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Navigating the Disinformation Maze: A Bibliometric Analysis of Scholarly Efforts

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Abstract: The increasing prevalence of disinformation has become a global challenge, exacerbated by the rapid dissemination of information in online environments. The present study conducts a bibliometric analysis of scholarly efforts made over time in the research papers associated with the disinformation field. Thus, this paper aims to understand and help combat disinformation by focusing on methodologies, datasets, and key metadata. Through a bibliometric approach, the study identifies leading authors, affiliations, and journals and examines collaboration networks in the field of disinformation. This analysis highlights the significant growth in research on disinformation, particularly in response to events such as the 2016 U.S. election, Brexit, and the COVID-19 pandemic, with an overall growth rate of 15.14% in the entire analyzed period. The results of the analysis underscore the role of social media and artificial intelligence in the spread of disinformation, as well as the importance of fact-checking technologies. Findings reveal that the most prolific contributions come from universities in the United States of America (USA), the United Kingdom (UK), Spain, and other global institutions, with a notable increase in publications since 2018. Through thematic maps, a keyword analysis, and collaboration networks, this study provides a comprehensive overview of the evolving field of disinformation research, offering valuable insights for future investigations and policy development.

Keywords: disinformation; thematic map; bibliometric analysis; biblioshiny

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1. Introduction

The problem of disinformation has become a major international challenge in an era marked by the extremely rapid spread of information in the online environment. Additionally, the occurrence of fake news has played an important role in manipulating the masses, creating propaganda, and changing mentalities based on false information. As has been observed, this type of news has an influence across various fields, producing negative effects both economically and psychologically.

There is an important difference between fake news and disinformation that must be addressed. Fake news, according to the UK Cambridge Dictionary, is a false narrative which could be used as news and distributed on the internet via social media platforms, with the purpose of influencing political views [1]. Disinformation focuses on misleading on purpose by manipulating stories based on a biased information, also known as propaganda [1]. Zimdars and McLeod [2] consider fake news to be intentional information that has been created in full in order to mislead and increase the emotions of readers, replicating mainstream news. Disinformation consists of false information that is intentionally promoted, with the aim of harming others [3]. In order to better understand the difference

between disinformation and fake news, a Venn diagram has been created using Microsoft Visio, as presented in Figure 1.

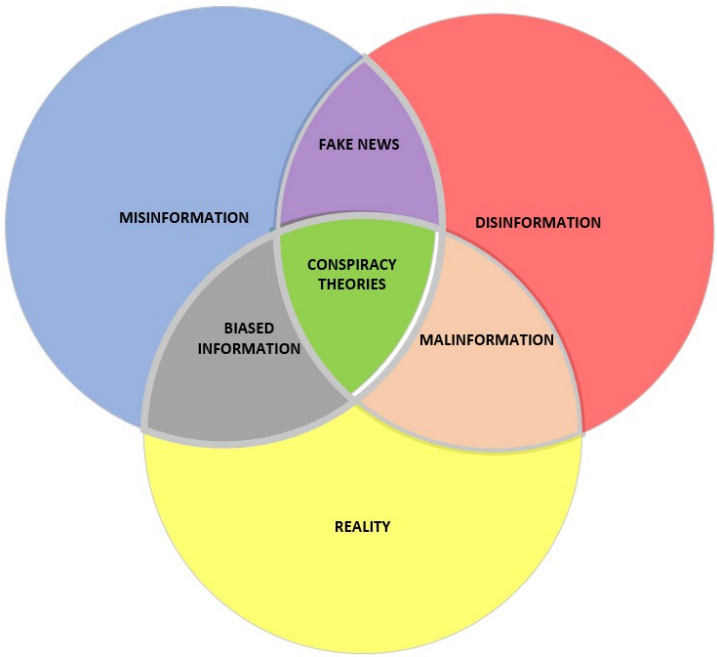

Figure 1. Venn diagram.

Figure 1 thus highlights the differences between disinformation, misinformation, reality, fake news, and conspiracy theories. Misinformation's definition is the distribution of false information without having an intention to emotionally damage people, while disinformation is the intention of sharing false information to influence public opinion and policies [4]. Malinformation is founded on partially real information that is promoted out of context in order to harm the public. Biased information appears at the intersection of reality and misinformation, while malinformation is at the intersection of reality and disinformation. At the intersection of disinformation and misinformation is fake news. At the intersection of misinformation, disinformation, and reality are conspiracy theories. Conspiracy theories focus on people's secret activities and plans, with a refusal to accept existing evidence which denies the theory. Numerous conspiracy theories that are promoted are dangerous for society [4].

While the definition of disinformation is straightforward—the process of the voluntarily spreading misleading information which affects people in a direct or indirect manner [5]—the effects of disinformation can have a major impact on people's lives.

At present, disinformation has affected various areas of our life [6]. As Wang et al. [7] identify in their research, there are four major areas closely related to the disinformation domain: the heterogeneity of misinformation in memory, the mechanisms of disinformation on social media, public health during the COVID-19 pandemic, and the use of big data technologies in the infodemic.

Through this bibliometric study, we aim to understand and gain a deeper insight into the current state of the disinformation that appears in the online environment, as well as to highlight the efforts being made to combat this phenomenon. This study discusses both the methodologies and the datasets that are being used, but also metadata from the papers included in this analysis. Considering the increasing number of papers published in the field and the growing interest in the fast development that artificial intelligence has had in recent years, we hope that the present study will be of interest to researchers in the disinformation field.

Considering that disinformation, misinformation, and fake news have reached a historical maximum, discussions regarding this field are also in the foreground. A major factor that has had a great impact in disseminating these types of information to the public has been social media platforms, as stated in Lewandowsky et al. [8] and Vosoughi et al. [9]. Another key factor in the spread of disinformation has been the advancement of artificial intelligence. In addition to the disastrous effects that it can bring to the economy, disinformation can also bring negative effects on a psychological level [4].

The spread of false information in political areas impedes individuals from creating their own opinions and affects democracies. Two of the most representative examples are the United States of America's (USA) elections in 2016 and the United Kingdom (UK) Brexit referendum, which occurred in the same year, events that became key milestones for researchers who are becoming more and more interested in the disinformation and fake news domain [10]. Another period of exponential disinformation growth occurred during the COVID-19 pandemic, which led governments to adapt different policies, such as passing various laws to reduce infection rates, though these measures faced significant protests and opposition [10].

Various studies have been conducted in the field of disinformation throughout its history. For example, Belen et al. [11] argued that by sharing false or misleading news in the media, the most vulnerable individuals could easily be manipulated. The method that the authors developed learns the characteristics and weaknesses of individuals, but also points out the vulnerabilities that people have to deal with when they interact with fake news or misinformation. Chung and Kim [12] conducted two experiments and their results show that fact-checking information neutralizes social media's impact and that without fact-checking, social media would have a greater impact, generating more intentions to share the information. Based on the scientific literature, it has been observed that some studies have focused on better delimitating the field of disinformation from other types of information [5,13] or on identifying types of disinformation [14], while other studies have considered context-specific situations in which disinformation has occurred, such as natural disasters [15], climate change [16,17], politics [18–20], or health issues [21–23]. The rise of social media and the disinformation associated with this type of media has been studied in the scientific literature, from the organization of social media disinformation campaigns [24] to issues related to combating disinformation in the social media age [25,26].

Researchers have also focused on identifying the best methods to mitigate the spread of disinformation. One of the best machine learning (ML) algorithms is the recurrent neural network (RNN). Long Short-Term Memory (LSTM) and the Gated Recurrent Unit (GRU) are algorithms that are also relevant in disinformation's detection [27–29]. During the COVID-19 pandemic, numerous pieces of disinformation were distributed. In order to combat this disinformation, bag-of-words or N-grams methods were developed, which are part of natural language processing [30]. Kumar and Geethakumari [31] explored the spread od disinformation, propaganda, and misinformation online and used multiple algoirthms that are able to categorize whether information is fake or not, such as the J48 learning method, RankSVM, Relevance, and PageRank. Soe [32,33] explored the PHEME-project, which detects whether information is the truth, disinformation, or misinformation. Galitsky [34] proposed an algorithm that detects disinformation, finding the source of text on the internet and comparing it with fake information using parse ticket technology.

The aim of our analysis is to synthesize the body of literature published in this field and to emphasize the most significant findings. In order to better understand the impact of researchers on the domain and how its interests have evolved in recent years, there is a focus on universities that have been releasing scientific articles, together with an investigation into the scientific production in this area, the collaboration network of the authors publishing, journals, and keywords. As Sierra et al. [35] explained in their paper, authors have a prominent role in work related to disinformation, which has a larger impact on their research career. The number of publications from universities demonstrates the complexity and the quality of this research. By employing a bibliometric approach, we seek

to identify and extract the key elements that contribute to the evolution of disinformation, addressing the following scientific questions:

- SQ1: Which are the universities that have published the most scientific papers?
- SQ2: How has annual scientific production evolved?
- SQ3: Do any collaboration networks between authors exist?
- SQ4: Who are the authors with the most crucial impact, taking into account their number of publications?
- SQ5: Which are the most relevant journals related to misinformation?
- SQ6: Which are the most used keywords and those most used by authors?

In order to achieve the objectives described above, the first step is to extract the most relevant documents in the research area that will be investigated [7,36]. This process uses Biblioshiny, a library from the R programming language and a scientific tool used for bibliometric analysis, which offers a great variety of graphics and insights on the imported dataset, as Aria and Cuccurullo [37] noted in their article. Biblioshiny allows for the rapid extraction of information about authors, countries, and journals and visualizes the temporal evolution of the domain and its authors. Additionally, Biblioshiny offers a series of detailed visualizations such as thematic maps, co-occurrence networks, and three-field plot graphics [37]. The graphics in this study were generated using the Biblioshiny library and the selection of the figures align with other scientific papers related to the field of disinformation [38–40].

This paper is divided into multiple sections, as follows: Section 2 offers an overview of the methods used for the bibliometric analysis, presenting the main steps that have been applied. Section 3 presents the results of the research, explaining who the most relevant authors are, in which journals they publish, which countries they are from, how they collaborated, and which groups of words are most used. Section 4 focuses on limitations and a discussion, while Section 5 contains our concluding remarks.

