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Responsible Opinion Formation on Debated Topics in Web Search

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Abstract. Web search has evolved into a platform people rely on for opinion formation on debated topics. Yet, pursuing this search intent can carry serious consequences for individuals and society and involves a high risk of biases. We argue that web search can and should empower users to form opinions responsibly and that the information retrieval community is uniquely positioned to lead interdisciplinary efforts to this end. Building on digital humanism—a perspective focused on shaping technology to align with human values and needs—and through an extensive interdisciplinary literature review, we identify challenges and research opportunities that focus on the searcher, search engine, and their complex interplay. We outline a research agenda that provides a foundation for research efforts toward addressing these challenges.

Keywords: web search · opinion formation · debated topics

1 Introduction

Web search engines provide fast and convenient access to the often overwhelming amount of resources that could potentially satisfy users' information needs [70]. Nevertheless, search engines are not merely neutral tools for retrieving relevant resources; they act as information gatekeepers and, as a result, play a vital part in shaping individual and collective knowledge [34,68,78].

A. Rieger and T. Draws—Contributed equally.

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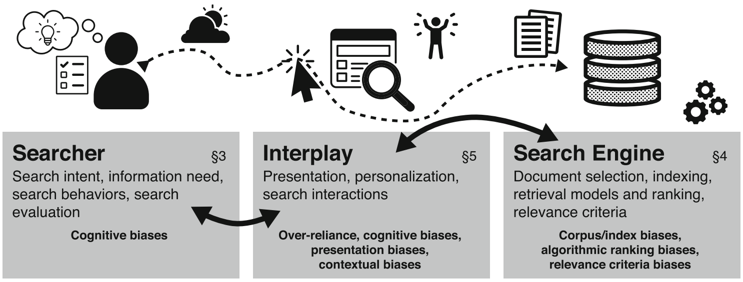

Fig. 1. Search on debated topics. Biases hindering interactions to gain well-rounded knowledge can emerge from the searcher, the search engine, and their interplay. Ultimately, search on debated topics can shape cognitive processes (e.g., attitude change) and concrete actions (e.g., voting in an election).

By providing access to information that can directly or indirectly shape users' views and beliefs, web search assumes an important role in opinion formation [35,52,58,59,124,160,181,208]–developing one's view on a topic to satisfy a personal interest or seeking advice on an issue of personal, business, or societal concern [36]. Opinion formation may involve shallow issues (e.g., outfit choices), but it can also refer to more impactful and even contentious matters: **debated topics**. Debated topics are socio-scientific issues of ongoing discussion that do not convey—at least according to some debate participants or observers—a straightforward solution [176]. They include extremely one-sided matters with clear scientific stances (e.g., whether the Earth is a sphere) and more divisive issues with legitimate arguments on both sides of the spectrum (e.g., whether zoos should exist). Searches on debated topics can impact individual users' opinion formation and subsequent decision-making (e.g., on whether to embrace veganism [59], what financial strategy to employ [208], or whom to vote for [52]) and thus, on aggregate, democratic societies at large.

Conventional search engines fall short of aiding complex, consequential information needs [64,126,181,183], prompting the question *how web search can support information seeking on debated topics*. By that, we do not mean guiding searchers toward a particular view or ideology but instead assisting and empowering them in actively and thoroughly engaging with diverse viewpoints; critically evaluating information to **form opinions responsibly** [102,151]. Although users may intend to expose themselves to diverse viewpoints when searching for debated topics [3,124], responsible opinion formation can be impeded by factors like over-relying on the system to provide accurate and reliable resources [183]. Engaging with information on debated topics is naturally demanding and can trigger emotionally charged behavior, as it has the potential to challenge the searcher's core beliefs and values [81,156]. Thus, search on debated topics inherently requires cognitive effort, particularly to overcome *biases* that can occur during the search process. Such biases may emerge from the user (e.g. cognitive biases) [79,213,217], the search engine (e.g., data, relevance criteria, and algorithmic ranking biases) [28,45,62], or the interaction between them (e.g., presentation, over-reliance, and contextual biases) [11,15,183]. These considerations highlight the complex, mutually evolving interplay of the searcher and the search engine (see Fig. 1), as illustrated in representations of the search process such as the *Information-Seeking and Retrieval Model* [86, Chapter 6].

