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# Adapting the Selective Exposure Perspective to Algorithmically Governed Platforms: The Case of Google Search

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## Abstract

Experimental research on selective exposure on online platforms is generally limited by a narrow focus on specific parts of the information selection process, rather than integrating the entire sequence of user-platform interactions. The current study, focusing on online search, incorporates the entire process that stretches from formulating an initial query to finally satisfying an information need. As such, it comprehensively covers how both users and platforms exercise agency by enabling and constraining each other in progressively narrowing down the available information. During a tailored online experiment, participants are asked to search for social and political information in a fully tracked, manipulated Google Search environment. Although the results show a structural impact of varying search result rankings, users still appear to be able to tailor their information exposure to maintain their prior beliefs, hence defying that algorithmic impact. This corroborates the need to conceptually and methodologically expand online selective exposure research.

## Keywords

online search, search engines, selective exposure, confirmation bias, algorithms

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Online platforms are increasingly curated by algorithmic mechanisms that filter available information, and hence selectively tailor exposure for its users. The use of algorithmic filtering mechanisms has been pinpointed as problematic because it allegedly reinforces echo chambers and filter bubbles, which are claimed to impact users (Pariser, 2011; Sunstein, 2007). For this reason, there has been considerable scientific interest in understanding how users navigate online platforms (e.g., Granka et al., 2004; Joachims et al., 2005; Pan et al., 2007), how they select information, and what the consequences of these selections are (e.g., Hastall & Knobloch-Westerwick, 2013; Iyengar et al., 2008; Knobloch-Westerwick, 2012; Knobloch-Westerwick & Kleinman, 2012; Knobloch-Westerwick, Johnson, et al., 2015; Messing & Westwood, 2014; Unkel & Haas, 2017; Westerwick et al., 2017). However, even though interacting with online platforms entails a complex sequence of user-platform interactions, research tends to focus on specific parts of the information selection process, usually at either the onset or the final stage. However, limiting the focus on specific parts of the information selection process makes little sense considering that during these sequential user-platform interactions, information is progressively narrowed down. Each prior action inevitably affects the next. For example, during online search users provide input for the search algorithm by freely composing a query which is processed by the system that filters and ranks results. Next, users interact with these search results, select and/or ignore them, and may even override them by rephrasing the initial query. On a larger scale, the implicit user feedback in the form of selecting, ignoring, or overriding search results refines the algorithms in their future filtering and ranking (Bozdag, 2013).

The aim of the present study is to challenge the current online selective exposure literature by explicitly considering these user-platform interactions. It conceptualizes each interaction as a fundamental step in progressively constructing selective exposure. The current study tests the reasoning that each user-platform interaction should be considered as a fundamental step in progressively constructing selective exposure on the case of Google Search. In an online experiment, participants are asked to search for social and political information in a fully tracked, manipulated Google Search environment. The dedicated research platform used in the current study captures every user-platform interaction, and even emulates varying platform behavior to test its impact on users.

## *Literature Review*

*Fundamental challenges for online selective exposure research.* For defining selective exposure we rely on the conceptualization of Knobloch-Westerwick (2015) in which selective exposure is not only considered as exposure to messages that underline one's own preferences, but as "any systematic bias in audience composition as well as any systematic bias in selected messages that diverges from the composition of accessible messages" (Knobloch-Westerwick, 2015, p. 6). The concept of selective exposure requires that (a) audiences are available to use media, that (b) they have a choice between different contents, and that (c) their choice for specific content is made in awareness of other alternatives. Choice occurs at different levels of the medium. In essence, the concept of "levels of choice" reflects how information is gradually funneled through selection. In the context of legacy media the different levels of choice involve, for instance, the choice to buy a specific newspaper but not others and the choice to read (portions) of a specific article in that newspaper while ignoring others.

Historically, research has mainly invested in finding a psychological rationale for such choices. A recurring explanation is that individuals select information that is in line with their previous preferences and beliefs to avoid the cognitive dissonance that comes with confronting counter attitudinal information (Festinger, 1957; Fischer et al., 2005). However, the status of cognitive dissonance as a cause for media selection has been contested (Donsbach, 2009), and other theories and concepts have been put forward to explain media selection. For instance, researchers have argued that individuals prefer information that they perceive as more credible (Metzger et al., 2020). As such, attitudinally consistent information might be preferred above inconsistent information not because it avoids dissonance, but because it is perceived to be higher in credibility. Moreover, information utility theory states that people prefer information that is of utility to them (Atkin, 1973). Information utility can provoke a confirmation bias as the reinforcement of information can be of utility to individuals.

Typically, empirical studies on online selective exposure involve experimental designs in which participants are presented with choices to explore information from multiple sources in a mock-up environment (e.g., Iyengar et al., 2008; Knobloch-Westerwick, 2012; Knobloch-Westerwick, Johnson, et al., 2015; Knobloch-Westerwick, Mothes, et al., 2015; Messing & Westwood, 2014; Westerwick et al., 2017; Metzger et al., 2020). The key objective, then, is to explain those choices and assess their psychological impact. Despite being valuable and innovative, these types of studies share a fundamental caveat: due to the highly controlled, experimental nature of these studies, participants are forced to choose from a limited set of choices that were handpicked by researchers. Although forcing participants to choose from a limited set of handpicked choices benefits internal validity, it undercuts the ecological validity of the findings. Indeed, it is more than reasonable to assume that participants in these types of studies are aware that there is more information available online than what they can access within the context of the experiment. Such a lack of availability and choice is in direct conflict with the conceptual requirements of selective exposure: participants are artificially constrained to the last level of choice, which means that all preceding steps are ignored. The exclusion of all levels of choice but the last signals a first fundamental challenge for empirical research on online selective exposure—that is, the challenge to explicitly factor in the entire sequence of user actions and all relevant *levels of choice* that characterize selective exposure.

A second challenge flows from the fact that for current day online platforms, users do not independently choose what information they interact with. Algorithms play a fundamental role in filtering information and affecting both the order and form in which online information is displayed. Conceptually, algorithms act as substantial "curators" in the selection of online information (Thorson & Wells, 2016), as dynamically evolving, active agents that narrow down information in tandem with platform users. Algorithms process user input according to their own hard-coded, but ever evolving, rules and shape the output the user may interact with. While it is explicitly recognized by the selective exposure literature that algorithms account for at least some of the levels of choice (Cinelli et al., 2020; Knobloch-Westerwick, 2015), it has remained largely unaddressed in empirical settings. When researchers try to account for algorithmic influence, they generally follow an observational approach, combining web logs with survey-based self-reports (e.g., Bakshy et al., 2015; Dvir-Gvirsman et al., 2014; Nelson & Webster, 2017; Schmidt et al., 2017). Their studies have generated valuable insights into the correlates of selective exposure, but it shied away from drawing causal inference through controlled and randomized experiments.