2. Materials and Methods

Based on the existing papers, Clarivate Analytics' Web of Science Core Collection database [41]—formerly known as the Web of Science (WoS)—has been selected. Bakir et al. [42] explained their reason for choosing Clarivate Analytics' Web of Science Core Collection, namely that it has wider coverage across numerous domains and contains a variety of highly regarded journals in the scientific community [43]. Compared with other databases, the WoS is less inclusive but is one of the most used databases in academic research [44–46].

A crucial step, as noted in the scientific literature [47–49], when utilizing the WoS database is to specify the indexes available during the data extraction process. This step is particularly important, as Liu has explained [50,51], because the choice of indexes directly impacts the results. The WoS database operates with a variety of indexes, many of which require paid subscriptions, thus influencing the scope and comprehensiveness of the research outcomes. In our case, we have access to the following indexes and for the below-mentioned periods:

- Emerging Sources Citations Index (ESCI), 2005–present;
- Conference Proceedings Citation Index—Social Sciences and Humanities (CPCI-SSH), 1990–present;
- Conference Proceedings Citation Index—Science (CPCI-S), 1990–present;
- Arts and Humanities Citation Index (A&HCI), 1975–present;
- Index Chemicus (IC), 2010–present;
- Current Chemical Reactions (CCR-Expanded), 2010–present;
- Book Citation Index—Science (BKCI-S), 2010–present;
- Book Citation Index—Social Sciences and Humanities (BKCI-SSH), 2010–present;
- Social Sciences Citation Index (SSCI), 1975–present;
- Science Citation Index Expanded (SCIE), 1900–present;

- In order to fulfill our objectives and achieve the purpose of this analysis, the second filter consisted of removing all papers which were not published in English, reducing the dimensionality of the database by 311 articles, thus reducing the dataset to a total of 2308 papers. This decision to remove papers written in other languages has been made in accordance with the scientific literature [52,53]. Also, as the bibliometric analysis conducted in this paper needs to extract specific keywords for the building up of word clouds and determining the research themes of the papers included in the dataset, keeping in the dataset only in English provides robustness to the obtained results.

The third filter was applied to the type of documents, as we only took into consideration publications which were checked as an "Article" in the WoS, reducing the size of the database by 663 papers, leaving a total of 1645 documents. It should be mentioned that even though the document type "Article" would suggest that only papers published in journals are included in the analysis, in the case of the WoS database, document types marked as "Article" cover to any research considered "relevant research" by the database [54]. Therefore, in the "Article" type might also display conference proceedings papers if these papers are considered new and relevant by the database.

The final filtering step excluded documents published in 2024, thereby reducing the database by 251 papers and resulting in a total of 1394 publications to be analyzed from a bibliometric perspective. The decision to remove 2024 publications was based on the fact that, at the time of the dataset's extraction, the year 2024 was still in progress. Including papers written and indexed thus far in the WoS would not have provided a comprehensive overview of the entire year. Additionally, citation indicators for 2024 publications would not have accurately reflected citation trends, as insufficient time would have passed for these papers to accrue citations, potentially misleadingly suggesting a decline in citation counts for 2024.

Table 1 presents the main steps that have been taken in order to extract the dataset from the WoS platform.

Table 1. Data selection steps.

Description	No. of Papers Removed	No. of Papers Included
Database Filtered: ISI Web of Science Search filters for titles and abstracts, TI = (disinformation) OR AK = (disinformation)		2619
Language Filter: Including only English language papers that have been published, LA = (English)	311	2308
Document type Filter: Including only publications which are checked as "Article", DT = Article	663	1645
Timespan Filter: Remove 2024, PY = 2024	251	1394

The first step included the filtering of titles and authors' keywords, keeping only the ones which contained "disinformation", resulting in a dataset consisting of 2619 documents.

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3. Dataset Analysis

In this section, a dataset analysis is conducted first from a general perspective by discussing the overall characteristics of the dataset, followed by a more focused analysis on specific elements such as sources, authors, universities, countries, and collaboration networks. While a traditional bibliometric analysis typically emphasizes these aspects, we have enhanced our approach by incorporating a review of the top 10 most cited papers to provide a more comprehensive understanding of the disinformation research field. Additionally, a thematic map is presented to better identify the fundamental, driving, niche, and emerging trends within the domain of disinformation.

Considering the content of this section, a brief overview its sub-sections is provided below:

- Section 3.1 presents an overview of the dataset, with an emphasis on the yearly scientific production which is the core element for answering SQ2;
- Section 3.2 provides an analysis of the sources and helps in obtaining the answers to SQ5;
- Section 3.3 discusses the authors and offers information relevant for answering SQ1 and SQ4;
- Section 3.4 brings to light the countries of the authors and brings an international context to the research associated with the selected field;
- Section 3.5 addresses the collaboration networks present, highligting the main points relevant to answering SQ3;
- Section 3.6 discusses our analysis of the scientific literature, shaping the answer to SQ6.

3.1. Dataset Overview

An exploratory analysis was conducted in this section to provide a comprehensive overview of the data. The field has developed rapidly, as indicated by its annual growth rate of 15.14%, showing a significant acceleration in recent years.

Table 2 includes an overview of the dataset. The analyzed period starts in 1980 and it ends in 2023, covering 711 sources and 1394 documents, with an average number of citations per document of 12.68 and an average of 3.4 years since these documents were published. In total, there 55,703 references were included.

Table 2. Main information about data.

Indicator	Value
Timespan	1980–2023
Sources	711
Documents	1394
Average years from publication	3.4
Average citations per documents	12.68
References	55,703

Between 1980 and 2006, the publication rate in the field of disinformation was minimal, ranging from 0 to 5 papers per year, as depicted in Figure 2. For example, the first document on disinformation was published in 1980, followed by five papers in 1982, while 1985 saw no publications at all. Until 2014, when eight articles were published, 1982 remained the year with the highest publication rate, except for 2011, which also saw five papers published. However, beginning in 2018, there was a marked increase in publication activity, reaching a peak in 2023 with 429 papers published. Sandu et al. [55] conducted a similar analysis on misinformation, reporting comparable findings, with a positive trend in annual scientific output over the analyzed period.

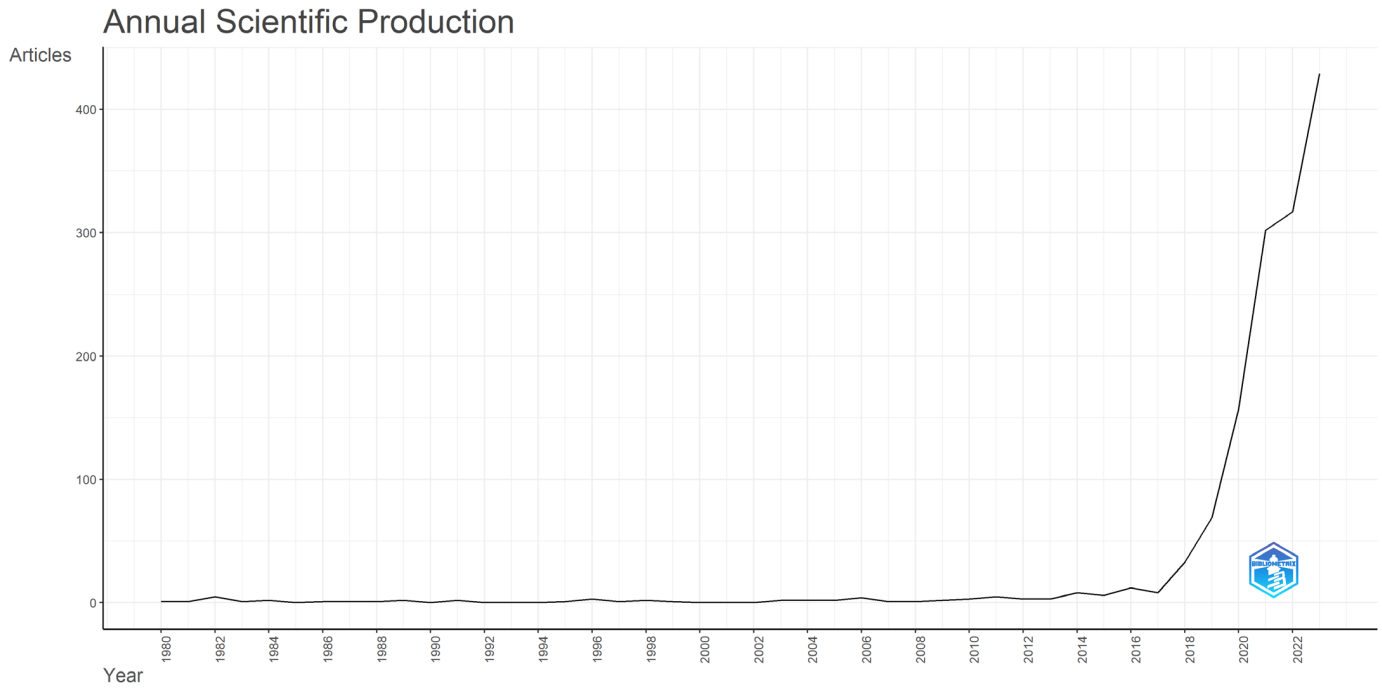

Figure 2. Evolution of annual scientific production.

Figure 3 presents the average yearly citation rate. The values between 1980 and 2003 were very small, averaging below one citation per year. In 2003, the average citation per year was 3.82, making this the first relevant year for the field of disinformation, which becaume very volatile in the next 20 years, having numerous spikes. The highest average per year was registered in 2018, at nine citations per year. Starting in 2020, the trend in the citation rate started to decrease, from 6 to 1.1 in 2023, but this trend might be explained by the increased number of papers which have been released recently. In 2018, at the peak of the citation rate, numerous papers related to the Brexit vote were published, describing the United Kingdom's process of leaving the European Union and how its people were disinformed through the promotion of the fact that numerous immigrants would enter the country if they remained in EU, as Vasu et al. [56] explained.

Sommariva et al. [57] focused on the health domain, investigating the disinformation related to the Zika virus and grouping that information into three different categories, known also as rumors: false connections, which mislead people about the correlation between content and its title; fabricated content that contains only fake information, without any scientific evidence; and misleading content which promotes inaccurate stories. Out of the total 120 stories analyzed, 27 were considered rumors. The impact was significant, since the Zika virus appeared mainly in Brasil, in 2016, when the South American country organized the Olympics.