As search engines are widely used, they can and should be platforms to explore debated topics in all their nuances. The information retrieval (IR) community has dedicated efforts to comprehending the evolving needs of searchers and society and developing technology to support them [142,181]. Given the role search engines play in opinion formation—a search intent they were not explicitly designed for—the importance of advancing the understanding of the associated challenges, as well as the development of system functions that foster responsible opinion formation becomes apparent. Although IR research has already explored and experimented with *fairness* [8,57,224], *diversity* [1,48,177], *argument retrieval* [27,50,150,158,206], and user interface adaptations [37,92,121,219], whether and how web search engines should cater to users' opinion formation and deal with debated topics remains largely unanswered. Resonating with the ideals for future technological development of *digital humanism*, web search should be shaped following individual and societal values and needs instead of letting web search shape individuals and society [209]. To do so, it is essential to recognize opinion formation on debated topics as a distinct search intent, characterized by (1) the heightened risk of searcher and search engine biases and (2) its consequential nature on individuals and society at large, and warranting dedicated research efforts. The IR community is uniquely positioned to spearhead interdisciplinary efforts to advance such socio-technical research endeavors.

In this paper, we delve into the role of web search engines in users' opinion formation, delineating the distinct characteristics of web search on debated topics through an extensive review of interdisciplinary literature. We illuminate the challenges inherent to the searcher (§3), the search engine (§4), and their interplay (§5) and outline a research agenda (§6) encompassing methodological considerations, high-level challenges, and initial research questions towards responsible opinion formation through web search.

2 Digital Humanism and Responsible Opinion Formation

Digital Humanism advocates for reflecting on the relationship between humans and technology. Fostering human-centered design, it prioritizes better lives and societal progress over mere economic growth [209]. Designing technology to embody these ideals is not a linear process as technology and humans co-evolve, mutually shaping one another in an intricately intertwined manner [140,214].

Web search is one of the primary information gateways, impacting searchers' knowledge, choices, and actions [34]. Searchers have cultivated a sense of trust that makes them rely on the system's evaluation and differentiation of resources on their behalf [183]. Yet, search engines are not subject to regulations for content quality and diversity necessary for an informed citizenry, unlike the standards applied for responsible reporting within traditional media outlets [75].

Opaque relevance and ranking criteria are far from value-neutral but function as algorithmic curators that serve a goal, e.g., user satisfaction and profit generation [34,138,210]. Given the profound impact of web search, recent work has called for revisiting relevance criteria and search system design to better align with the needs and values of individuals and democratic societies [32,64,181]. However, it is non-trivial to balance values that might be in tension with each other [34]. These tensions are particularly evident for search on debated topics, where relevance to user needs might not be aligned with relevance to democratic values, necessitating a critical evaluation of value trade-offs.

Forming opinions responsibly involves gathering evidence and critically assessing it [102,151]. In the context of web search, this translates to searchers actively and thoroughly engaging with search results encompassing **diverse viewpoints**. Yet, this is not the norm as *Search Engine Result Pages* (SERPs) often lack viewpoint diversity [45], and searchers tend to primarily interact with information that aligns with their own viewpoints [174,182,203,210].

