

“Is COVID-19 a hoax?”: auditing the quality of COVID-19 conspiracy-related information and misinformation in Google search results in four languages

Auditing
COVID-19 (mis)
information
quality

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Abstract

Purpose – Accurate information is the basis for well-informed decision-making, which is particularly challenging in the dynamic reality of a pandemic. Search engines are a major gateway for obtaining information, yet little is known about the quality and scientific accuracy of information answering conspiracy-related queries about COVID-19, especially outside of English-speaking countries and languages.

Design/methodology/approach – The authors conducted an algorithmic audit of Google Search, emulating search queries about COVID-19 conspiracy theories in 10 different locations and four languages (English, Arabic, Russian, and Hebrew) and used content analysis by native language speakers to examine the quality of the available information.

Findings – Searching the same conspiracies in different languages led to fundamentally different results. English had the largest share of 52% high-quality scientific information. The average quality score of the English-language results was significantly higher than in Russian and Arabic. Non-English languages had a considerably higher percentage of conspiracy-supporting content. In Russian, nearly 40% of the results supported conspiracies compared to 18% in English.

Originality/value – This study's findings highlight structural differences that significantly limit access to high-quality, balanced, and accurate information about the pandemic, despite its existence on the Internet in another language. Addressing these gaps has the potential to improve individual decision-making collective outcomes for non-English societies.

Keywords Conspiracy theories, Language divide, Search engine, Science literacy, COVID-19

Paper type Research paper

Introduction

The democratization of information on the web enables anyone to write and disseminate content with little gatekeeping and hardly any moderation (Molina *et al.*, 2021). The vast

Earlier versions of these findings were presented at the *PCST Conference: Creating Common Ground* in April 2023. The presentation was titled “The disparity in access to reliable online information regarding COVID-19 conspiracies across four languages.” Additionally, the findings were presented at the *ECREA Online Pre-Conference: Science and Environment Communication Section* in October 2022. The presentation was titled “Is COVID-19 a Hoax?: auditing the veracity, quality, and accessibility of Google search results for COVID-19 conspiracies in four languages”.



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amounts of content circulating online make it difficult for non-experts to make informed decisions on substantive issues (Baram-Tsabari and Schejter, 2019). It thus comes as no surprise that both established and social media have been accused of propelling the COVID-19 pandemic into an infodemic – a flood of misinformation that spreads quickly online – with a burst of conspiracy theories swirling all over the world (Bodrunova and Nepiyuschikh, 2022; WHO, 2020).

In turbulent times of uncertainty, it is crucial for individuals to have the skills to assess the veracity of available online information to make informed decisions. Osborne and Pimentel (2022) argued that science education should be part of the solution to scientific misinformation. This claim echoes work by the OECD (2020), which emphasized the importance of science literacy skills, including the ability to evaluate science-related information in an era where the available scientific information may be unreliable. Howell and Brossard (2021) highlighted the role of digital literacy in science literacy, which refers to the ability to use information and communication technologies in everyday life. However, individuals' ability to put their science literacy and digital literacy into practice is limited by structural factors such as the availability of relevant and reliable information (NASEM, 2016).

Search engines play a prominent role in directing people to online information and are generally considered by their users to be accurate, fair, and unbiased (Robertson *et al.*, 2018). Although search engines are widely used online and shape many decisions and social interactions (Shin *et al.*, 2022a, b; Kee and Shin, 2022), they have long been criticized for their proprietary nature and lack of transparency (Makhortykh *et al.*, 2020). In particular, it remains unclear how well the algorithms driving search engines perform for different scientific topics in different locations and languages, and in periods when scientific information is rapidly changing, e.g. during a pandemic.

Despite the egalitarian potential of the Internet, not everyone enjoys equal access to information, a phenomenon often referred to as the “digital divide”. One understudied aspect of the digital divide is the “language divide”, where there is an unequal distribution of languages on the Internet. The language divide is exacerbated by the dominance of certain languages on the Internet and the underrepresentation of others (Segev and Ahituv, 2010). In an analysis of canonical scientific terms such as atom or membrane, Zoubi *et al.* (2021) showed that there are vast disparities in quality between languages when searching from the same geographic location. For example, searches conducted in Israel in English produced significantly better-quality information than searches in Hebrew and Arabic. No previous work has examined these disparities in other locations and languages, extended this beyond canonical terms, or studied the availability of information via search engines across cultures at times when high-quality scientific information is most needed.

The context of COVID-19 is of particular importance here. The implications of being misinformed during a pandemic about health-related issues are potentially much graver than having a fuzzy grasp of a basic scientific concept such as “mitochondria”, which is often searched for educational purposes (Segev and Baram-Tsabari, 2012). Misinformation about the pandemic is a threat to public health. A large international study examined beliefs in misinformation about COVID-19 in the UK, Ireland, USA, Spain, and Mexico (Roozenbeek *et al.*, 2020), and found that erroneous beliefs are not particularly common, but that a significant portion of the public in each country perceives misinformation as reliable. Increased exposure to misinformation negatively affects health behavior during a pandemic and leads to less willingness to get vaccinated or compliance with public health guidelines. An overview by Mahl *et al.* (2022) found that most research on misinformation is conducted on English output, despite its prevalence in other languages. While individual attitudes and beliefs have been studied across cultures, there is no systematic study of the availability of high-quality information at the societal level, as reflected in search results in different countries and languages.

The goal of this study was to examine three COVID-19-related conspiracies and compare the ways these appear in four different languages and 10 different geographic locations. It thus extends the literature by examining available (mis)information about COVID-19 conspiracies, in more languages and locations than previously, and by evaluating the accessibility and veracity of information in addition to quality. In so doing it also contributes to works on the importance of science literacy at the societal level and its implications for the language divide.

Literature review

The digital divide and the language divide

Not all individuals have equal opportunities to benefit from the digital revolution, different societies are characterized by disparities in access to information, which are likely to impact people’s science literacy (Ladson-Billings, 2006; Bartikowski *et al.*, 2018). The digital divide refers to “any gap between people in awareness, ownership, use and skill ability related to technology” (Pearce and Rice, 2014, p. 2837). Rice and Pearce (2015) divide it into three levels: technology (e.g. access to the necessary equipment), knowledge of how to use the online space (e.g. search abilities, writing queries), and the ability to use the available information, i.e. the ability to evaluate information and use it in decision-making or when expressing opinions. The “digital divide” underscores the threat of these gaps to social and national cohesion, because it impedes full participation of groups left behind on the analog side of the gap (OECD, 2015; Rodicio-García *et al.*, 2020). For example, Ramsetty and Adams (2020) demonstrated that the digital divide can contribute to social inequality in the context of health factors during the critical period of the COVID-19 pandemic in the US. Indeed, access to digital resources has become an increasingly critical factor in influencing health outcomes as people search online for information on health issues. While gaps in social, economic, cultural, and personal offline resources affect individuals and society, digital exclusion and lack of engagement with digital resources also have negative effects (Suh *et al.*, 2022).

Norris (2001) also refers to a global divide in digital access, which refers to differences across countries. This type of digital divide is also characterized by the unequal distribution of languages on the Internet: 54% of the top ten million sites are in English, while only 1.7 and 5% respectively are in Chinese and Spanish, which are the first and the second most spoken languages in the world (Statista, 2019). This lack of online information in certain languages is likely to increase or perpetuate inequality in access to information (Amano *et al.*, 2016). Amano *et al.* (2016) found that 54% of a sample of Spanish executives indicated that languages constituted a barrier to the use of scientific articles as a source of information in the field of management.

A research gap concerning the language divide is its’ separated theorizing from the digital divide. Here, we expanded Rice and Pearce’s (2015) framework of the digital divide to better capture the potential influence of the language divide at each of its three levels (Table 1).

