

Web Search or Conversation with an Artificial Intelligence? Analysis of Misinformation and Relevance in the Case of Radon Gas

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Abstract

Health-related information plays a crucial role in public health management, empowering individuals to make informed decisions and adopt behaviours that mitigate the effects of potential risks. The internet and the emergence of new technologies, such as conversational models equipped with Artificial Intelligence, present opportunities, and challenges in this field. This research focuses specifically on the risk of radon, a natural radioactive gas recognised worldwide as one of the leading causes of lung cancer and a persistent threat over time. The aim of this study is to analyse the information provided for this specific risk by two key information access tools: web search engines and AI-based conversational agents (ChatGPT). To carry out this interdisciplinary research (journalism-communication-computer science) we employ a mixed methodological design (quantitative and qualitative) and apply methods from the areas of Information Retrieval (IR), Big Data, and Artificial Intelligence (AI). The results of this study show that information on the internet about the risk of radon often lacks relevance and does not meet the information needs of users. We also found that some websites provide a significant amount of good quality information but there are often some misleading contents. ChatGPT proves to be more accurate in providing relevant and good quality information but contains a higher proportion of misinformation. Consequently, this raises concerns about the integrity of the information provided and emphasises the need to monitor and improve the accuracy of these computational tools.

Keywords

Misinformation, Disinformation, Communication, Journalism, Digital Communication, Health, Web Search, Internet, Health Information, ChatGPT, Radon, Artificial Intelligence, Big Data, Conversational Agents, Risk Communication.



1. Introduction

In the last two decades, we have witnessed two major changes: the Fourth Industrial Revolution, characterised by the integration of new technologies into society (Schwab, 2020), and what some call the Fifth Revolution, driven by Artificial Intelligence (AI) (Sung; Stewart; Freedman, 2020). Both phenomena have left a profound mark on society, generating significant changes in our interaction with the world and access to information (Schwab, 2016).

Amid this era of change, where diverse technological processes converge, access to health-related information through web search has become crucial for health promotion and disease management. The consolidation of the web as the main source of health information for society (Finney Rutten *et al.*, 2019) and the appearance of AI tools, such as ChatGPT, which present themselves as potential allies for advanced and accurate information search (Rotman, 2023), compels reflection and analysis.

The Fourth Industrial Revolution has completely changed the information connected to the health sector. The accessibility of online medical or health information is a valuable resource and benefit to society, playing a key role in educating, supporting, and assisting people. Web search plays a significant role in society, and more people are turning to web search engines for information (Bujnowska-Fedak; Waligóra; Mastalerz-Migas, 2019). Despite this, the abundance of data and the speed with which it is disseminated pose a challenge in differentiating between facts and misinformation (Montoro-Montarroso *et al.*, 2023). This is particularly important given the increased use of the web and the proliferation of online health information, factors that have a crucial influence on the medical decisions made by users (Chen *et al.*, 2018). The exchange of quality health-related information has the potential to improve health care delivery (Menachemi *et al.*, 2018) and to promote changes in people's behaviours and attitudes (Wartella *et al.*, 2016) to improve their knowledge and health status (Mitu, 2016).

On the other hand, AI and its intensive use, which had already marked the fourth wave of digital democracy (García-Orosa, 2021), now seems to be leading, together with a series of other technological advances, a new phase in the evolution of humanity. This is what some authors call the Fifth Industrial Revolution or Society 5.0 (Sarfraz *et al.*, 2021). The evolution and advances of AI have brought about changes in different sectors such as journalism, education, security, production, or health, among others (Feshina; Konovalova; Sinyavsky, 2019; Stanfill; Marc, 2019; Gutiérrez-Caneda; Vázquez-Herrero; López-García, 2023). This new digital revolution with the rise of AI and its ability to process large amounts of data much faster than humans brings with it a new range of possibilities. However, these new opportunities can have both positive and negative effects on people's lives (Taplin, 2023).

One of the most famous AI tools is the ChatGPT language model, created by OpenAI and launched in late 2022. It is a language model with advanced conversational capabilities and uses an artificial neural network architecture called 'transformer' (Vaswani *et al.*, 2017). The most prominent feature of ChatGPT is its ability to produce coherent and contextually relevant text to, for example, respond to natural language questions or requests (OpenAI, 2023b). This technology has advanced analysis and reasoning capabilities, offering promising paths for contributing to people's decision-making (Biswas, 2023a). For example, as a support tool in the field of healthcare (Stanfill; Marc, 2019). However, these advanced information access tools can exacerbate the problem of disinformation and misinformation. In fact, ChatGPT is neither a repository of factual knowledge nor an advanced database of what is written on the web. It draws on the web (with its certainties, falsehoods, and biases) to generate a network of neurons where it stores its "parametric knowledge" (stored in its multilayered network of neurons with millions of connections and weights). In addition, it has the inventiveness to go beyond what it has learned in its training collections. This creativity is useful in some scenarios (for instance, as an advanced tool to support content creation). Nevertheless, it poses a risk in other domains, which suffer from severe problems related to invention and falsification (Montoro-Montarroso *et al.*, 2023).

In this context, it is crucial to examine how information on health risks is sought and presented on the web and on ChatGPT, in order to understand its implications for decision-making and public health. To illustrate this, we will address a case study on radon, a natural radioactive gas present in the earth's crust, recognised as a leading cause of lung cancer globally (WHO, 2021). The seriousness of the potential negative public health effects and impacts of radon gas, the significant lack of social science research on this topic, and the evidence of information gaps on the web underline the need for a more comprehensive analysis of this issue (Perko; Turcanu, 2020).