*Addressing the challenges: The case of google search.* Based on the challenges outlined above, we argue that online selective exposure research needs to account for all levels of choice: selective exposure progresses as a function of consecutive user-platform interactions, and algorithms play an active part. To make the point that research on online selective exposure should account for all the levels of choice more tangible, we apply our conceptual logic to the case of Google Search. With a global market share of over 90% in online search (Statcounter, 2020), it is needless to emphasize the relevance of Google Search in shaping the online experience of internet users. An important point to consider is that by starting with a specific search engine, we exclude the levels of choice that take place in the pre-communicative stage. That is, the focus of the current study will be with all levels of choice during information retrieval, and after the choice of the specific medium has already been made. In the following sections, drawing on a generalized model of information retrieval (Hiemstra, 2009), we unpack the sequential nature of user-platform interactions on Google Search (Figure 1). At each step, we hypothesize how at each level of choice, user and platform characteristics progressively co-shape selective exposure and its outcomes.

*Selection of an initial search query.* The first level of choice occurs at the selection of an initial search query (Figure 1a). The query is the key input for the search algorithm to sift through indexed information and return results to users. Because it is open-ended, it allows virtually unlimited variability between users. As such, a very similar information need might incite significantly different queries, both in form and substance. Research on query formulation indicates that the form and substance of the query is affected by someone's prior knowledge on the search topic. More prior knowledge results in the use of longer, more complex queries, that contain more topic-specific vocabulary (Tamine & Chouquet, 2017; White et al., 2009; Zhang et al., 2005). Since prior knowledge plays a major role in the formation of a query, it is also fairly possible that other prerequisites, such as prior beliefs, play a role. Literature on confirmation bias indicates that people are likely to seek out information that confirms their own preferences and to ignore information that contradicts them (Garrett, 2009; Jonas et al., 2001). Because the query has such a strong impact on the information that can be consulted, it is plausible that search users formulate search queries in line with

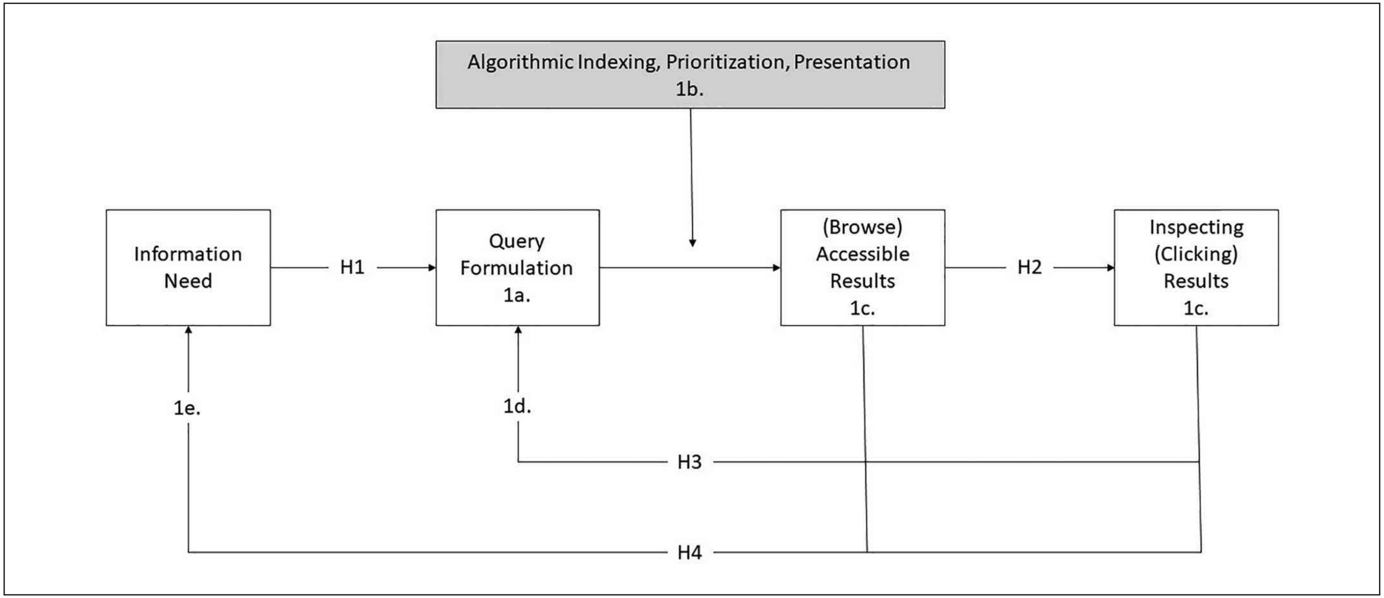


**Figure 1.** Conceptual model, including hypotheses, based on a generic model of information retrieval.

their prior belief on the search topic. Hence, the formulation of two complementary hypotheses:

(H1a) Search users with a high prior truthfulness assessment toward a belief statement are more likely to formulate confirmatory search queries.
(H1b) Search users with a low prior truthfulness assessment toward a belief statement are more likely to formulate disconfirmatory search queries.

*Platform selection of search results.* The next step in the search process takes place during the matching of the query with potential search results by the platform using algorithmic filtering processes (Figure 1b). Search engines such as Google draw upon complex inter-related algorithms to select the online sources that are indexed, and to determine how these sources are prioritized, presented, and even personalized (Bozdag, 2013). The mechanics of these algorithms, and the results they produce, have been subject to continuing scrutiny in the past two decades. Studies have focused on general bias in search results. For example, indexation bias means that the algorithm does not index certain web domains or pages, making them unfindable via Google Search (Vaughan & Zhang, 2007). In addition, prioritization bias means that the nature of the algorithm causes the systematic prioritization of certain webpages over others—for example by the use of Google-bombing techniques (Bar-Ilan, 2007; Gillespie, 2017). Moreover, researchers have focused on biases in search results due to personalization. Personalization in online search implies that the search algorithm tailors the presented content based on individual user data such as user preferences, past surf behavior, and contextual cues (Smyth et al., 2011). Apart from personalization based on location (Kliman-Silver et al., 2015), not much evidence has been found for personalization bias within Google search results (Courtois et al., 2018; Haim et al., 2017; Puschmann, 2019).

*Users' selective exploration of search results.* The subsequent level of choice occurs during users' selection and exploration of the search results (Figure 1c). When the search results are displayed, it is up to the user to assess their informational value. Titles and descriptions are eyeballed and particular results are potentially selected (i.e., clicked) for further exploration. Prior research has strongly indicated that users highly trust search engines, such as Google, and believe search engines objectively return the most relevant results (Purcell et al., 2012; Sanz & Stančík, 2014). A substantial body of observational research has shown that Google users are more likely to consider the top-ranked results than the lower-ranked results (Bar-Ilan et al., 2009; Cutrell & Guan, 2007; Joachims et al., 2005). The preference for top-ranked results could be explained by the fact that users genuinely assess the first results as sufficiently relevant. However, prior research has shown that top-ranked results are even selected in cases in which these results were less relevant than lower ranked results (Bar-Ilan et al., 2009; Pan et al., 2007). The preference of less relevant top-ranked results suggests that users might hold a somewhat blind trust in Google's search algorithms' ability to select and prioritize the most valuable information.