Viewpoint diversity in people's exposure to information concerning debated topics represents a long-standing research topic in the communication sciences [14,25,54,117,215]. Different democratic notions of viewpoint diversity can be applied depending on the objectives of a system [74]. Which particular notion of viewpoint diversity is appropriate in an opinion formation-related search scenario, however, might depend on both the topic and the user [74,204,205]. For instance, one could argue that viewpoint diversity is vital for unresolved issues but that web search engines should represent topics with a solid scientific basis in a more one-sided fashion. While it may seem obvious that scientifically answerable topics should be presented as such, previous research has shown that exposing strongly opinionated users to nothing but opposing viewpoints can result in a backlash effect; where they become more entrenched in their beliefs [141]. This can increase polarization by leading users to shift their attention away from mainstream and toward more niche information sources [141]. Similarly, increased diversity can also lead to false perceptions of existing evidence, e.g., balancing climate change believers and deniers can create a false image of an open debate that may be worse than an approach that accounts for different weights of evidence [40]. The desirable degree of viewpoint diversity may thus not always be either the minimum or maximum [16] and can depend on the topic and individual user characteristics [122,134].

IR research has largely used binary (e.g., democrat/republican) or ternary taxonomies (e.g., against/neutral/in favor) [60,155,162,221] as *viewpoint representations* for search results. Recent work, however, has shown that such labels unnecessarily reduce complex viewpoints to generic categories, which limits the insight gained in research using them [42]. Researchers have added more nuance to such labels by using ordinal scales [46,172], continuous scales [105,106], multi-categorical perspectives [38], or building on outcomes from communication sciences [13,25] to yield a two-dimensional viewpoint label that includes a nuanced notion of *stance* (e.g., strongly supporting) and *logics of evaluation* (i.e., representing the reasons underlying a stance, e.g., supporting zoos because of their animal conservation efforts) [42]. Despite these advancements, there is a need to analyze existing viewpoint representation frameworks for comprehensibility, practical applicability, and meaningfulness for users and practitioners.

3 The Searcher

The searcher (*information seeker*), turns to a search engine to execute a search intent, motivated by an underlying *information need*. This develops from a perceived problem, a knowledge gap, an internal inconsistency related to their understanding, or some conflict of evidence [19]. Once the searcher enters a *query* into the system, their interaction with the system begins (§5). Such interactions include evaluating the information encountered in search results and can affect searchers' knowledge and attitude towards the search topic [52,99].

Research on how users search the web for debated topics [79], or how they form opinions in non-biased scenarios [61,124] is in its infancy. Progress depends on conducting user studies into behavioral patterns as users search for debated topics (e.g., queries used [3], if they engage with counter-attitudinal viewpoints, or when they stop searching) and searchers' preferences (e.g., whether users prefer diverse or filtered viewpoints [96]). Also crucial are methods to correctly interpret user behavior, e.g., clicks on search results are often seen as a proxy for engagement [46,172] but users may engage with them in a variety of ways that can be just as meaningful for opinion formation [101]. Researchers should investigate how to support users' reflections on their search processes and outcomes (e.g., awareness of their biases and knowledge level) and investigate long-term opinion formation (e.g., changes in search behavior and opinions over time).

Cognitive Biases. To reduce the cognitive demands of processing information on debated topics, searchers frequently (and subconsciously) employ shortcuts, which can introduce cognitive biases [11,61,197]. *Confirmation bias*, searchers' tendency to prioritize information that confirms prior attitudes [136,203,210], can prevent engagement with diverse viewpoints during search on debated topics. This bias has been observed at various stages of the search process, e.g., query formulation [79], and search result selection [145,203,217]. Other studies have noted searchers' inclination to engage with positive (i.e., query-affirming) [213] and mainstream content [61]. Triggered by the search result presentation, other cognitive biases that hinder diligent search behavior can arise (§5). Identifying how to facilitate search in this context requires a thorough understanding of factors affecting searchers' intentions, behavior, vulnerability to biases, and evaluation of the encountered information. It also requires approaches to support and empower searchers for unbiased and diligent search behavior.

Context. The vulnerability to biased search behavior is contingent upon the searcher's context. For instance, when searching purposelessly, as opposed to specifically looking for information on a particular debated topic, searchers' vulnerability to cognitive biases increases [217]. Stressful conditions (e.g., time pressure) may strengthen the influence of cognitive biases [153, 180]. This calls for investigating how the searcher's context influences search behavior and the vulnerability to cognitive biases when engaging with debated topics; also how to create search environments that foster unbiased and diligent search behavior and reduce contextual conditions leading to high vulnerability to biases.