1.1. Web Search for Health-related Information Needs

The web has become a reference source for the seeking of health information (Nguyen; Mosadeghi; Almarino, 2017; Amante *et al.*, 2015). Web search engines have brought about a significant change in the dissemination of information. Their tracking, indexing and information retrieval capabilities facilitate access to content published on servers residing anywhere in the world. In addition, they execute searches in time spans that were previously completely unthinkable (Van Laer; Van Aelst, 2010). Tools such as Google or Bing have become an indispensable part of modern life (Cheng; Dunn, 2015) and their use continues to increase (Masilamani; Sriram; Rozario, 2020; Calixte *et al.*, 2020). The search for health-related information has not been unaware to this growth (Zschorlich *et al.*, 2015). It should also be noted

that web search is essential for vulnerable communities with barriers in accessing information (Lin *et al.*, 2015) and that its role has positive effects on improving public health (Hunsaker; Hargittai, 2018). The availability of a large amount of information on the web and its reduced cost holds great potential as a source of health-related information for the population (Osei Asibey; Agyemang; Boakye Dankwah, 2017; Hermes-DeSantis *et al.*, 2021), as well as for people's own health literacy (Cheng; Dunn, 2015).

People also turn to the web for documentation and additional information following a medical consultation or to decide whether or not to see a doctor, allowing them to play a more active role in managing their own health (Medlock *et al.*, 2015). In turn, online health or medical information plays a key role, especially for those who experience difficulties in accessing health care services (Amante *et al.*, 2015).

Online health information is positively and beneficially associated with a range of health-related behaviours, regardless of the level of education, age, gender, or race of the person seeking the consultation (Wimble, 2016). Despite this, there are a number of barriers and complex processes that interfere with people's ability to adapt to or process this type of information available through digital spaces (O'Connor *et al.*, 2016). Web search can have negative effects on the population when it provides erroneous or false information. The information available is not always correct or verified. It can even be misleading or misinterpreted, which can compromise people's behaviours and health status (Mitu, 2016). In addition, the presence of misinformation disguised to intentionally mislead, also called misinformation, increases the dangers of using web searches for health purposes. At times, various interested agents in the dissemination of misinformation distort the truth, they influence opinions and impair informed decision-making (Fallis, 2015). In addition, there are other factors that play an important role in how people perceive the available health-related information and in the population's medical decision-making. These are primarily the credibility of the source and the quality and accuracy of the information (Chen *et al.*, 2018; Morgan *et al.*, 2001; Gutteling; Wiegman, 2013; Jacobs; Amuta; Jeon, 2017; Osei Asibey *et al.*, 2017).

In general, when users access health-related information on the internet, they tend to do so through web search using different search engines and do not directly access specific sources (Moreno, 2017). This results in most people accessing websites that they are unfamiliar with, rather than specific medical portals or proven resources (Eysenbach; Köhler, 2002). Search results often combine websites of high credibility, such as government sources or pages written by health professionals, with websites of lower credibility such as online forums or blogs without any cross-checking of information (Lagoe; Atkin, 2015). Usually, the information consulted is basic and does not go into depth (Laugesen; Hassanein; Yuan, 2015).

Studies highlight the importance of ensuring more accurate and higher quality health information (Amante *et al.*, 2015; Wartella *et al.*, 2016; Finney Rutten *et al.*, 2019). There is a need to create an online environment of trust, with less incorrect or false information, thus benefiting behaviours and attitudes that improve public health status (Jiang; Liu, 2020). Therefore, there is a need for new research that explores information and internet use through web searches with new approaches to measurement and analysis (Hunsaker; Hargittai, 2018).

1.2. ChatGPT and New Opportunities for Consultation of Health-related Information

The development of online communication technologies has changed the way patients use health-related information for medical purposes (Bujnowska-Fedak *et al.*, 2019). In addition, the crisis caused by the COVID-19 pandemic has exposed the various weaknesses of current healthcare systems and highlighted the need for people to increase their engagement with their own health by making use of the possibilities offered by new technologies (Costa-García *et al.*, 2022). In this sense, ChatGPT or other similar models can play a positive and innovative role by providing information and promoting behaviours that seek to improve public health in society (Biswas, 2023b). Since its appearance in 2022, ChatGPT has attracted a lot of attention due to the possibilities it offers, and its potential uses in a wide range of fields.

As indicated above, ChatGPT's features incorporate new ways of obtaining health-related information in a way that is, in advance, simpler and more efficient. ChatGPT or other similar language models could be the protagonists of a new shift in the way people access health or medical information online. However, both because of the quality of the information they feed on (training collections from the web that usually have not been sufficiently curated and therefore contain errors, misinformation, and biases) and because of their ability to go beyond what is seen in training, it is necessary to put this new type of tool under close scrutiny, even more so when we are talking about access to health-related information.

ChatGPT is based on a large language model developed by collecting online articles and learning from large volumes of data (Karako *et al.*, 2023). It consists of two stages: pre-training and fine adjustment. In the pre-training phase, the model 'ingests' a massive dataset of text in various languages, which allows it to learn linguistic and semantic patterns, developing a general understanding of the language and topics covered in those texts. Since ChatGPT is a general-purpose tool, the texts it pre-trains with are diverse in subject matter, coming from billions of web pages and some specialised repositories. In the fine adjustment phase, the model is specifically adapted to particular tasks, such as answering questions or holding conversations. To do this, the model is adapted by training with a more specific dataset. The final model takes a text input from the user, processes it through its layered architecture and generates coherent

responses. To do this, it relies on the information present in the user's input, its general knowledge acquired during pre-training and adaptations made in the fine adjustment phase (**OpenAI**, 2023a).