However, it is important to consider what constitutes a worthwhile search result for a search engine user. The literature on attitude formation and maintenance has extensively shown that people prefer and value information that confirms and reinforces their beliefs (Garrett, 2009; Jonas et al., 2001). Moreover, prior research in the context of selective exposure in online search corroborates that participants prefer search results that are consistent with their prior beliefs (Knobloch-Westerwick, Johnson et al., 2015; Knobloch-Westerwick, Mothes et al., 2015; Westerwick et al., 2017). Therefore the two following competing hypotheses are formulated:

(H2a) Search users select (i.e., click on) the highest ranked results, regardless of whether it is consistent with their prior beliefs.
(H2b) Search users select (i.e., click on) results that are consistent with their prior beliefs, regardless of the search results' ranking.

*Selection of a follow-up search query.* There is considerable user agency in selecting search results for further exploration. Users are not confined to the results of a single query. Empirical research has shown that 37% up to 52% of search queries are re-formulations of earlier queries (Jansen et al., 2005, 2007). When users decide to reformulate initial queries, information is further narrowed down (Figure 1d) in order to overturn unsatisfactory and irrelevant results. Elaborating on the notion of valuing belief-consistent over belief-inconsistent search results, the following hypothesis is proposed:

(H3) Users confronted with search results that contradict prior beliefs share a higher likelihood of reformulating their initial query.

*Users' final selection of information.* Once the user has viewed or selected a search result, the information is evaluated (Figure 1e). In light of the literature on confirmation bias and attitude formation, we propose two possible ways in which the viewing and selection of information may impact users' beliefs. On the one hand, people are likely to stick to prior beliefs even when confronted with counter-attitudinal information (Chaiken et al., 1995; Vogel & Wänke, 2016). As Taber and Lodge (2006) have argued, disconfirmation bias causes people to unwittingly refute belief-inconsistent information which, in turn, reinforces prior attitudes. Especially for politically knowledgeable people with a strongly opinionated belief (Taber & Lodge, 2006), a swift online search may already be enough to have a reinforcing effect. Consequently, it is proposed that:

(H4a) Users maintain their prior beliefs, even if their search environment contains a considerable amount of belief-inconsistent search results and/or if they select belief-inconsistent search results.

On the other hand, research has shown that online information has the potential to alter users' beliefs (Epstein & Robertson, 2015; Knobloch-Westerwick, Johnson et al., 2015; Knobloch-Westerwick, Mothes et al., 2015; Westerwick et al., 2013). Within this respect, Redlawsk et al. (2010) argue that when there is a repeated exposure to attitude incongruent information audiences reach a tipping point, after which previous held beliefs are updated. Moreover, in a widely cited paper, Epstein and Robertson (2015) have demonstrated through a series of studies how a manipulated mock-up search engine was able to sway undecided voters in favor of a higher-ranked candidate. As such, a final hypothesis is formulated:

(H4b) Users are susceptible to change in their prior beliefs, especially when their search environment repeatedly confronts them with belief-inconsistent search results and/or when they select belief-inconsistent search results.

## Method

### Overview

The current study requires a method that grasps the entire online search process from information need to final choice, and every step in between. In a response, we developed an online research platform that emulates Google Search in real-time (For screenshots, see Supplemental Appendix). The platform was coded in Python programming language and worked as follows: when a participant typed in a query, the system fetched the 30 first actual search results for that query from Google, stored these results in the research database, and portrayed the results within the platform interface. The search results were spread over three search results pages. Each result could be clicked and assessed, and queries could be refined indefinitely. Each interaction was observed and stored in the database.

As the hypotheses imply a causal impact of algorithmic interventions, the search results shown to participants were manipulated by varying the ranking of belief-confirming and disconfirming search results. The manipulation of the search results happened through a rule-based intervention that occurred between fetching the search results from Google Search and showing them to participants. The intervention worked as follows: prior to launching the experiment, nine socio-political belief statements were drawn up by the authors (cf. Table 1). Subsequently, two lists enumerating the root web domains of organizations that were positioned either in favor of or against the belief statement were drawn up for each belief statement. The lists were used to automatically push the search results harvested from Google Search either to the top or the bottom of the 30 available search results. Per statement, three randomly assigned conditions were implemented: a control condition in which results were shown in their original rank order, a confirmatory condition in which the available results in line with the statement were pushed to the top of the search results, and a disconfirmatory condition in which results that counter the statement were displayed at the top.

The construction of the socio-political belief statements and lists happened in three steps. In the first step, the authors analyzed the policy domains of the eight largest

**Table 1.** Socio-Political Belief Statements Used in the Pre and Post-Test of the Study.

| Belief statements as shown to participants in Dutch | English translation of belief statements |
|---|---|
| Immigratie zet de sociale zekerheid onder druk | Immigration pressures social security. |
| Een basisinkomen is een goed middel om de algemene welvaart te laten stijgen. | Basic income is a useful tool for increasing overall welfare. |
| Een verplichte gemeenschapsdienst voor OCMW-cliënten zal ervoor zorgen dat mensen sneller op de arbeidsmarkt geraken | A compulsory community service for public social welfare office-clients will speed up people's entry into the labor market. |
| Anderstalige leerlingen toelaten hun moedertaal te spreken op school zal de integratie van deze leerlingen in de weg staan | Allowing non-Dutch speaking pupils to speak their mother tongue at school will hamper the integration of those pupils. |
| De toenemende migratie is de oorzaak van de toename in criminaliteit | The increase in migration is the cause of the increase in crime. |
| Het behoud van kernenergie is essentieel om tegelijk de klimaatdoelstellingen te halen en in onze energiebehoeften te blijven voorzien | The preservation of nuclear energy is essential to simultaneously meet the climate objectives and our energy needs. |
| De legalizering van cannabis zal de criminaliteit doen dalen | The legalization of cannabis will reduce crime. |
| De recentste taxshift heeft de koopkracht verhoogd | The latest tax shift has increased purchasing power. |
| Een versnelde daling van de werkloosheidsuitkering zal leiden tot meer armoede | An accelerated decline in unemployment benefits will increase poverty. |

political parties in the region where the study took place. The analysis indicated nine policy domains on which each political party held particular positions. The policy domains were: taxation, social security, education, national security, ecology, health care, economy and poverty. In a second step, one socio-political issue was searched within each domain on which at least two political parties held opposing views. On the basis of each issue, one belief statement was drawn up (cf. Table 1). As such, for each belief statement there was at least one political party that was in favor of it and one political party that was against it. In this way, the belief statements reflected the most salient socio-political debates in the region where the study took place. In a third step, the authors created two lists for each statement. One list contained the root web domains of organizations that agreed with the statement, the other list contained the root web domains of organizations that did not agree with the statement. The authors found the organizations by analyzing the viewpoints of publicly known opinionated organizations (e.g., political parties, civil organizations, opinion leaders, and alternative media outlets) and adding their root web domains to the pro or con lists. In addition, in order to be as complete as possible, the authors conducted google searches with queries for, against, or neutral with respect to the belief statements and added the root web domains of the obtained opinionated organizations to the lists.

## Sample and Procedure

The participants for the current study were sourced from a research seminar at a Dutch-speaking Belgian university in the Spring of 2019. Specifically, enrolled students were asked to gather up to ten participants, taking into account a uniform distribution for gender and age. A sample with 163 participants was established (70 male, 92 female, and one participant indicated no gender). The average age was 35.25 years ($SD = 15.76$) and 65.1% had a degree in higher education.