User Characteristics. Search behavior, susceptibility to cognitive biases, and reaction to elements of the user interface are affected by *situational* and *stable* user characteristics [198]. Situational factors include attitude strength and certainty [98, 201] and involvement with and prior knowledge of the topic [116, 133, 211]. Stable factors that affect engagement with debated topics include searchers' *need for cognition* (i.e., an individual's tendency to organize their experience meaningfully) [33, 152, 196], *receptiveness to opposing views* (i.e., willingness to impartially access and evaluate opposing views) [128], and *intellectual humility* (i.e., an individual's tendency to recognize the fallibility of their beliefs and the limits of their knowledge) [30, 41, 63, 104, 112, 156]. Open research directions include advancing the understanding of how different user characteristics affect search on debated topics throughout the search process, from search intent to search evaluation, and if concepts such as searchers' *moral values* [115, 170] play a role. Researchers should also investigate how efforts to support unbiased and diligent search behavior may require adaptation to cater to the diverse needs of searchers with distinct characteristics.

Vulnerable Groups. It is crucial to study and accommodate vulnerable user groups such as children, elderly people, or neurodivergent users in search for opinion formation. These users have certain characteristics (e.g., fewer cognitive resources or low technological literacy) that may make them more vulnerable to viewpoint biases and less likely to enact responsible opinion formation [94, 108, 118, 127]. For instance, children are less likely to judge or explore search results [108] and are more susceptible to opinion formation through misinfomation [118]. Elderly users similarly have increased tendencies toward sharing and interacting with fake news [66, 91]. Research is needed to identify who those vulnerable groups are specifically, what particular factors make them vulnerable, and how web search engines can support these users in their opinion formation.

Boosting Searchers' Competencies. Boosting interventions are effective in fostering web literacy skills, such as resilience to misinformation [113, 175], detecting micro-targeting [119], and improving privacy behavior [144]. These interventions, which promote individuals' cognitive or motivational competencies [77, 103, 120], contain a learning component and thus could remain effective even after the intervention. The specific challenges posed by web search on debated topics might require an expansion of traditional web and information literacy constructs [69], for instance by incorporating intellectual virtues [64]. Although boosting interventions that target such virtues have been suggested [171], their effect on search behavior and opinion formation is not fully understood.

4 The Search Engine

Contemporary search engines provide a means of sifting through large volumes of information to find the proverbial *needle in the haystack*. Key to search engines are three inputs: (i) a **document index**, a data structure representing a collection of documents (or corpus, typically a *crawled* [95] collection of web documents for web search engines); (ii) a **retrieval model**, that is responsible for identifying and scoring (and ranking) documents that are deemed *relevant* to what is being searched for, based on a series of *relevance criteria* (e.g., [89,186,220]); and (iii) a **query**, a construct of an *information need* as provided by the searcher, typically formulated as a series of tokens, e.g., `'should zoos exist'`. Search engines—as with other systems—are not immune from biases [132]. Indeed, the design of the retrieval model can raise several areas in which biases can (and do) arise, such as leading to *undue emphasis* on particular perspectives [106].

Corpus/Index Biases. Search results can only list documents that are included in a web search engine's index. With commercial web search engine crawlers indexing huge swathes of the *World Wide Web*, the population of content creators who generate the documents in this collection is unlikely to represent the global human population [62], and follows a highly unequal distribution concerning the number of documents generated per content creator [5,7,200]. Such collections may thus include a *creation bias*, i.e., they do not contain balanced or society-representative viewpoint distributions on all debated topics [146,184]. Moreover, the way in which a retrieval system indexes documents can affect the distribution of available documents. An *indexing bias*—whereby the search engine is programmed to systematically ignore particular documents—may further skew the data that the retrieval system can process [28,154,202].

