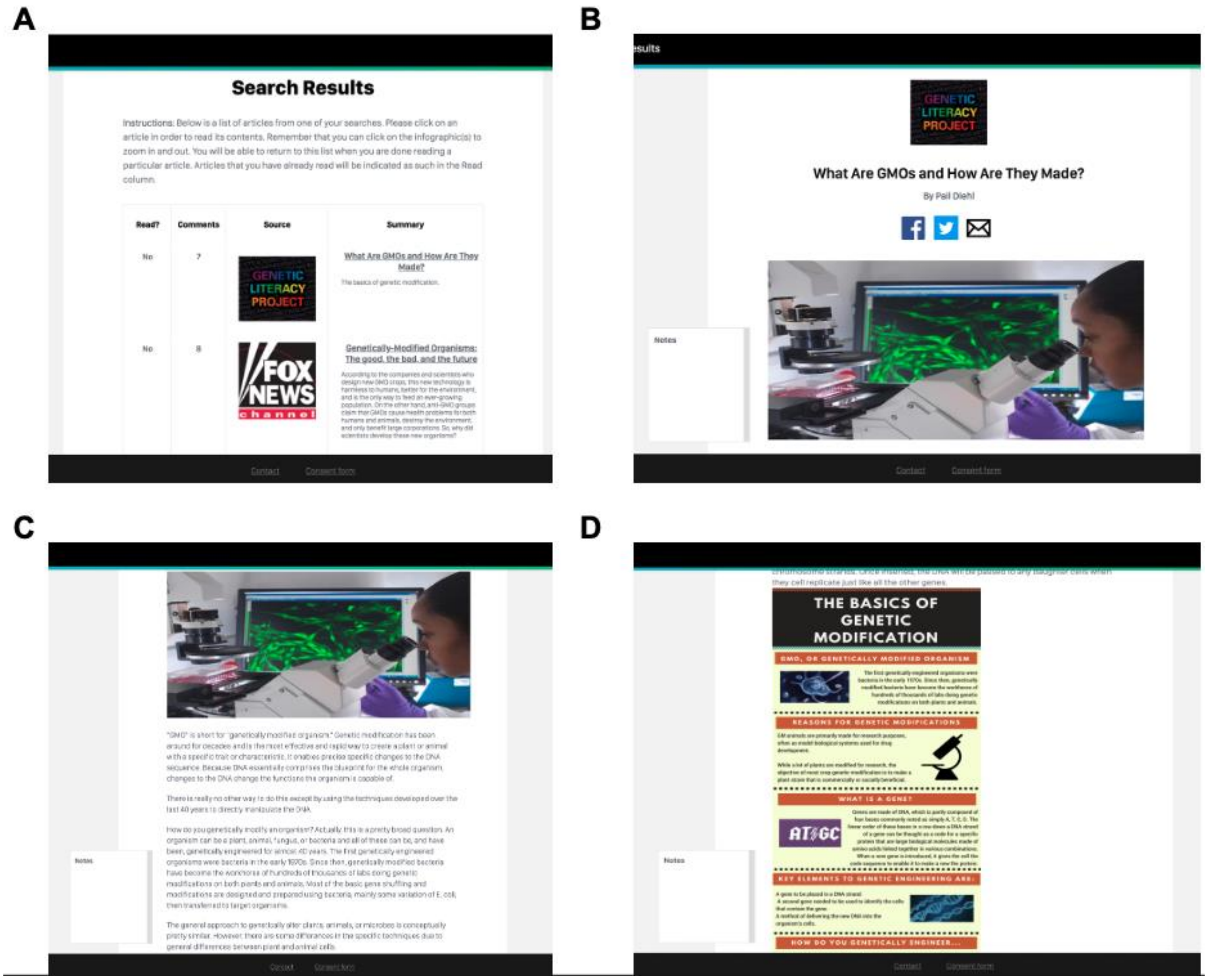


Figure 2

Content Task Pages. A. The search results page provided information relevant to use of the page, a list of clickable search results with titles, brief descriptions, and sources. B. Upon clicking the title of an article on the search results page, the clicked content was displayed. Each article contained a title, author name, image, and shareable links at the top of the content. C. Article text was displayed underneath the opening image. Participants scrolled to read the full article content. D. Custom clickable infographics were displayed with each article, which provided summary information about the article content.

Decision-Making Task

To assess consumer decision-making behavior vis a vis GMO foods, a paired item shopping task was developed (Figure 1C). The task displayed 16 pairs of identical items. One food item was labeled “conventional”, and the other “Non GMO”. The Non GMO item was consistently more expensive than the conventional item by a fixed percentage across pairs of food items. The shopping task was administered in Part 1, and reassessed in Part 2 after participants had searched for and consumed content about GMO foods.

Analysis

Data was organized and cleaned using Microsoft Excel and Python 3.6x, and subsequently imported into R v3.50 for analysis. Path modeling was performed using the lavaan package version 0.6-3.

Participants

345 participants (180F, M(age) = 35.07) were recruited via flyers on the Columbia University campus, online social media posts, and through Amazon's Mechanical Turk ("MTurk") platform, and completed the study. An additional 78 participants completed Part 1 (see below for study description) of the study but failed to complete Part 2. Incomplete data was not analyzed. Participants recruited through social media were paid $20 for completion, while Mturk workers were paid $3 to complete Part 1, $9 to complete Part 2, plus a full completion bonus of $1.50. Recruitment protocols adhered to procedures approved by Columbia University's Morningside Institutional Review Board requirements.

Procedures

Study 1 consisted of two parts, separated by at least 24 hours. Once Part 1 was completed, the server initiated a 24-hour timer, after which an email with a link to Part 2 was delivered to an email address provided by the participant.

Part 1

Part 1 was hosted and delivered on the Qualtrics platform via a link on the searchsci.org website. Participants first provided consent via digital signature and then completed the Decision-Making task, followed by the position portion of the GMO Knowledge and Position Scale, the Science Uncertainty Scale, and finally the knowledge portion of the GMO Knowledge and Position Scale (see Supplemental Materials for details). The Qualtrics ID, group assignment, and score information was sent to the SearchSci server in order to generate a participant specific link and to track the participant throughout Part 2. Group assignment was randomized based on a pool of three (3) possible groups. Part 1 duration was approximately 20 minutes.

Part 2

24 hours after completion of Part 1, participants received a link to begin Part 2 on searchsci.org. Participants first completed the search generation task, followed by the search selection task. Participants were then told that their search terms had been used to generate a search results page, where the content task was completed. The search results page contained all 23 articles selected by the researchers. The structure of the search results was manipulated such that participants assigned to group one (1) were shown Pro GMO articles first; group two (2) was shown Anti GMO articles first; and group three (3) was shown Neutral articles first. The remaining articles were displayed in random order. The content task required a mandatory reading period of 35 minutes. Participants could spend as much time as desired on any given article. Articles read for greater than 90 seconds triggered a survey upon exit of the article page, prior to returning to the search results page. Articles read for fewer than 90 seconds were excluded from analysis and not counted towards the article selection bias variable. After 35

minutes elapsed, an adaptive memory task (not reported) was administered. Next, the server automatically redirected to Qualtrics, where participants completed the decision-making task, the position portion of the GMO Knowledge and Position Scale, selected GSS questions to assess political leaning, demographic questions, and the Moral Purity Scale. Part 2 duration was approximately 60 minutes.

Results

Relationships Between Prior Attitudes and Search Modalities, Content Selection, and Attitude Change

We first examined the correlational structure of the primary reported data to confirm the existence of coupled relationships of attitudes, search, content selection, and decision-making variables. These correlations are presented in Table 1. Prior attitude correlates with all task related variables, indicating the presence of a significant motivational factor in these behaviors. Search selection, but not search generation, was associated with article selection bias (pro-anti). Neither search modality related to the shopping decision-making task at time 1, however both modalities exhibited a robust relationship with the shopping decision-making task at time 2. Neither search modality correlated with attitude change. Notably, article selection bias was strongly correlated with the shopping decision-making task at time 2 despite no significant relationship with the shopping decision-making task at time 1. Article selection bias was also strongly associated with attitude change, such that the tendency to click on more pro-GMO articles tracked more pro-GMO movement on attitudes. Finally, the shopping decision-making task at time 2 was significantly inversely related to attitude change, such that a tendency to select fewer non-GM food items correlated significantly was associated with attitudes more favorable to GM foods. See Table 1 for details pertaining to the correlational data.

A

	Prior Attitude	Search Generation	Search Selection	Article Selection Bias (Pro-Anti)	Shopping Time 1	Shopping Time 2	Attitude Change
Prior Attitude	1						
Search Generation	0.24***	1					
Search Selection	0.30***	0.28***	1				
Article Selection Bias (Pro-Anti)	0.28***	0.08	0.19***	1			
Shopping Time 1	-0.46***	-0.06	-0.08	-0.09	1		
Shopping Time 2	-0.58***	-0.18**	-0.18***	-0.34***	0.47***	1	
Attitude Change	-0.24***	-0.03	0.04	0.32***	0.11*	-0.18***	1

* p < 0.05, ** p < 0.01, *** p < 0.001

B

	Prior Attitude	Search Generation	Search Selection	Article Selection Bias (Pro-Anti)	Shopping Time 1	Shopping Time 2	Attitude Change
Prior Attitude	345	332	345	345	345	344	344
Search Generation	332	332	332	332	332	331	331
Search Selection	345	332	345	345	345	344	344
Article Selection Bias (Pro-Anti)	345	332	345	345	345	344	344
Shopping Time 1	345	332	345	345	345	344	344
Shopping Time 2	344	331	344	344	344	344	344
Attitude Change	344	331	344	344	344	344	344

Table 1. Correlation matrix of identified variables of interest. A. Pearson correlations shown. Prior attitudes were significantly associated with each observed variable of interest (leftmost column). Search selection, but not search generation, was significantly associated with an article selection bias. Attitude change was significantly associated with both prior attitudes and article selection bias. Sample sizes utilized for each set of correlations is provided in panel B. Different sample sizes reflect incomplete data for some participants. * p < 0.05; ** p < 0.01; *** p < 0.001.