Participants opened the research platform in their browsers on their personal computer, which did not require any particular installs. Upon active informed consent, they were directed to a short initial self-report survey. Next, a first belief statement out of the pool of nine was randomly presented (cf. Table 1). The pre-test of the experiment consisted of a truthfulness and certainty assessment regarding that belief statement. After filling in the pre-test, participants were redirected to a Google Search interface where they were prompted to search for information on the belief statement. At the top of the interface, there was a green light bulb button with the text "I have seen enough information." Clicking the light bulb button led to the post-test on which the truthfulness and certainty assessments regarding the belief statement were repeated. The pre-test, search, post-test sequence was repeated seven times. In order to account for fatigue and learning effects we randomized the order in which each belief statement was presented to the participants. In addition, we abstained from presenting nine belief statements and instead randomly presented seven out of the pool of nine. At the end of the session, participants were debriefed on the occurrence of rank order manipulations during the experiment. The complete procedure, together with the initial self-report survey, corresponded to an effort of about 20 to 30 minutes.

## Measures

*Self-report measures.* The initial *survey* involved questions on participants' age, gender, and education. Moreover, political interest was measured by asking to rate the degree to which participants felt interested in political current affairs on a Likert-type item with five response categories ranging from "*not at all interested*" to "*very interested*" ($M = 3.07$, $SD = 1.19$).

The *pre-* and *post-tests* showed the same random belief statement (cf. Table 1), of which participants were asked to rate its truthfulness on a four-point Likert-type item with following anchors: (1) *completely false*, (2) *mostly false*, (3) *mostly true*, (4) *completely true* ($M_{pre} = 2.68$, $SD_{pre} = 0.72$, $M_{post} = 2.69$, $SD_{post} = 0.77$). Next, participants were required to rate how sure they felt about their prior truthfulness assessment on a Likert-type item with five response categories ranging from "*very unsure*" to "*very sure*" ($M_{pre} = 3.65$, $SD_{pre} = 0.88$, $M_{post} = 3.88$, $SD_{post} = 0.80$).

*Behavioral measures.* Participant behavior was captured throughout the entire experiment, registering each query, click, and page visit in the platform's database.

## Content Coding

After data gathering, content coding was performed. First, the *textual similarity* between the provided belief statements and the participant search query was calculated using the Dutch-language version of the natural language processing Python package spaCy (spaCy.io, 2019). The textual similarity variable indicates the extent to which the words in the query correspond to the words in the statement. The variable was measured as a decimal number with values between zero and one, with zero meaning no similarity and one meaning complete similarity. It was used to control for the possibility of participants simply typing over or copying belief statements as queries ($M$=0.58, $SD$=0.20).

Next, *the evaluative direction* of the queries with regards to the original statement (i.e., confirmatory/disconfirmatory/neutral) was coded manually. The first and second author of the study coded 100% of the unique queries independently ($N$=1006). Coding was performed on a dataset that solely included the unique queries, blinding the coders toward other variables. Search queries that did not reveal a specific direction were coded as "neutral." Queries in favor of the statement were coded as "confirmatory," whereas those that undermined the statement were coded as "disconfirmatory." For example, participants were presented the statement that "Immigration pressures social security." A query such as "immigration social security" was coded as neutral, because it does not impose any evaluative content, whereas "immigration undermines social security" or "immigration no effect on social security" obviously do. The agreement between the two independent coders proved satisfactory (Krippendorff's $\alpha$=.80). Of the unique queries, 64.2% were coded as neutral, 31.9% as confirming the statement, and 1.7% as disconfirming the statement.

Moreover, via the same procedure, the queries were coded for the inclusion of background information. If participants included the name of a media outlet, politician, political party, civil society organization, or opinion maker, the query was dichotomously coded for including background information (1.9% of the queries). Again, a high inter-coder reliability was established (Krippendorff's $\alpha$=.87).

The *displayed search results*, as shown to the participants on the platform after manipulation, were automatically coded by means of an expanded version of the lists used for manipulating the search results ranks. The authors slightly expanded the lists because a manual visual inspection of the harvested search results after data gathering revealed that not all confirmatory and disconfirmatory web domains had yet been coded. In compiling scores for the degree to which a search results page was either confirmatory or disconfirmatory, the authors designed an algorithm in Python language code to run through the first ten original Google Search results (i.e., first page) and match them with the web domains in the expanded lists. The authors excluded the search results on the second and third page from the analyses as the clicks on the second and third page accounted for only 6% of the total number of clicks. Next, rank was taken into account by multiplying the dichotomous scores of the matches with the inverse rank. Hence, a top-ranked result on the first place was given a higher score (i.e., score of 10) than a low-ranked result on the tenth place (i.e., score of 1). As such, a first page of results entirely dominated by confirmatory results would get a raw score of 55, whereas a page with no confirmatory results got a 0. The raw score was then transformed by dividing it by the theoretical maximum of 55, leading to a score with a minimum of 0 and a maximum of 1.

Based on the clickstream data logging, clicked search results were coded as either confirmatory, disconfirmatory, or neutral. Again, the authors used the expanded lists to automatically assess the nature of the search results that were selected by the participants. On average each participant selected 1.71 search results per search problem ($SD = 2.43$, min = 0, max = 21). Of the selected search results 16% were confirming and 11.6% disconfirming. Finally, based on the query data logging by the platform, the authors assessed whether a query was a reformulation or not. In total, 219 queries were reformulations which corresponds with 16.4% of all queries.

### *Manipulation Check*

The top three displayed search results contained on average 11% confirmatory and 5% disconfirmatory search results in the control condition, 47% confirmatory and 0% disconfirmatory search results in the confirmatory condition, and 1% confirmatory and 37% disconfirmatory search results in the disconfirmatory condition ($\chi^2(2) = 82.84$, $p < .001$).

We did not use a categorical condition variable in the subsequent analyses to model the exposure to confirming and disconfirming information. Instead, we used continuous variables that express the actual weighted occurrence of confirmatory and disconfirmatory search results: even if exposure is markedly different *between* conditions, there is still ample room for variance *within* conditions that would be insufficiently reflected by a simple dichotomization. The current experiment differs conceptually from a classical experiment in the sense that, in a classical experiment, every participant is exposed to the same stimuli within the same condition. In the current study, however, participants have an impact on the exposure to the experimental stimuli by (re)formulating queries. Therefore, exposure to the stimuli also varies within conditions. This corresponds to actual exposure on online platforms which vastly increases the ecological validity of the findings of the current study.