	The traditional interpretation of the digital divide	The language divide as a type of digital divide
First level: Access to the Technology	Lack of access to the necessary equipment	Lack of online information in different languages
Second level: An understanding of how to use the online space	Lack of search abilities, not knowing how to formulate effective queries	Searching for information in a non-native language
Third level: The ability to use the available information	Lack of digital literacy, not knowing how to use the information effectively	The challenge of grasping complicated scientific terms and content not in one’s native language
Source(s): Author’s own creation/work		

Table 1.
Conceptual framework
for the language divide
as a type of digital
divide

Science literacy and digital literacy

Science literacy is defined as the ability to explain scientific phenomena, understand scientific practices, and understand science as a social process (NASEM, 2016). Science literacy shapes the ways in which people search, collect, find, interpret, and apply the information available to them. Today, online information systems play an important role in the public's decision-making processes. This is why Howell and Brossard (2021) included digital literacy within science literacy. Digital literacy refers to the ability to use information and communication technologies in everyday life for a variety of purposes and needs. The need for digital literacy stems from the nature of media environments that shape what information people can access, how they see it, and what conclusions they draw from it. Digital literacy may help people effectively navigate complex and dynamic science issues such as a pandemic, but even under ideal conditions, most people struggle to reliably assess the quality of information they encounter online (Howell and Brossard, 2021).

While much of the literature on science literacy and information assessment views it as an individual proficiency (Roth and Lee, 2002), another perspective that is attracting growing attention engages with the importance of science literacy at the societal level. Science literacy at the societal level focuses on structural factors, and how they shape the distribution of literacy and the opportunities to acquire it (NASEM, 2016).

Online access to scientific information is one such societal structure. Science-related information is likely to be harder to come by for people who are not fluent in English, in particular when there is not a great deal of online content in their native language (Politzer-Ahles *et al.*, 2016). The notion of inclusive science communication refers to efforts to communicate science-related topics, with the explicit goal of promoting equality across cultures (Canfield and Menezes, 2020). However, language divides may prevent those who do not speak English from actively participating in the scientific process as citizens (Márquez and Porras, 2020).

In this study, we address a major research gap: the lack of empirical studies regarding science literacy at the societal level, by highlighting its expression in the diversity of online science-related resources available to different people. This is relevant to the first level of the language divide as a digital divide (Table 1): Lack of online information in different languages.

Misinformation, fake news, and conspiracy theories

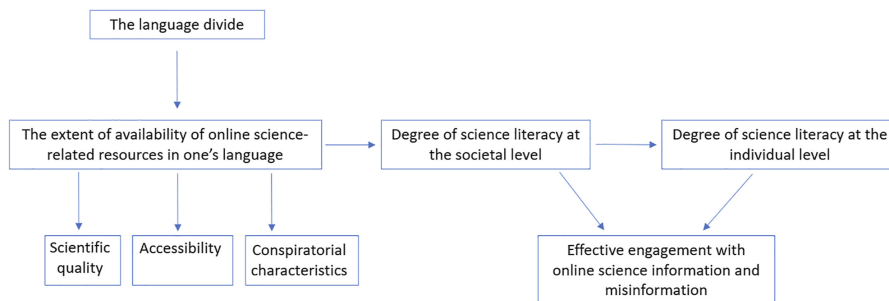
In 2020, in response to the global outbreak of COVID-19, the Director General of the World Health Organization stated: "We are concerned about the levels of rumors and false information. We are not just fighting a pandemic; We are fighting an infodemic. Misinformation spreads faster and more easily than this virus, and is no less dangerous" (WHO, 2020). Infodemic is one of the manifestations of "post-truth", namely a reduction in the role of facts in public life (Osborne *et al.*, 2022). The infodemic, alongside fake news and conspiracy theories, makes it difficult to paint a fact-based picture of the world.

COVID-19 misinformation has spread widely online (Brennan *et al.*, 2020). According to the Reuters Institute, 33% of Americans, 28% of Germans, and 44% of Spanish respondents reported being exposed to false or misleading information about the virus on social media (Nielsen *et al.*, 2020). On search engines, the numbers were lower at 17% of Americans, 16% of Germans, and 24% in Spain. Misinformation about the pandemic has affected public behavior and health: misleading information about methanol and ethanol cures for COVID-19 led to the death of over 100 people in Iran (Lima *et al.*, 2022), in Nigeria, health officials discovered several cases of chloroquine overdose after misinformation was spread about its effectiveness against COVID-19 (Tasnim *et al.*, 2020). In addition, the psychological theory highlights the link between the abundance of misinformation and conspiracy theories on the Internet, and vaccine hesitancy during the pandemic (Chaney and Lee, 2022; Visentin *et al.*, 2021). Furthermore, belief in conspiracy theories about COVID-19 remains associated with

less likelihood to take protective measures such as handwashing and social distancing, suggesting that misinformation may contribute to the severity of the pandemic (Himelein-Wachowiak *et al.*, 2021).

More generally, post-truth phenomena may lead to anti-social behavior such as intolerance, and the intensification of racism. Extremist groups may display threatening behavior steeped in anti-Semitism and Islamophobia (Barua *et al.*, 2020). Importantly, fake news and conspiracy theories increase distrust in science, experts, and establishments, leading citizens to oppose the management of the pandemic (Wu *et al.*, 2022). A high level of government trust encourages people to get vaccinated, use health services, and take precautions during pandemics (Swire and Lazer, 2019). When trust is impaired, people may ignore expert advice, resulting in serious consequences. For example, Di Domenico *et al.* (2022) have conducted a study that recognizes how social media legitimizes and disseminates various types of misinformation, thus emphasizing significant policy implications for addressing vaccine misinformation.

The spread of misinformation has direct implications in terms of the online language divide. A lack of reliable online science-related information in languages other than English may exacerbate or maintain inequality, specifically by biasing accessibility to reliable information about the pandemic. The dominance of misinformation can impact decision-making processes, which have individual and societal implications. How people differ in their exposure to misinformation is mostly being studied at the individual and community levels, but not at the societal level. Here we use an algorithmic audit to contribute to our understanding of the spread of misinformation at the global level by studying its availability in different languages. For a summary of the conceptual framework see Figure 1.



Source(s): Author's own creation/work

Figure 1.
The conceptual
framework of the study

Method

The vast majority of studies analyzing misinformation in recent years have focused on online sources, and in particular on social media in the online space (Cacciatore, 2021; Bodrunova and Nepiyuschikh, 2022). Mahl *et al.* (2022) found that 81.2% of all the studies examining conspiracy theories focused on social media platforms whereas only 2% dealt with search engines. The current study focuses on search engines since they are an understudied primary player in the online information landscape, and primarily Google Search (Juneja, 2021; Robertson *et al.*, 2018). To obtain content for analysis, we conducted an algorithmic audit of Google Search. Sandvig *et al.* (2014) define algorithmic audits as a “field experiment in which researchers or their confederates participate in a social process” of which algorithms are a part. This kind of audit analyzes the inputs and outputs of an algorithmic system to understand its functions (Shin *et al.*, 2022a, b). While there are various search engines

available online, Google Search is the most widely used search engine in the world with a global market share (and dominance) of about 92% (Statista, n.d.). Therefore, we focus on Google Search as a major provider of search results in many countries and one that can reach large audiences.