ChatGPT offers a variety of opportunities that can be applied to the field of health. For instance, it can answer questions about disease prevention behaviours, provide information about programmes and other health services, or supply information about public health issues such as diseases or health risks, among others (**Biswas**, 2023b). These new types of conversational tools also have a number of limitations that may affect their success as a source of information. Some of these derive from technical limitations, such as contextual understanding or lack of emotional intelligence. There are also potential dangers, as they may provide incorrect or harmful advice, lacking a code of ethics or ignoring professional consensus knowledge (**Arslan**, 2023). On the other hand, the quality of their responses can vary greatly with small or subtle variations in the wording of the questions, or the configuration of the textual input provided by the user (**OpenAI**, 2023a).

Nowadays, ChatGPT has two publicly available versions ChatGPT 3.5 and 4.0. Version 3.5 is currently free, and version 4.0 is paid and includes a number of additional functionalities. The main differences between these two versions lie in the evolution of the model. ChatGPT 4.0 represents a more advanced version, with extended text processing capabilities. In addition, this version has significantly improved reasoning capabilities, making it more suitable for tasks that require advanced logical thinking. Moreover, its security and usability have been adjusted with feedback from users and experts, making this version more reliable. In other words, ChatGPT 4.0 is a significant improvement in size, reasoning capability and versatility compared to its predecessor, ChatGPT 3.5 (**ChatGPT**, 2023).

1.3. The Risk of Radon Gas

This research analyses information from web search and conversational agents in a specific case: radon gas. We use a transnational and timeless risk that allows for an analysis distant from specific crises in which those involved tend to change their role temporarily, affected by responsibility or fear (**Klemm; Das; Hartmann**, 2019). Moreover, we are working with a serious risk to public health, as it is the second leading cause of death from lung cancer among smokers and the first cause among non-smokers. Furthermore, it is often misunderstood and not perceived as a risk by the inhabitants of the most affected areas (**WHO**, 2009) and rarely seen in the media (**García-Orosa; Forja-Pena**, 2024).

Radon is a colourless, odourless, and tasteless gas of natural origin (**WHO**, 2021). Radon exposure is the main source of ionising radiation for the population and accounts for more than half of the radiation that a human being will receive during their lifetime (**Fernández Villar**, 2017). The factor that determines the radon concentration in a geographical area is the uranium content of the subsoil rocks. Therefore, radon levels vary and are not the same in all areas (**Ruano-Raviña; Quindós-Poncela; Barros-Dios**, 2014). The control of radon in air poses a unique and unprecedented challenge, as the vast majority of radon sources are of natural origin and can be found in every household (**Samet**, 1989). Its seriousness is evidenced by its persistence over time and the severe health effects demonstrated. Both the World Health Organisation and the European Union emphasise the importance of their public health hazards and the importance of publicly available information on this risk. In this context, there is a clear need for public participation in mitigating the effects of radon.

2. Methodology

The overall purpose of this research is to analyse the results provided by two of today's main sources of information access: web search engines and conversational agents equipped with AI. Specifically, we put under scrutiny here their capabilities to inform about health risks from a series of queries about radon, simulating the questions of a real user. From this general objective, a number of secondary objectives are drawn:

- Analysing the level of **relevance** of the information provided through web search and ChatGPT (3.5 & 4.0) to a given radon query or needed information.
- Examining the level of **quality** of the information provided by these sources.
- Identifying the percentage of **disinformation** or **misinformation** provided by these tools and explore its origin and content.

This research uses a mixed qualitative and quantitative methodological design and has been carried out by an interdisciplinary team (journalism-communication-computer science). This configuration has made it possible to approach the challenges of this study from different perspectives and methodologies. This work is based on a complex method of analysis that provides a series of results of significant robustness and richness.

Firstly, state-of-the-art methods in the field of Information Retrieval (IR) are used to perform the information search, supported by Big Data technologies to index, and access large document repositories. Searching against online search engines, such as Google, has the disadvantage that search experiments would not be reproducible. Due to the inherent dynamism of the web, the inverted indexes of search engines are constantly being updated with new pages, so the results fluctuate depending on when the experiments are launched. In addition, the ranking criteria for the results are derived from a proprietary algorithm whose specifics are unknown. This is why we prefer to use transparent technology here, whose search models are known to the scientific community, so that any researcher can reproduce our runs and obtain similar results.

Traditionally, in the field of IR, public corpuses with millions of web pages that can be indexed and searched for a range of queries are used for research (Baeza-Yates; Ribeiro-Neto, 1999; Croft; Metzler; Strohman, 2010). In this work, this strategy is followed to simulate an internet web search for information related to radon gas. Once the most relevant documents for a given query have been retrieved, AI techniques are used to help estimate the most important passage in the document to answer the query (Nogueira; Jiang; Lin, 2020). Alternatively, ChatGPT-3.5 and ChatGPT-4.0 models are used to obtain a direct answer to the same radon-related queries. Both types of tools produce imperfect results. The information provided may not be relevant to the query or may be of low quality. Therefore, it is necessary to define a set of criteria and carry out a process of labelling the relevance and quality of the retrieved results (Fernández-Pichel et al., 2023).

In summary, the contribution of this research is dual. On the one hand, we systematically compare web search on the internet versus solving the same questions with a conversational agent such as ChatGPT. This comparison is contextualised in the field of information related to radon and its risks. On the other hand, our research generates a labelled resource of annotated web pages based on their relevance and quality. This valuable result is made available to the scientific community and can be exploited by different research groups in many fields.

As a first step, a group of experts defined a set of queries related to radon gas. These short queries represent what a conventional non-expert user might ask a search engine or conversational agent. In total, 51 queries were generated in English. For instance, ‘How to avoid radon?’, ‘Radon causes cancer’, ‘Effects of radon’, etc. Given the set of queries, different techniques were designed and carried out to analyse each of the tools, as detailed in the following sections.