Algorithmic Ranking Biases. Search engines may (unintentionally) exacerbate viewpoint biases in the indexed corpus through algorithmically-biased relevance criteria [57,147,148]. *Ranking biases* may cause documents that express certain viewpoints to rank higher than others, and therefore receive more attention from searchers (§ 5). This can occur when search result rankings solely focus on relevance criteria that optimize for maximizing searchers' satisfaction [199].

Relevance Criteria Bias. Determining the relevance of a search result is central to search engines. With debated topics, the relevance criteria employed by conventional search engines—which mostly target user satisfaction to maximize profit and efficiency [199]—may prove inadequate. Disregarding relevance to the unbiased knowledge gain of the searcher—as well as relevance to society and public welfare—can impede searchers from gaining a comprehensive understanding of a debated topic and its various arguments [64,68,75,186]. Prior work has found viewpoint biases in highly-ranked search results concerning health information [210,212], politics [161], and other debated topics [45].

Research and practical applications require automatic viewpoint classification methods to evaluate and foster viewpoint diversity. This primarily concerns the development of bias metrics and diversification algorithms.

Viewpoint Detection. Applications for search on debated topics need efficient and reliable methods to assign viewpoint labels to documents, e.g., measuring or mitigating search result viewpoint biases in real-time. Recent research has seen the emergence of *Natural Language Processing* (NLP) tasks like *stance detection* [9,71,129,130,185,207] and *argument mining* [31,109,110,114,137,187], which aim to automatically detect different viewpoint components in text. Other works have used unsupervised topic models [192,194,228] or hybrid approaches (i.e., automatic methods combined with crowdsourcing) [12] to overcome the limitations of supervised stance detection models. However, practitioners will ultimately need fully automatic methods to classify search results into broad viewpoint representations. *Large Language Models* (LLMs) have recently shown promise in this area, still further work is needed. Researchers should build on the existing efforts in stance detection, argument mining, and argument retrieval [2,26] to develop such advanced methods.

Viewpoint Bias Assessment. Assessing viewpoint bias requires metrics that accommodate the chosen ethical notion of viewpoint diversity and viewpoint representation. Current rank-aware viewpoint bias metrics applicable to search results consider categorical stance labels (e.g., against/neutral/in favor) [204, 218], continuous stance labels (e.g., ranging from -strongly opposing to strongly supporting) [106], or multi-dimensional viewpoint labels (i.e., stance and logic of evaluation [45]. Thus far, viewpoint biases in search results are primarily assessed as a deviation from viewpoint balance [45,47,52], deviation from the overall distribution across ranks [57,106], or the presence of scientifically false information [155,212]. Yet, it is unclear what metric may best apply in what scenario, how metrics compare, and what intuitive degrees of viewpoint bias different metric scores suggest. Existing metrics do not distinguish among data, algorithm, or presentation bias, and there is no guideline as to what specific *discount factor* to apply for rank-awareness [178]. There is a need to develop comprehensive viewpoint bias metrics, (simulation) studies to compare metrics, interpretation guidelines (i.e., including metric thresholds where viewpoint biases may become problematic), and best practices for using those metrics.

Viewpoint Diversification. Earlier work has diversified search results for more general user intents [1,82,93,177,226], and even made first steps to manually or automatically diversify viewpoints [45,53]. While some of these works have considered advanced viewpoint labels [45], how to diversify search results for different diversity notions or viewpoint representations, and how to dynamically adapt diversification algorithms to searcher needs (e.g., due to changes in search topic or user context) remains to be determined. Researchers could further explore solutions for data, algorithmic, and presentation biases individually and develop pipelines that increase diversity at each level.

5 The Searcher and Search Engine Interplay

Search engines present the SERP to the searcher, featuring search results that may be personalized, taking into account several contextual factors, such as previous search interactions [100,190]. Searchers interact with the SERP, for instance by querying, scanning the results, and clicking on selected items to access the web page. Substantial challenges associated with searching on debated topics emerge from the intricate interplay of the searcher and the search engine.