The ranking algorithm behind Google Search, however, is proprietary, which prevents us from precisely determining which elements of the search (e.g. query, content, user, or context) affect the rankings. To address this, we conduct an algorithmic audit that emulates searching the same queries from different geographic locations and languages. To the best of our ability, we verified that the search results obtained as part of the audit were the same as the ones available to users searching the same terms “organically” in that country, language, and over time. While this approach cannot capture all personalization that search engines may apply to different users, prior work showed that only 11.7% of Google search results are personalized (Hannak *et al.*, 2013), non-local queries receive virtually no personalization (Kliman-Silver *et al.*, 2015), and much of the personalization, if at all, occurs in the components surrounding the main list of ranked results (Robertson *et al.*, 2018). More recently, Ashraf *et al.* (2023) conducted a study to examine whether Google presents different search results to users when they search for a query using a regular browser versus a private browser (incognito). The authors found that there was no distinction between the search results in both scenarios, indicating a lack of personalization in the display of search results. Similarly, a study by Tong (2021) found that Google search results returned from queries led conservatives and liberals to different sets of information, but search result differences were driven largely by specific search queries than by the political ideology of the searchers.

We also limit our analysis to the first 10 search results since eye-tracking studies show that users hardly pay attention to anything other than the first 10 organic results (Granka *et al.*, 2004; Cutrell and Guan, 2007; Dumais *et al.*, 2010). Recently, marketing experts argued based on click rating analysis, that fewer than 1% of individuals who perform a Google search bother to check results beyond the first page (Dean, 2022). Therefore, we focus our analysis on the top 10, non-personalized search results that represent the bulk of content available to users and that people are most likely to pay attention to.

We included three COVID-19 conspiracy theories that are common in the literature (McCarthy, 2020; Douglas, 2021; Mahl *et al.*, 2021; Hartman *et al.*, 2021): “5G causes COVID-19”, “COVID-19 is a hoax” and “COVID-19 is a biological weapon”. We used Google Trends to confirm the actual popularity of these searches for the queries in English. “5G COVID-19”, for example, was a “breakout” search term according to Google Trends around April 2020, as well as the related queries: “5G and Covid-19” and “coronavirus 5G”. According to Google Trends since the beginning of the pandemic, these three conspiracy theories have been searched massively and repeatedly.

The queries were searched in four languages: English, Arabic, Russian (three of the ten most spoken languages in the world (The world FactBook, n.d.)), and Hebrew. These languages are the mother tongue of approximately 15% of the world’s population (Statcounter Global Stats, n.d.). The queries were searched from 10 countries: the USA, the UK, Nigeria, the Philippines, Russia, Belarus, Kazakhstan, Egypt, Iraq, and Israel. The US and UK were chosen to represent the English language. Nigeria and the Philippines were included as former colonies where English remains the official language. Egypt and Iraq are among the three largest countries where Arabic is the official language (The world FactBook, n.d.). Russia, Belarus, and Kazakhstan were selected as countries where Russian is the official language. Israel (Arabic and Hebrew) was selected to enable a comparison with previous findings on canonical science search queries. About 20% of the population in Israel speak Arabic as their first language. Data on the countries examined are detailed in Table 2. The queries in Arabic and Russian were translated by two native speakers of these languages, both of whom have academic scientific backgrounds and are

Country	Population*	Language*	Internet penetration**	Google users among internet users ***
USA	337,341,954	English	94%	87%
Nigeria	225,082,083	English	67.5%	98%
Russia	142,021,981	Russian	80%	47%
Philippines	114,597,229	English	85%	92%
Egypt	107,770,524	Arabic	52%	97%
UK	67,791,400	English	93%	93%
Iraq	40,462,701	Arabic	64%	97%
Kazakhstan	19,398,331	Russian	77%	87%
Belarus	9,413,505	Russian	82%	78%
Israel	8,914,885	Hebrew/Arabic	80%	98%

Note(s): *The world FactBook. (n.d.), available at: <https://www.cia.gov/the-world-factbook/countries/>, accessed (1 May, 2022)

** World Internet Users and 2022 Population Stats (2022), available at: <https://www.internetworldstats.com/stats.htm>, accessed (1 May, 2022)

*** Statcounter Global Stats (n.d.), Statcounter global stats - Browser, OS, search engine including mobile usage share, available at: <https://gs.statcounter.com/>, accessed (15 September 2021)

Source(s): Author's own creation/work

Table 2.
Language and Internet
users in the countries
examined in this study

likely to have encountered the concepts in some way, in their own language, and in English. We compared at least two translations in each language to ensure high quality. When differences were found between translators, all the options were back sent to the translators so they could choose the most appropriate search query.

Data collection and sample

We examined the first page of the Google search results for each of the three conspiracy theories related to COVID-19 listed above (10 search results per page) in each of the countries listed in Table 2 (see Appendix 1 for the translated queries). The data collection was conducted using the SerpAPI.com service, which enabled us to execute Google Search queries in different languages and locations, similar to the approach used by Robertson *et al.* (2018). As described earlier, this approach is strictly limited to non-personalized search results, which represent the vast majority of available results (see, e.g. Hannak *et al.*, 2013). Our sample consists of a total of 330 search results, broken down into English (overall 120 search results, 80% of the search results appeared in more than one country), Arabic (overall 90 search results, 84% of the search results appeared in more than one country), Russian (overall 90 search results, 82% of the search results appeared in more than one country), and Hebrew (30 search results). Almost all 330 search results were collected on April 10, 2022, except for queries from Belarus and Kazakhstan that were collected on May 18, 2022. An additional iteration of data collection was performed on May 25, 2022, confirming that the individual results did not change over time, although in a few cases, their order differed.

Data analysis

Although there are various research methods used in the field of misinformation research, manual content analysis is the most common (Mahl *et al.*, 2022). It involves analyzing and interpreting communication content to identify patterns, themes, and relationships within the data. With the goal of analyzing aspects of quality in COVID-19 conspiracy-related search results, we use content analysis as our research method (Krippendorff, 2004).

A comparative content analysis was employed to enable a high-quality evaluation of the information available on the Google SERP in these languages (corresponding with the first level of the language divide as a digital divide as presented in [Table 1](#)), based on [Zoubi et al. \(2021\)](#) which discusses criteria for evaluating the quality of online scientific information. To analyze the search results, we developed a codebook that included four clusters of criteria.

- (1) Type of source, based on the site's "about" description. The categories included media, scientific journals, social media sites, and additional reliable sources, including government bodies, non-governmental organizations, international organizations, institutions of higher education, informal science education institutions, encyclopedias or dictionaries, and fact checkers' sites.
- (2) Scientific quality, detailed in [Appendix 2](#), adapted from [Zoubi et al. \(2021\)](#).
- (3) Accessibility, detailed in [Appendix 3](#), adapted from [Zoubi et al. \(2021\)](#).
- (4) Conspiratorial characteristics, detailed in [Appendix 4](#). The codebook examined fundamental aspects of conspiracy theories as identified in an extensive literature review that included conspiracy belief studies ([Wood, 2017](#); [Stojanov et al., 2020](#); [Fong et al., 2021](#); [Bensley et al., 2020](#); [Shermer, 2020](#); [Kim and Kim, 2021](#)), and definitions of conspiracy theories (including [Andrade, 2020](#); the [European Commission, 2021](#); [van Prooijen, 2017](#); [Baden and Sharon, 2021](#); [Banas and Miller, 2013](#); [Goertzel, 2010](#)). The literature review identified four recurring themes characterizing conspiracy theories that we used in the analysis.

In addition, we calculated the average score for categories b, c, and d. The codebook was written in English and was initially validated by two coders, who used it to classify 5% of the search results in both Hebrew and English.