2.1. Web Search on the Internet

To simulate the first scenario of web-based information access on the internet, a large corpus called C4 was used (Raffel et al., 2020). This corpus consists of 1,590,000 English web pages crawled from the Web in April 2019. Simulating web searches against a static corpus is a standard technique in Search Technologies, since it allows comparison of algorithms and search variants against a centralised repository (that is, under the same conditions). In addition, it does not require reliance on real users or access to query logs of online searches (Baeza-Yates; Ribeiro-Neto, 1999; Croft et al., 2010).

In order to be able to carry out searches, the corpus was indexed in an inverted index structure, similar to that used by search engines. Next, we searched for pages relevant to the previously defined queries. This was done using standard search techniques based on word matching between the search and the documents. In particular, the well-known BM25 search algorithm was used (Robertson; Zaragoza, 2009). Recent research has shown that these techniques may not be sufficient to find the most relevant documents for a given search because, for example, they do not consider possible synonyms of words or their context. Therefore, the top 100 documents retrieved for each search were re-ranked using techniques based on deep neural networks that estimate the semantic similarity between the search and the document (Nogueira et al., 2020). Additionally, for the 100 most relevant pages for each search, we performed the extraction of relevant passages within those pages. This was implemented with a passage-finding AI algorithm that estimates which part of the page is most central to answering the search.

Table 1: Example of a Passage Obtained from a Website and Estimated as Relevant.

Search	Passage
Effects of radon	<i>Radon is a carcinogen designated by the World Health Organization and is the second-leading cause of lung cancer following smoking. Approximately 3-14% of all lung cancers worldwide are estimated to be caused by radon exposure, and an association between radon and lung cancer has been consistently reported in studies investigating work environments of mine workers and indoor radon exposure. However, associations between radon and other diseases have yet to be established due to inconsistent study results and low biological relevancy....</i>

2.2. Web Search Resource Tagging on the Internet

Web search on the internet is imperfect and it could happen, for example, that the information retrieved is not relevant to the search. An important part of this research focused on generating a labelled resource of **relevance of web passages** for each of the searches. For this purpose, a set of criteria were defined in order to be able to categorise whether a passage retrieved from the web is irrelevant, partially relevant, or very relevant to a given radon-related search.

Irrelevant (0): the passage does not answer the search or information need. For example, the passage talks about radon and/or cancer, but not about a causal relationship between the two.

Partially Relevant (1): the passage responds partially to the search or information need. For example, the passage talks about the relationship between radon and cancer and the possibility of radon causing cancer. However, it does not give complete information on the topic the user is asking about.

Very relevant (2): The assessor will find the information in the passage very relevant because it clearly responds to the information need. For example, the passage will contain a direct answer (incorrect or not) as to whether radon causes cancer.

It is also important to note that we are not assessing any kind of correctness, quality, or credibility here. For example, a document that talks about the possibility of radon causing cancer would be relevant, even if it denies this possibility.

Defining solid criteria for making relevance judgements is a standard technique in massive data tagging processes in Information Retrieval (Fernández-Pichel *et al.*, 2023).

As an initial step, a draft version of the relevance guides was created. To validate these guidelines, assessors labelled an initial sample of passages. We then calculated Cohen's Kappa linearly weighted pairwise to assess agreement between individual assessors (McHugh, 2012) and Krippendorff's alpha for ordinal scales to assess agreement between all assessors (Krippendorff, 2018). After some adjustments to the relevance guidelines, the median Kappa value was 0.72 and Krippendorff's alpha (agreement among all assessors) was 0.83. The guidelines were therefore given the green light to carry out a global labelling of all consultations and passages.

At the end of the labelling of the global set of searches, we obtained a resource of 5,100 passages extracted from the internet web search and its relevance tagging for radon-related searches. We consider this as the first milestone of this study, as this resource can be used for other studies in different fields such as Communication or Computer Science.

In a second labelling phase, we focused on estimating the quality of the retrieved passages. For this phase, only the passages estimated as partially relevant or very relevant in the previous step were labelled. For the particular case of a health-related information need such as radon gas, it is crucial to consider a number of variables that help to estimate the quality of the extracted passages. One of them is the reference in the text to reputable or authoritative sources of information (e.g. WHO). Another is the correctness of the information provided in the passage. In addition, further evidence related to the passage is the non-inclusion of commercial or marketing information. Based on these three variables, a set of criteria was again defined to label the quality of the passages. The process was analogous to the relevance case: after a first labelling of a random subset of searches, the agreement between human assessors was calculated. The resulting Kappa (median value) was 0.90, and Krippendorff's alpha was 0.90. These guidelines were therefore given the green light for global quality labelling.

Based on the annotations made by the experts, a level of preference or documentary quality was defined, considering the potential harm to individuals. For instance, the most harmful content is that which cites reputable sources but contains incorrect information and also seeks to market some kind of product or service. Such information, by referring to authoritative institutions or bodies, can mislead people into making dangerous decisions that can lead to personal harm. On the contrary, the best content is that which is correct, refers to reputable sources and has no marketing intention. Aggregate quality levels can be positive or negative, depending on the estimation of how harmful they are likely to be. The following table details the established quality levels.

Table 2: Relationship Between the Variables Labelled in the Guides and the Levels of Documentary Quality or Preference.

Citation of a Reputed Source	Marketing Intention	Correct Information	Quality Level
✓	×	✓	3
✓	✓	✓	2
×	×	✓	2
×	✓	✓	1
×	×	×	-1
×	✓	×	-2
✓	×	×	-2
✓	✓	×	-3

The result of this tagging is a resource of 2,056 passages extracted from the internet and their estimated quality for radon-related queries. Again, we believe this is a valuable resource in itself for possible future research in multiple disciplines.