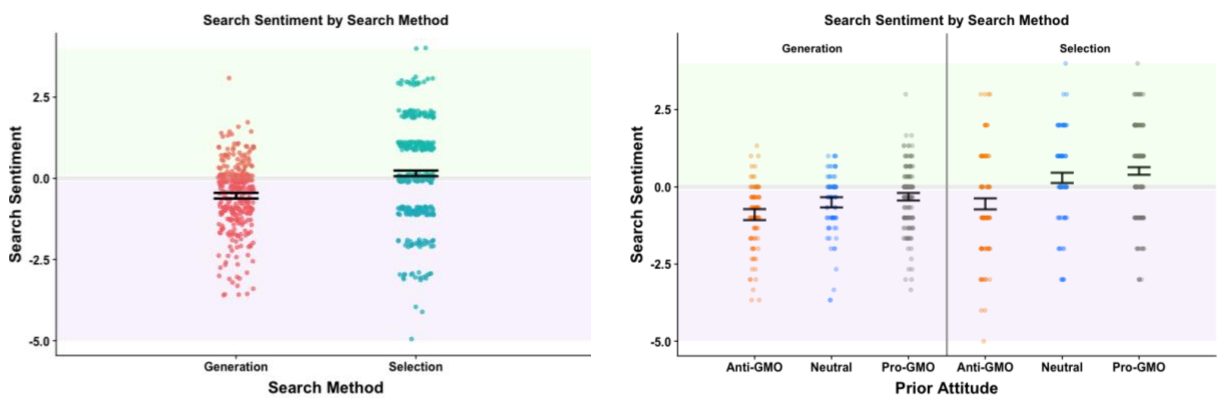
Motivation in Search

Consistent with our hypotheses we found an overall anti-GMO search generation bias compared with a zero baseline (indicating no bias) ($t(331) = -9.5$, $M = -0.53$; $SD = 1.02$, $p<0.001$; one sample, non-paired, one-sided t-test vs. 0); and search generation bias corresponded with prior attitudes (Pearson's $r = 0.24$, $t(330) = 4.46$, $p<0.001$, 95% CI = [0.13, 0.34]. Consistent with the search generation results, search selection bias also tracked with prior attitudes about GMO (Pearson's $r = 0.30$, $t(343) = 5.80$, $p < 0.001$, 95% CI = [0.20, 0.39]. Notably, search selection bias skewed more towards neutral than search generation bias (Figure 3, Panel A) as these values differed significantly (paired $t(331) = -8.07$, M(search generation) = -0.53, M(search selection) = 0.15, $p < 0.001$, 95% CI difference = [-0.88, -0.53]. While search generation skewed negative, search selection sentiment was neutral and this effect was driven by sentiment increases across all categories of prior attitudes, however, based on effect sizes, greater movement was observed for the neutral and Pro-GMO prior attitude participants (Figure 3, Panel B; Table 2; search generation vs. search selection: Anti-GMO:

t(97) = 2.06, p = 0.04, 95% CI = [0.01, 0.72]; Neutral: t(79) = 4.83, p < 0.001, 95% CI = [0.47, 1.13]; Pro-GMO: t(154) = 7.13, p < 0.001, 95% CI = [0.63, 1.12]. Notably, sentiment was negative for both search generation and search selection only for participants expressing an Anti-GMO prior attitude (search generation: Anti-GMO: t(97) = -8.73, M = -0.90; SD = 1.01, p < 0.001; one sample, non-paired, one-sided t-test vs. zero; Anti-GMO: t(99) = -3.38, M = -0.55, SD = 1.63, p = 0.001; one sample, non-paired, one-sided t-test vs. zero. Confidence Intervals for differences in mean values of search sentiment for each combination of search method and prior GMO attitudes are displayed in Figure 3, Panel C.

A

B



C

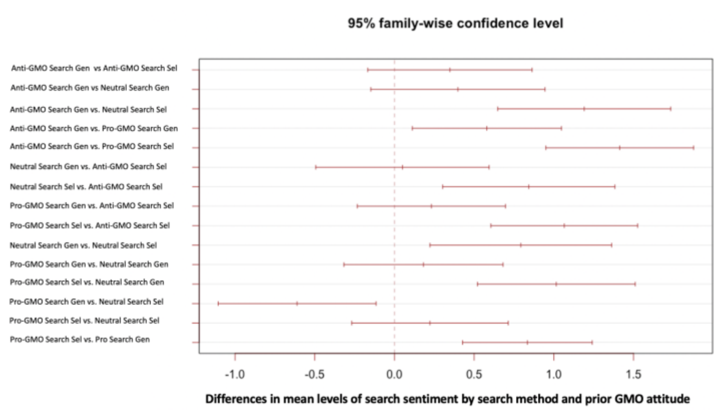


Figure 3
Search Sentiment by Search Method. **A.** Search generation sentiment, i.e. Google-style searching, regarding GMOs, was biased towards Anti-GMO sentiment (p<0.001), and statistically different from search selection sentiment, i.e. menu-style searching (p<0.001). Bottom shaded region below neutral zone of zero (0) indicates an Anti-GMO bias.
B. Search sentiment by search method by prior attitude. While all attitude categories shifted search sentiment towards more Pro-GMO attitudes when selecting search terms from among a menu, only participants holding Anti-GMO prior attitudes selected an Anti-GMO set of search

terms (see Table 2 for comparisons and effect sizes). Higher search sentiment scores indicate more Pro-GMO search terms. Upper shaded region above neutral zone of zero (0) indicates a Pro-GMO bias. **C.** 95% family-wise confidence intervals for each combination of search method and prior GMO attitude. Search Gen: Search Generation; Search Sel: Search Selection. Values reflect correction for multiple comparisons using the bonferroni method. Error bars represent standard error of the within subject difference. Sample size of n= 332 used to derive error bar statistics.

Prior Attitude	t-statistic	Difference of Means	p-value	Cohen's d	Cohen's d 95% CI	Effect Size
Anti-GMO	2.06	0.37	0.04	0.21	0.01, 0.41	small
Neutral	4.83	0.80	<0.001	0.54	0.31, 0.78	medium
Pro-GMO	7.13	0.87	<0.001	0.57	0.40, 0.74	medium

Table 2
Search Generation vs. Search Selection by Prior Attitude. Search sentiment increased (towards neutral) across all attitude categories as a function of search method. Average search generation sentiment skewed negative (anti-GMO), while average search selection sentiment revealed no bias. The effect was largely driven by the Neutral and Pro-GMO attitude categories based on effect size. Sample sizes: Anti-GMO = 97; Neutral = 79; Pro-GMO = 154.

Motivation and Interaction with Digital Technology
Interactions of users with our manipulated search results pages revealed that structure of results pages was a powerful predictor of first click behaviors, with content positioned at the top of results pages receiving an outsized number of first clicks (Supplementary Figure 1). We first assessed search results page clicking behavior and its correlation with search generation sentiment. Search generation sentiment did not correspond with the sentiment of first clicks on search results pages (Pearson's r = -0.02, t(317) = -0.32, p=0.75, 95% CI = [-0.13, 0.09], however, first click sentiment was strongly associated with group assignment, such that participants were more likely to select an article consistent with the manipulation (Figure 4; Group1, Pro-GMO: Pearson's $\chi^2(2) = 67.19$, p < 0.001; Group 2, Anti-GMO $\chi^2(2) = 15.95$, p < 0.001; Group 3, Neutral: $\chi^2(2) = 39.61$, p <0.001). Despite the finding that first clicks echoed the group manipulation, group assignment did not have an effect on attitude change (Pro-GMO first vs. Anti-GMO first: unpaired t(244.85) = 1.27, M(Pro-GMO) = 1.35, M(Anti-GMO) = 0.86, p=0.21, 95% CI = [-0.27, 1.27]; Pro-GMO first vs. Neutral first: unpaired t(226.52) = 0.48, M(Pro-GMO) = 1.35, M(Neutral) = 1.15, p=0.63, 95% CI = [-0.61, 1.00]; Anti-GMO first vs. Neutral first: unpaired t(200.56) = -0.77, M(Anti-GMO) = 0.86, M(Neutral) = 1.15, p=0.44, 95% CI = [-1.06, 0.46]. A Kruskal-Wallis test indicated that first click sentiment was not associated with attitude change (H(20) = 24.59, p = 0.22), nor was first click sentiment a significant predictor of attitude change based on a linear model controlling for the effects of prior attitudes and article sentiment bias (Table 3; B(Anti vs Neutral) = 0.12, t = 0.29, p = 0.77; B(Anti vs Pro) = 0.54, t = 1.39, p = 0.17; Full Model: F(4, 325) = 22.79, p<0.001, $R^2 = 0.22$, $R^2_{adusted} = 0.21$).

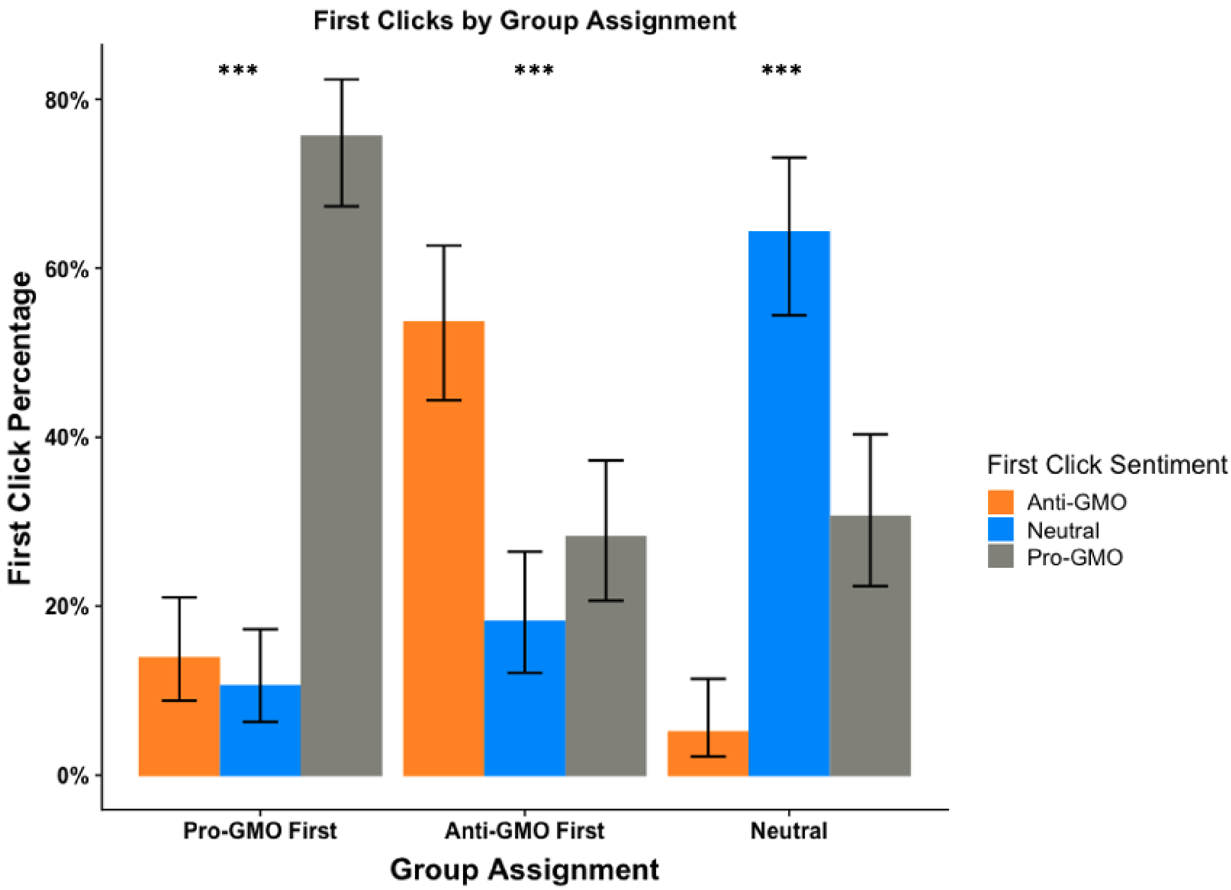


Figure 4

First Click Sentiment by Group Assignment. The percentage of first clicks consistent with group assignment manipulation. Participants were more likely to select content congruent with the group manipulation (articles displayed at the top of the search results list) than content that was incongruent. Confidence intervals computed using the Wilson method. Sample sizes: Group 1 = 123; Group 2 = 110, and Group 3 = 98. *** p < 0.001

Predictor	b	b 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]	Fit
(Intercept)	4.26**	[3.00, 5.51]			
First article sentiment-Neut	0.12	[-0.69, 0.93]	.00	[-.00, .00]	
First article sentiment-Pro	0.54	[-0.22, 1.30]	.00	[-.01, .02]	
Article Sentiment Bias	0.66**	[0.48, 0.84]	.13	[.06, .19]	
Prior Attitude	-0.26**	[-0.33, -0.18]	.11	[.05, .17]	
					R^2 = .219** 95% CI =[.14,.29]

Table 3

Regression Results Predicting Attitude Change. A multiple linear regression model indicated that first article sentiment (first clicked content) was not a significant predictor of attitude change when prior attitudes and overall article selection bias were taken into account. Prior attitude and article sentiment bias predicted attitude change. Reference level for first article sentiment: Anti-

GMO. Model terms First article sentiment-Neut and First article sentiment-Pro indicate contrast with the reference level.