The search results were analyzed by native speakers, except for English which was analyzed by proficient English speakers (ESLs). The coders had relevant content expertise, such as science teachers and science communicators. To assess inter-rater reliability, a reliability test of the data was run between two coders in each language. This included English: 25% out of the 120 search results, Russian: 30% out of the 90 search results, Arabic: 30% out of the 90 search results, and Hebrew 100% of the 30 search results. Gwet's AC1 test indicated a score exceeding 0.70 in all languages, with a score of over 0.80 for the conspiratorial trait categories. This score is considered to represent high agreement ([Gwet, 2008](#)). In addition, the first author went through 10% of the results in all languages using Google Translate to assure the equitability of coding.

[Figure 2](#) presents examples of result pages with varying scientific quality. While both pages are free of scientific errors, they vary in all other criteria evaluated in the codebook. Panel A shows an example of medium scientific quality where only the author's name appears, without any details about the background, and no scientific components (see [Appendix 2](#) for the codebook). Panel B shows an example of a high-quality page where the author has relevant expertise in the content area and all scientific components are included. Note that these criteria refer solely to the scientific quality of the search result, not to its attractiveness or suitability for wider audiences.

[Figure 3](#) provides two examples of content with varying accessibility. Panel A presents results with some scientific jargon and no supporting components (see [Appendix 3](#) for the codebook). The example in Panel B presents content that is free of scientific jargon and contains almost all of the supporting components as described in the codebook.

[Figure 4](#) illustrates examples of conspiratorial and non-conspiratorial content.

Medium scientific quality (Arabic translation)

BBC News

BBC NEWS
عربي

Journalism video health science and technology Scientist Middle East key

رئيسية الشرق الأوسط عالمنا وتقنياتنا صحة عالمنا صحة العالم أخبارنا بؤركم

Our programs

Coronavirus: I lost my wife because I thought the virus was a hoax

Maxima Spring
Disinformation Correspondence
August 27, 2020



A taxi driver from the US state of Florida lost his wife, who died of Covid-19, after he believed that the Corona virus was a hoax.

<https://www.bbc.com/arabic/science-and-tech-53917721>

(a)

Source(s): Author's own creation/work

High scientific quality Academic Paper

PLOS ONE

PLOS ONE

MEDICAL MISINFORMATION

Medical disinformation and the unviable nature of COVID-19 conspiracy theories

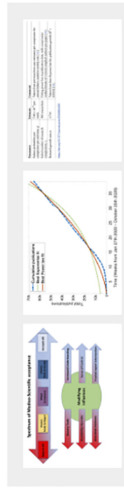
Evan D. Blum, Robert Colwell, et al. 2021 • <https://doi.org/10.1371/journal.pone.0245900>

ARTICLE	AUTHOR	RESEARCH	COMMENTARY	VIDEO	FIGURE
ARTICLE	ARTICLE	ARTICLE	ARTICLE	ARTICLE	ARTICLE

Abstract

The coronavirus pandemic has seen a marked rise in medical disinformation across social media. A variety of claims have garnered considerable traction, including the assertion that COVID is a hoax or deliberately manufactured, that 5G frequency radiation causes coronavirus, and that the pandemic is a ruse by big pharmaceutical companies to proliferate a vaccine. An estimated 30% of some populations subscribe to some form of COVID medico-scientific conspiracy narratives, with detrimental impacts for themselves and others. Consequently, exposing the lack of veracity of these claims is of considerable importance. Previous work has demonstrated that historical medical and scientific conspiracies are highly unlikely to be sustainable. In this article, an expanded model for a hypothetical en masse COVID conspiracy is derived. Analysis suggests that even under ideal circumstances for conspirators, commonly encountered conspiratorial claims are highly unlikely to endure, and would quickly be exposed. This work also explores the spectrum of medico-scientific acceptance, motivations behind propagation of falsehoods, and the urgent need for the medical and scientific community to anticipate and counter the emergence of falsehoods.

Figures



<https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0245900>

(a)

Auditing COVID-19 (mis) information quality

Figure 2. Differing levels of scientific quality in the search results for COVID-19 conspiracy theories: (a) medium scientific quality, (b) high scientific quality

Statistical analysis

To examine the differences between countries and languages, a Kruskal–Wallis analysis was used with a significance level set to $p = 0.05$ after Bonferroni correction (Kruskal and Wallis, 1952).

Auditing COVID-19 (mis) information quality



Source(s): Author's own creation/work

Figure 4. Differing levels of conspiratorial content in the search results for COVID-19 conspiracy theories: (a) conspiratorial content, (b) Legitimate content

Results

We first tested for significant differences in the quality of information found in Google Search using the same search language but different geographic locations: 4 countries in English, 3 countries in Russian, and 3 countries in Arabic (Table 2). No significant differences ($p > 0.05$) were found between the English-speaking countries, the Arabic-speaking countries, or the Russian-speaking countries in terms of scientific quality, level of accessibility, and the level of conspiratorial characteristics. In other words, when searching for COVID-19-related conspiracy theories in English, it appears to make no difference whether one does so from the US or Nigeria because there is a large overlap of search results across countries using the same language. Thus, for the remainder of the analysis, we used the superset of search results in each language and focused on the differences *across* languages, rather than the 11 pairs of country-language presented in Table 2.

Types of sources

Figure 5 shows the composition of the different sources across the four languages (Appendix 5 lists the frequencies of all types in the four languages). Over 40% of the results in English originated from scientific journals, whereas in all other languages, no content was available at all from scientific journals. It is important to note that two of the search results originating from scientific journals appearing in English were conspiratorial in nature: one was from a predatory journal and the other referenced a non-peer-reviewed letter to a journal editor. The non-English results were dominated by media sources (Arabic 86%, Hebrew 67%, and Russian 60%), whereas in English only 26% of the search results originated from the media. Even after excluding scientific journals, media sources accounted only for 46% of the results in English, which was significantly lower than the proportion in any of the other languages, and none of the results in English originated from social media sites, unlike in other languages (Arabic 11%, Hebrew 7% and Russian 1%).

Thus, the findings show that English has a specific type of source - scientific journals - that is not present in any other language we examined. These results suggest that information consumers in non-English languages are much more likely to be (mis)informed by social and “alternative” media, even without using social media directly or visiting these sites, due to their positioning as first-page Google search results.

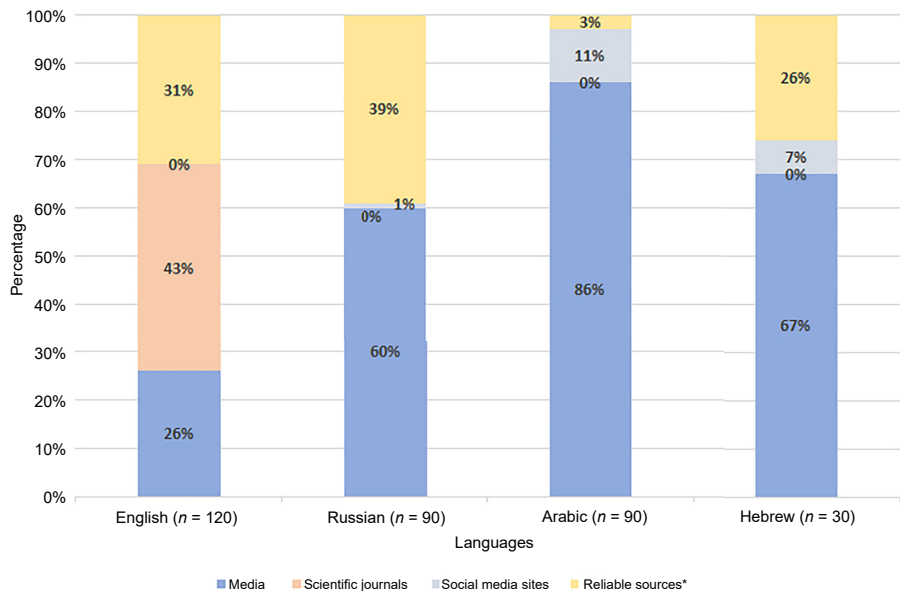


Figure 5.
The distribution of
types of sources in the
four languages

Note(s): * The reliable sources were defined as government bodies, non-governmental organizations, international organizations (e.g. WHO), institutions of higher education, informal science education institutions, encyclopedias or dictionaries, and fact checkers’ sites. Scientific journals are presented separately due to their very uneven distribution across the languages