2.3. ChatGPT

The 51 previously defined searches were launched against ChatGPT versions 3.5 and 4.0. Upon receiving this input, ChatGPT generates a relatively short text response (two or three paragraphs at most). For our study, we directly store the response provided by the intelligent agent, without carrying out any selection of main passages. This decision is motivated by the fact that this type of AIs already provide a direct answer to the question (unlike a web page, which typically contains the desired information scattered among the various contents of the page).

Table 3: Example of ChatGPT-4.0's Answer to One of the Queries.

Example query to ChatGPT-4.0	ChatGPT-4.0 answer
Radon causes cancer	Yes, you're correct. Radon is a naturally occurring radioactive gas that can cause lung cancer. It's the second leading cause of lung cancer in the U.S. after cigarette smoking. Radon can enter homes through cracks in floors, walls, or foundations, and collect indoors. It can also be released from building materials, or from water obtained from wells that contain radon.

2.4. Labelling of the ChatGPT resource

In order to make the results comparable to those of the internet web search, the same relevance and quality criteria

were used to evaluate the ChatGPT output. The labelling of ChatGPT-3.5 responses generated a Kappa with a median of 0.75, while the Krippendorff's alpha was 0.76. For ChatGPT-4.0, Kappa produced a median of 0.92 and Krippendorff's alpha estimated the overall agreement at 0.92.

For quality estimation, responses estimated as *partially relevant* or *very relevant* were again selected. In the case of ChatGPT-3.5, agreement on the assignment of quality labels produced a median Kappa of 0.90, while Krippendorff produced an overall agreement of 0.92. For ChatGPT-4.0, the median Kappa value was equal to 1 (perfect agreement) and therefore the Krippendorff value of overall agreement was also 1.

This rigorous process therefore generated a solid resource, labelled in terms of relevance and quality, of responses from these AIs to radon-related questions. In the following sections, the relevance and quality of the information obtained through the web search and through the conversational AIs will be compared in depth.

3. Results

3.1. Relevance of web Information on the Internet

After analysing the data obtained, the results reveal that a considerable proportion of the information retrieved lacks relevance with respect to the search made. Specifically, 56.5% of the fragments do not provide significant information to satisfy the user's information needs. It is also observed that 30.7% of the pages provide *partially relevant* information, while only 12.8% present *very relevant* information, offering clear answers to the user's information needs. The fact that less than 13% of the results provide highly relevant information indicates that, at least in the case of radon, web search needs to be improved in order to promote content that is highly relevant to the user's interests.

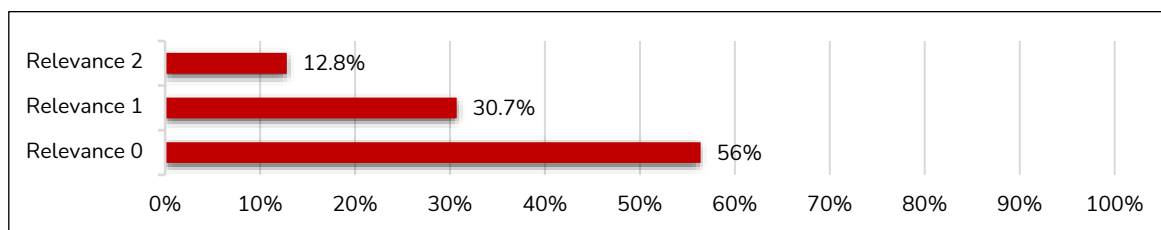


Figure 1: Ranking of Retrieved Passages by Type of Relevance.

Analysing the origin of the pages that provide the different types of information, websites with *.com* domains are the main source of *irrelevant* information, accounting for 24.5% of the total. In addition, 11.7% of the irrelevant web pages come from official sources with *.gov* and *.org* domains. On the other hand, we should mention that a considerable percentage, 10.3%, is linked to *.us* domains registered in or belonging to the United States. In the two categories of relevant passages, the *.com* domain prevails, representing 23.1% and 23.9%, respectively. This undoubtedly stems from the higher prevalence on the web of pages originating from this domain.

The following table shows for each domain the percentages of pages in the respective classes. The *.org* and *.us* domains retrieve the highest percentage of non-responsive information (63.5% and 66.3%, respectively) and also provide the lowest percentage of *very relevant* information. Interestingly, *.edu* is the domain that provides the most *partially relevant* information (32.1%) but, at the same time, shows the lowest percentage of *very relevant* information, with 8.5%. On the other hand, the *.gov* domain, which is exclusively for governmental organisations and public control entities, stands out by retrieving one of the highest percentages of *partially relevant* or *very relevant* information. 30.2% of the information is *partially relevant*, and 13.7% is *very relevant* information. Finally, in terms of *very relevant* information, the *.com* and *.net* domains stand out, together with the *.gov* mentioned before, as they offer the highest percentage of information that clearly responds to users' information needs.

Table 4: Distribution of the Different Categories of Relevance for Different Domains.

Domain	Relevance 0 (irrelevant)	Relevance 1 (partially relevant)	Relevance 2 (very relevant)
<i>.gov</i>	56.1%	3.2%	13.7%
<i>.org</i>	63.5%	24.9%	11.5%
<i>.com</i>	56.5%	28.8%	14.7%
<i>.net</i>	56.5%	30.1%	13.4%
<i>.edu</i>	59.4%	32.1%	8.5%
<i>.us</i>	66.3%	23.1%	10.6%
<i>.mil</i>	57.5%	30.0%	12.5%
Total	56.4%	30.7%	12.8%

3.2. Information Quality in Web Search

The quality of the information obtained, following the criteria explained above, mostly belongs to the three positive

quality levels (that is, those providing correct information). Specifically, 99.77% is correct information, while 0.23% is disinformation or misinformation, as shown in the following graph.