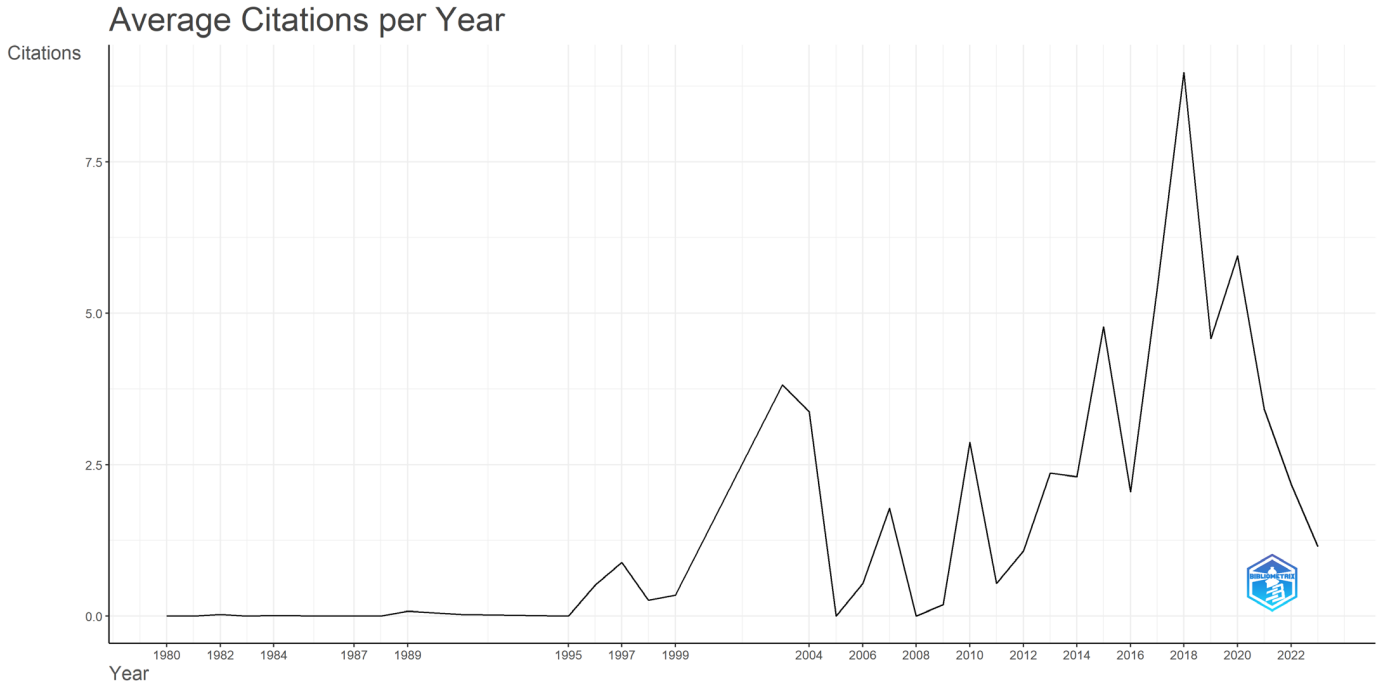

Figure 3. Evolution of annual average article citations per year.

3.2. Sources

Sources are analyzed in this section: the number of articles published, the number of keywords used, the most relevant sources, and their impact.

Table 3 summarizes the types of the documents included in this research. Most of the papers (1273 papers) are, as expected, in the "Article" category, while 65 papers are "Early Access Articles", 50 papers are "Book Chapters", 5 papers are "Proceedings Papers", and 1 document is a "Book". As mentioned above in the methodological section, this situation occurred due to the fact that the WoS includes in its "Article" category documents that are considered "relevant research" [54].

Table 3. Document types.

Indicator	Value
Article	1273
Book	1
Book Chapter	50
Early Access Article	65
Proceedings Paper	5

Table 4 presents the number of authors keywords and keywords plus used in all publications included in this research. There are 3118 authors keywords and only 1160 keywords plus. Garfield [58–60] explained that keywords plus can contain some of the content of a paper, presenting information at a higher depth and variety; they are used to extract research trends from various domains. The keywords plus are extracted from titles and articles, contain more terms than the authors keywords, and are recommended for use in bibliometric analyses. Keywords plus highlight the articles which might not have authors' keywords and could include terms that are not included in the authors' keywords [61].

Table 4. Document contents.

Indicator	Value
Authors' keywords (DE)	3118
Keywords Plus (ID)	1160

Table 5 details information about the authors. The current database includes 3091 unique authors; 421 of them contributed to the creation of single-authored documents, and 467 papers in the database are single-authored papers. On average, there are 2.67 co-authors per article, and the international co-authorship rate is 20.16%.

Table 5. Author information.

Indicator	Value
Authors	3091
Authors of single-authored docs	421
Single-authored docs	467
Co-authors per doc	2.67
International co-authorship (%)	20.16

Figure 4 describes the most important sources within the disinformation domain. The most important source, based on the number of publications, is *Profesional de la Informacion* with 36 papers, and in a very close second place is *Social Media + Society* with 35 documents. In third place is the *International Journal of Communication*, with 32 articles. *Media and Communication* has 26 publications, while *Journalism Practice* has 19. The rest of the journals listed have less impact but are still relevant for the domain: *New Media & Society* has 16 papers, *Information Communication & Society* and *Revista Icono 14-Revista Cientifica de Comunicacio* each have 15 articles, and *Political Communication* and *Revista Latina de Comunicacion Social* published 13 documents each.

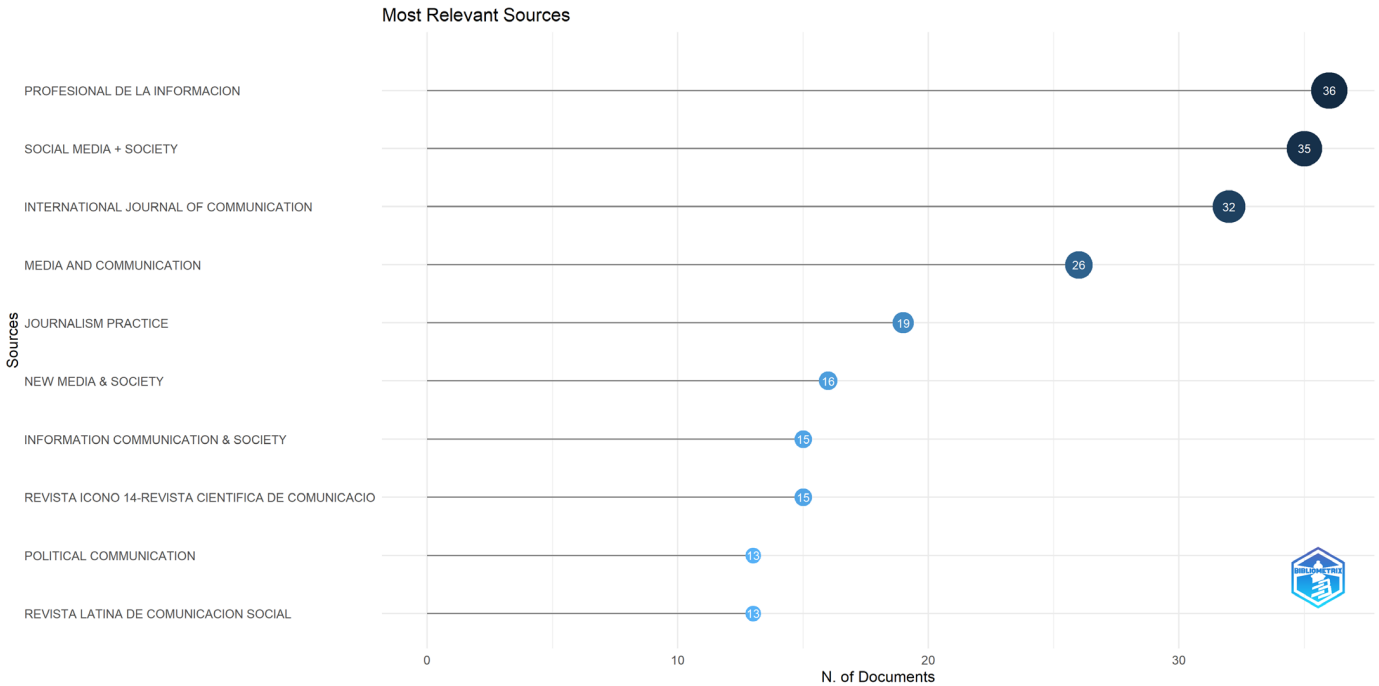

Figure 4. Top 10 most relevant journals.

The investigation of journals is a crucial step in bibliometric research, and the most important sources are presented in Figure 5 using Bradford's Law, which focuses on the most cited journals, separating them from those with a smaller impact.

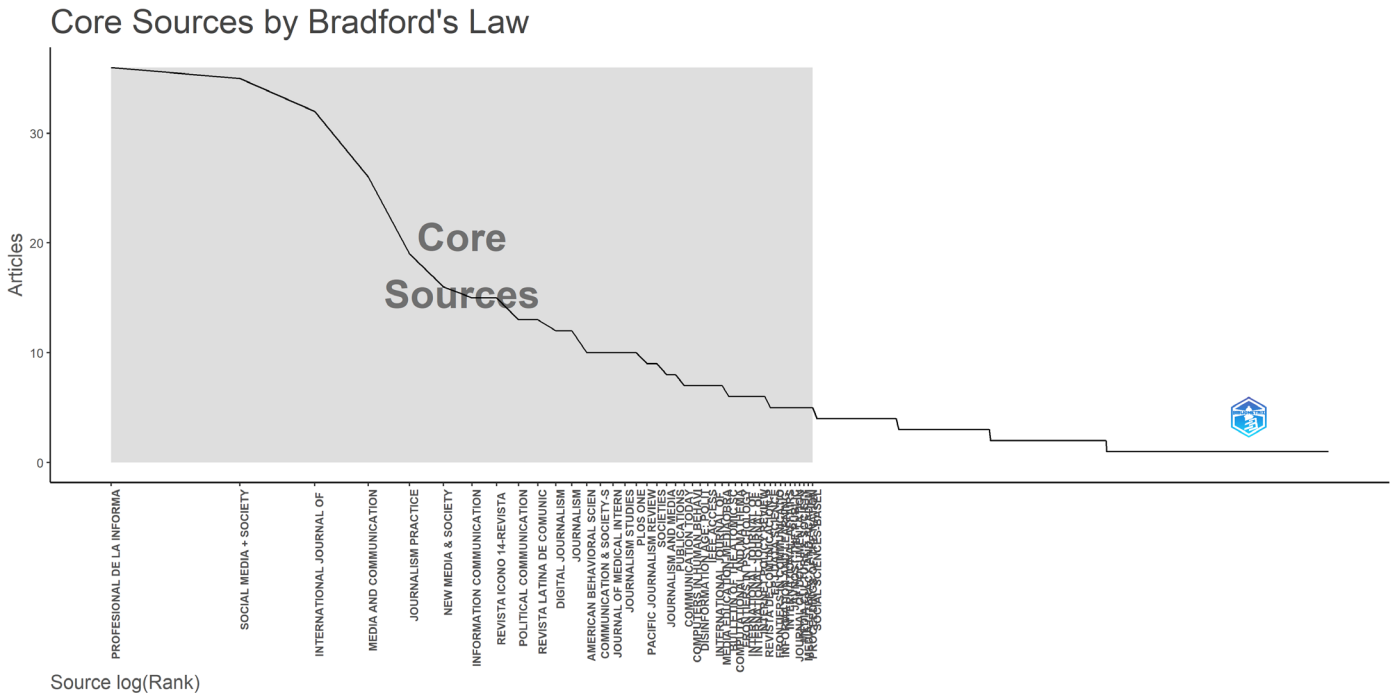

Figure 5. Bradford's Law of source clustering.