Source(s): Author’s own creation/work

Scientific quality

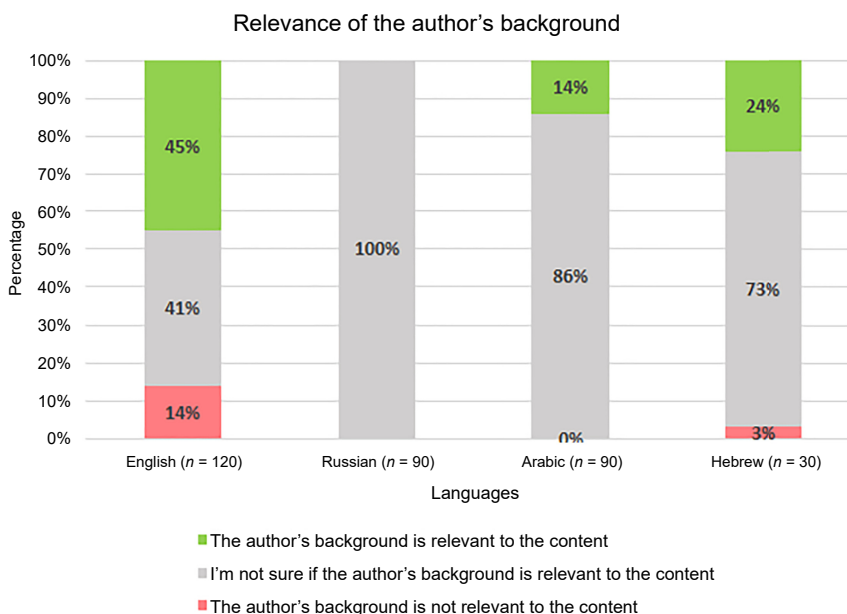
Scientific quality was assessed for Authority, Accuracy, and Scientific components. [Appendix 2](#) lists the frequencies of all criteria in the four languages, and [Appendix 6](#) lists all the significant differences.

The author’s background is an important criterion for evaluating source reliability. However, as shown in [Figure 6a](#), the availability of the author’s background varied considerably. No author information was provided in 67% of the Russian search results and 48% of the Arabic search results. There was a significant difference between Russian and English ($X^2 = 68.093, p < 0.001$), Russian and Hebrew ($X^2 = 66.421, p < 0.001$), and Arabic and English ($X^2 = 36.083, p < 0.01$). These differences are also apparent when addressing the relevance of the author’s background ([Figure 6b](#)). Whereas in English, 45% of the results were written by an author with a relevant background according to the details provided by the website, in Russian none were (0%) ($X^2 = 52.688, p < 0.001$) and in Arabic only 14% of the results ($X^2 = 30.371, p < 0.05$) were authored by authors with a relevant background. In all the search results (100%) in Russian and 86% of the results in Arabic, it was unclear whether the author had any relevant background, mostly because the author’s name was unknown.

To test for scientific accuracy, we examined whether the text itself included significant scientific errors. This included for example a book that directly claims that the climate crisis is not man-made and provides “scientific explanations” in support of its case. Indirectly describing falsehoods, by reporting the fact that some people believe in scientific errors and explaining why they do so, was not considered inaccurate. This was listed under “claims



(a)



(b)

Figure 6.
Is the author's
background known to
the readers (a), and is it
relevant to the content
(b)? Distribution of
search results in the
four languages

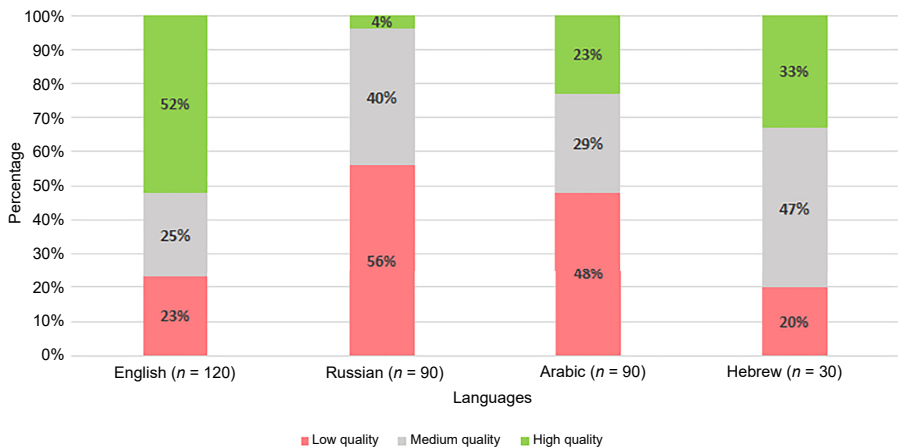
Source(s): Author's own creation/work

Figure 7.
Distribution of
scientific quality: the
average score for the
search results in the
four languages

contradict accepted scientific explanations” in the conspiratorial features. Based on these operationalizations in all languages, the analysis showed that most of the content was free of major scientific errors (Arabic 99%, Hebrew 93%, English 89%, Russian 89%), with no significant differences between languages.

Coding for the scientific components included the use of citations or references, lists of sources, and numerical data (see [Appendix 2](#) for the codebook). In Hebrew and English, only 7 and 10% of the results, respectively, did not include any component that contributed to the quality of the content, compared to Russian, where 54% of the results did not include any such component (Hebrew: $X^2 = 72.056, p < 0.001$, English: $X^2 = 106.108, p < 0.000$). Furthermore, there was a significant difference between English and Arabic, where 28% of the results in Arabic did not include any component that contributed to the quality of the content ($X^2 = 74.197, p < 0.000$).

Finally, as presented in [Figure 7](#), the average quality score of the English-language results was significantly higher than in Russian and Arabic: 52% of the English results were scored as being high quality compared to 4% in Russian ($X^2 = 111.955, p < 0.000$) and 23% in Arabic ($X^2 = 67.527, p < 0.000$).



Source(s): Author’s own creation/work

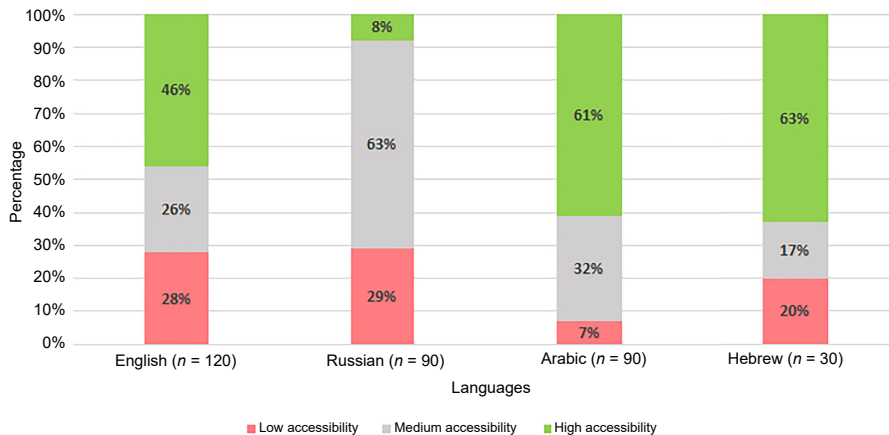
Accessibility of information

The accessibility of information was assessed in terms of jargon and supporting components (see [Appendix 3](#) for the codebook). The distribution of content accessibility varied considerably across languages. However, there was lower accessibility in Russian than in the other languages.