Note. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.

* p < .05. ** p < .01.

Motivation in Search, Selection, and Consumption Relating to Attitudes

To assess when and where motivation operates in the complete search engine experience, we deployed path analysis, a special case of structural equation modeling (SEM) in which a series of multiple regressions produce path coefficients. Path analysis is particularly well-suited to analyze the current dataset because the path follows the task sequence and enables simultaneous estimation of coefficients associated with the suite of variables of interest, and does so in a linear fashion, such that causation within the model flows according to the path. That is, each endogenous variable is caused by the exogenous variables that precedes it, flowing from left to right. The path model generated for this purpose is depicted in Figure 5. Causal paths are denoted by one way arrows, while covariances are represented by curved double-sided arrows. Standardized path coefficients from exogenous to endogenous variables represent the amount of change in the endogenous variable for a one standard deviation unit change in the exogenous variable, holding all other node connections constant. Robust maximum likelihood was selected as the estimator to account for non-normality of the dependent variables. Path coefficients derived from the model are summarized in Table 4.

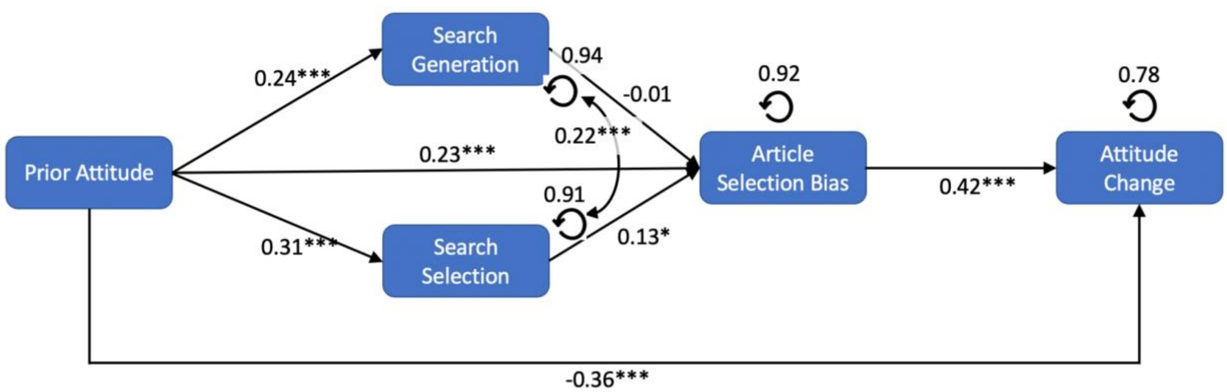


Figure 5. Path diagram illustrating the path to attitude change. The path follows the temporal sequence of tasks, from left to right. Prior attitude was measured first, followed by the search generation and search selection tasks. Once search was completed, search results were generated and participants selected and consumed content, from which an article selection bias could be calculated. After completing a mandatory reading period, participants' attitudes were reassessed and an attitude change score reflecting the difference between the attitude measure after content consumption and the prior attitude measure, was calculated. All directional relationships were significant except the path from search generation to article selection bias.

* p<0.05; *** p<0.001.

Left	Right	Beta	std.error	z-value	p-value	ci.lower	ci.upper
Prior Attitude	Attitude Change	-0.36	0.04	-8.33	0.000***	-0.44	-0.27
Article Selection Bias	Attitude Change	0.41	0.04	9.42	0.000***	0.33	0.50
Prior Attitude	Article Selection Bias	0.23	0.05	4.68	0.000***	0.13	0.32
Search Generation	Article Selection Bias	-0.01	0.05	-0.24	0.81	-0.11	0.09
Search Selection	Article Selection Bias	0.13	0.06	2.32	0.02*	0.02	0.23
Prior Attitude	Search Generation	0.24	0.05	4.43	0.000***	0.13	0.35
Prior Attitude	Search Selection	0.31	0.06	5.52	0.000***	0.20	0.42

Table 4. Path analysis coefficients, Attitude Change. Standardized coefficients are provided for the paths depicted in Figure 5 above. Each relationship is specified on the left hand side of the table. Sample size utilized in path model n = 331. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

The hypothesized path model fit the data well. A CFI (comparative fit index) of 0.999 and TLI (Tucker-Lewis index) of 0.995, and Robust RMSEA of 0.016 were obtained. An R-squared value of 0.222 for the attitude change variable indicated the model accounted for approximately 22% of the variance. The path model indicates that prior attitudes significantly influenced search behaviors, however the relationship between prior attitude and search generation (beta = 0.24, z-value = 4.43, p=0.02, 95% CI = [0.13, 0.35]) was weaker than that of prior attitude to search selection (beta = 0.31, z-value = 5.52, p<0.001, 95% CI = [0.20, 0.42]. Specifically, the relationship between prior attitude and article selection bias was mediated by search selection (indirect effect: 0.31*0.13 = .04, p=0.03, 95% CI = [0.00,0.08], but not search generation (indirect effect: 0.24*-.01 = -.00, p=0.81, 95% CI = [-0.03,0.02]). Article selection bias had a strong effect on the attitude change variable, such that the tendency to click on more pro-GMO content was associated with attitudes changing towards pro-GMO (beta = 0.42, p<0.001, 95% CI = [0.33,0.50].

Motivation in Search, Selection, and Consumption Relating to Decision-Making

We fit an analogous path model changing only the dependent variable from attitude change to the shopping decision-making task, to assess when and where motivational predilections influenced behavior (Figure 6). The model was run using robust maximum likelihood as the estimator. Consistent with results from the attitude change model, the decision-making path model fit the data well, obtaining a CFI of 0.996, TLI of 0.982, Robust RMSEA of 0.031, and R-squared of 0.12. Paths identical to the attitude change model obtained identical coefficients, with the only differences between the models deriving from paths from prior attitude and article selection bias, to the shopping decision-making task score change. Article selection bias was strongly associated with the shopping decision-making task score change, such that the tendency to click on more Pro-GMO content was associated with reduction in the number of Non-GMO food items selected (beta = -0.24, p<0.001, 95% CI = [-0.35, -0.14].

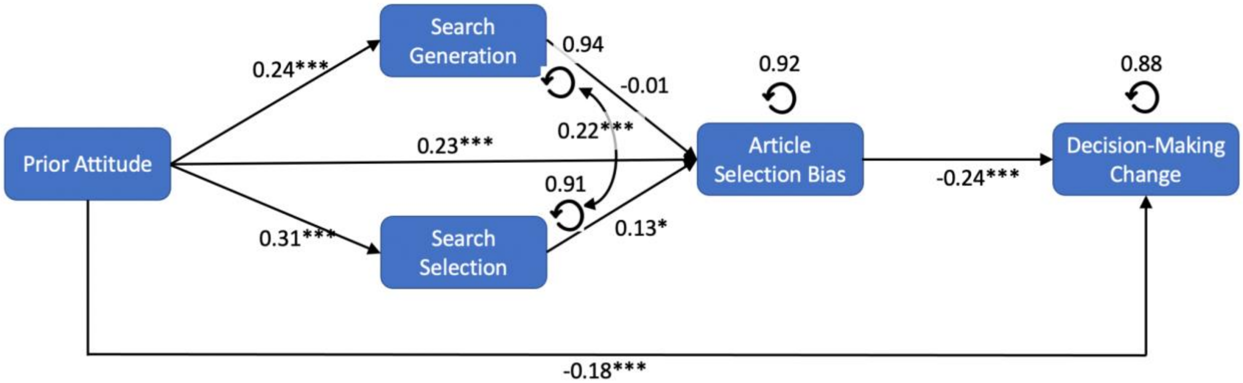


Figure 6. Path diagram illustrating the path to decision-making change. The path follows the temporal sequence of tasks, from left to right. Prior attitude was measured first, followed by the search generation and search selection tasks. Once search was completed, search results were generated and participants selected and consumed content, from which an article selection bias could be calculated. After completing a mandatory reading period, participants' decision-making on a shopping task offering GMO and Non-GMO items was reassessed and a shopping change score reflecting the difference between the number of Non-GMO items selected after content consumption and the number of Non-GMO items selected prior to the search engine tasks, was calculated. All directional relationships were significant except the path from search generation to article selection bias. * p<0.05; *** p<0.001.

Left	Right	Beta	std.error	z-value	p-value	ci.lower	ci.upper
Prior Attitude	Decision-Making Change	-0.18	0.05	-3.59	0.000***	-0.29	-0.08
Article Selection Bias	Decision-Making Change	-0.24	0.05	-4.53	0.000***	-0.35	-0.14
Prior Attitude	Article Selection Bias	0.23	0.05	4.68	0.000***	0.13	0.32
Search Selection	Article Selection Bias	0.13	0.06	2.32	0.02*	0.02	0.23
Search Generation	Article Selection Bias	-0.01	0.05	-0.24	0.81	-0.11	0.09
Prior Attitude	Search Generation	0.24	0.05	4.43	0.000***	0.13	0.35
Prior Attitude	Search Selection	0.31	0.06	5.52	0.000***	0.20	0.42

Table 5

Path analysis coefficients, Decision-Making. Standardized coefficients are provided for the paths depicted in Figure 6 above. Each relationship is specified on the left hand side of the table. Sample size utilized in path model n = 331. * p < 0.05; ** p < 0.01; *** p < 0.001.

Discussion

We developed a custom-designed search engine and content delivery system that closely aligns with an everyday search engine experience to probe a naturalistic encounter with interactive digital technology. The platform enabled examination of the interaction of attitudes, motivational processes, and behavioral tendencies with interactive technology, and how and when these factors influence information search and selection behaviors, attitudes and decision making. SEM path modeling permitted assessment of the relationships and effects of each experimental task as a function of their natural sequence, providing novel insights into the temporal aspects of attitudinal influences, and contribution of various motivational processes to measure attitude change and decision-making. The results obtained demonstrate that search behavior reflects prior attitudes, however differential access to information (i.e. memory vs. directly observable) likely affects memory accessibility, and produces significant differences in the bias of search terms. Relying on memory skews search towards the dominant sentiment in the media, which is Anti-GMO (Royzman et al., 2020). Relying on a diverse menu of GMO-related search terms results in selection of terms that more closely aligns with prior attitudes, such that individuals with prior Anti-GMO attitudes continue to search primarily using terms that reflect perceived risks and dangers of GM foods, and those with neutral and Pro-GMO attitudes select terms consistent with either perceived uncertainty or benefits. While initial (i.e. first click) content selection followed common online behavioral tendencies, such as a preference to click on the first or second search result across manipulations, overall content consumption reflected the sentiment of search behavior and prior attitudes. Finally, attitude change and decision-making change are affected primarily by content selection. Importantly, we demonstrated converging evidence of attitude change and decision-making behavior via our reassessment of GMO-related attitudes and shopping decisions in the binary choice food selection task.