Bradford's Law divides journals into three separate categories based on their total number of publications, with all three categories containing the same proportion of papers: one third. In the end, Bradford's Law groups proportionally, with a ratio of $1{:}n{:}n^2$, as Yang et al. [62] explained. Meller et al. [63] explained the importance of Bradford's Law, which is able to perform an online-based multi-sectional analysis while also providing a robust distribution of the journals into three different categories. Bookstein [64] demonstrated that the main use of Bradford's Law is on the citations of journals, together with the number of articles appearing in journals, as is being tested in many domains. *Profesional de la Informacion* is ranked as the most important journal by Bradford's Law, as it has, in total, 36 articles, followed by *Social Media + Society* with 35 papers and *International Journal of Communication* with 32 documents. *Media and Communication* published 26 papers related to the field of disinformation, *Journalism Practice* has published 19 papers, and *New Media & Society* has 16. *Information Communication & Society*, and *Revista Icono 14-Revista Cientifica de Comunicacion Y Tecnologias* each have 15 papers, while *Political Communication* and *Revista Latina de Comunicacion Social* each have 13 documents. All 10 journals that have been described above are in Zone 1, which is the most important [64].

Figure 6 illustrates the local impact of various academic journals within the disinformation field, measured by their H-index. This value reflects not only the number of published articles, but also their impact on the scientific world.

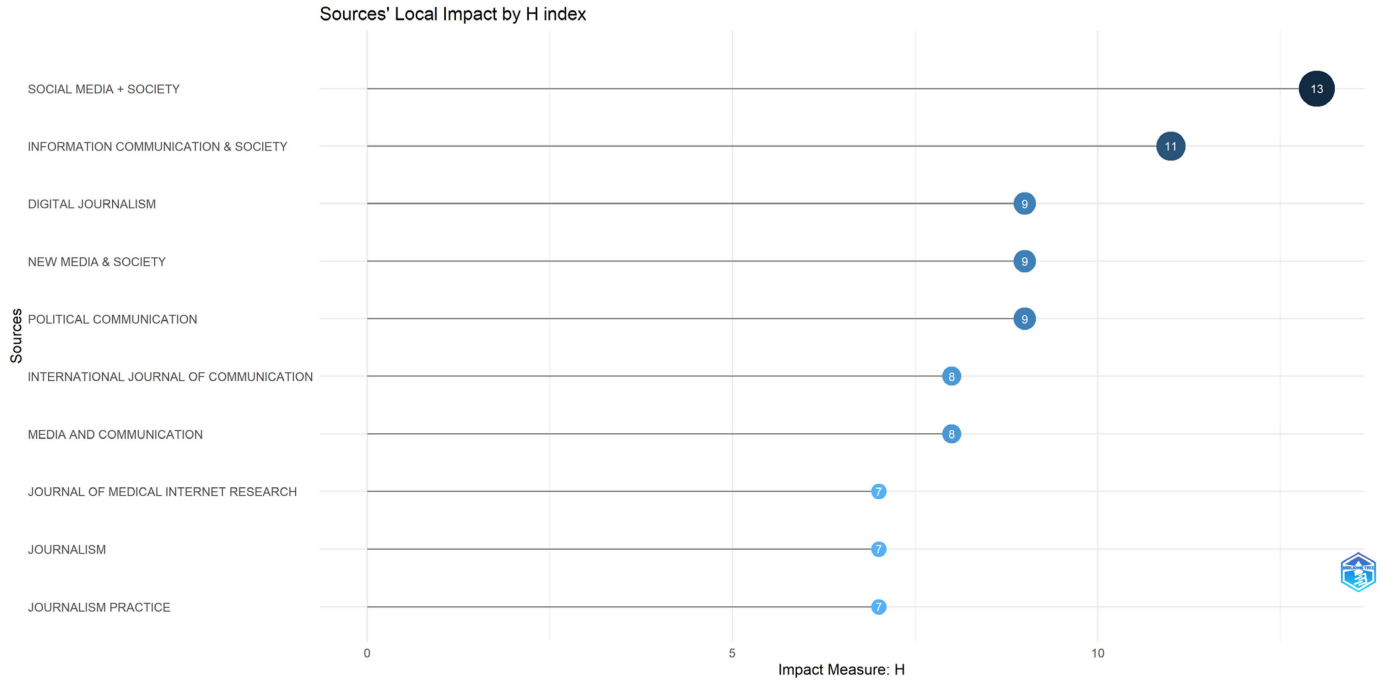

Figure 6. Journals' impact based on their H-index.

As can be observed, *Social Media + Society* leads, with an H-index of 13, followed by *Information, Communication & Society*, which has an H-index of 11. The top positions occupied by these two sources indicate their strong impact on the field. Furthermore, journals like *Digital Journalism* and *New Media & Society* also show notable influences, with an H-index of 8. Other journals such as *Political Communication* and the *International Journal of Communication* display a moderate impact, while sources like *Journalism* and *Journalism Practice* have lower H-indexes, indicating a more specialized influence. When considering all the journals included in this list, it can be observed that most of them specialize in communication and media studies, highlighting once more the connection between disinformation and the communications channels through which disinformation takes place.

In Figure 7, the top 10 most relevant sources based on the number of articles they published during the reviewed timespan are explored. It can be observed that for the 1980–2017 period, none of the top 10 journals included in Figure 7 published any papers related to disinformation, which can be observed through the horizontal line seen in this period in the case of all 10 sources. In 2018, the first article in the disinformation domain was published in *Political Communication* and in 2019 four other journals published documents on similar topics: *Social Media + Society* published four articles, *International Journal of Communication* published one paper, *New Media & Society* released two publications, *Information Communication & Society* published three articles, and *Political Communication* published one paper. Starting in 2020, the publication rate increased exponentially; all ten journals included in this analysis started to publish papers, the most significant of which are *Social Media + Society*, which published 15 papers in 2020, 21 papers in 2021, 25 documents in 2022, and 35 articles in 2023. *International Journal of Communication* is also very important, as it published 7 papers in 2020, 19 in 2021, 26 in 2022, and 32 in 2023. *Profesional de la Informacion* also had 2 publications in 2020, 6 in 2021, 14 in 2022, and 36 in 2023, which puts this journal at the top of all the sources at the end on the timespan, based on the number of articles published in one year. The full list of journals is presented in Figure 7.

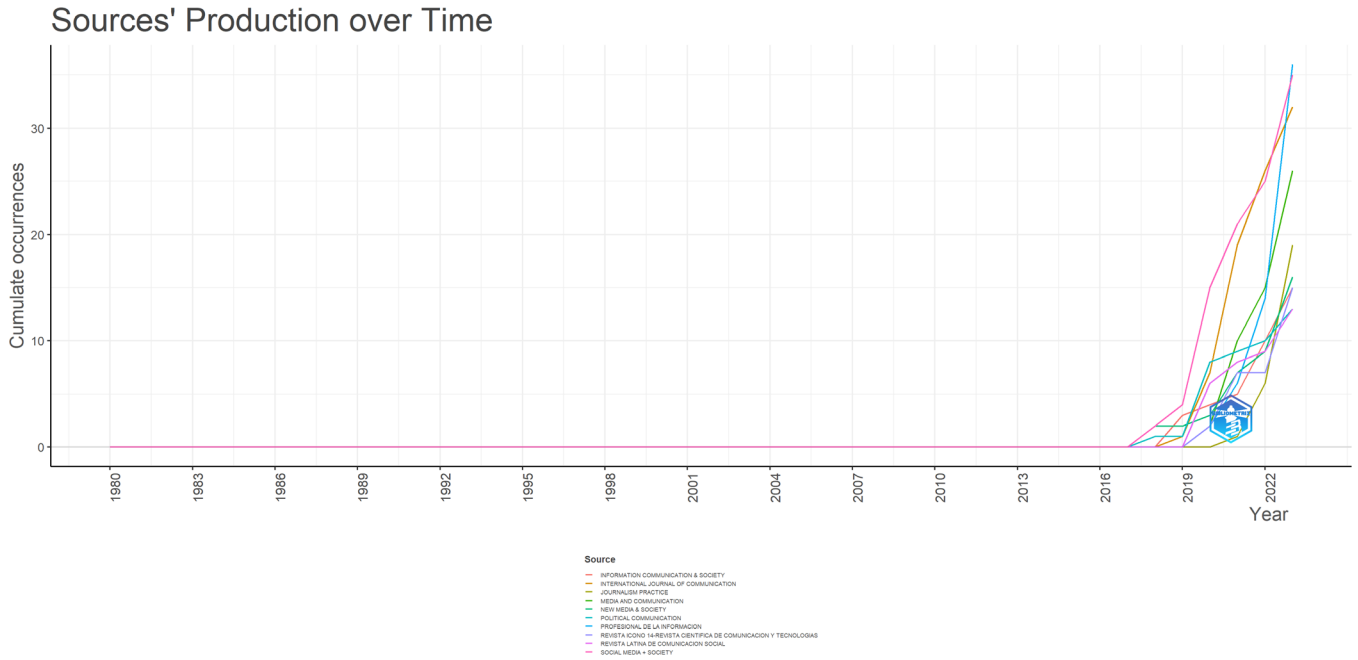

Figure 7. Journals' growth (cumulative) based on the number of papers published.