Scientific jargon, i.e. scientific terminology, was used in all languages but varied in quantity. Hebrew had significantly less jargon: 77% of the content in Hebrew did not include scientific jargon compared to 56% in English ($X^2 = 52.926, p < 0.05$) and 7% in Russian ($X^2 = 101.337, p < 0.000$). In Russian, the vast majority of the content (67%) included some scientific jargon without any explanation, compared to 4% in English ($X^2 = 48.410, p < 0.001$), 10% in Hebrew ($X^2 = 101.337, p < 0.000$), and 22% in Arabic ($X^2 = 92.681, p < 0.000$), thus implying that the content was less accessible in Russian (see [Appendixes 3 and 6](#) for the codebook and the significant differences).

The codebook tested for the presence of supporting components including graphs and/or pictures, hyperlinks, and a place for leaving comments. In all languages, most contents had at least one supporting component, most commonly hyperlinks and least commonly graphs. Russian had the largest percentage of search results with no supporting component at all, however, no significant difference was found across the languages for this criterion (see [Appendixes 3 and 6](#) for the codebook and for the significant differences).

Finally, as presented in [Figure 8](#), the distribution of content accessibility varied considerably across languages. Only 8% of the search results in Russian were characterized as highly accessible compared to 63% in Hebrew ($X^2 = 113.896, p < 0.000$), 61% in Arabic ($X^2 = 88.474, p < 0.000$), and 46% in English ($X^2 = 61.967, p < 0.000$).



Source(s): Author's own creation/work

Figure 8.
Distribution of
accessibility: average
scores for the search
results in the four
languages

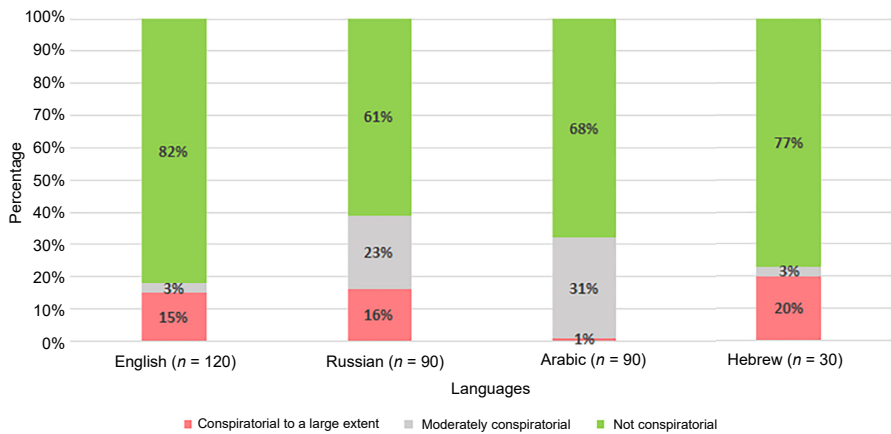
Conspiratorial characteristics

The assessment of conspiratorial characteristics was based on four criteria (see [Appendix 4](#) for the codebook). Overall, most of the search results displayed on the first pages of Google in all four languages provided readers with legitimate content. However, in Russian, there were more conspiratorial characteristics in the search results than in the other languages examined.

In all the languages, most of the content rejected the conspiracy theory in question (Hebrew 87%, English 74%, Russian 70%, and Arabic 56%), did not openly contradict accepted scientific claims (Arabic 84%, English 82%, Hebrew 73% and Russian 64%), and did not present specific groups as “enemies” (English 79%, Arabic 71%, Hebrew 70% and Russian 65%). There were no significant differences across the four languages for these criteria. In all languages, most of the content did not include malicious meanings (Arabic 87%, English 85%, Hebrew 77%, and Russian 61%). However, there was a significant difference between Russian and Arabic ($X^2 = -44.207, p < 0.000$), and English ($X^2 = -34.844, p < 0.002$). Russian had more malicious meanings clearly presented in the content: 39% in Russian compared to 13% in Arabic and 15% in English (not present or somewhat present).

Finally, the average conspiratorial score demonstrated that COVID-19-related conspiracy search results in Russian were significantly more conspiratorial than the content presented to a surfer searching for the same terms in English ($X^2 = -37.911, p < 0.01$): 18% of the content in English was fully or moderately conspiratorial compared to 39% of the content in Russian ([Figure 9](#)). There was no significant difference between the other languages.

Figure 9. Distribution of conspiratorial characteristics: the average score for the search results in the four languages



Source(s): Author's own creation/work

Discussion and conclusion

How is the language divide being expressed in the framework of the digital divide? This study provides a content analysis of Google Search results from different languages and locations to evaluate the quality of information available worldwide when searching for COVID-19-related conspiracies. Each query was translated and searched for in English, Arabic, Russian, and Hebrew in several countries where these languages are spoken. We found significant differences in search results across languages. Overall, the quality of search results in English was significantly higher than in Russian and Arabic, and search results in Russian were significantly more conspiratorial than those found in English. While most of the first page results did not contain major scientific errors (English 89%, Russian 89%, Arabic 99%, Hebrew 93%), they did give plenty of room to unsubstantiated conspiratorial claims that contradict accepted scientific explanations ("clearly presented" or "somewhat present": English 18%, Russian 36%, Arabic 16%, and Hebrew 27%). This was done, for example, by media reports on individuals espousing beliefs in conspiracies that cite their explanations for their ideas but fail to provide a consensual scientific explanation.

While a previous study pointed to the differences in the pedagogical quality of search results for canonical scientific terms (Zoubi *et al.*, 2021), the current study underscores a much graver problem where differences in truth value – the veracity – of online search results in different languages on a scientific issue that can have direct life and death decision-making consequences. Our findings thus point to the existence of a digital divide in the search results accessible to people searching for the same terms using different languages. The societal implications of being at greater risk of exposure to conspiracy theories include erosion of trust in the medical community, vaccination hesitancy, and less compliance with health guidelines (Himelein-Wachowiak *et al.*, 2021).

Search engines are a major source of information in this day and age, particularly when it comes to learning new topics and making evidence-based and scientifically grounded decisions during a pandemic. Alongside and perhaps because of their widespread use for finding information, users generally believe that the results they receive from search engines are accurate, fair, and impartial (Robertson *et al.*, 2018). Based on their capacity to influence beliefs, attitudes, and behavior (Epstein *et al.*, 2017), search engines have a significant role as either help or hindrance to a nation's preparedness efforts during times of crisis. Our findings, however, show that the most dominant search engine in the world with a 92% market share presents users with information that varies drastically in levels of reliability. We assume that

a disparity in the amount of quality science-related information is the driving force behind the language divide rather than a bias in the Google search algorithm. Nevertheless, our findings raise some important normative questions regarding the role that online search engines should play in response to conspiratorial queries.

In terms of practical implications, our findings highlight a few avenues for next-step research to improve the quality of scientific search results in general and at times of crisis in particular. First, the existence of high-quality information in other languages for the same information need suggests that search engines can make better use of multilingual models to retrieve, rank, and deliver results to end-users, either directly in a second-language they are proficient in or in a translated form to their native language. [Google's mission \(n.d.\)](#) is “to organize the world's information and make it universally accessible and useful”, but paradoxically segregated language and retrieval models per country prevent high-quality scientific information from becoming universally accessible and useful, and may even inadvertently broaden the gap between languages and cultures. Second, our findings call for closer attention to the ranking done in certain languages where conspiratorial content is more prevalent. It may be possible for search engines to identify reliable and persistent sources of information to make sure high-quality content populates the top of the result pages in those cases. Finally, search engines can combine the above two approaches to deliver more content from trusted sources, potentially translated, at times of crisis. Determining the precise weight at different times is not an easy task, but one that search engines are fully capable of and one that can have a meaningful impact on public health and beyond.