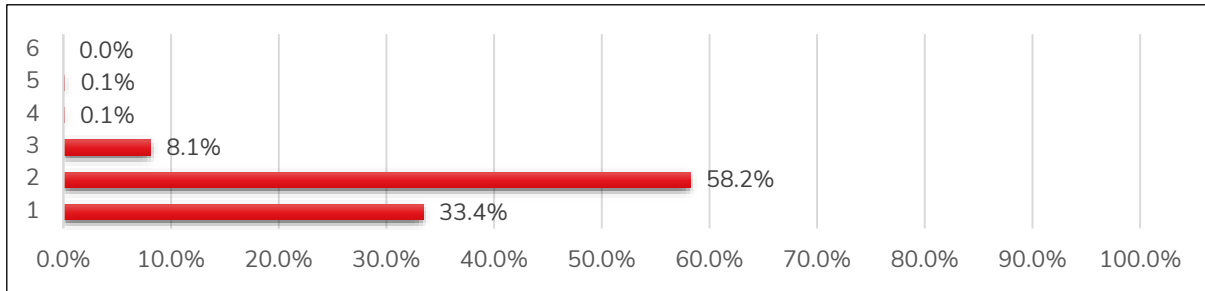


Figure 2: Ranking of Relevant Passages by Quality Categories.

The 33.4% of the information provided for our consultations is correct information, citing reputable sources and containing no commercial or marketing intentions (quality level 3). However, 66.34% (the sum of the percentages of quality levels 2 and 1), despite being correct information, may not cite reputable sources or contain commercial or marketing intentions.

Table 5: Distribution of the Different Quality Categories for Different Domains.

Domain	Quality level 3	Quality level 2	Quality level 1	Quality level -1	Quality level -2	Quality level -3
.gov	47.3%	51%	1.6%	0.0%	0.0%	0.0%
.org	52.5%	43.1%	4.4%	0.0%	0.0%	0.0%
.com	30.2%	60.9%	8.7%	0.1%	0.1%	0.0%
.net	39.1%	55.8%	3.9%	0.0%	1.2%	0.0%
.edu	25.9%	67.8%	6.3%	0.0%	0.0%	0.0%
.us	33.0%	57.5%	9.4%	0.0%	0.0%	0.0%
.mil	70.2%	26.2%	3.6%	0.0%	0.0%	0.0%
Others	34.7%	52.8%	11.3%	0.9%	0.0%	0.0%
Total	33.44%	58.22%	8.11%	0.09%	0.14%	0.0%

As the table above shows, websites with .org, .gov and .mil domains provide the highest percentage of information with the highest quality (level 3). All the present disinformation or misinformation comes from .com, .net or other domains. For example, we observed that within the ‘others’ category there was the domain .ge, with pages hosted by or belonging to Georgia, associated with various pages providing incorrect information on radon gas. This result naturally corresponds to the type of websites hosted by those respective domains, since .org and .gov for example tend to host institutional or government websites, while .com for example tends to be associated with commercial websites. Fortunately, in our study we did not find any -3 quality sites (with misinformation, marketing intentions and using reputable sources or quotes with the purpose of misleading the reader).

3.3. Relevance of the Information Provided by ChatGPT

Both versions of this AI offer very similar and practically identical data in terms of the average relevance of the information provided in response to queries related to radon gas risk. The high percentage of very relevant information and the scarce presence of irrelevant or partially relevant information stand out. The data show that users when using ChatGPT are very likely to obtain information that fully responds to the query or previous information need. This contrasts with the situation in web search where more than half of the content analysed provided irrelevant information.

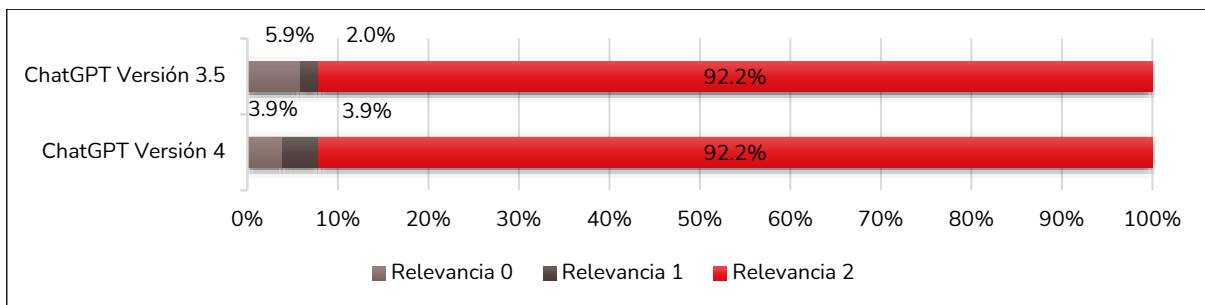


Figure 3: Ranking of Responses by ChatGPT Version for each Level of Relevance.

3.4. Quality of the Information Provided by ChatGPT

Regarding the quality of the information provided by ChatGPT for the queries made, 93.8% is correct information (quality levels greater than 0), compared to around 6% of false or incorrect information. As shown in table 6, we found only three different quality levels (3, 2 and -1) with ChatGPT.