3.3. Authors

The most important authors, based on the number of documents they have written, are detailed in Table 6. The fractional number of articles was also evaluated, which shows the individual contribution of each author to the number of articles that have been published [65]. *Hameleers M.* is the most relevant author based on the number of documents published, with a total of 29 publications to their name. They also have the highest contribution to fractionalized articles, with a value of 17.21. The difference between first and second place is notable: 20 articles. *Carley KM.* is placed second based on their number of published papers, namely 9 articles, and the value of their fractionalized articles is much smaller compared to that of the first author, at only 3.17. *Farkas J.* authored 7 papers, with a fractionalized article value of 4.33, while *Bastos M.*, *Chadwick A.*, *Herrero-Diz P.*, *Humprecht E.*, and *Hurcombe E.* have 6 publications each, and fractionalized article values of 3.83, 2.33, 2.17, 2.98, and 1.77. The list of top 10 most productive authors is completed by *Ahmed S.* and *Buchanan T.*, who have 5 publications each, while their fractionalized article values are 3.83 and 3.33. The number of articles that the authors have been first or last author on has been counted, in order to better understand their impact on the analyzed domain. *Hameleers M.* has been listed as first author 24 times and as the last author only 4 times. *Carley KM.* was the last author in all papers he has published, while *Farkas J.* was first author in six papers and last author in only one document. *Bastos M.* appeared as the first author five times and as the last author only once, while *Chadwick A.* appeared as the first author three times and as the last author twice. *Herrero-Diz P.* was the first author in five articles and was the last author in one, while *Humprecht E.* was the first author four times and never the last author. *Hurcombe E.* appeared as the first author once and as the last author once. The last two authors, *Ahmed S.* and *Buchanan T.* have five papers, respectively; four papers where they are the first authors and none where they are the last author.

Table 6. Top 10 authors based on number of documents published.

Author Name	First Author Frequency	Last Author Frequency	Number of Documents	Articles Fractionalized
Hameleers M	24	4	29	17.21
Carley KM	0	9	9	3.17
Farkas J	6	1	7	4.33
Bastos M	5	1	6	3.83
Chadwick A	3	2	6	2.33
Herrero-Diz P	5	1	6	2.17
Humprecht E	4	0	6	2.98
Hurcombe E	1	1	6	1.77
Ahmed S	5	0	5	3.83
Buchanan T	4	0	5	3.33

The most important universities based on the number of publications they have produced are listed in Table 7. It can be observed that there are four universities from the USA, two from the UK, two from Spain, one from the Netherlands, and one from Singapore. The university that has published the most articles is *The University of Texas Austin*, which has 71 papers. The *University of Amsterdam* is second with 52 articles, followed by the *University of Washington* with 44 documents, *Harvard University* and the *University of Oxford* have each published 25 papers. The *University of California System* and *University of London* each have 24 publications, while the *University of Navarra*, *Complutense University of Madrid*, and *Nanyang Technological University* have published 21, 19, and 19 papers.

Table 7. Top 10 most relevant affiliations.

Affiliation Name	Frequency (No. of Documents Published)
University of Texas Austin	71
University of Amsterdam	52
University of Washington	44
Harvard University	25
University of Oxford	25
University of California System	24
University of London	24
University of Navarra	21
Complutense University of Madrid	19
Nanyang Technological University	19

It should be noted that Wang et al. [7] also analyzed the disinformation domain using a bibliometric approach and their results are similar, with the *University of Washington*, *University of Texas*, and *Harvard University* listed as the most relevant affiliations.

Figure 8 depicts the prolificity of the top 10 authors in the disinformation domain over time, highlighting their publication frequency. As expected from the previous analysis, which reflected the overall number of papers published, *Hameleers M.* stands out with consistent contributions, particularly from 2019 to 2023, with a peak in 2023, which indicates their strong and ongoing influence in the field. *Carley KM.* and *Farkas J.* also show steady output. It can be observed that *Carley KM.* has contributed consistently over the years and has increased their number of publications in the later stages of the timeline. Furthermore, *Bastos M.*, *Chadwick A.*, and *Herrero-Diz P.* have more sporadic publication patterns, which also reflect their overall number of publications, while the remainder of the authors have mainly made their contributions in recent years.

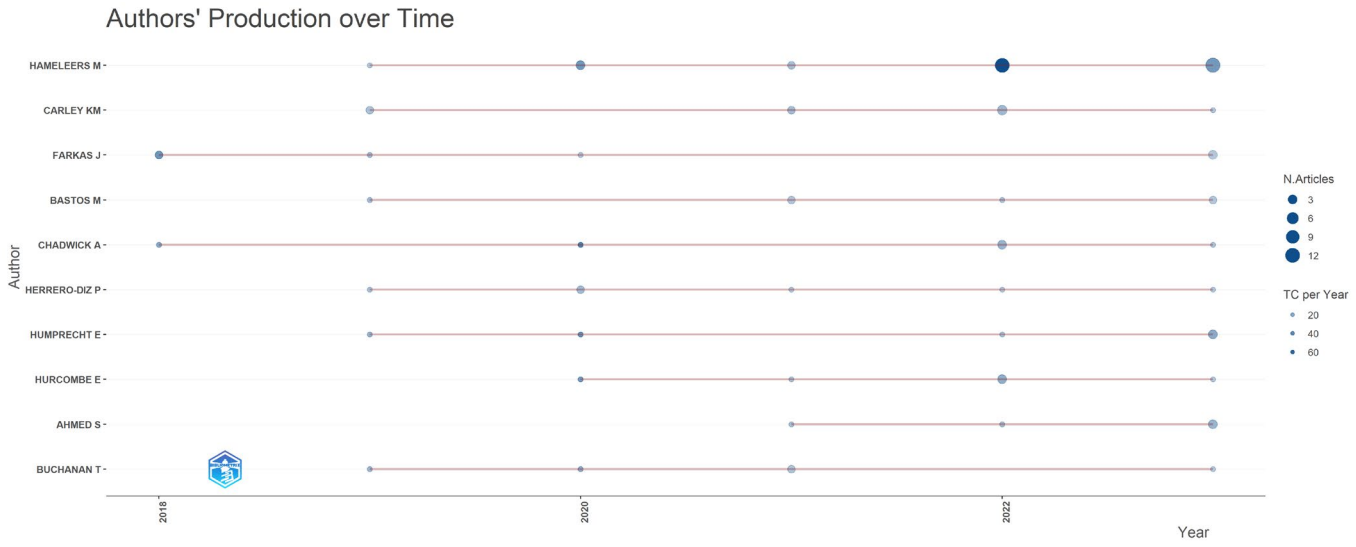

Figure 8. Top 10 authors' production over time.

3.4. Countries

In order to have an overview of the domain, the scientific production of different countries must be investigated, and this is strongly correlated with the investigation into authors.

Figure 9 reveals which are the most influential countries in the disinformation domain and illustrates the distribution of the publications from two different perspectives: the first approach investigates Single-Country Publications (SCPs), while the second one focuses on Multiple-Country Publications (MCPs).

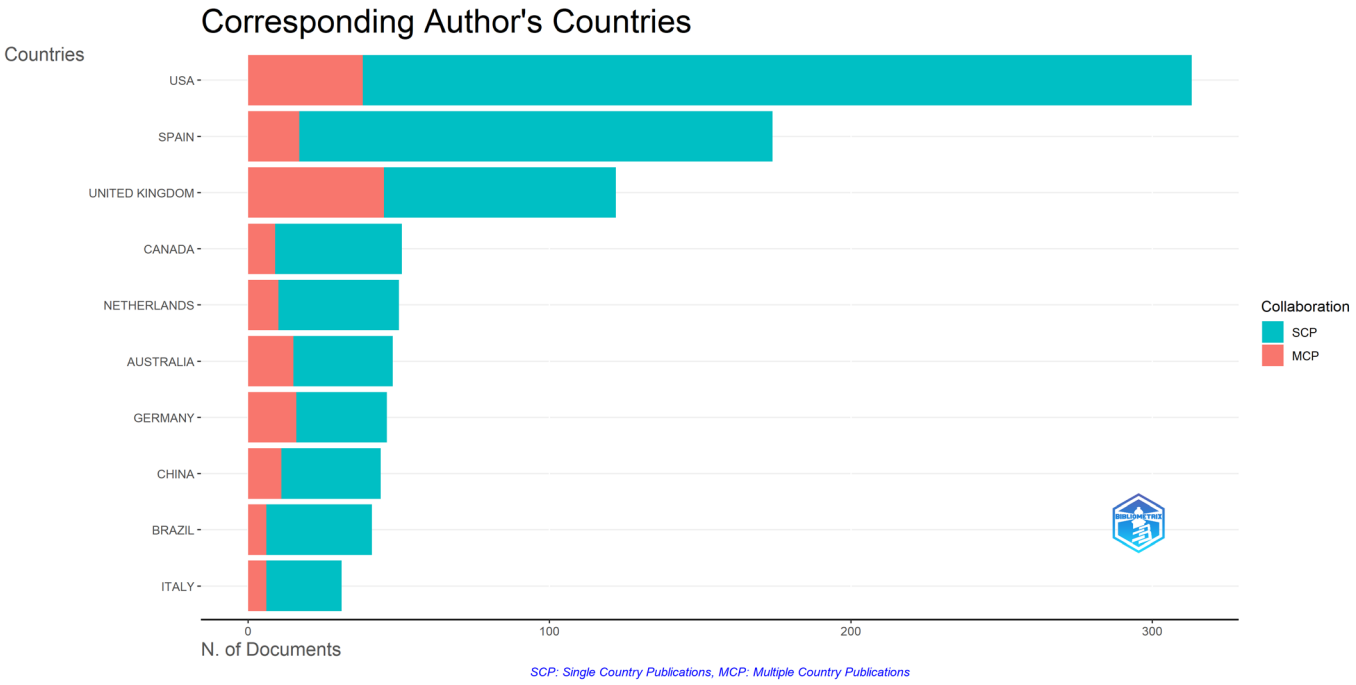

Figure 9. Top 10 most relevant countries in terms of corresponding authors.