In terms of theory, considerable attention has been paid in recent years to people's ability to assess information. In their recent paper, [Osborne and Pimentel \(2022\)](#) stated that in order for science education to be effective, students must be equipped with the tools to evaluate the reliability of science-related information, even when they lack knowledge of the specifics of the topic. Empirical research emphasized individuals' specific competencies and limitations. For example, [Swami and Coles \(2010\)](#) and [Britt *et al.* \(2019\)](#) explored how cognitive biases affect the way individuals evaluate information. [Scherer *et al.* \(2021\)](#) and [van Prooijen \(2017\)](#) examined individual factors that can influence the evaluation of online information, such as educational level and knowledge.

In contrast, our findings suggest that the quality, accessibility, and veracity of information are deeply embedded in sociocultural factors that are beyond the individual's control and expose entire communities to a greater risk of being misinformed. Therefore, regardless of individuals' digital skills ([Kahne and Bowyer, 2017](#)), critical thinking ([Lantian *et al.*, 2021](#)), science literacy ([Osborne and Pimentel, 2022](#)), or general education ([van Prooijen, 2017](#)), seeking the truth may require more resources and effort depending on one's cultural embedding.

Our study extends the traditional understanding of the digital divide to include the language divide in each one of its levels ([Table 1](#)). In terms of the first level, we documented a lack of online information as a function of language. For example, Russian readers had access to much less reliable information about COVID-19-related conspiracies. In terms of the second level, searching for information in a non-native language is harder, which means that people compromise for lower-quality information (even when they have some proficiency in English as a second language). In terms of the third level, beyond the challenge of grasping complicated novel scientific terms and content, our findings indicate that the accessibility of information in some languages also varies ([Figure 8](#)). The differences in the quality of online content across languages are likely to contribute to the digital gap, by affecting people's ability to evaluate information and use it in decision-making. For example, Russian readers cannot evaluate the relevance of the author's expertise and background, simply because it is never mentioned (in 67% of the results, the author's name was not even mentioned either). Therefore, Russian readers' ability to critically assess the results was not determined by their individual digital literacy but rather by the (absence of) available (re)sources.

This brings us back to the tension between societal resources and individuals' competence when using them. Historically, most definitions of science literacy have focused on personal knowledge and skills. However, one of the claims made in the [National Academies of Sciences Engineering and Medicine report \(2016\)](#) is that the ability of communities and individuals to develop and apply scientific literacy skills depends on social contexts and resources. The report suggests that structural factors shape, when they do not determine, the distribution of scientific literacy across communities. Social resources such as online information in one's language shape the distribution of literacy and differences in opportunities to acquire information across people and societies. Our findings reinforce the need to understand digital literacy and science literacy at the level of resources and not only at the level of the individual.

This research also raises an array of important normative questions. What role should online search engines play in response to user queries seeking conspiratorial content? At what threshold does a down-ranking of information and misinformation qualify as censorship? Should search engines rely more heavily on third-party fact-checkers and tag content as "disputed"? Or the key is really about algorithmic transparency, which search engines have long been criticized for ([Makhortykh et al., 2020](#)). This research paves the way for a broader public discussion of these issues, including whether times of crisis such as a pandemic merit tighter control over the quality and accuracy of information provided to the public.

Our findings highlight structural differences that significantly limit access to high-quality, balanced, and accurate information about the pandemic, despite its existence on the Internet in other languages. One language might hold people captive on an information island – even on the global net. Addressing these gaps has the potential to improve individual decision-making as well as provide more just access to high-quality scientific information worldwide with the potential to improve collective outcomes during a pandemic and beyond. Raising awareness of these issues is crucial for grappling with the challenges and consequences of the digital divide in different cultures, and a first and necessary step toward closing these gaps in the future.

Study limitations and future research

This study has a number of limitations. First, Google is only the second most widely used search engine in Russia with a market share of 47% (May, 2022), unlike other countries in our sample where Google has a much larger market share. Although our results are meaningful for a major part of the Russian population, it is possible that other search engines such as Yandex or Bing may exhibit other behavior. Another limitation is that the Web and the search engines that curate it are dynamic in nature. The contents of a page may change over time, e.g. as new evidence emerges, and the ranking of pages may change substantially – a top-rated page at one time may not even appear on the first page of results at a different time. Third, while we did our best to translate, validate the accuracy of the translations and their prevalence, and ensure the reliability of coders, seemingly minor differences in semantic meaning or the ambiguity of certain words in different languages may still have impacted our results to some extent. Fourth, the classification of sources of information may be contaminated, as journalists, for example, may draw on social media and official sources for their stories, while established media and official sources may use social media platforms to disseminate their products. For this reason, we highlighted mainly the relative abundance of journal articles and official sources in English, and did not emphasize differences in media and social media sources.

What is the mechanism behind the findings? While this is beyond the scope of this paper it is worth noting that the search engine content curation and management processes, which combine AI and human judgment to create hybrid solutions, have been criticized for bias, both on the AI side and the human component ([Jiang et al., 2020](#)). Various studies have shown the existence of bias in the content selection processes of people, for example, [Bakshy et al.](#)

(2015) indicated that a lack of exposure to cross-cutting content on Facebook is rooted more in individual choice than an algorithmic bias. Further research should investigate the origins of the differences observed here and whether they stem from differences in content availability, different practices of content moderation, or an algorithmic bias.

We presented two ways to interpret the findings – one – is that this divide can be attributed to the bias in Google’s search algorithm, and the second is that this difference can be attributed to the difference in the content available and published in non-English languages. Since the language divide is characterized by the unequal distribution of languages on the Internet, it is likely there is a lack of content available. While we studied only the first page results due to their prominence, a potential future study could examine the quality characteristic of search results also on pages 2 to 3 of the SERP. If the quality of results improved on pages 2 to 3 for non-English language search, it may indicate a bias with Google’s non-English content search algorithm. If the quality remained the same or reduced, however, it would hint at an issue with the amount of content that is available in these languages. It could also mean other factors, e.g. the extensive use of black hat SEO techniques with implications for media companies, governments, etc. (we thank reviewer 2 for these insights).

Implications

Several implications emerge from this study. As this is one of the first works to “map” the gaps in quality across languages on this important topic, we believe that highlighting where the problems lie is a major part of the solution. Search engines can use our findings to improve their products when quality information does exist in the target language and consider initiatives that could create high-quality information when such content is lacking. Professional science communicators – journalists, educators, scientists, and others – can use our findings to identify areas in need of further quality content in their language. This can include original texts or translations of new content, but also relatively easy fixes such as adding the author’s name and expertise to help readers identify and choose reliable sources. Finally, much of the non-English conspiracy content in our sample was advanced in the form of media reports about conspiracy theorists. Some elaborated on these individuals and their beliefs but did not present a compelling scientific explanation for why these ideas are wrong. A straightforward implication of our findings is based on [Lewandowsky et al. \(2012\)](#): journalists and editors should be encouraged to start and end their reporting with the facts, rather than leaving the audience with the myth.