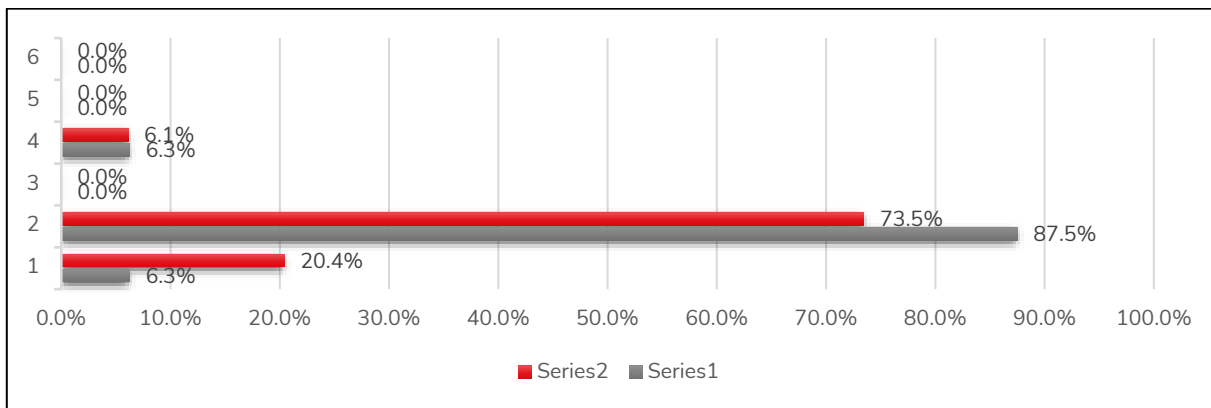


Figure 4: Ranking of ChatGPT Responses by ChatGPT Quality Category.

It is noteworthy that ChatGPT version 4.0 retrieves more information citing reputable sources such as governmental, official bodies, scientific or medical, specifically a 20.4% compared to 6.3% in version 3.5. In addition, ChatGPT 4.0 shows a slight improvement in the percentage of incorrect documents of quality -1 (6.12% compared to 6.3% in version 3.5). In any case, the presence of low-quality content (levels -1 or lower) is considerably higher for these conversational agents compared to the web search situation where, as can be seen in table 6 (last row), the percentage of harmful documents does not reach 1%.

3.5. Qualitative analysis of misinformation on the Web and ChatGPT

3.5.1. Web

The misinformation detected in the web analysis belongs to only 3 classes: (i) incorrect information that does not cite reputable sources and does not contain marketing intentions (quality -1), (ii) incorrect information that does not cite reputable sources and contains marketing intentions (quality -2) and (iii) incorrect information that cites reputable sources and does not contain marketing intentions (quality -2). Some misinformation websites have been qualitatively analysed.

Some of these websites contain misinformation while citing reputable sources. They address the public perception that indoor exposure of radon causes cancer, pointing out that there is no conclusive evidence to support this claim. It points out that even the EPA (United States Environmental Protection Agency) has no evidence of an increased risk of cancer due to radon exposure in homes. It also indicates that some studies suggest that lung cancer rates decrease with increasing indoor radon concentrations. The scientific support for risk estimates is questioned. In general, doubts are raised about public perception, scientific/medical evidence and policy related to environmental risks.

Despite the fact that some of these passages analysed do not contain marketing intentions, if we delve deeper into other sections of their respective websites, we find that they are created to present radon therapy facilities and services offered by the companies to which they belong. In other words, these companies offer customers the option of receiving radon treatment. These websites refer to these treatments and provide information on the therapeutic effects caused by radon on the human organism. These effects, according to their websites, would have a beneficial impact on a variety of medical conditions, including musculoskeletal system, cardiovascular, nervous system, female reproductive organs, urological and gastrointestinal diseases. It is clear how damaging this information can be to people who are unaware of radon toxicity in humans.

3.5.2. ChatGPT

ChatGPT has provided around 6% of false or incorrect information that does not cite reputable sources and does not contain marketing intentions (category -1). If we synthesise the misinformation from this conversational model, we could divide it into three themes or topics. All of the following information is neither scientifically proven nor supported by any official or health body. These themes or topics would be:

- In some cases, it provides information on other possible health effects such as cough or shortness of breath, or even chronic obstructive pulmonary disease (COPD). This is the case for queries such as: Effects of radon (ChatGPT 3.5 and 4.0), How Radon Affects Children (ChatGPT 3.5), Radon Hazards (ChatGPT 4.0).

Query to ChatGPT-3.5	ChatGPT-3.5 answer
Effects of radon	[...] Exposure to high levels of radon gas can have several negative effects on human health. The primary concern is its link to lung cancer. [...] Other potential health effects of radon exposure include respiratory issues such as coughing, wheezing, and shortness of breath. Long-term exposure to high levels of radon may also increase the risk of other respiratory diseases, such as chronic obstructive pulmonary disease (COPD). [...].

- Provides information on specific health problems related to radon exposure in children, such as reduced lung function and possible cognitive or behavioural problems. Example query: How Radon Affects Children (ChatGPT 3.5).

Query to ChatGPT-3.5	ChatGPT-3.5 answer
How Radon Affects Children	<p>[...] Exposure to high levels of radon can be harmful to anyone, but children are particularly vulnerable due to their developing bodies and higher breathing rates. Here are some ways radon can affect children: [...].</p> <p>2. Respiratory problems: Radon gas can irritate the respiratory system, leading to symptoms such as coughing, wheezing, and shortness of breath. Children with asthma or other respiratory conditions may experience worsened symptoms. [...].</p> <p>4. Developmental issues: Some studies suggest that exposure to radon during childhood may have an impact on cognitive development and behaviour. [...].</p>

- Provides information about the potential benefits of radon exposure, such as pain relief for conditions like arthritis (radon therapy) or its use in cancer treatment. Example queries: What is good about radon (ChatGPT 3.5 and 4.0).

Query to ChatGPT-4.0	ChatGPT-3.5 answer
What is good about radon	<p>Radon is a naturally occurring radioactive gas that is colourless, odourless, and tasteless. While it is generally considered harmful due to its radioactive nature, it does have some beneficial uses:</p> <p>1. Health Therapy: Some health spas use radon in small amounts for therapeutic purposes, such as pain relief for conditions like arthritis. This is known as radon therapy. [...]</p> <p>5. Cancer Treatment: In some cases, radon has been used in experimental cancer treatment. [...]</p>

4. Discussion

In this study, we have analysed the information provided by the internet web search and ChatGPT, both versions 3.5 and 4.0, in response to queries about radon and its health risks. The results confirm some trends identified in previous studies, but above all, given their novelty, they highlight challenges that will need to be addressed in the coming years by the people involved.