The country that has published the greatest number of papers is the USA, with 313 articles, which represents 22.5% of the total papers published. Most of the papers (275 or 87.9%) are SCPs, which shows the interest of USA authors in the domain. Only 38 papers

(12.1%) are MCPs. In second place is Spain, with 174 articles published, of which 167 are SCPs (90.2%) and only 17 are MCPs (9.8%), representing 12.5% of the total articles published. The UK is in third place, accounting for 8.8% of the total articles published. Of its total of 122 articles, 77 are SCPs (63.1%) and 45 are MCPs (36.9%), representing the highest value for MCPs within the top 10, indicating a preference among UK authors towards collaboration. Canada published 51 papers, representing only 3.7% of all papers, with 42 of them being SCPs (82.4%) and 9 being MCPs (17.6%). The Netherlands published only 50 documents during the analyzed timespan, 40 of which are SCPs (80%) and 10 are MCPs (20%), for a total percentage of 3.6%. Australia has 46 publications, 33 of which are SCPs (68.7%) and 15 are MCPs (31.3%), for a total percentage of 3.4%. Germany has 46 articles, which is 3.3% of the total papers published. German authors have published 30 single-author papers (65.2%) and 16 MCPs (34.8%), which is the second highest value after the UK, describing the initial steps of German authors into the new area of disinformation. China has 44 publications, 33 SCPs (75%) and 11 MCPs (25%), resulting in a total percentage of 3.2%. Brazil has published 41 documents, which represents only 2.9%; 35 of them (85.4%) are SCPs and 6 MCPs (14.6%). The last country in the top 10 is Italy, which has 31 papers, 25 SCPs (80.6%) and 6 MCPs (19.4%), representing 2.2% of the total papers published. Akram et al. [38] obtained similar results in their research, identifying the USA as the most influential country.

Figure 10 explores these countries' scientific production, offering a perspective regarding the number of appearances of their authors in academic articles [65]. It should be noted that, in Figure 10, the countries have been depicted in shades of blue based on their number of publications in the disinformation domain. As a result, the countries shown in dark blue have had the highest contributions, while different shades of light blue depict a medium-to-lower contribution. Furthermore, the countries in gray have made no contribution in terms of publishing papers in the disinformation domain.

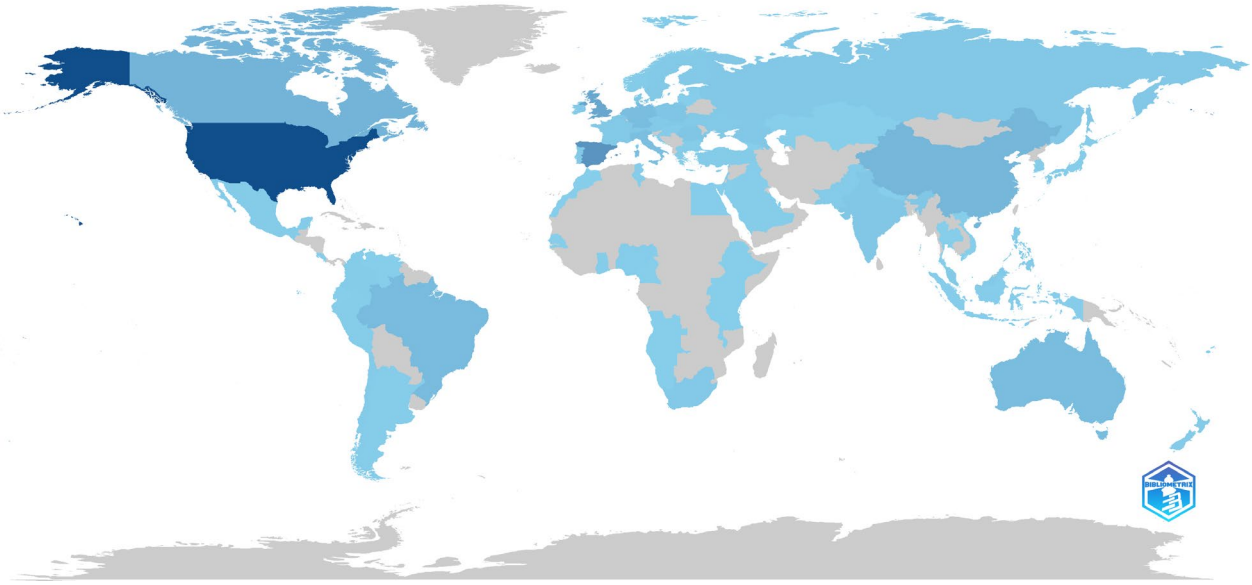

Figure 10. Scientific production based on country.

The most important country is the USA, which had authors on 754 papers, followed by Spain with 329 articles. The UK ranks third, with a total of 217, while Canada is fourth with 142, China fifth with 127, and Brazil sixth with 103. The rest of the countries have authors on less than 100 papers, and their impact is smaller, but it is also important to mention them: Australia, with 96 appearances; Germany, with 95; Netherlands, with 90; and Italy, with 83.

Figure 11 encompasses one of the most crucial elements of a bibliometric analysis, namely the most cited countries. Based on this information, some patterns can be observed. The USA is the most cited country, with 6758 citations, making it the leading country in the disinformation domain, followed at a significant difference by the UK, with 3053 citations. The difference between second and third position is also significant, 2110 citations, which shows the smaller impact of the rest of the countries. Spain is third with 943 citations, followed by the Netherlands with 684 citations, Germany with 664 citations, and Australia with 650. Canada has 474 citations, Sweden 374, Switzerland 373, and the last country in the top 10 is Singapore, with 359 citations.

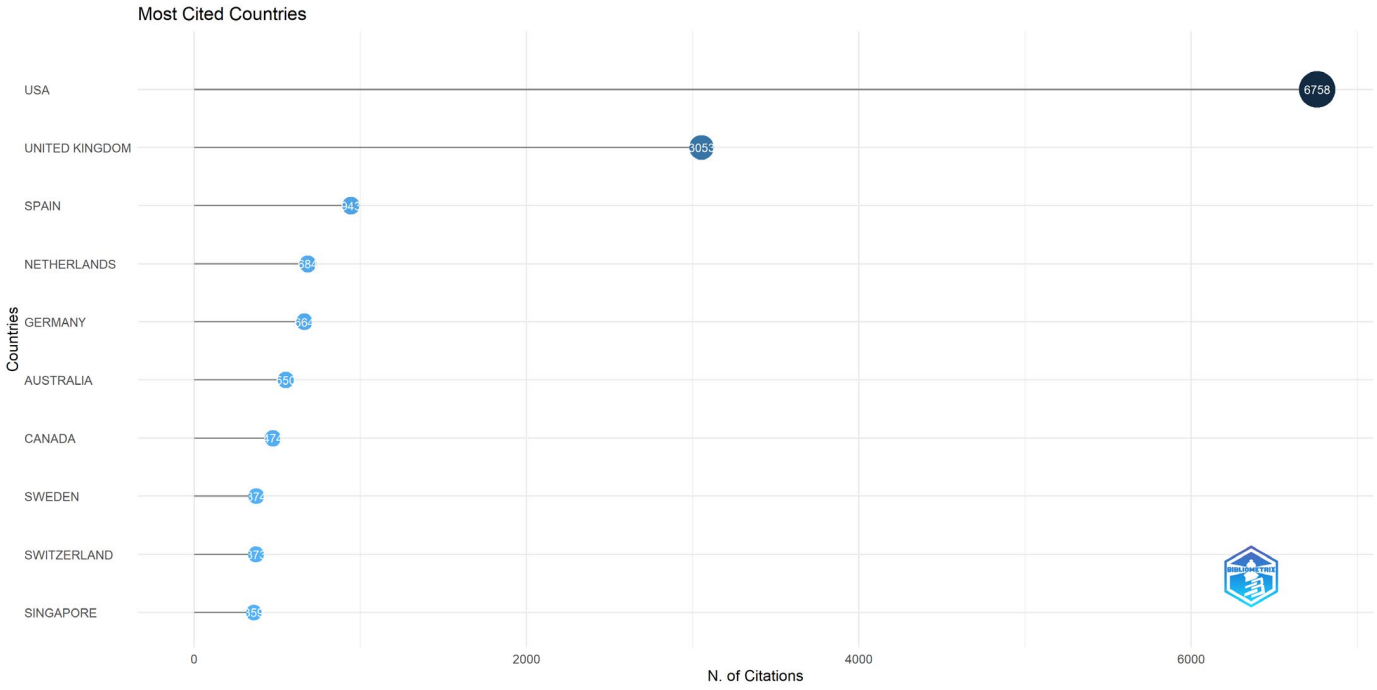

Figure 11. Top 10 countries with the most citations.

3.5. Collaboration

As authors collaborate, the evolution of the domain continues. In this section, the most important collaborations between countries and authors will be described.

Figure 12 highlights the collaboration between countries. In Figure 10, countries are colored in shades of blue (from dark blue to light blue) or gray based on the number of papers they have contributed to the disinformation domain according to the extracted dataset. Furthermore, the lines in red depict the collaboration between countries—the thickness of the lines symbolizes the degree of collaboration.

Therefore, it can be observed that the most fruitful collaboration is between the USA and the UK, with a total of 20 papers published. The second most important collaboration is between the UK and Germany, generating 15 documents, followed by the USA and China, which led to 14 publications. The USA and Australia have co-authored 12 papers together, while the USA and Germany have generated 12 articles. The UK and Australia collaborated on creating 11 documents and the USA and Canada worked on publishing 10 scientific articles, while UK and Canada published 9 papers together. The last two collaborations are between the UK and the Netherlands and the UK and South Africa, leading to nine and eight papers each.

Figure 13 displays the 50 most important authors grouped into nine clusters, creating a collaboration network. The size of the text corresponds to the contribution of an author—in terms of the number of papers published—to the disinformation field. As expected from

the above analysis, it has been noted that the author *Hameleers M.* has been depicted in the figure using a larger font.