Over-Reliance and Cognitive Biases. Searchers rely on search engines and assume that highly-ranked search results are relevant and accurate [61,183] - a notion that may be explained with the perceived quality of top-ranked results (e.g. see work on the related context of news selection [65]), or as a response to information overload. Indeed, prior work shows that when the amount of available information exceeds one's processing capacities, searchers tend to be more selective and prone to cognitive biases [188]. For complex tasks, this reliance may impede searchers from expending the needed cognitive effort, thus turning into over-reliance [183]. Opaque relevance criteria further hinder searchers' ability to assess information completeness [126]. Reliance on the search engine is exemplified in searchers' *position bias* (i.e., users typically tend to pay much more attention to search results at higher ranks [88,149]) as well as the *Search Engine Manipulation Effect* (SEME) [21,52,155], where users tend to change their attitudes following viewpoint biases in search results. So far, little prior work has explored what gives rise to phenomena such as SEME [46]. Effects emerging from the interplay between the searcher and search engine might also be related to additional cognitive biases, such as the *availability bias* (i.e., overestimate the prevalence of information that is easily accessible) [11], or *anchoring bias* (i.e., the top-ranked search result may color the searcher's attitude) [11,139,213]. Such phenomena typically occur without users' awareness [61] and are unlikely what users aim for when they search the web for debated topics. Moreover, as web search results get increasingly augmented or replaced by highly pleasing and personalized answers from artificial intelligence chat systems (e.g., *ChatGPT*) that require exerting even less cognitive effort when searching, over-reliance and cognitive biases among users may become even more prevalent.

Presentation Biases. Search results are typically presented as ranked lists (i.e., split into pages of ten search results each; although other presentation formats have been proposed [90]). Each result is displayed with a *title*, a *snippet* (i.e., a brief excerpt from the document text), and the relevant *URL*. Common web search engines often display additional information such as *entity cards* [29], direct answers [20], or suggestions for alternative queries [125]. These different factors provide ample room for presentation biases in search results [15,17,222]. Viewpoint-related presentation biases could occur due to a more prominent presentation of particular viewpoints, e.g., by more favorable snippets [21,22] or representation in entity cards [121]. Moreover, the impact of presentation biases could be largely hidden as users often engage with search results without clicking on them (e.g., only reading the titles and snippets) [101].

Context. Contextual factors emerging from the searcher-system interplay may aggravate biases [85]. For instance, search result rankings may be affected by users' prior searches, preferences, or location [143,223], viewpoint biases in earlier interactions may lead to biased follow-up search queries [3], and presentation biases may depend on the device that users employ [97].

The biases and artifacts arising from the mutually evolved interplay between searchers and search engines can obstruct fruitful searches that facilitate responsible opinion formation. Thus, there is a need to disentangle and understand this convoluted interplay and design search interfaces that facilitate and motivate thorough engagement with diverse viewpoints.

Exposure and Interaction. The search results users are exposed to (and subsequently interact with) can strongly influence users' opinions [4,21,52,155]. *How* users interact with search results plays an important role here: even when exposed to viewpoint-biased search results on social and political information, search behavior is still characterized by searcher-rooted interaction bias, with searchers prioritizing search results that align with their beliefs [174,182]. While searchers may somewhat defy the impact of exposure effects, they could still lead to more subtle and enduring consequences over time [174]. These observations stress the need for deeper insights into the dynamics of exposure and interaction biases. Considering that viewpoint changes often begin with information encounters on social media [73,124], researchers should moreover explore the relation of exposure and interaction effects across different information settings.

Interfaces. Interface modifications can support unbiased and diligent search behavior, e.g., presenting search results in alternate formats [92], providing information about the search topic or the ranking [121,219], visualizing viewpoints and biases in search results [37,53,216], suggesting alternative queries [157], or highlighting documents with diverse viewpoints [39,221]. Also promising are behavioral interventions to support unbiased search interactions (e.g. warning labels) [53,152,172,173]. Researchers should investigate how different viewpoint representations, notions of viewpoint diversity and additional features, e.g., search result explanations affect searchers [43,166,216]. Interventions that can be customized by the searcher (i.e., *self-nudging* [167]) have worked in the news context [18,24,72] and merit investigation in the realm of web search. As users sparingly utilize customization features and adhere to default configurations [24,191], research is needed to identify user-friendly options and optimize default settings. Increasing search engine *transparency* (e.g., by explaining what factors influenced the ranking or providing meta-information for search results) as a means to raise awareness of system biases and foster appropriate reliance should be investigated. This could boost searchers' technological and information literacy [76,183]. Still, providing meaningful explanations poses several challenges, including decisions regarding the level of detail and presentation [49].