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Further reading

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Appendix 1

Table A1.
The translated queries

English	Russian	Arabic	Hebrew
5G Covid-19	5G КОВИД	الجيل الخامس وفيروس كورونا	נגיף הקורונה ורשת ה-5G
Covid-19 hoax	ковид 19 обман	لتوفيدي 19 خدعة	נגיף הקורונה שקר
Biological weapon	биологическое оружие	حرب بيولوجية لتوفيدي	נגיף הקורונה נשק ביולוגי
Covid-19	ковид 19	19	
Source(s): Author’s own creation/work			

Appendix 2

Auditing COVID-19 (mis) information quality

Criterion	Description	Possible codes	English	Frequency		
				Russian	Arabic	Hebrew
<i>Scientific Quality</i>						
Gwet's AC1 > 0.7						
Authority	What is the author's background?	The author's background and name are known to the readers (2)	75%	33%	52%	73%
		The author's background and name are unknown to the readers (1)	25%	67%	48%	27%
	Is the author's background relevant to the topic? * When the name of the author or his/her background was not known it was scored 2	The author's background is relevant to the content (3)	45%	0%	14%	24%
		I'm not sure if the author's background is relevant to the content (2) *	41%	100%	86%	73%
		The author's background is not relevant to the content (1)	14%	0%	0%	3%
Accuracy	Is the content free of major scientific errors and inaccuracies?	There are no major scientific errors in the content (2)	89%	89%	99%	93%
		There are major scientific errors in the content (1)	10%	11%	1%	7%
Scientific components	Does the search result contain (1) citations or references, (2) a list of sources, (3) Numerical data	Three components (4)	31%	2%	0%	3%
		Two components (3)	24%	10%	15%	27%
		One component (2)	35%	34%	57%	63%
		None (1)	10%	54%	28%	7%
	Each component was scored 1 point (no component was encoded as 1)					
Average quality score	Average of all scientific quality criteria (normalized)	High quality (1)	52%	4%	23%	33%
		Medium quality (0.8)	25%	40%	29%	47%
		Low quality (0.5)	23%	56%	48%	20%
Source(s): Author's own creation/work						

Table A2.
Scientific quality
codebook

	Criterion	Description	Possible codes	Frequency					
				English	Russian	Arabic	Hebrew		
Table A3. Accessibility codebook	<i>Accessibility</i> Gwet's AC1 > 0.7								
	Scientific jargon (Jargon is defined as a complex language associated with a particular subject)	How much scientific jargon is used in the content?	The content is very accessible (there is no scientific jargon at all) (5)	56%	7%	65%	77%		
			The content is accessible (there are fewer than 5 scientific terms with an explanation) (4)	10%	0%	10%	3%		
			The content is moderately accessible (there are fewer than 5 scientific terms without an explanation) (3)	4%	67%	22%	10%		
			The content is inaccessible (there are more than 5 scientific terms with an explanation) (2)	11%	0%	0%	3%		
			The content is very inaccessible (there are more than 5 scientific terms without an explanation) (1)	19%	26%	3%	7%		
			Supporting components	Does the search result contain (1) graphs and/or pictures, (2) hyperlinks, and (3) space for comments Each component was scored 1 point (no component was encoded as 1)	Three components (4)	9%	9%	0%	16%
					Two components (3)	39%	28%	28%	30%
	One component (2)	43%			44%	69%	47%		
	Average accessibility score	Average of all accessibility criteria (normalized)	None (1)	9%	19%	3%	7%		
			High accessibility (1)	46%	8%	61%	63%		
			Medium accessibility (0.5)	26%	63%	32%	17%		
			Low accessibility (0)	28%	29%	7%	20%		
	Source(s): Author's own creation/work								

Appendix 4

Auditing COVID-19 (mis) information quality

Criterion	Description	Possible codes	English	Frequency			Hebrew
				Russian	Arabic		
<i>Conspiratorial Characteristics</i>							
Gwet's AC1 > 0.7. [* over 0.8]							
A contradiction of the conspiracy	The search result includes two or more opposing views; i.e. conflicting views are represented	Reinforce the conspiracy (3)	26%	30%	44%	13%	
		Unsure (2)	0%	0%	0%	0%	
		Rejects the conspiracy (1)	74%	70%	56%	87%	
Claims contradict accepted scientific explanations *	The content makes claims that contradict accepted scientific explanations. [e.g. The Ministry of Health claims that 5G is not responsible for Coronavirus outbreaks, but the text contradicts that claim]	Clearly present (3)	12%	14%	16%	23%	
		Somewhat present (2)	6%	22%	0%	4%	
		Not present (1)	82%	64%	84%	73%	
Blaming specific groups *	Are specific groups in society (pharma, Jews, Muslims, etc.), institutions or governments presented as the enemy?	Clearly present (3)	18%	20%	25%	30%	
		Somewhat present (2)	3%	15%	4%	0%	
		Not present (1)	79%	65%	71%	70%	
Malicious meaning *	Is malicious meaning described in the text? ("We are being tricked"). e.g. "Covid-19: The Greatest Hoax in History: The startling truth behind the planned world takeover"	Clearly present (3)	12%	18%	13%	20%	
		Somewhat present (2)	3%	21%	0%	3%	
		Not present (1)	85%	61%	87%	77%	
Average Conspiratorial score	Average of all conspiratorial criteria	Very conspiratorial (3)	15%	16%	1%	20%	
		Moderately conspiratorial (2)	3%	23%	31%	3%	
		Not conspiratorial (1)	82%	61%	68%	77%	

Source(s): Author's own creation/work

Table A4.
Conspiratorial
characteristics
codebook

Appendix 5

Criterion	Description	Possible codes	Frequency			
			English	Russian	Arabic	Hebrew
Type of source	Who is the content producer? Based on the site's "about" description	Media	26%	60%	86%	67%
		Scientific journals	43%	0%	0%	0%
		Social media sites	0%	1%	11%	7%
		Reliable sources (government bodies; non-governmental organizations); international organizations; institutions of higher education; informal science education institutions; encyclopedias or dictionaries; fact checkers' sites)	31%	39%	3%	26%

Table A5.
Type of source codebook

Source(s): Author's own creation/work

Appendix 6

The author's background	EN > RU ($X^2 = 68.093$ $p < 0.001$)	HE>RU ($X^2 = 66.421$ $p < 0.001$)	EN>AR ($X^2 = 36.083$ $p < 0.01$)
The relevance of the author's background	EN > RU ($X^2 = 52.688$ $p < 0.001$)	EN>AR ($X^2 = 30.371$ $p < 0.05$)	
Major scientific errors	No significant difference between languages		
Scientific components	EN > RU ($X^2 = 106.108$ $p < 0.000$)	HE>RU ($X^2 = 72.056$ $p < 0.001$)	EN>AR ($X^2 = 74.197$ $p < 0.000$)
Average quality score	EN > RU ($X^2 = 111.955$ $p < 0.000$)	EN>AR ($X^2 = 67.527$ $p < 0.000$)	
Use of scientific jargon	HE > EN ($X^2 = 52.926$ $p < 0.05$)	HE> RU ($X^2 = 101.337$ $p < 0.000$)	AR>RU ($X^2 = 92.681$ $p < 0.000$)
	EN>RU ($X^2 = 48.410$ $p < 0.001$)		
Supporting components	No significant difference between languages		
Average accessibility score	EN > RU ($X^2 = 61.967$ $p < 0.000$)	HE> RU ($X^2 = 113.896$ $p < 0.000$)	AR>RU ($X^2 = 88.474$ $p < 0.000$)
A contradiction of the conspiracy	No significant differences between languages		
Claims contradict accepted scientific explanations	No significant difference between languages		
Blaming specific groups	No significant difference between languages		
Malicious meaning	RU > EN ($X^2 = -34.844$ $p < 0.002$)	RU>AR ($X^2 = -44.207$ $p < 0.000$)	
Average conspiratorial score	RU > EN ($X^2 = -37.911$ $p < 0.01$)		

Note(s): EN = English
RU = Russian
AR= Arabic
HE = Hebrew

Source(s): Author's own creation/work

Table A6.
The significant differences

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