## Results

H1a posits that a high prior truthfulness assessment results in the use of search queries confirming the belief statement, and H1b states that a low prior truthfulness assessment results in the use queries disconfirming the belief statement. Both hypotheses are tested by a cross-classified hierarchical binary regression model, with observations nested in individual participant sessions and varying search problems. The basis of the analyses is a dataset in which each observation reflects a submitted search query. One

**Table 2.** Effect of Prior Belief on Query Formulation ($N = 1{,}330$).

| | Model 1: dependent variable: formulation of search queries confirming the belief statement | Model 2: dependent variable: formulation of search queries disconfirming the belief statement |
|---|---|---|
| Fixed effects | B (se) | B (se) |
| Intercept | −7.79*** (1.02) | −9.68* (4.17) |
| Query similarity | 10.62*** (0.80) | 1.51 (2.31) |
| Age | 0.13 (0.13) | −0.06 (0.64) |
| Gender | −0.04 (0.26) | 0.16 (1.33) |
| Education | −0.57* (0.25) | −0.31 (1.24) |
| Political interest | −0.12 (0.11) | −0.34 (0.56) |
| Prior truthfulness assessment | 0.38* (0.18) | 0.26 (0.92) |
| Confidence in | 0.05 (0.14) | −0.19 (0.67) |
| Background | 0.94 (0.64) | 2.56 (1.42) |
| Random effects | Variance (se) | Variance (se) |
| Session ID | 1.04 (1.02) | 36.87 (6.07) |
| Problem ID | 2.04 (1.42) | 1.39 (1.18) |
| Goodness of fit | | |
| $R^2_{GLMM}$ (marginal) | 0.44 | 0.01 |
| $R^2_{GLMM}$ (conditional) | 0.71 | 0.92 |

***$p < .001$. *$p < .05$.

model explains the occurrence of queries that align with the phrasing of the stimulus (i.e., queries confirming the belief statement), whereas the other explains the occurrence of queries that counter the phrasing of the stimulus (i.e., queries disconfirming the belief statement). Both models share the same three sets of independent variables. The first variable is the textual similarity of the query and the statement, which controls for the effect of participants simply copying or typing over the presented belief statements. The second set of variables consists of demographics (i.e., age, gender, education level). The third set contains the personal characteristics relating to participants' interest and prior beliefs: political interest, their assessment of the belief statement's truthfulness, their degree of certainty regarding their assessment, and the inclusion of additional knowledge in the formulated query.

The results, summarized in Table 2, show that the participants, when controlling for queries that closely resembled the presented belief statements, shared a tendency to formulate queries confirming the belief statement when they personally assess the presented belief statement as more truthful ($b = 0.38$, $p < .05$). Moreover, the tendency to formulate queries confirming the belief statement is also explained by the absence of higher education ($b = -0.57$, $p < .05$). None of the modeled independent variables in the disconfirmatory model were statistically significant at the $\alpha = .05$ level. However, only 1.7% of the entered queries qualified as disconfirming toward the statement, which flattens out variation and, therefore, decreases power of the null hypothesis test. Still, the analyses presented here only provide support for H1a.

H2 involves two rivalling hypotheses: the anticipated effects of search result rank order, and the effects of participants' prior beliefs on clicking search results. H2a is based on the reasoning that individuals give primacy to rank, rather than prior beliefs. H2b reflects an opposite logic: the effect of prior belief negates that of ranking. We set up a single cross-classified binary regression model on a dataset in which each row presented (a) the displayed search result, and (b) an indicator of whether that search result was clicked or not. The model includes four control variables (i.e., gender, age, education, political interest) and four additional independent variables: prior truthfulness assessment of the presented belief statement, confidence in set prior belief, the rank of the search results (the lower the rank, the higher the score), and the type of the search results (confirming or disconfirming, contrasted to a neutral result). A subsequent model also contained four interaction terms that combine (a) prior belief in truthfulness with type of results, and (b) rank with type of results.

The results in Table 3 show a main effect of rank on click behavior: the higher up in the ranking, the higher the likelihood of clicking the search result ($b = 0.31$, $p < .001$). There is a negative main effect between prior truthfulness assessment and clicking on a search result. The lower someone's prior truthfulness assessment, the higher the chance that a search result will be selected ($b = -0.11$, $p < .05$). Furthermore, results that are either confirmatory ($b = -0.61$, $p < .001$) or disconfirmatory ($b = -0.62$, $p < .001$) share a lower likelihood of getting selected than neutral results. In the model with interaction terms, there is no effect of confirmatory search results type. However, there is an interaction effect of prior truthfulness assessment and confirmatory search results on click behavior ($b = 0.35$, $p < .01$). The plot in Figure 2 displays the relation between prior truthfulness assessment and the probability of clicking a search result for confirming, disconfirming and neutral search results. The plot indicates an increased probability of clicking on neutral and disconfirmatory results when participants initially considered a statement as untruthful, and a relatively increasing probability of clicking confirmatory results when participants believe a statement is truthful. This implies that people's tendency to click less often on confirmatory search results (compared to neutral ones) becomes less pronounced when prior truthfulness assessment is high. In short, the results provide evidence for both hypotheses H2a and H2b. Ranking seems the most impactful predictor: individuals have a stable tendency to select higher ranked search results while neutral search results are always preferred above search results that confirm or disconfirm individuals' prior belief.

H3 proposes that the likelihood of reformulating a search query increases when users are confronted with search results that contradict their prior beliefs. H3 is tested with a cross-classified Poisson multilevel regression model with number of query reformulations as dependent variable. The supporting dataset aggregates the number of search queries per experimental trial. The model includes four control variables (i.e., age, gender, education, political interest) and three independent variables:

**Table 3.** Effect of Rank and Prior Belief on the Selection of Search Results ($N = 13{,}306$).

| Fixed effects | Model 1: without interaction terms<br>*B* (*se*) | Model 2: with interaction terms<br>*B* (*se*) |
|---|---|---|
| Intercept | −3.99*** (0.27) | −3.85*** (0.28) |
| Age | −0.02 (0.09) | −0.02 (0.09) |
| Gender | 0.12 (0.19) | 0.12 (0.19) |
| Education | 0.09 (0.19) | 0.09 (0.19) |
| Political interest | −0.00 (0.10) | −0.01 (0.10) |
| Prior truthfulness assessment of belief statement (PT) | −0.11* (0.05) | −0.14* (0.06) |
| Confidence in prior truthfulness assessment | −0.05 (0.04) | −0.05 (0.04) |
| Confirmatory search result (reference: neutral search result) | −0.61*** (0.09) | −1.78** (0.55) |
| Disconfirmatory search result (reference: neutral search result) | −0.62*** (0.10) | −0.76 (0.67) |
| Rank | 0.31*** (0.01) | 0.30*** (0.01) |
| Rank*confirmatory search result | | 0.03 (0.05) |
| Rank*disconfirmatory search result | | 0.05 (0.06) |
| Confirmatory search result*PT | | 0.35** (0.13) |
| Disconfirmatory search result*PT | | −0.12 (0.14) |
| **Random effects** | **Variance (*se*)** | **Variance (*se*)** |
| Session ID | 1.05 (1.02) | 1.05 (1.02) |
| Problem ID | 0.01 (0.10) | 0.01 (0.10) |
| Goodness of fit | | |
| $R^2_{GLMM}$ (marginal) | 0.14 | 0.14 |
| $R^2_{GLMM}$ (conditional) | 0.35 | 0.35 |

***$p < .001$. **$p < .01$. *$p < .05$.

(a) prior truthfulness assessment of the belief statement, (b) the weighted percentage of confirmatory search results and, (c) the weighted percentage of disconfirmatory search results. Subsequently, two interaction terms were added that combine prior belief with type of results.