Personalization. Users have diverse characteristics, tendencies, and pre-search opinions [21,46]. This raises the question whether degrees of viewpoint diversity or presentation formats (e.g., stance labels) should be adapted to different searchers [169,172]. Personalization with regards to searchers' opinions, cognitive biases, moral values, and other relevant constructs would require methods to automatically predict these psychometric variables [123]. However, such endeavours would also raise substantial privacy concerns [193]. Whether and how to customize search results and the interface based on factors like user characteristics, past behavior, and the specific topic remains an open question that warrants ethical and research discussion. This may also affect general personalization efforts by web search engines [100,159,190].

6 Research Agenda

The intricate dynamics among the searcher, the search engine, and their interplay (§ 3–5) call for reflecting on research methods and broader research challenges. We outline some of these considerations and challenges, along with research questions to guide efforts on web search on debated topics.

Data Collection and Public Data Sets. Developing and evaluating methods to assign viewpoint labels or foster viewpoint diversity in search results, and user studies on search behavior require high-quality, human-annotated ground truth data sets with search results and viewpoint labels. Creating such data sets is not easy: recent research has shown that different worker characteristics and cognitive biases can reduce the quality of data annotations, especially in subjective tasks such as annotating viewpoints [44,47,51,83]. More work is needed to identify best practices and publish openly available data sets with search results and comprehensive viewpoint labels for different debated topics.

User Studies. Evaluating perceptions of viewpoint representations and viewpoint diversity, understanding factors influencing searchers' behavior, and determining how to support unbiased and diligent search requires qualitative and quantitative studies. Winter and Butler [214] stress the value of ongoing dialogues between the technology developers and users, for responsible technology design. As we delve into issues concerning information access and societal well-being, it is crucial to comprehensively and longitudinally assess design choices and interventions in real-world settings, ensuring that they do mitigate harm rather than inadvertently exacerbating it [56]. Comprehending the impact of various factors on searchers and their behavior needs carefully designed, controlled studies with large sample sizes to grasp subtle differences [111]. Simultaneously, the uncertainty of the complex socio-technical dynamics, normative dimensions, and related risks might necessitate more exploratory research methods [179]. A promising new avenue in this regard that has recently gained traction in the communication sciences may be data donations. While they present legal, ethical and technical challenges, data donations offer externally valid and highly granular insights by enabling researchers to retroactively analyse authentic search queries (e.g. from donated browser histories) [6,23,80].

Cultural Diversity. Different societies, countries, and cultures have vastly different ways of searching about and discussing debated topics [84,107]. Contemporary academic research is almost exclusively conducted in English, so is previous work related to web search on debated topics. Yet, web searchers across the globe may experience viewpoint biases and their undesired effects. It is therefore essential that future research considers web search on debated topics and all related challenges from a multi-lingual and multi-cultural perspective.

Misinformation. Balancing the dangers of exposing users to search results containing false claims with viewpoint diversity while preserving freedom of speech and avoiding (perceptions of) censorship is a particularly difficult issue that requires further investigation. Researchers and practitioners who work in the search for opinion formation space should be aware that misinformation may be particularly impactful here, and therefore closely monitor and leverage ongoing research efforts on misinformation detection and mitigation [55,189,225,227].