Motivation and Search

Motivation operates during information search, influencing the response of real-world search engines, and hence the specific content that is displayed and consumed by searchers. The results reported herein demonstrate a clear link between prior attitudes on an important scientific topic and the manner in which search terms are formulated, that reflect both 1) the nature of prior attitudes; and 2) the background media sentiment about the topic. Exposure to content suggesting GM goods are dangerous or risky is more likely than positive encounters, thereby likely increasing both availability and accessibility of negative information in memory. The finding of a negative bias in search generation provides an additional explanatory avenue as to why sentiment about GMOs (and perhaps other scientific topics such as climate change, or vaccines) among the public is at stark odds with the scientific consensus, which indicates support for GM technology on par with that of climate change (Pew, 2015).

Search behaviors that echo background sentiment will return results consistent with the sentiment of the query, given the relevance focus of search engine algorithms. Lack of understanding of how search engines work, and scrutiny of not just the results, but also the search process itself can facilitate background sentiment confirmation bias, leading to inaccurate beliefs without an explicit intention of doing so. Polls specific to search engines demonstrate a concerning lack of understanding regarding how search engines function (Pew, 2008), and combined with significant trust assigned to search engines and mistaken equivalence of knowledge with access, likely contribute to a false sense of knowledge (Fisher et al., 2015). For example, as of the date of this publication, using the seemingly innocuous search term “gmo” in Google produces results for a company that has purchased the domain gmo.com, followed by two results from The Non-GMO Project, an anti-GMO institution that has extensive and far-reaching influence on the GM food debate. These results appear prior to the Wikipedia entry (rank 4). Since the majority of clicks occur among the first three search results (Beus, 2020), and skew significantly towards the top results, searchers that are uncertain about a topic or that halt the search process after selecting a single result, may inadvertently be reinforcing common views encountered elsewhere via confirmation bias, but with the sincere belief of having acquired objective knowledge.

In contrast to the search generation task, the search selection task did not require the cognitive effort of formulating search terms, and was more akin to social media feeds, in which content is selected from among a stream of stimuli. The finding that search selection tracks closer to prior attitudes is unsurprising since a full menu of preordained terms is likely to contain information beyond what sampling memory typically affords. Search selection more closely aligned with prior attitudes, which in our view reflects 1) a significant reliance on search engines to provide objective information with minimal effort, i.e using simple two to three word search terms (according to Statista, 80% of search queries contain three or fewer words (Statista, 2020)); 2) difficulty formulating search terms given the cognitive effort required to source information from memory; and 3) when sampling memory, salience, availability and accessibility of information tend to dominate recall (Blanchette & Richards, 2009; Higgins, 1996; O'Reilly, 1982). Extensive use of platforms that curate content based on past behavior, and / or provide recommendations reduces the cognitive effort required in information search. The ease of use and effectiveness of search engines to deliver results related to a query may be convenient, but to the extent the searcher exerts little reflection about the search process, may also degrade the ability to conduct searches that promote acquisition of accurate knowledge.

Two complementary strategies may improve our relationship with search engines. The first strategy is to significantly improve the public understanding about the mechanics of search, recommendation, curation and other algorithms that dominate the most used digital platforms, and to provide continuing education throughout primary and secondary schooling regarding searching and information seeking in digital contexts. Specifically, adapting information search models, i.e. Kulthau's Information Search Process (ISP) (Kuhlthau, Heinström, & Todd, 2008)to modern contexts, along with an extensive understanding of how search and retrieval technologies function, including primary directives (i.e. relevance, in the case of Google and other search engines), may assist in identifying when and where mistakes or biases arise during search and content selection processes. The second strategy is regulation or reforming search, i.e. mandate that providers of technology create outreach programs and disseminate educational material explaining how their products work; and adjusting search algorithms such that the primary directive is not always relevance-focused, but category dependent. Evidence exists that providing a diverse set of results about a topic can be effective in reducing preference-consistent content behaviors and inducing critical thinking (Schwind, Buder, Cress, & Hesse, 2012). For such categories of information, the ranking criteria could be prioritized for information quality and authoritative sources, while maintaining relevance-focus for other searches, such as location-based information.

Motivation and Interaction with Digital Technology

Consistent with real-world findings, common digital behaviors were observed, even in the context of a novel platform, evidenced by an average search term length of 2.95 (SD = 1.73) words, and click through rates that closely tracked Google data (Southern, 2020). These data suggest that habitual online behaviors transfer across platforms, enabling interactive technology designers to efficiently leverage common tendencies. Similar design patterns across platforms also serve another purpose - familiarity, which has been shown to positively influence perceptions (Lowry, Vance, Moody, Beckman, & Read, 2008; McCoy, Loiacono, Moody, & Fernández Robin, 2013) through exposure effects (Moreland & Zajonc, 1976; Zajonc, Swap, Harrison, & Roberts, 1971), and enhances adoption and continued use of applications and platforms. While convenient for enabling the current study to collect highly valid naturalistic data, the transference of assumptions does not appear to be limited to aesthetic or use factors. Similar behavior across sites also appears to import beliefs about the underlying functionality, along with perceptions of credibility and trust (Sbaffi & Rowley, 2017), important research areas that deserve attention given the potential implications for public understanding of scientific topics and technology, public health, and other public policy issues.

Motivation in Content Selection, Attitude Updating, and Decision-Making

While initial efforts have been made to examine effects of manipulating search results (Epstein & Robertson, 2015), to our knowledge, the findings reported herein provide the first set of experimental results that capture a naturalistic search engine experience in which search terms were collected, and search results were displayed via a fully functioning content delivery system with interactive content. The full search experiences enabled us to examine the natural progression of tasks a searcher completes in an encounter with search engine technology. Path modeling is ideally suited to follow the temporal flow of the task structure, providing insights regarding the role of motivation in each of our tasks, from generating search terms to clicking and reading search results, and how these factors influence attitudes and decision-making. While our results were consistent in some aspects with prior attitude research regarding interactions with search engines (Epstein & Robertson, 2015), such as observing behavioral tendencies with respect to content selection, our findings also differ in important ways.

Based on research and web statistics demonstrating a primacy effect (i.e. links at the top of the page receive more clicks), we predicted, consistent with prior research, that group manipulation influences first clicked content. However, despite the attraction to top ranked search results, attitude change was not associated with the group assignment manipulation, or first clicks, per say. Rather, attitude change was predicted by prior attitude and article selection bias, whereby article selection bias fully mediated the apparent relationship between first click sentiment and attitude change. However, upon examining the content selection data post hoc, first click sentiment mattered insomuch as the sentiment was congruent or incongruent with prior attitudes (Supplementary Figure 4). Reinforcing prior attitudes with the first click led to enhanced confirmation bias, evidenced by more extreme article selection bias in the direction of prior attitudes. Crucially, first clicks that were incongruent with prior attitudes were associated with a tendency to select less motivationally aligned content. Since exposure, operationalized in the current study as article sentiment bias, is a critical variable in attitude change (Cappella et al., 2015), factors that influence content selection deserve closer inspection, i.e whether the first click sentiment is congruent or not with prior attitudes, and the sentiment of search terms. Here, we show that search terms provide a guide for predicting content selection, however finding a relationship that predicts whether or not first clicks will be congruent with prior attitudes may further elucidate the motivational mechanisms underlying online content selection behaviors.

Limitations and Future Directions

While our platform is versatile, flexible and capable of a fully-functioning search engine and content delivery experience, other aspects of our design may limit the generalizability of some of our findings. Specifically, we mandated approximately 35 minutes for clicking on and reading content. However, we did not enforce any content rules, allowing participants to navigate naturally without experimenter requirements. We are not aware of web statistics that indicate the typical length of time or number of results a search engine user will spend and click on for topics such as GMOs or other complex or scientific topics when attempting to form or update opinions. To the extent a typical session is closer to five (5) minutes, engagement per article or number of articles selected may be less than the data we observed. The dynamics of attitude change may shift when more reliance is placed on one or two pieces of content. Further research can manipulate the amount of time provided to interact with search terms in order to determine if time alters the dependent measures collected, such that less time may result in a more reliable manipulation effect more dependent on group assignment than article selection bias, per say. Other factors not included in the authors' prior hypotheses may also contribute to attitudes and attitude change, such as prior knowledge about GMOs, attitudes associated with trust in scientists, political affiliation, among other factors. The relationship of some of these variables with prior attitudes about GMO can be found in Supplementary Information, Figures 5-8.

Summary and Implications

The psychological and behavioral consequences associated with human-search-engine and other digital interactions extend beyond the topics covered in this work. Overwhelming quantity of information and inherent cognitive resource limitations, along with assumptions about search engine content coerce reliance on a limited sample to form attitudes (Roetzel, 2019), and coupled with latent motivational forces may contribute to premature decisions to halt search and consumption of information. Further, to the extent knowledge is not extant in the mind, information is not available or accessible to engage in meaningful internal or external deliberation about a topic. Yet, despite these concerns, digital information technologies and systems hold significant potential to deliver accurate information, close educational and knowledge gaps, and improve support for public policies based on the best available science. A critical step towards these goals is the development of educational programs that enhance the understanding of how search engines and other interactive digital platforms function, and explicitly teach how to search. Historically, very little explicit instruction has been implemented (Walraven, Brand-gruwel, & Boshuizen, 2008). Most students use search engines to find singular facts (Andersson, 2017), and typically do not sample using different sets of search terms. Search engines that limit the catalog of information (e.g. university library sites, Google Scholar) also hold promise to enhance the quality and integrity of the sample pool, by including only sources that pass some 'meritocratic' filtering process.

Unfortunately, improving digital literacy alone will not close partisan gaps for topics that have become ideologically radioactive. Motivationally-mediated behaviors are becoming more extreme in online environments, which may be increasing use of processes such as identity-protective cognition (Kahan, 2017), in which reasoning about individuals or subject matter is driven by goals linked to identities rather than accuracy. Under such circumstances, no amount of education into the inner workings of technology will alter attitudes or support for public policies. Instead, we face a steep climb to adjust the weight society places on information integrity and accuracy, and the desire to allow the data to lead to conclusions, instead of the conclusions leading to a selective search for confirming data. Individuals must learn how to search and select content as responsible digital citizens, becoming aware of the ways in which their own motivational biases and those of the digital platforms influence behavior and attitudes. In turn, policy makers, scientists, and private companies responsible for disseminating information online must take responsibility to discourage and disincentivize the politicization of information on interactive platforms in order to ensure timely and accurate information about important societal topics is not only delivered but effectively communicated to the public. While attitudes for some topics, especially those that have no necessary causal connection to consequences, such as voter preference (vs. actual voting), may not typically be determined solely by a methodical build-up of empirical data over time, this is not true of science. Science can reliably inform us of impending consequences based on empirical data; we cannot apply *de gustibus non est disputandum* (there is no disputing about tastes) to attitudes about science and expect to be able to tackle upcoming challenges that require remedial actions. Fortunately, awareness of scientific consensus has been demonstrated to shift attitudes (McComas, Besley, & Steinhardt, 2014; McPhetres, Rutjens, Weinstein, & Brisson, 2019; Mielby, Sandøe, & Lassen, 2013), providing hope, and evidence, that with greater awareness and responsibility, our encounters with interactive digital technology will lead us in the same direction as the evidence.