The results in Table 4 show that the likelihood of query reformulation generally decreases when statements are priorly considered truthful ($b = -0.33$, $p < .001$), and with increased percentages of both confirmatory ($b = -1.17$, $p < .001$) and disconfirmatory results ($b = -1.28$, $p < .01$). This is however nuanced in the model that includes the interactions. The results, as plotted in Figure 3, reveal that participants who consider a belief statement to be untrue are more likely to reformulate a query when they are confronted with less search results that disconfirm the belief statement ($b = 1.05$, $p < .05$). Hence, when the presented results do not align with what they priorly believe, participants have a higher chance to keep trying. In turn, higher levels of confirmatory

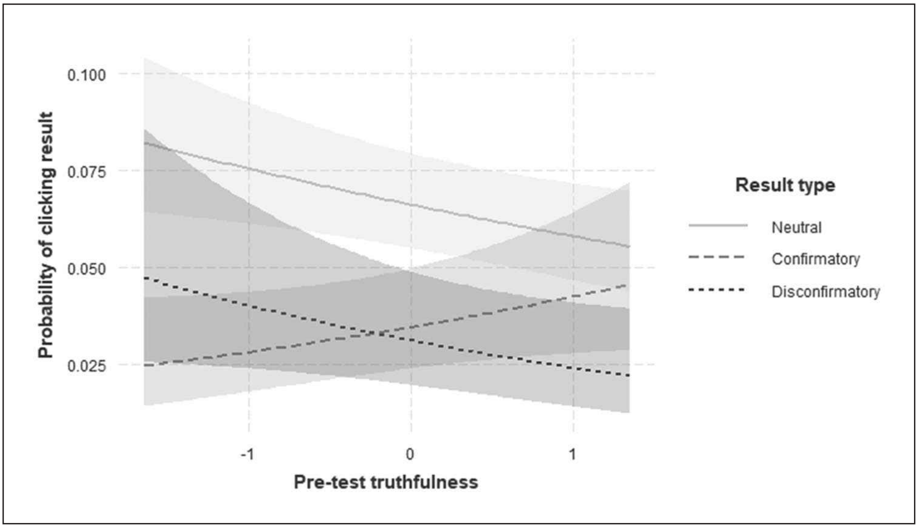


**Figure 2.** Prior belief in truthfulness of the statement and probability of selecting a search result for confirming, disconfirming and neutral search results.

results are generally related to a decreased likelihood for reformulating a query, regardless of prior beliefs ($b = -2.77$, $p < .01$). This suggests a general tendency to increasingly refrain from changing queries when the search results progressively support the statement. Hence, the data partially supports H3.

H4a supposes that users maintain their prior beliefs, even if their search environment contains belief-inconsistent search results. H4b forwards an opposite expectation, namely that users can be persuaded to change their minds when their search environment challenges them with belief-inconsistent search results, and when they interact with these results.

These hypotheses are tested with a cross-classified multilevel regression model that explains the assessment of truthfulness of the belief statement after searching. Each row in the supporting dataset reflects an experiment trial. The model is composed of four control variables (i.e., age, gender, education, political interest) and six independent variables: (a) prior truthfulness assessment of the belief statement, (b) confidence in prior assessment, (c) weighted percentage of confirmatory search results, (d) weighted percentage of disconfirmatory search results, (e) number of clicked confirmatory search results, and (f) number of clicked disconfirmatory search results. In an additional model, seven two-way-interaction terms and two three-way interaction terms were added.

The main effects model in Table 5 indicates a stability of the truthfulness assessment, although there is an effect of clicking on confirming and disconfirming search results. The more confirming results are selected, the stronger the increase in post-test truthfulness assessment ($b = 0.07$, $p < .05$). The more disconfirming results are

**Table 4.** Effect of Search Environment and Prior Belief on Number of Query Reformulations ($N = 1{,}330$).

| | Model 1: without interaction terms | Model 2: with interaction terms |
|---|---|---|
| Fixed effects | *B* (*se*) | *B* (*se*) |
| Intercept | −1.04*** (0.33) | −0.52 (0.40) |
| Age | −0.16 (0.10) | −0.16 (0.10) |
| Gender | 0.23 (0.21) | 0.21 (0.21) |
| Education | 0.15 (0.21) | 0.14 (0.21) |
| Political interest | 0.16 (0.11) | 0.16 (0.11) |
| Weight percentage of confirmatory search results (WCSR) | −1.17*** (0.31) | −2.77* (1.10) |
| Weight percentage of disconfirmatory search results (WDSR) | −1.28** (0.93) | −3.86** (1.26) |
| Prior truthfulness assessment of belief statement (PT) | −0.33*** (0.09) | −0.53*** (0.13) |
| WCSR*PT | | 0.63 (0.40) |
| WDSR*PT | | 1.05* (0.47) |
| Random effects | Variance (*se*) | Variance (*se*) |
| Session ID | 0.64 (0.80) | 0.64 (0.80) |
| Problem ID | 0.03 (0.18) | 0.02 (0.15) |
| Goodness of fit | | |
| $R^2_{GLMM}$ (marginal) | 0.07 | 0.07 |
| $R^2_{GLMM}$ (conditional) | 0.28 | 0.28 |

***$p < .001$. **$p < .01$. *$p < .05$.

selected, the stronger the decrease in post-test truthfulness assessment ($b = -0.11$, $p < .05$). The model including interaction effects sketches a nuanced picture. As shown in Figure 4.1, participants with a high initial confidence in their truthfulness assessment are less likely to change that assessment based on their search activities than participants who expressed initial doubt ($b = 0.12$, $p < .001$). The plot shown in Figure 4.2 indicates that participants who previously considered a belief statement to be untruthful progressively adjust their assessments by clicking more search results that confirm the belief statement ($b = -0.19$, $p < .01$). Inversely, as plotted in Figure 4.3, participants who strongly believe a belief statement to be truthful before searching adjust their assessments as they repeatedly select disconfirming search results ($b = -0.17$, $p < .01$). Both findings are unaffected by the level of confidence in prior truthfulness assessments. In sum, our results point into the direction of H4b. However, it appears that merely encountering belief-inconsistent search results is not sufficient; individuals must first select search results before an effect is likely to occur.

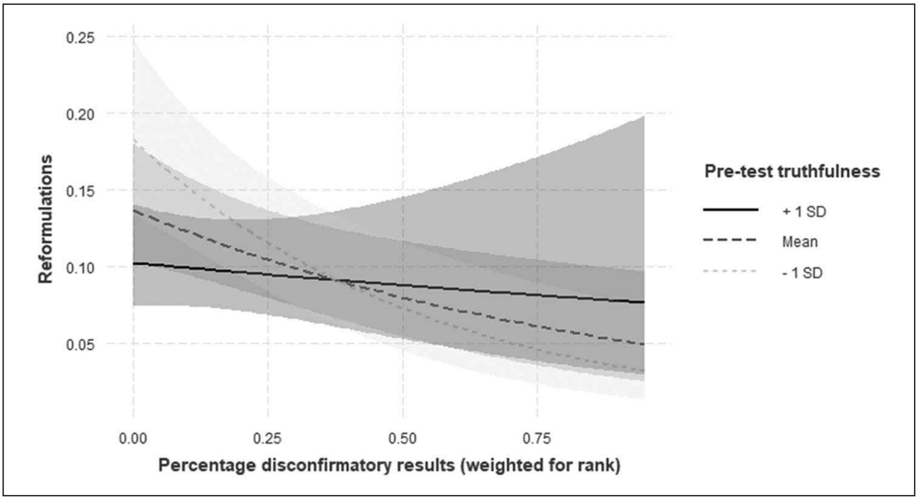


**Figure 3.** Percentage of disconfirming search results weighted for rank and number of query reformulations for different levels of prior belief in truthfulness of the statement.