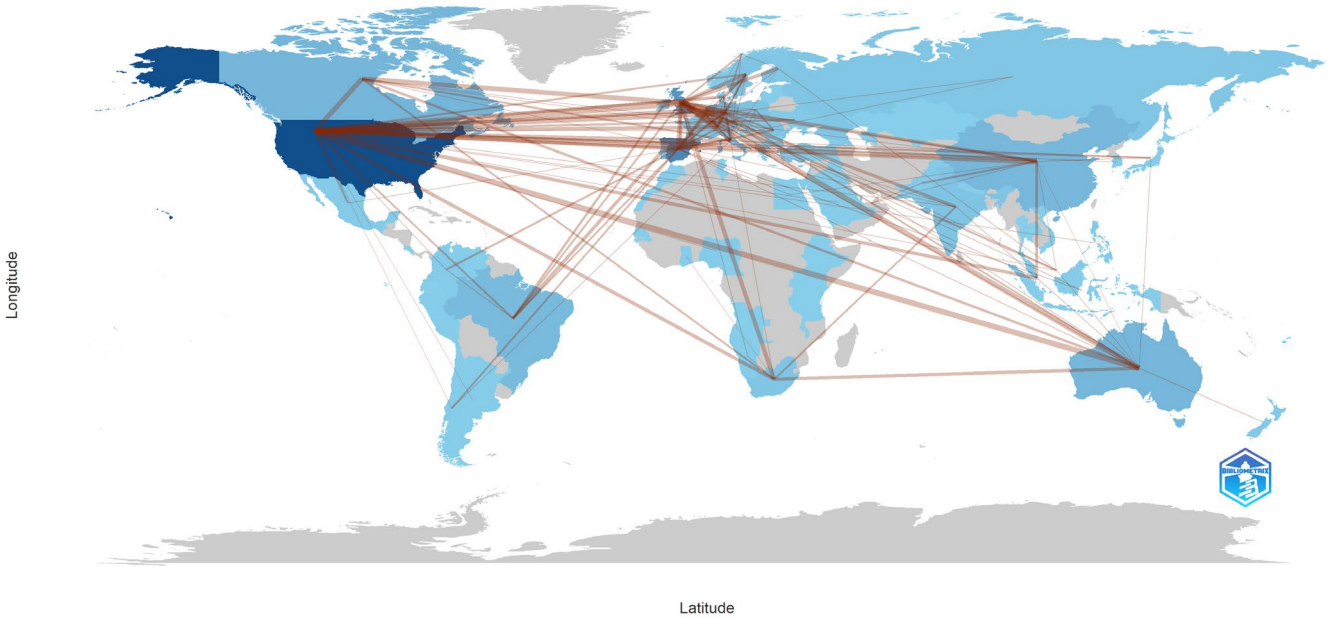

Figure 12. Country collaboration map.

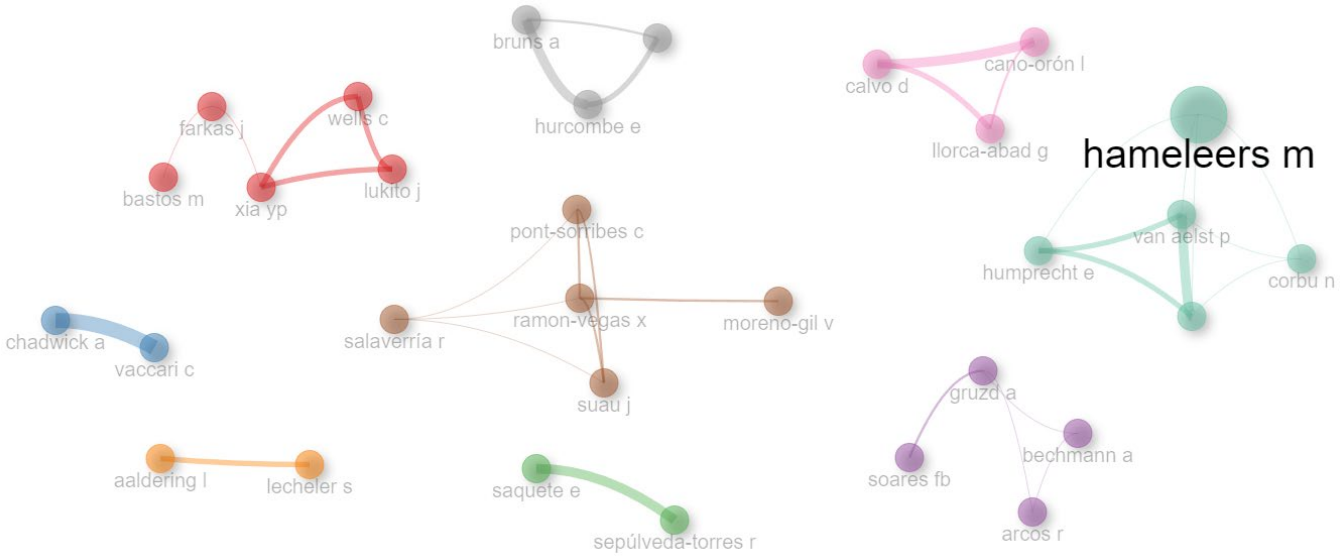

Figure 13. Collaboration network of the top 50 authors.

In the following section, we will describe the nine clusters in terms of the authors involved and their research conducted in the field of disinformation.

Cluster #1, depicted in turquoise, contains the following authors: *Hameleers M.*, *Humprecht E.*, *Corbu N.*, *Esser F.*, and *Van Aelst P.* Their research primarily focuses on populist disinformation in the Netherlands and the consequences of disinformation in terms of cross-national resilience [66–68].

Cluster #2, highlighted in red, is formed by *Farkas J.*, *Bastos M.*, *Lukito J.*, *Wells C.*, and *Xia YP.* The authors explore the propaganda which is promoted on the internet, especially in the USA's presidential elections, and what the impact of social media disinformation is [69,70].

Cluster #3, colored in blue, contains *Chadwick A.* and *Vaccari C.*, and their main focus is on analyzing the impact of deepfakes and disinformation on politics in Russia, the UK and elections held in 2019 in the UK [71–73].

Cluster #4 is formed by just two authors, *Saquete E.* and *Sepulveda-Torres R.*, and highlighted in green. Their work is mainly on identifying methods of detecting disinformation using automated recognition methods [74,75].

Cluster #5, colored in purple, contains *Bechmann A.*, *Gruzd A.*, *Soares FB.*, and *Arcos R.* Their published papers explore COVID-19 disinformation, Russian propaganda, and potential exposures to COVID-19 anti-vaccine videos [76–79].

Cluster #6, colored in yellow, is formed by two authors, *Lecheler S.* and *Aaldering I.* They explore the impact of disinformation on the EU and how the attitudes of politicians promote disinformation [80,81].

Cluster #7, highlighted in brown, contains *Moreno-Gli V.*, *Salaverria R.*, *Pont-Sorribes C.*, *Ramon-Vegas X.*, and *Suau J.* These authors analyze the influence of age and education level on identifying disinformation in Spain, how the disinformation research domain will evolve in the future, and how disinformation can affect diplomacy [82,83].

Cluster #8, colored in pink, is represented by *Calvo D.*, *Cano-Oron I.*, and *Llorca-Abad G.* These researchers analyze the Catalan conflict on Twitter, disinformation in Spanish mass media, Spanish general elections, and developing models using AI that can detect disinformation and misinformation [84–87].

Cluster #9, highlighted in gray in the top part of Figure 13, contains three authors, *Bruns A.*, *Angus D.*, and *Hurcombe E.* These authors analyze the dynamics of tweets related to COVID-19 restrictions and how information is shared on Facebook [88,89].

3.6. Analysis of the Literature

A crucial step to understanding how the has domain evolved is to investigate the top 10 most globally cited documents, presenting their approaches and the objectives of this research.

3.6.1. Top 10 Most Cited Papers—Overview

In the forthcoming section, we will focus on the most cited articles within the disinformation domain, with a focus on identifying the distinct contributions of each author. Table 8 presents an overview of the top 10 most globally cited documents, including details on the number of authors, their area, total citations (TCs), total citations per year (TCY), normalized total citations (NTCs), number of self-citations, and % of self-citation. It is noted that while the TC and TCY indicators are self-evident, the NTC indicator should be further explained. In order to determine the value for the NTCs, one should divide the number of citations of a paper by the average number of citations received for the papers published in the same year as the analyzed paper that are included in the dataset.

It is worth noting that the United States leads with six entries, followed by the United Kingdom and Germany with one entry each, with China, Pakistan, Ireland, Australia, Turkey and Bosnia and Herzegovina together contributing one entry.

With a citation count per year (TCY) of 83.43 and a total of 584 citations (TCs), Bennett and Livingston's paper [3] is the most cited. Nonetheless, this article's normalized total citations (NTCs) of 9.29 are rather low. Comparatively speaking, this value is less than the NTCs noted for the other products in Table 7. This statistic offers a more meaningful foundation for assessing the impact of citations and assists in accounting for differences in citation patterns among fields. Using the average number of citations per paper found in the database for the year the article was published, the NTC metric seeks to award equal credit for citations to each author of an article. For instance, our statistics show that the 19 articles published in 2018 received 62.87 citations annually on average. The NTCs were calculated by dividing the TCd of the Bennett and Livingston [3] publication, a two-authored work with 584 total citations, by the average citation count (62.87) of all 19 papers published in the same year. Bennett and Livingston's [3] NTC is therefore 9.29.

This method was also used in another 2020 paper, the one authored by Zhou et al. [4] and rated second in terms of TCs. By dividing TCs (403 citations) by the average number of citations for 2020, an NTC value of 13.55 was achieved.

Furthermore, in terms of the number of self-citations, it can be observed that in the case of the papers listed in the top 10 most globally cited documents, this number usually ranges beween 0 and 9, with an exception for the papers located in the third and seventh positions, where the number of self-citations is higher, namely 13 and 34, respectively. Consequently, usually, the percentage of self-citations within the top 10 most globally cited documents ranges between 0.00% and 3.66%, with an exception represented by the paper authored by Su et al. [90], whose self-citations come to a total of 14.16% of their citation number. It should be noted that these self-citations have been manually found based on the citations made by all authors on the paper and not only the first author, and these self-citations have only been considered within the period from which the data were extracted.

3.6.2. Top 10 Most Cited Papers—Review

In the first article, Bennett and Livingston [91] bring to light the problem of fake news in the field of politics, which is on the rise. The authors present the problem of political websites that try to imitate the format of news journals. Usually, these actions are associated with far-right parties, which try to manipulate supporters to turn against other political ideologies. As a result, the trust of many citizens is steadily decreasing, and the public is trying to seek alternative sources of information. These alternative sources of information play a crucial role in misinforming and manipulating voters, as they are predominantly associated with nationalist movements but could also represent foreign interventions. They are designed to destabilize governments and create propaganda, thus undermining the government's authority. Among the most popular examples mentioned in the article are the UK's Brexit from the European Union and the election of US President Donald Trump in 2016.