Alternative Search Paradigms. In this paper, we have focused on the traditional and dominant idea of search engines that present results as ranked lists. However, there are several alternative paradigms for which the retrieval process, result presentation, and user behavior diverge. Considering these differences becomes pivotal when designing interfaces that synthesize results from different resources into seemingly relevant and coherent written or spoken text [165,168,195]. Conversational interfaces are relatively more engaging than conventional web interfaces in various contexts [10,67,131,163], including potential in supporting long-term memorability [164]. Notably, the pursuit of improving user engagement and experience can be orthogonal to supporting responsible opinion formation. This dichotomy is perfectly captured by the well-established notions of '*seamless*' versus '*seamful*' design in human-computer interaction

(HCI). While seamless design emphasizes clarity, simplicity, ease of use, and consistency to facilitate interaction with technologies, seamful design emphasizes configurability, user appropriation, and the revelation of complexity, ambiguity, or inconsistency [87]. There are several arguments in favor of creating *seamless* interactions with search systems to satisfy user information needs. However, such design choices may not adequately foster responsible opinion formation. Users may also turn towards LLM-based tools like *ChatGPT* [135], which may provide incomplete, misleading, or even inaccurate information due to model hallucinations. Natural language aids comprehension and offers opportunities to directly provide diverse viewpoints (i.e., serving as a *seamless* mode of interaction). However, Shah and Bender [181] warn that such interactions can hinder users' ability to identify incorrect or biased information and to actively explore different resources to construct a model of the knowledge space, building information literacy (i.e., facets that can be supported through *seamful* design). More research is urgently required to better understand whether and how responsible opinion formation can be supported in the context of such emerging search paradigms.

Malicious Intent. Thus far, we have assumed no malicious intention from any actor, i.e., framing biases and harmful effects as unintended byproducts of web search. Yet, malicious actors may use research findings and practical applications for their purposes, e.g., to steer public opinion or manipulate targeted individuals. This solicits methods to detect and safeguard against such actions. Researchers and practitioners need to discuss this possibility in their work.

Research Questions

The research opportunities and challenges discussed in this paper may appear abundant and intimidating. To provide a more approachable starting point, we propose a set of research questions, which are by no means exhaustive.

Foundations: (i) What obligations should search engines bear concerning individual and societal well-being? (ii) Which values and principles should guide the system design process? (iii) What framework can comprehensively represent viewpoints on SERPs? (iv) Which notions of viewpoint diversity would benefit individuals and society? (v) Should the notion of viewpoint diversity be adjusted depending on the specific topic and searcher?

Searcher: (i) Which patterns of search behavior and searcher characteristics can be linked to knowledge gain and attitude change? (ii) Which traits affect searchers' vulnerability to ranking and cognitive biases? (iii) What user-centered interventions can empower unbiased and diligent search behavior?

Search Engine: (i) How should relevance criteria be adjusted for search on debated topics? (ii) What crowdsourcing, automatic, or hybrid methods can accurately and efficiently detect viewpoints expressed in search results? (iii) Which re-ranking strategies meaningfully increase viewpoint diversity?

Interplay: (i) What factors shape the interplay of search engine-rooted exposure biases and searcher-rooted interaction biases? (ii) What interface-centered interventions can empower unbiased and diligent search behavior? (iii) How can the interface be leveraged to enhance the transparency of relevance criteria to the searcher?

7 Concluding Remarks

Drawing upon perspectives from digital humanism and an extensive body of interdisciplinary literature, we offer an in-depth analysis of the distinguishing characteristics and challenges associated with web search on debated topics. We outline a research agenda toward web search that fosters responsible opinion formation by focusing on the searcher, the search engine, and their complex interplay. While rooted in IR, advancements in this area demand a multi- and interdisciplinary approach with input from various domains, including philosophy, psychology, information science, and the communication sciences. With this paper, we aspire to motivate researchers, practitioners, and policymakers across domains to engage in the collective effort of addressing the pressing sociotechnical challenges and creating an enriching, unbiased, and trustworthy web search experience. Ultimately, the pursuit of such endeavors would benefit both individuals and society by promoting democratic values, such as an informed citizenry, opinion diversity, and tolerance for differing viewpoints.

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