The web appears to be a poor source of information for users as a large proportion of the information retrieved is irrelevant and does not meet the user's information needs. As for ChatGPT, it is more accurate in providing information that is very relevant to information needs but offers more disinformation or misinformation. This confirms previous analyses indicating that conversational models offer a number of advantages over more traditional tools such as web search (Biswas, 2023b), but also carry a number of risks that can translate into negative effects on people's health (Taplin, 2023). In the health field, sources that are more trusted and credible among users, such as official sources, have the greatest impact on generating the desired effects from the information they provide (Chen et al., 2018; Gutteling; Wiegman, 2013; Jacobs et al., 2017; Morgan et al., 2001). However, the results show that official sources are scarce and, where they do appear, the information they provide is often not entirely relevant. This suggests that governmental sources could take steps to improve the relevance of their content, bearing in mind that the web is a key environment for dissemination to society. Irrelevant or partially relevant information (such as that found in most cases from official sources) could have negative effects on motivating changes in users' behaviour with the aim of improving their health habits.

On the other hand, when assessing the quality of the relevant information provided, the results obtained by ChatGPT and, specifically, ChatGPT 4.0 stand out as it retrieves a higher percentage of information that contains references to official or reputable sources. Therefore, this conversational model may be a promising option for the consultation of health-related information, given that it is necessary to ensure that the information is accurate and of quality (Finney Rutten et al., 2019; Wartella et al., 2016; Amante et al., 2015). In turn, as for the incorrect information provided, all of it is misinformation but does not cite reputable sources and does not contain marketing intentions. Although it does not generally provide very low-quality information, the percentage of misinformation it produces highlights the weaknesses of ChatGPT as a tool for accessing health-related information (Arslan, 2023; Montoro-Montarroso et al., 2023). This limitation reduces its potential to become a tool that contributes to building an online environment characterised by greater trust and less proliferation of misinformation.

On the other hand, the information retrieved from the web search mainly fits into the first three categories of quality or order of preference. More than half of the information is either correct information that cites reputable sources and contains marketing intentions or information that does not cite reputable sources but lacks marketing intentions. Secondly, it is correct information that is cited by reputable sources and does not contain marketing intentions, followed by correct information that does not cite reputable sources but includes marketing intentions. Only a small percentage falls into the three categories reflecting incorrect information or misinformation.

The results obtained from the information retrieved through web search based on its quality show that web search can play a positive role in the medical decision-making of the population by offering mostly quality information (Osei Asibey et al., 2017). Even so, it should be noted that, within the disinformation or misinformation detected, one of the two most significant percentages relates to misinformation citing reputable sources, that is very harmful information. Furthermore, it is important to mention that neither web search nor ChatGPT retrieve information from the lowest quality and most harmful category, which is incorrect information or misinformation citing reputable sources and containing marketing intentions.

With regard to the disinformation or misinformation detected, the dangerousness of the information retrieved through the

web search is evidenced by its typology. This search provides disinformation or misinformation in which reputable sources are cited in order to covertly promote their services. Most notably, this type of information is provided by companies that advertise on websites offering radon therapy services. These cases underline that health-related information often poses a challenge when it comes to differentiating between facts and misinformation (Montoro-Montarroso *et al.*, 2023). In some detected cases, even these websites question the scientific evidence supported by official bodies.

In addition, ChatGPT, in its versions 3.5 and 4.0, retrieves a significant percentage of incorrect information or misinformation. It generally provides incorrect information on possible health effects on people from radon exposure. These findings suggest the need for more rigorous monitoring of the information generated by ChatGPT to ensure the accuracy and completeness of the information provided to users. Therefore, despite the many advantages offered by these new technologies in the field of health (Costa-García *et al.*, 2022; Biswas, 2023b), the dangers and disadvantages that these tools also possess must be considered.

5. Conclusions and Limitations of this Research

This study has shed light on the quality and relevance of information related to radon and its risks, available through web search and ChatGPT. The results show that online information often lacks relevance and does not meet users' information needs, which can negatively influence users' perception of the information. It also highlights that web search, while offering a significant amount of good quality information, also presents a significant risk of misinformation. Despite positive aspects, such as the lack of low-quality information in general in web search, the presence of misinformation citing reputable sources with commercial or marketing intentions is a worrying factor. Although ChatGPT is more accurate in providing relevant information, it also provides a higher proportion of incorrect information, which raises concerns about the veracity of the information provided and highlights the importance of monitoring and refining the accuracy of these conversation models. In relation to the sources of information, it is worth noting that official sources are scarce and, when they do appear, they tend to provide little relevant information.

Moreover, it is worth noting that this study provides a number of labelled resources that can be exploited for a variety of purposes by research groups in many different fields in future research. Ultimately, these findings highlight the need to proactively address risks and challenges in online information seeking and the use of conversational technologies in the context of public health.

In conclusion, it is essential to recognise certain limitations of this study. The tagging of the web resource is based on specific passages, and the source pages may have other parts with different levels of relevance/quality. However, we have used state-of-the-art technology for the extraction of passages from the pages. In any case, our project has to be continued by future research to deepen a more precise understanding of online information on radon and its impact on public health. It should not be forgotten that this study is based on a case study, and it is not intended at any point to extrapolate the main findings to different cases of other health risks or threats. This study aims to shed light on the possible advantages, disadvantages, risks, and possibilities offered by web search and ChatGPT for accessing health-related information, using the case study of radon gas. Ideally, it will serve to inform future research that will contribute to further academic debate on the information provided by web search and conversational models such as ChatGPT and on new methodologies that can be addressed and developed in this field.

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