Supplementary Materials

Methods and Materials

Article content included a comment section, notes section, and survey questions. Comments were populated by the researchers to express a range of sentiments. In Study 1, participants were invited but not required to comment or reply to an existing comment. In Study 3 participants were asked to leave at least one comment or comment reply. No limits were placed on the number of comments that could be added by the participant. A notes section captured text highlighted by the participant using their mouse or trackpad. Participants were encouraged to highlight sentences or phrases of the article that they felt were important or noteworthy. If an article was read for greater than 90 seconds, the participant would be queued with a set of three (3) to five (5) survey questions, which probed subjective perceptions of the article. The search engine results page functioned identical to commonly used websites, except that navigation was constrained only to pages within SearchSci.org (i.e. links to external sites were removed).

GMO Scales and Scoring

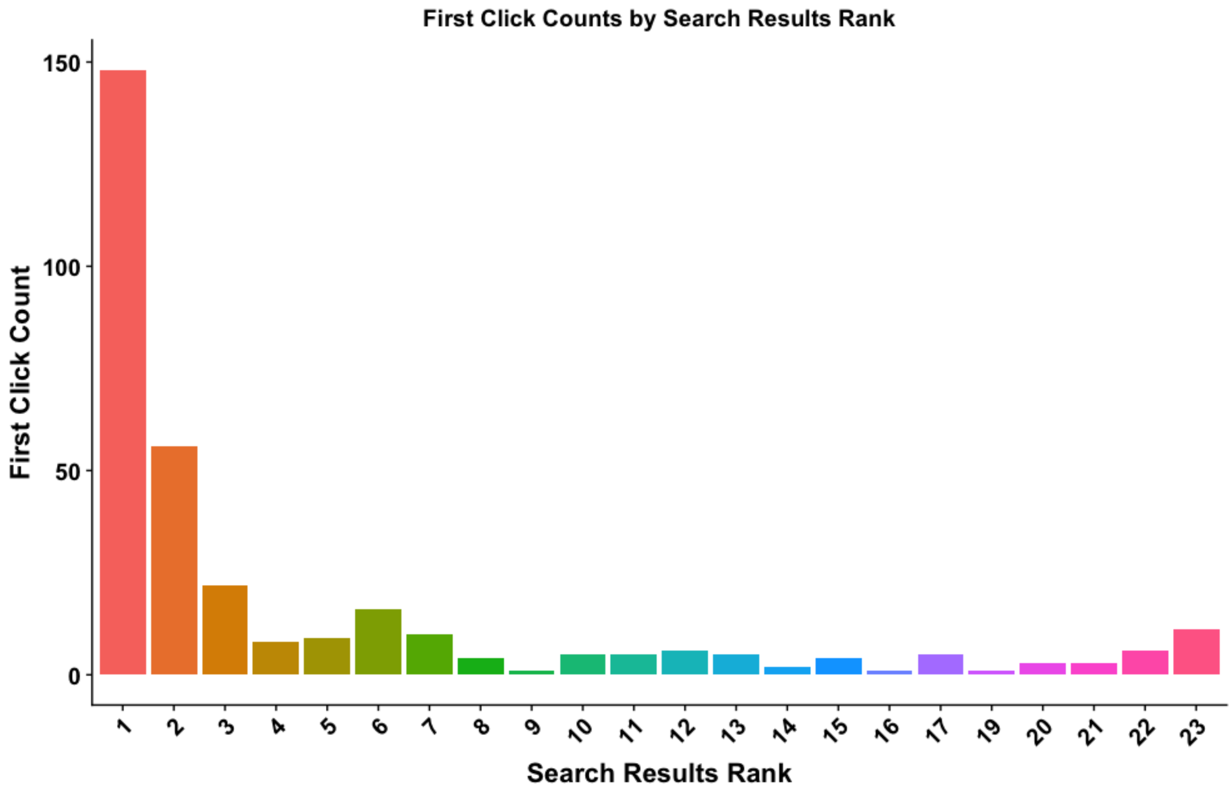
Scores on the GMO Knowledge and Position Scales were calculated as sums of the set of questions pertaining to knowledge or position. Based on the qualitative responses for questions on the position scale, we categorized participants into three (3) groups: 1) anti-GMO; 2) Neutral (i.e. neither anti-GMO nor pro-GMO); and 3) pro GMO. Lower scores indicated an anti-GMO position, higher scores indicated a pro-GMO position, while scores in the middle of the possible range indicated a Neutral position. These scores were cross-referenced with 7-point likert single-item questions added in Study 3 designed to directly measure opposition to GMO foods and concern regarding GMO foods. The correlation between the position component of the GMO Knowledge and Position Scales and the GMO opposition item indicated a close relationship ($r=-0.77$, $t(170) = -15.74$, $p<0.005$, 95% CI = [-0.82, -0.70]. Likewise, the position component of the GMO Knowledge and Position Scales also captured concern regarding GMO ($r=-0.75$, $t(170) = -14.83$, $p<0.005$, 95% CI = [-0.81, -0.68]. Scoring for the knowledge portion of the GMO Knowledge and Position Scales was calculated as the sum of correct responses. Scales not listed in this section were scored according to published guidelines.

Content and Content Task

Source assignment attempted to recreate the natural ecology of the GMO reporting space. Scientific sources including Scientific American and National Geographic were associated with either Pro GMO or Neutral articles, but never Anti GMO articles. The Genetic Literacy Project is a Pro GMO organization and was associated only with Pro GMO articles. Natural News and GMO Awareness are prominently Anti GMO and were associated exclusively with Anti GMO articles. Fox News and MSNBC displayed both Pro GMO and Anti GMO articles.

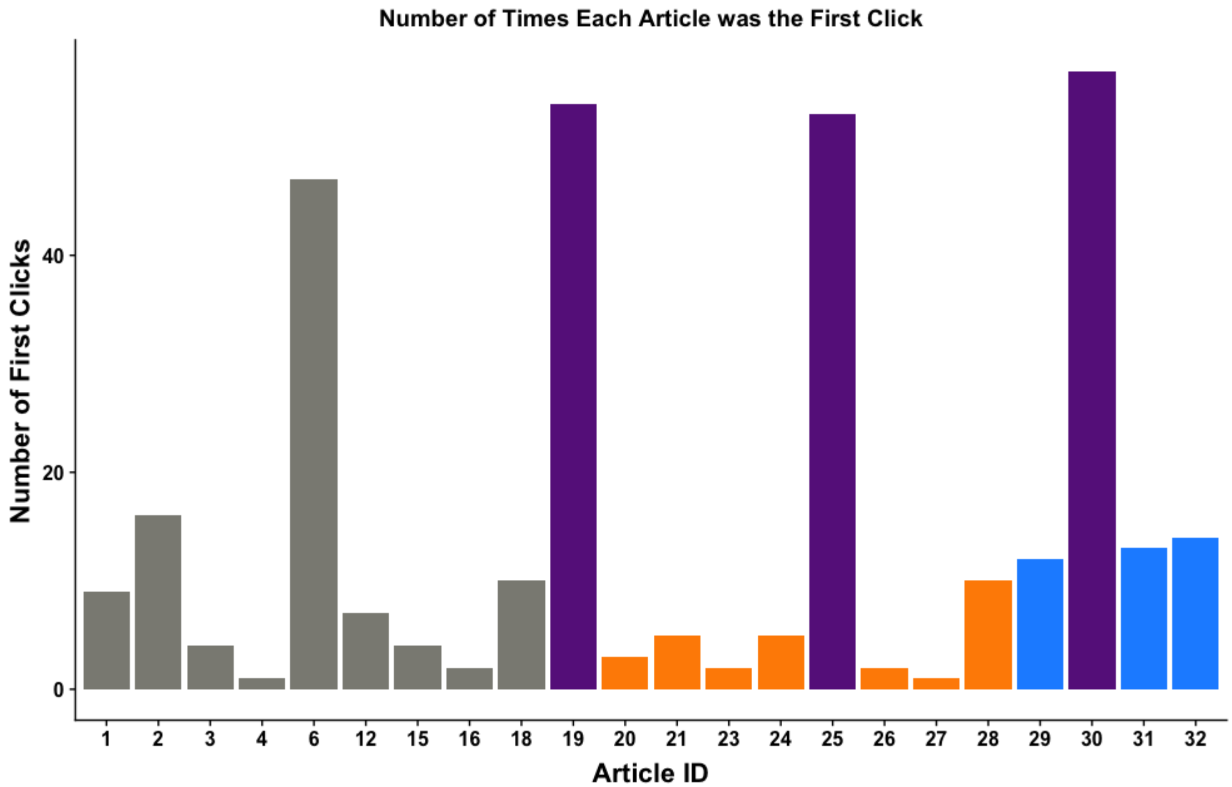
Naturalistic and Manipulation Verification

Search engine results click through rates follow a consistent pattern in which the first result receives some ~30% share of clicks, while ranks two (2) and three (3) attract approximately 16% and 11%, respectively (Southern, 2020). Clicks on remaining results fall to low single digit rates. Behavior on our search engine mirrored this pattern (Supplemental Figure 1), with the first result receiving the preponderance of clicks, followed by the second and third result. Together, the first three (3) search results positions accounted for 68% of first clicks, compared with 56% for the Google search engine. First clicks for the specific articles in the study are shown in Supplementary Figure 2.



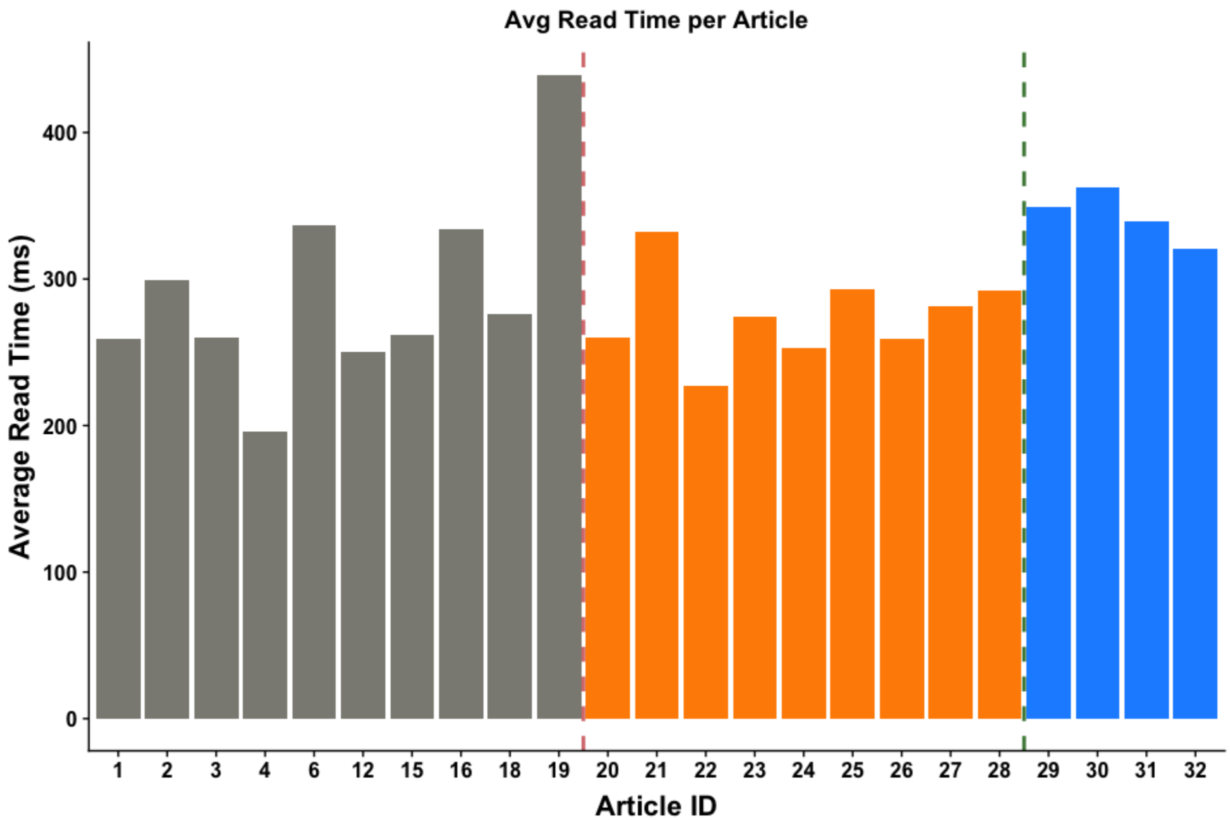
Supplementary Figure 1

First clicks by search engine position ranking. Consistent with Google search engine data, participants prioritized the first three (3) results and clicked on other links in similar proportion.