## Discussion

The present study conceptually and methodologically challenged the selective exposure paradigm in the context of online platforms. It built on two conceptual premises that challenge the existing body of research: (a) online selective exposure must be understood as an integrated sequence of levels of choice, in which selection progressively takes place, and (b) algorithms play a role as active agents shaping online exposure, in tandem with user's agency. In order to address these conceptual challenges, a novel methodological approach was developed that accounted for the entire process of user-platform interactions at every stage. On the one hand, the method did not impose an all too artificial situation by restricting research to the final stage of selection. Instead it allowed participants to interact with the platform as if it were the real Google Search. On the other hand, the experimental setting allowed for sufficient control and covert researcher-induced manipulation to warrant causal inferences.

The results clearly show that algorithmic selection and ranking of search results have a considerable impact on what results are being selected, which aligns with prior findings (Joachims et al., 2005; Pan et al., 2007). The importance of rank in the context of search behavior has implications for information utility theory (Atkin, 1973), in which it is stated that individuals prefer information that is of utility to them. Our results indicate that individuals prefer higher ranked results, which implies that individuals, for the most part, outsource their utility assessment to the search technology.

Regarding the impact of search results, our findings point in the direction of a tipping point during an online information search process, as the repeated exposure to belief disconfirming information is likely to cause belief updating (Redlawsk et al.,

**Table 5.** Effect of Search Environment, Clicked Search Results, and prior Belief on Post Belief ($N = 1{,}113$).

| | Model 1: without interaction terms | Model 2: with interaction terms |
|---|---|---|
| Fixed effects | *B* (*se*) | *B* (*se*) |
| Intercept | 0.99*** (0.13) | 2.25*** (0.35) |
| Age | 0.00 (0.00) | 0.00 (0.00) |
| Gender | −0.06 (0.04) | −0.05 (0.04) |
| Education | −0.02 (0.04) | −0.02 (0.04) |
| Political interest | 0.01 (0.02) | 0.01 (0.02) |
| Prior truthfulness assessment of belief statement (PT) | 0.59*** (0.03) | 0.12 (0.13) |
| Confidence in prior truthfulness assessment (PC) | 0.01 (0.02) | −0.32*** (0.08) |
| Weight percentage of confirmatory search results (WCSR) | 0.15 (0.09) | 0.17 (0.32) |
| Weight percentage of disconfirmatory search results (WDSR) | −0.01 (0.12) | −0.51 (0.45) |
| Number of clicked confirmatory search results (CCSR) | 0.07* (0.04) | 0.51** (0.19) |
| Number of clicked disconfirmatory search results (CDSR) | −0.11* (0.05) | 0.26 (0.35) |
| PT*PC | | 0.12*** (0.03) |
| PT*WCSR | | −0.01 (0.11) |
| PT*WDSR | | 0.19 (0.16) |
| PT*CCSR | | −0.19** (0.06) |
| PT*CDSR | | −0.17** (0.07) |
| PC*CCR | | 0.03 (0.03) |
| PC*CDR | | 0.02 (0.05) |
| Random effects | Variance (*se*) | Variance (*se*) |
| Session ID | 0.00 (0.05) | 0.00 (0.07) |
| Problem ID | 0.04 (0.19) | 0.04 (0.19) |
| Goodness of fit | | |
| $R^2_{GLMM}$ (marginal) | 0.33 | 0.35 |
| $R^2_{GLMM}$ (conditional) | 0.39 | 0.42 |

***$p < .001$. **$p < .01$. *$p < .05$.

2010). Consequentially, we do not find evidence for the existing of a disconfirmation bias (Taber & Lodge, 2006). Indeed, in correspondence with prior findings (Knobloch-Westerwick, Johnson et al., 2015; Knobloch-Westerwick, Mothes et al., 2015; Westerwick et al., 2017), the results indicate that selected search results have the potential to impact priorly held beliefs. The potential of selected search results to

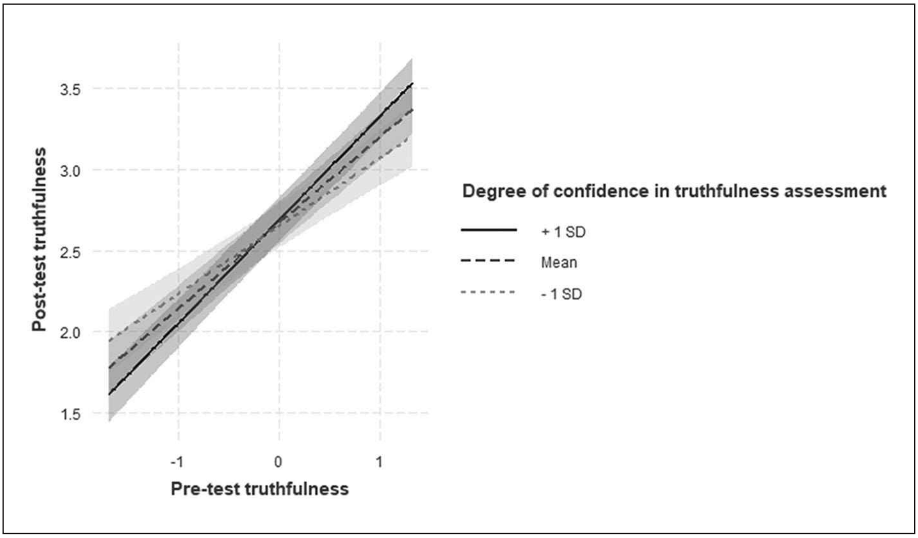


**Figure 4.1.** Prior belief in truthfulness and post belief in truthfulness of the statement for different levels of confidence in prior belief.

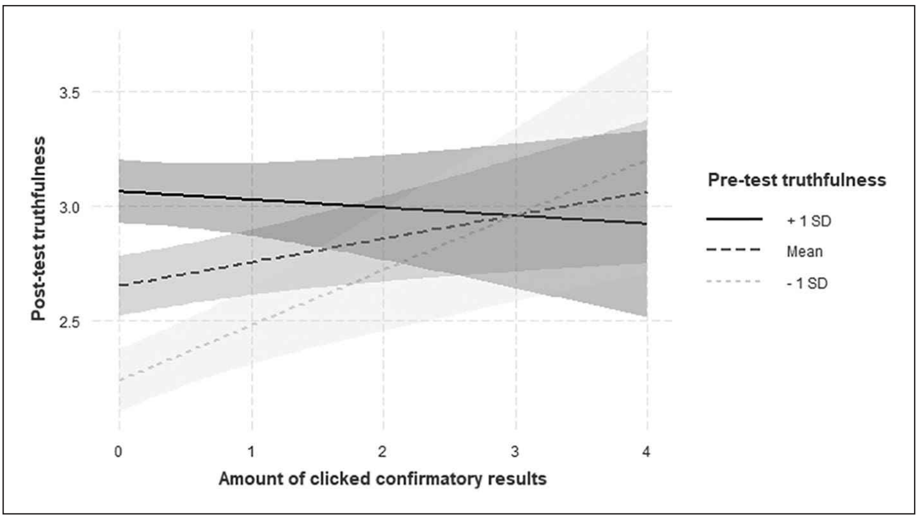


**Figure 4.2.** Number of selected confirmatory search results and post belief in truthfulness of the statement for different levels of prior belief.