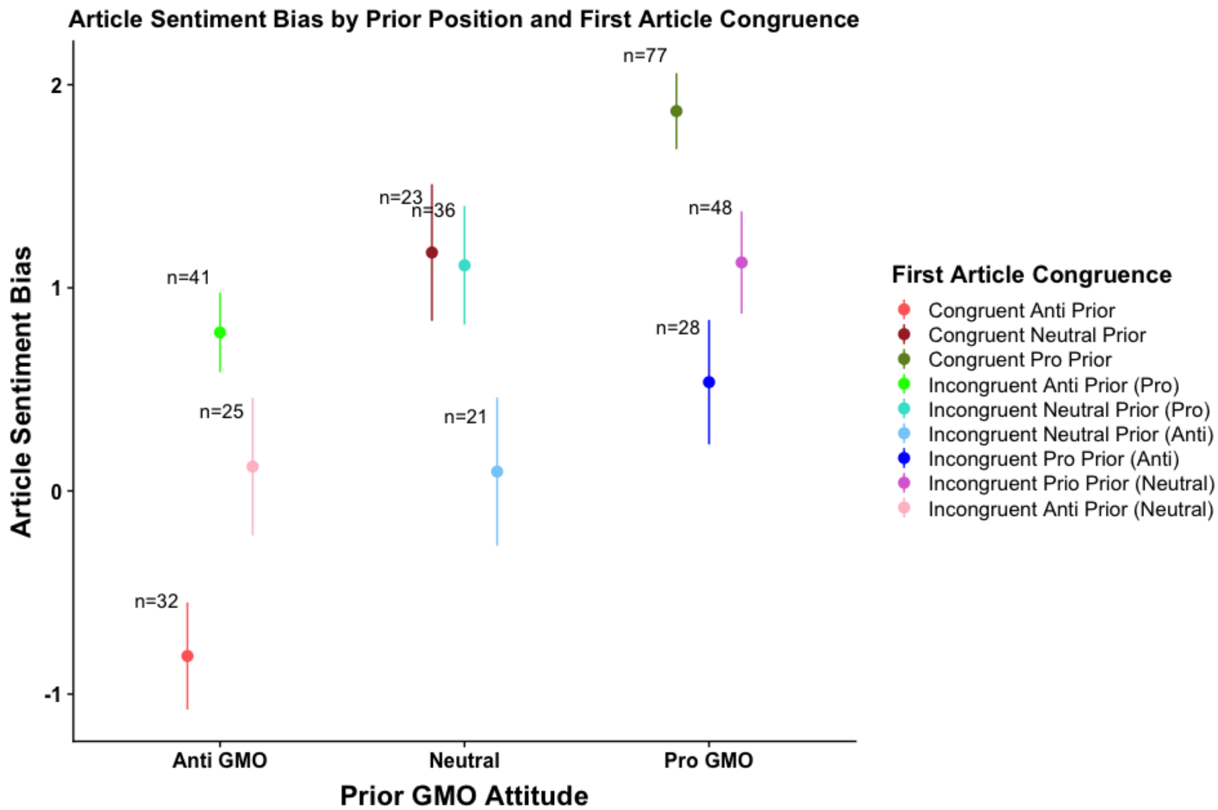
Supplementary Figure 2

First clicks by article. Articles shown in purple were presented first to participants across the three (3) groups. Article six (6), entitled “The Truth About Genetically Modified Food”, was an exception to this trend. Article six (6) appeared as the second (2nd) ranked position for group 1; 22nd ranked position for group 2; and 17th ranked position for group 3. However, over 80% of clicks on article six (6) derived from group 1, where the article appeared in position rank two (2). Gray: Pro-GMO articles; Orange: Anti-GMO articles; Blue: Neutral articles.



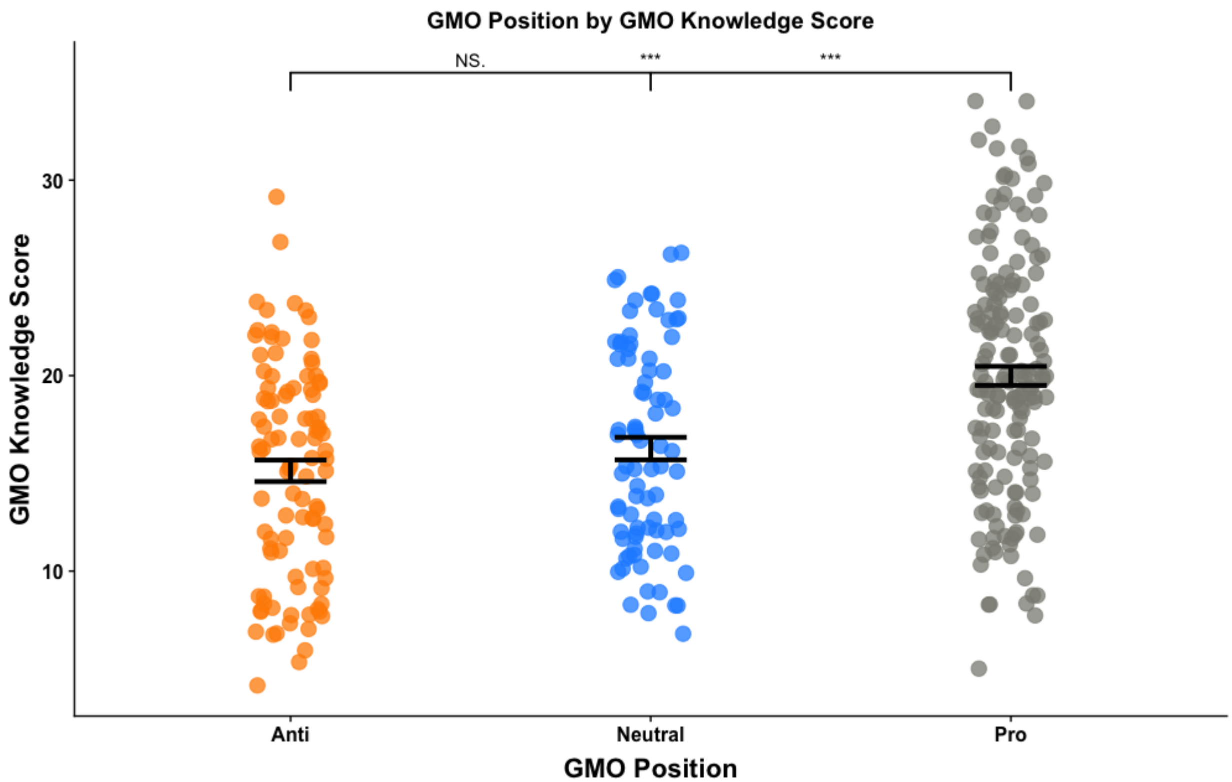
Supplementary Figure 3

Average read times by article. Average read times are shown for all article content. Gray columns: Pro-GMO content, average read time = 291.3s; Orange columns: Anti-GMO content, average read time = 274.9s; Blue columns: Neutral content, average read time = 343.3s. No significant differences were observed in read times between content types (One-way ANOVA: f(2) = 2.72, p = 0.09).

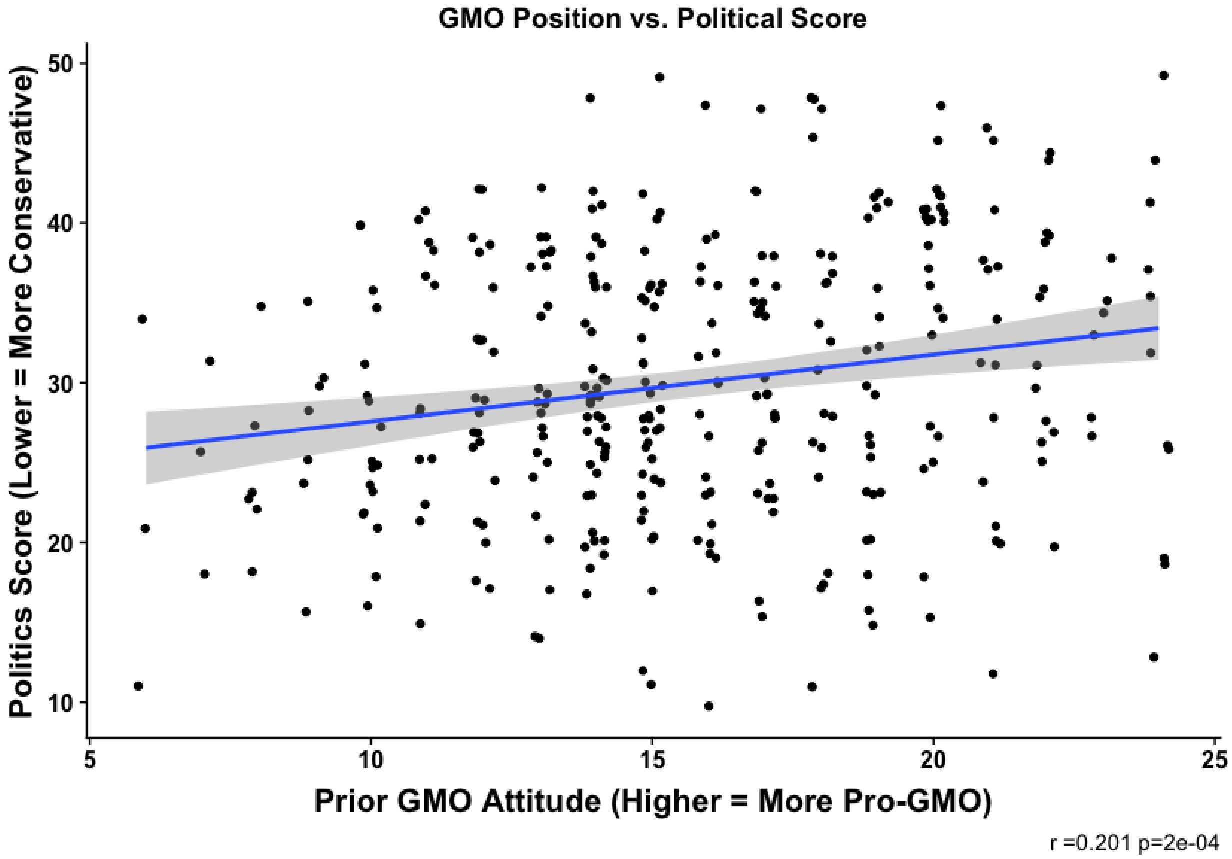


Supplementary Figure 4

Article sentiment bias as a function of first click congruence. First click sentiment affected attitudes depending on whether first click sentiment was congruent or incongruent with prior attitudes. For example, participants with Anti-GMO prior attitudes whose first click was an Anti-GMO article selected more Anti-GMO content overall than participants with the same prior attitudes that clicked on a neutral or Pro-GMO article first (Congruent Anti Prior (M=-0.81) vs. Incongruent Anti Prior (Pro) (M=0.78): unpaired t-test, t(60.46) = -4.85, p <0.001, 95% CI = [-2.25, -0.94]; Congruent Anti Prior (M=-0.81) vs. Incongruent Anti Prior (Neutral) (M=0.12): unpaired t-test, t(48.22) = -2.17, p = 0.03, 95% CI = [-1.80, -0.07]. Directionally, the same relationship was observed for Pro-GMO participants Congruent Pro Prior (M=1.87) vs. Incongruent Pro Prior (Anti) (M=0.54): unpaired t-test, t(48.48) = 3.72, p=.001, 95% CI = [0.61, 2.06]; Congruent Pro Prior (M=1.87) vs. Incongruent Pro Prior (Neutral) (M=1.13): unpaired t-test: t(95.18) = 2.37, p=0.02, 95% CI = [0.12, 1.37]. Notably, neutral participants whose first click was either neutral or Pro-GMO selected more Pro-GMO articles than Anti-GMO articles, while neutral participants that clicked on an Anti-GMO article first displayed no content selection bias (Congruent Neutral Prior (M=1.17) vs. Incongruent Neutral Prior (Anti) (M=0.10): unpaired t-test, t(41.33) = 2.17, p = 0.04, 95% CI = [0.08, 2.08]; Congruent Neutral Prior (M=1.17) vs. Incongruent Neutral Prior (Pro) (M=1.11): unpaired t-test, t(49.86) = 0.14, p = 0.89, 95% CI = [-0.83, 0.96]. Error bars represent standard error of the mean. Sample sizes used to derive error bars for each group are displayed in the figure.

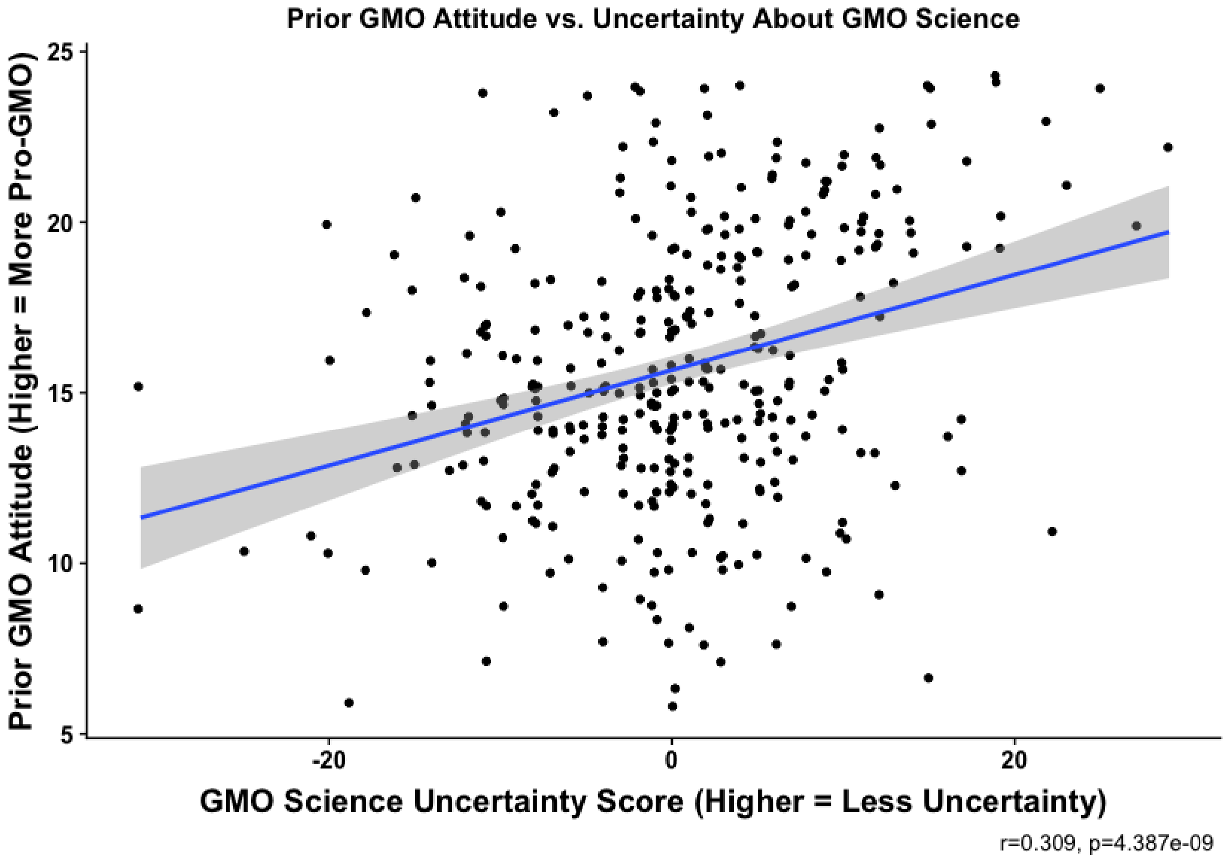


Supplementary Figure 5
GMO knowledge vs. prior attitudes about GMO. Knowledge about GMOs was highest in the subset of participants expressing a Pro-GMO prior attitude (unpaired t-test, Anti-GMO vs. Pro-GMO: $t(229.09) = -6.62$, $p<0.001$, bonferroni adjusted; Neutral vs. Pro-GMO: $t(189.25) = -4.92$, $p<0.001$, bonferroni adjusted). No relationship was found between knowledge about GMOs and search sentiment for either method of search.



Supplementary Figure 6

GMO attitudes vs. political leaning. Participants expressing more conservative leaning political attitudes measures by a composite of questions from the General Social Survey (GSS), provided below, tended to hold less Pro-GMO prior attitudes than more liberal leaning participants (Pearson's $r = 0.20$, $t(342) = 3.79$, $p = 0.002$, 95% CI = [0.10, 0.30].



Supplementary Figure 7. Prior GMO attitude vs. perceived uncertainty about GMO science. A robust correlation was observed between prior GMO attitudes and perceptions about the certainty of GMO science (as compared to other scientific fields) using the Public Perception of Scientific Uncertainty Scale (Pearson's $r = 0.31$, $t(343) = 6.02$, $p<0.001$, 95% CI = [0.21, 0.40].

Supplementary Figure 8. Prior GMO attitude and trust in scientists. Participants expressing an Anti-GMO prior attitude trust scientists less than those expressing either neutral or Pro-GMO attitudes (unpaired t-test: Anti-GMO vs Neutral: t(159.72) = 3.00, p=0.01, 95% CI = [0.12, 0.56], bonferroni adjusted; Anti-GMO vs. Pro-GMO: t(167.38) = 2.29, p = 0.03, 95% CI = [0.03, 0.47], bonferroni adjusted).

Supplemental Study

Participants

127 participants (54F; M(age) = 39.3) were recruited online through social media postings and on Amazon's Mechanical Turk workplace. Participants recruited through social media were paid $10, and MTurk workers were paid $8 to complete the study. Recruitment protocols adhered to procedures approved by Columbia University's Morningside Institutional Review Board requirements.

Supplemental Study Procedures

The Supplemental Study was completed in one session. Participants first completed the Decision-Making task, GMO Knowledge and Position Scale, and demographic questions on the Qualtrics platform. Upon submission of the survey, participants were assigned to one (1) of a pool of five (5) groups, and redirected to SearchSci.org.

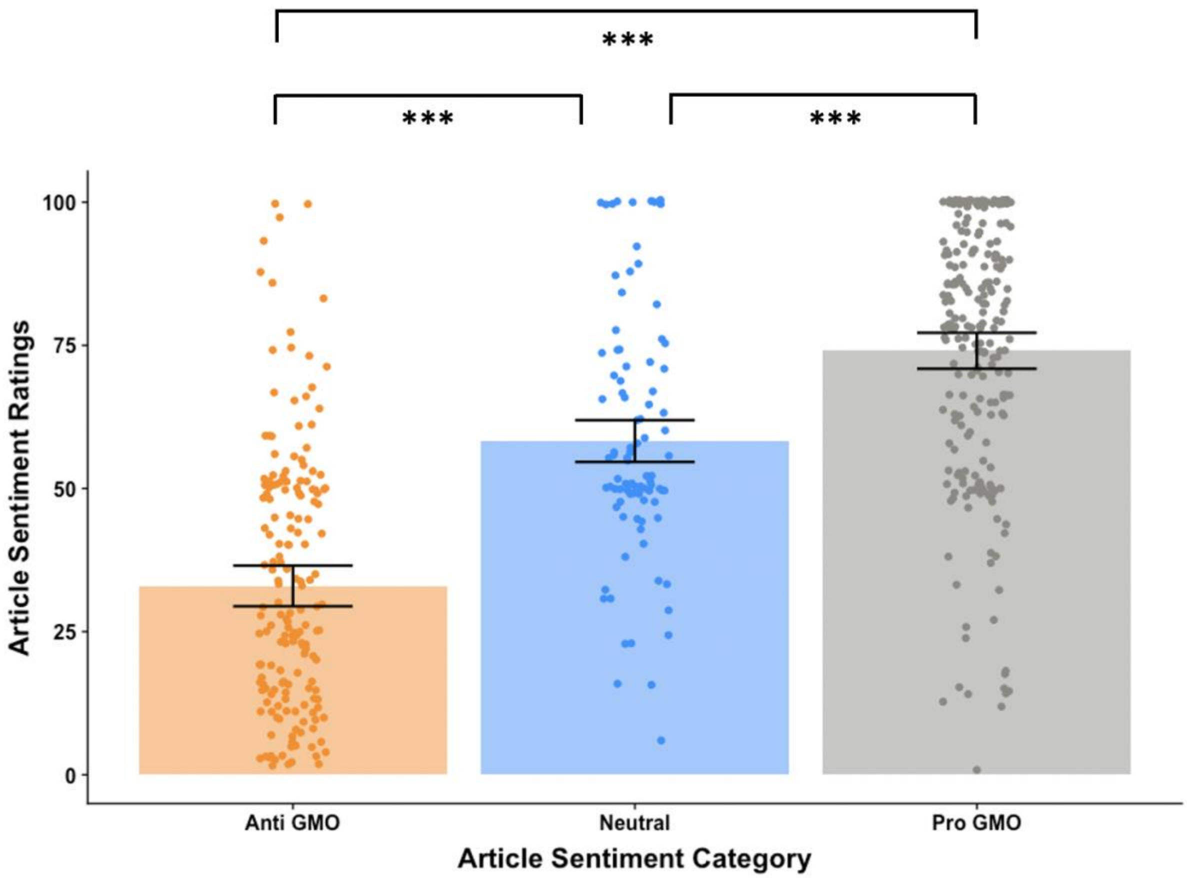
All groups were allocated five (5) articles, the difference being the specific articles associated with a group, and the order in which the articles were presented. For example, group one (1) viewed a set of five (5) articles in which Pro GMO articles were presented first, followed by a mix of Anti GMO and Neutral articles. Groups were counterbalanced to mitigate potential bias effects in content presentation order. Participants were free to select the order in which they consumed the content, however a minimum reading duration time of two (2) minutes was required. After reading an article, a set of survey questions probed subjective perceptions of the article, including ratings of bias towards either Anti GMO or Pro GMO; how much the participant learned about the benefits and costs of GMOs; informativeness and how much the participant agreed with the content. Once an article was read beyond the minimum time threshold, it was automatically removed from the list of articles on the article display page. The Study concluded after five (5) articles were read at or above the minimum time threshold and survey question data was collected, or upon expiration of a 40 minute timer. The duration, including the portion completed on the Qualtrics platform, averaged approximately 50 minutes.