impact priorly held beliefs nuances prior insights by Epstein and Robertson (2015) and Epstein et al. (2017) whose findings suggested that mere exposure to higher ranked search results impacts beliefs. The fact that explicit selection of search results precedes its impact is not that surprising; literature on attitude formation has long indicated that

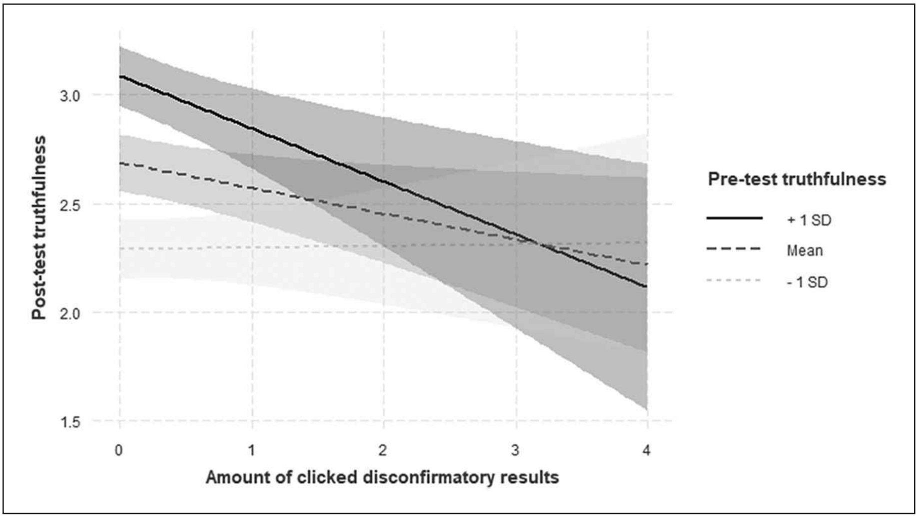


**Figure 4.3.** Number of selected disconfirmatory search results and post belief in truthfulness of the statement for different levels of prior belief.

attitudes are hard to change (Chaiken et al., 1995; Vogel & Wänke, 2016). Hence, a swift search through search results (which only contains short or half outlined arguments due to wording restrictions in the accompanying text snippets) is likely not enough to change opinions.

Aside of the impact of ranking, our findings also highlight the influence of users' degrees of freedom in narrowing down their exposure to information—albeit to a lesser extent. As predicted, selection starts at the stage of choosing a search query, which is, at least in part, explained by user characteristics, such as education level and belief toward a search topic. Furthermore, the finding that users are likely to select search results that confirm their prior beliefs corresponds with prior research which indicates that users prefer attitude consistent information regardless of ranking (Knobloch-Westerwick, Mothes et al., 2015; Westerwick et al., 2017). However, our results still point to ranking as the most important factor for search result selection. Moreover, we find evidence that queries are more likely to be reformulated, and thus counteracted, when users are exposed to highly ranked information contradicting their prior beliefs than when users are exposed to highly ranked information neutral toward or confirming their prior beliefs. This indicates that users show some amount of resistance toward algorithmic filtering and ranking when exposed to belief contradicting search results.

In addition to its findings on selective exposure within search engines, the current study offers important conceptual and methodological contributions. As each level of choice shapes the available information, the current study demonstrates that research on online platforms and selective exposure needs to take all the different levels of choice into account. The method used in the current study offers a first example of how this conceptual idea can translate into new method: the method allows participants to, at least in part, have an impact on the content that they get to see, which also corresponds with the reality of online user-platform interactions. Hence, the approach as outlined in the current study offers higher ecological validity than a traditional experimental design with fixed and predetermined stimuli. The disadvantage of the method in the current study is that it complicates causal inference given the possible mutual constitutive impact of the user and the platform. Consequently, it is not straightforward to assess whether an effect is caused *only* by the platform *or* by the user. Nevertheless, the decrease in internal validity can be justified because, in reality, such an either-or-situation will never truly occur.

In all, it would seem valuable if future researchers could extend the scope of the current study to other online platforms. An important difference between Google Search and other online platforms is the relatively low level of personalization induced by Google Search. Apart from location-based personalization (which is determined by Google) (Kliman-Silver et al., 2015), personalization on Google Search is mainly caused by the use of different search queries and is, therefore, user-induced. The high use of user-induced personalization differs from other online platforms where system-induced personalization largely determines the presented content (e.g., Facebook, Instagram, . . .) (Dylko, 2016). Therefore, emulating a search platform that looks and feels like Google Search is relatively easy in comparison with emulating, for instance, an accurate Facebook news feed.

Evidently, the current study also comes with limitations. Despite the high investment in an ecologically valid method, the study still took place in an experimental research context: participants were confronted with artificial search needs, which is a substantial departure from everyday information seeking and limits the external validity of the results. Future research can account for this by taking knowledge, involvement and motivation with respect to the different search issues into account. In addition, it is important to consider that the current study only focused on the levels of choice that occur during information retrieval and not during the pre-communicative stage, such as the selection of a medium and the selection of a specific search engine. Future research could take account for these levels of choice as well. Moreover, the completion of seven search tasks on seven different socio-political topics can create fatigue within participants which could lead to a decrease in performance for the last presented search tasks. We tried to minimize possible error induced by fatigue by randomizing the order in which the search tasks were presented to the participants. Another limitation relates to the content coding of the search results, which took place on the domain level of the search results. To model the direction of the displayed search results we used web domains of organizations of which we were certain that they take a clear stand regarding the belief statement. Search results stemming from mainstream media outlets were coded as neutral. This can be justified because in the region where the study took place an internal pluralistic media system is installed, which is marked by mainstream media sources that are hardly opinionated in one particular direction and when they are, they even each other out (Hallin & Mancini, 2004; Valcke et al., 2016). However, this method is not completely firm as we are not certain whether a mainstream media search result is in fact always neutral. It is still possible that one particular mainstream media article puts forward one particular point of view and another article presents the other point of view. A possible solution would be to code all the displayed search results post hoc. However, manual coding is a time-consuming and therefore costly process where the possibility of errors is substantial. Automatic content coding based on content recognition could offer a solution. However, the use of algorithms for the valid and reliable coding of digital contents in a way that would be feasible for the current study is technically not possible yet.

Despite its limitations, the implications of the current study are substantial. The current study shows that search engine users exhibit agency during their search for information. Education and prior beliefs, at least in part, impact the content a person ultimately chooses to select. Given the importance of ranking, search engine providers are responsible to monitor possible biases in their search results and address the loopholes in their algorithms. The results of the present study clearly show that the outcomes of an online search are formed by both the user and the platform with its corresponding algorithms. Therefore, in a broader scientific context, the current study calls for more empirical research closely mimicking actual situations, thereby acknowledging that users and algorithms jointly shape the outcomes of online activities.

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## Supplemental Material

Supplemental material for this article is available online.

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