Supplemental Study Results

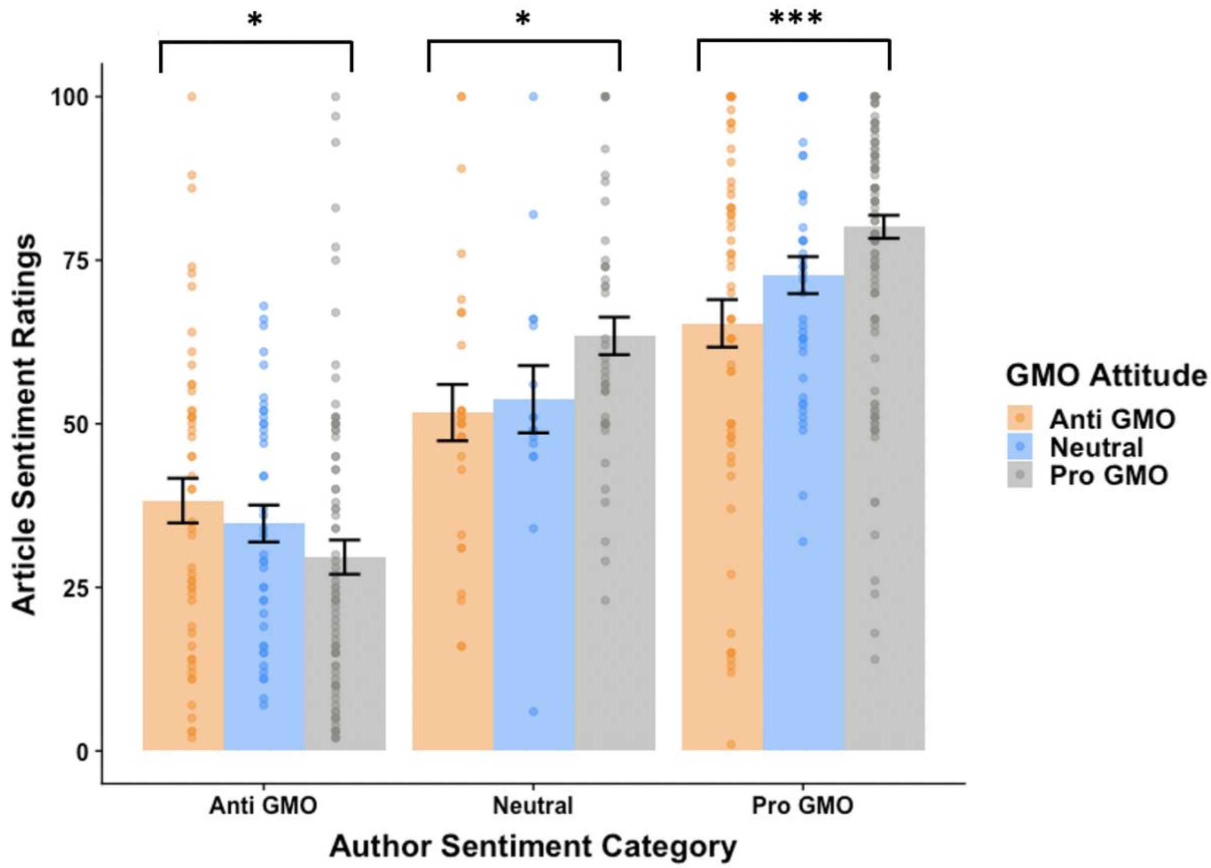
Article Sentiment Ratings

Article sentiment ratings were consistent with author categorizations, overall (Supplementary Figure 9), such that articles categorized as Anti GMO were rated lower than articles rated Neutral ($t(199.63) = -8.85$, $p<0.001$, 95% CI = [-30.30, -19.26], M(Anti GMO) = 33.43, M(Neutral) = 58.22) and Pro GMO ($t(374.89) = -18.14$, $p<0.001$, 95% CI = [-45.92, -36.93], M(Pro GMO) = 74.86); and articles categorized as Pro GMO were rated higher than articles rated Neutral ($t(181.05) = 6.25$, $p<0.001$, 95% CI = [11.39, 21.90]). Article ratings varied as a function of prior attitudes, most notably we found differences in ratings between participants holding Pro GMO and Anti GMO prior attitudes for all three author categories (Supplementary Figure 10). Participants holding Pro GMO prior attitudes rated author categorized Anti GMO articles more negatively than participants holding Anti GMO prior attitudes (Anti GMO category, Anti GMO vs. Pro GMO participants: $t(102.29) = 2.01$, $p = 0.047$, 95% CI = [0.11, 17.17], M(Anti GMO) = 38.26, M(Pro GMO) = 29.62; and both Neutral and Pro GMO author categorized articles more positively than participants holding Anti GMO prior attitudes (Neutral category, Anti GMO vs. Pro GMO participants: $t(48.98) = -2.27$, $p = 0.028$, 95% CI = [-22.13, -1.32], M(Anti GMO) = 51.70, M(Pro GMO) = 63.43; Pro GMO category, Anti GMO vs. Pro GMO: $t(87.97) = -3.66$, $p < 0.001$, 95% CI = [-22.77, -6.74], M(Anti GMO) = 65.35, M(Pro GMO) = 80.11). No differences were observed in ratings between Anti GMO and Neutral participants. A ratings difference was observed for author categorized Pro GMO articles between participants holding Pro GMO prior attitudes and those holding Neutral attitudes ($t(75.56) = -2.22$, $p = 0.029$, 95% CI = [-14.02, -0.75], M(Neutral) = 72.71, M(Pro GMO) = 80.11).

These results validate the author assigned categories for article content.



Supplementary Figure 9. Article sentiment ratings by author categories. Article sentiment ratings collected were consistent with author categorizations. Articles categorized by the authors as Anti GMO were rated lower than both Neutral and Pro GMO; articles categorized by the authors as Pro GMO were rated higher than both Neutral and Anti GMO; articles categorized as Neutral by the authors were rated lower than Pro GMO articles but higher than Anti GMO articles.



Supplementary Figure 10. Article sentiment ratings by author categories and prior attitudes. Ratings differed for the same author category between participants with Anti GMO and Pro GMO prior attitudes for each sentiment category, such that participants with Anti GMO prior attitudes rated Anti GMO articles less negatively than participants with Pro GMO prior attitudes, however this trend was reversed for Pro GMO articles, for which participants with Pro GMO attitudes rates Pro GMO articles more positively than participants with Anti GMO prior attitudes.

Rating Counts

Rating counts for each article are displayed below, in Supplementary Table 1. Inequalities in the number of ratings reflect partial task completion (i.e. some participants did not rate all five (5) articles that were presented) and duplication of articles 12, 21 and 24 to create equal groups of five (5) articles.

Article ID	Ratings Count	Author Category
1	24	Pro GMO
2	28	Pro GMO
3	25	Pro GMO
4	25	Pro GMO
6	23	Pro GMO
12	53	Pro GMO
15	22	Pro GMO
16	20	Pro GMO
18	24	Pro GMO
19	24	Pro GMO
20	21	Anti GMO
21	46	Anti GMO
22	21	Anti GMO
23	24	Anti GMO
24	51	Anti GMO
25	27	Anti GMO
27	22	Anti GMO
28	28	Anti GMO
29	24	Neutral
30	30	Neutral
31	27	Neutral
32	23	Neutral

Supplementary Table 1. Article Rating Counts. Each article was rated a minimum of 21 times with mean of 27.82 times and SD of 9.42. Means and standard deviations by author category: M(Pro GM) = 26.8, M(Anti GMO) = 30.0, M(Neutral) = 26.0; SD(Pro GMO) = 9.44, SD(Anti GMO) = 11.78, SD(Neutral) = 3.16.

Search Selection Terms

GMO not necessary for agriculture
GMO more insecticide use
GMO decreased yield
GMOs and disease
GMO corporate monopoly
GMOs, who profits?
GMOs cause cancer
GMO Monsanto

GMOs pesticides and bad health
GMO Benefits Overrated
GMOs Exploitative to 3rd World
What are GMOs?
GMO good or bad for farmers?
GMO technology explained
GMO health safety
GMO risks and benefits
GMO science
GMO labeling
Why do we use GMOs?
GMO and developing children
GMOs products and foods
Effects of GMOs biodiversity
GMO same nutrition as Non-GMO
GMO better nutrition than Non-GMO
GMOs safe studies
GMO more affordable than Non-GMO
GMO less herbicide use
GMOs not Harmful
GMO and safer pesticides
GMO scientific consensus safe
Anti-GMO misconceptions about GMO science
GMOs solution to feed growing population
GMO Tech Innovative Better Foods

Political Scale - Selected GSS items

1. Do you think it should be possible for a pregnant woman to obtain a legal abortion if the woman wants it for any reason?

2. Do you think the law should or should not allow a pregnant woman to obtain a legal abortion if there is a strong chance of serious defect in the baby?

3. Do you think it should be possible for a pregnant woman to obtain a legal abortion if the woman’s own health is seriously endangered by the pregnancy?

4. Do you think it should be possible for a pregnant woman to obtain a legal abortion if she became pregnant as a result of rape?

5. Which of the following four statements about the Bible most closely matches your own view?

6. What do you think about sexual relations between two adults of the same sex?

7. If a man and woman have sex relations before marriage, do you think it is...

8. Some people say that because of past discrimination, African-Americans should be given preference in hiring and promotion. Others say that such preference in hiring and promotion of blacks is wrong because it discriminates against whites. What about your opinion -- are you for or against preferential hiring and promotion of blacks?

9. Do you favor or oppose the death penalty for persons convicted of murder?

10. Some people think that African-Americans have been discriminated against for so long that the government has a special obligation to help improve their living standards. Others believe that the government should not be giving special treatment to African-Americans. Where would you place yourself on this scale, or haven't you made up your mind on this?

11. In your view, the number of immigrants from foreign countries who are permitted to come to the United States to live should be…

12. How do you feel about the following statement?
    Irish, Italians, Jewish and many other minorities overcame prejudice and worked their way up. Blacks should do the same without special favors.

13. Some people think that the government in Washington ought to reduce the income differences between the rich and the poor, perhaps by raising the taxes of wealthy families or by giving income assistance to the poor. Others think that the government should not concern itself with reducing this income difference between the rich and the poor.

    Please rate your own view on this issue on a scale from 1 to 7. Think of a score of 1 as meaning that the government ought to reduce the income differences between rich and poor, and a score of 7 meaning that the government should not concern itself with reducing income differences. What score between 1 and 7 comes closest to the way you feel?

14. We are faced with many problems in this country, none of which can be solved easily or inexpensively. What is your view on government spending on welfare?

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