The study published by Zhou [92] discuss the urgent need for the detection of fake news, emphasizing the negative effects that fake news can bring to various fields, such as justice and politics. It analyzes the detection of fake articles from four different perspectives: the level of false information, writing style, propagation patterns, and the credibility of the sources. Another topic touched on in this article is the expansion of online news due to social networks and social media. These types of online sites have much faster dissemination rates and lower dissemination costs than traditional media. Fake news also has a major effect on stock markets and the global economy. One example of fake news that has influenced the stock market, causing losses of more than USD 130 billion involves Barack Obama, the 44th president of the United States, who was alleged to have died in an explosion. Another example would be the story of some young adults in Macedonia who made around USD 60.000 each, according to NBC, due to the creation of various fake news stories during the US presidential election.

Zubiaga et al. [93] discuss the impact of social media platforms on spreading false or misleading information. At present, news is spreading much more frequently online, and media platforms are the most common platform for spreading news. At the same time, we can use these platforms to collect data and validate it using natural language processing techniques. With this paper, the authors aimed to create a rumor classification system that consists of four components: rumor detection, rumor tracking, rumor stance classification, and rumor veracity classification. Also, another very important aspect in this paper is the division of rumors into two classes, namely, long-lived rumors and short-lived rumors. In the case of short-lived rumors, they are usually breaking news, and their sources are not verified. In contrast, long-lived rumors occur over long periods of time.

Table 8. Top 10 most globally cited documents.

No.	Paper (First Author, Year, Journal, Reference)	Number of Authors	Region	Total Citations (TCs)	Total Citations Per Year (TCY)	Normalized TCs (NTCs)	Number of Self-Citations	% of Self-Citations
1	Bennett WL., 2018, *European Journal of Communication* [91]	2	USA	584	83.43	9.29	2	0.34%
2	Zhou XY., 2020, *ACM Journals* [92]	2	USA	403	80.60	13.55	4	0.99%
3	Zubiaga A., 2018, *ACM Journals* [93]	4	UK, Germany	395	56.43	6.28	13	3.29%
4	Scheufele DA., 2019, *Proceedings of the National Academy of Sciences* [94]	2	USA	386	64.33	14.04	8	2.07%
5	Shu K, 2020, *Big Data* [95]	5	USA	288	57.60	9.68	9	3.12%
6	Jones-Jang SM., 2021, *American Behavioral Scientist* [96]	3	USA	254	63.50	18.56	0	0.00%
7	Su ZH., 2021, *Globalization and Health* [90]	12	USA, China, Pakistan, Ireland, Australia, Turkey, Bosnia and Hertegovina	240	60.00	17.53	34	14.16%
8	Freelon D., 2020, *Political Communication* [97]	2	USA	220	44.00	7.40	1	0.45%
9	Supran G, 2017, *Environmental Research Letters* [98]	2	USA	218	27.25	5.04	8	3.66%
10	Vaccari C, 2020, *Social Media + Society* [72]	2	UK	217	43.40	7.30	2	0.92%

The study conducted by Scheufele and Krause [94] is specific to misinformation occurring at the U.S. level and encompasses several domains of interest, from politics to science-related fields. Their study highlighted that the detection of misinformation depends on everyone's motivation to try and detect fake news. However, other external groups and societal factors could increase the chances of detecting it.

Databases are the main topic that Shu et al. [95] investigated. Although there are different shortcomings at the computational level, they consider one of the main problems that exists at the level of false content detection in the online environment to be the limited databases on which models are trained. At this level, two problems of major interest have been observed; datasets are often sparse and non-contiguous. Moreover, the datasets often lack a multitude of critical features, such as social context and various spatial–temporal information. Thus, the researchers of this paper created a data warehouse for training models called FakeNewsNet. This repository contains two datasets with social context and spatial–temporal information. The article describes this dataset, the benefits it brings to the scientific world, and potential applications that could utilize the newly created database.

The article published by Jones-Jang [96] is concerned with the media literacy of the population. The increasing number of fake articles that we find online encourages us to find various solutions in the fight against deepfakes. Thus, in the article they study whether a higher degree of public literacy will also help in recognizing fake news. After conducting various studies, it was concluded that a higher degree of information literacy (but not other literacies) would have a positive impact on the identification of fake news. Information literacy is defined as the ability of an individual to search for, critically analyze, and filter available information to avoid misinformation and other fake news.

Su et al. [90] studied how the communication of information during a major crisis happening across a whole society can cause problems for the mental health of individuals. In particular, they analyzed the COVID-19 pandemic and its global effects, which started in 2019. The authors argue that during the pandemic, the plethora of news that was published online about high death rates and exponentially increasing infection cases led to the imminent rise of the risk of mental health problems. Thus, due to the premature dissemination of information through media channels and clickbait news, major crises in society may also impact the mindset of all individuals. Thus, the need for research on improving communication between media channels and the public in moments of major risk for society is a must. A collaborative environment between media representatives is also desired so that information can be person-centered. In this way, crisis moments can be resolved as quickly as possible, and the wellbeing of individuals will not be affected.

Freelon and Wells [97] introduced us again to the world of disinformation in politics. The article is divided into four sections of interest in order to have a better understanding of disinformation from different perspectives. Section 1 discusses the disinformation that occurs in political communication. Section 2 deals with a historical analysis of the issues in communication, with a focus around the new ones that have been discussed from 2016 to the present. The third point of the list is the classification of the findings in two categories: studies on disinformation's content and studies of disinformation's reception. Section 4 presents suggestions for the scientific world for further research on disinformation.

Supran and Oreskes [98] study the case of the ExxonMobil Corporation, which is alleged to have misled society about global climate changes. In their analysis, they studied more than 187 communications, including advertorials published by The New York Times. Advertorials are paid advertisements that are written and published in an editorial style. The study concluded that 80 of ExxonMobil's internal documents acknowledged that climate change is due to human intervention. In contrast, of the advertorials produced by The New York Times, only 12% recognize this, casting doubt on the subject. Thus, by looking at this case study it is possible to analyze the phenomenon of deception at the macro level and how it affects society.

Vaccari and Chadwick [72] explore the insecurity generated among the public by false online stories. In a study carried out in the United Kingdom, it was observed that

among a large sample of the population, users tend to be insecure and their trust of social networks tends to be low. Political deepfakes play an important role in changing the public opinion of society and will become more and more crucial, as companies focus on creating AI software tools which generate synthetic representations of humans. Journalists must constantly check the authenticity of their information and inform the public about the potential danger. At the same time, AI can be used for education, demonstrating the potential of political deepfakes, and increasing trust in news or social media, as the authors presented. This is exemplified by two videos made by artificial intelligence. One of these videos depicts Barack Obama insulting his political rival Donald Trump, while the other depicts the kidnapping of a child in India.

Table 9 describes the most cited 10 documents, the data that have been analyzed, the title of the article, and the purpose of the research.

Table 10 investigates the most cited documents that included a case study related to the analyzed domain.

The most cited paper was published by Humprecht et al. [99] and it focuses on online disinformation, which is becoming more and more dangerous for democracies. The initial assumption of the authors was that some countries are more resilient than others to online disinformation. A framework was used to compare different countries' conditions, and then the importance of quantifiable indicators was measured in 18 Western countries and the results grouped the countries into two different categories based on online disinformation. The first group had a high resilience, and it included Northern European countries, while low resilience was found in Southern European countries and the USA. In the final part of their analysis, a comparative review of political speeches was conducted. In total, there are three authors from Switzerland and Belgium, who have a total of 158 citations, with a total citations per year of 31.60 and a normalized total citation of 5.31.

Farkas et al. [100] suggest that fake information has become more and more relevant, especially in politics, offering examples of Donald Trump when he was the president of the USA. They used data from social media between November 2016 and March 2017, as well as articles from various newspapers and magazines such as *The Washington Post*, *The New York Times*, *The Wall Street Journal*, and many others. The aim of the research was to point out the political struggles that fake information is promoting and what the consequences are. In total, two authors from Sweden contributed to the paper, which obtained a total of 152 citations, with an average yearly citation of 21.71 and a normalized total citation of 2.24.

Tandoc et al. [101] investigated the behavior of social media users responding to disinformation, analyzing 2501 responses from Singapore. The majority of the social media users in Singapore ignore social media disinformation and corrections appear only when the problem is relevant to them or their close friends. Other participants confirmed that they respond to disinformation only when they are interested in the topic, because they might not be emotionally connected to the news or they lack motivation. Social media platforms have started to implement fact-checkers in order to reduce the amount of disinformation on their sites. In total, three authors from Singapore contributed, with a total citation of 141, an average annual citation of 28.20, and a normalized total citation of 4.74.

Jaiswal et al. [102] detailed the problems that public health systems had during the COVID-19 pandemic. The lack of consistency, the fear, uncertainty, social media pressure, prevention methods, and treatments that were promoted increased people's frustration level. Disinformation occurred mainly when the COVID-19 vaccine appeared. One of the main problems was the promotion of disinformation by the federal government, and this inequality created false opinions. Conspiracy theories, which constantly try to explain the cause of an event and are strongly correlated with disinformation, make it more and more difficult to change people's opinions, even if evidence is presented, since sometimes experts also promote conspiracies. Upon analysis, three authors from the USA participated, obtaining a total of 140 citations, with an average yearly citation of 28 and a normalized total citation of 4.71.

Table 9. Brief summary of the content of top 10 most globally cited documents.

No.	Paper (First Author, Year, Journal, Reference)	Title	Data	Purpose
1	Bennett WL., 2018, *European Journal of Communication* [91]	The disinformation order: Disruptive communication and the decline of democratic institutions	-	To present the threats of deepfake technology in the field of politics.
2	Zhou XY., 2020, *ACM Journals* [92]	A Survey of Fake News: Fundamental Theories, Detection Methods, and Opportunities	Authors did not use data; they explained the concepts in a theoretical manner.	To analyze the detection of fake articles from different perspectives.
3	Zubiaga A., 2018, *ACM Journals* [93]	Detection and Resolution of Rumours in Social Media: A Survey	Authors used multiple databases: some of them are public (PHEME, Ferreira, and Vlachos) and some are private.	To discuss the impact of social media platforms in spreading false or misleading information.
4	Scheufele DA., 2019, *Proceedings of the National Academy of Sciences* [94]	Science audiences, misinformation, and fake news	The authors did not use data; they explained the concepts in a theoretical manner.	To present the misinformation occurring in politics and science-related fields.
5	Shu K, 2020, *Big Data* [95]	FakeNewsNet: A Data Repository with News Content, Social Context, and Spatiotemporal Information for Studying Fake News on Social Media	-	To present the benefits of the FakeNewsNet database brings to the scientific community.
6	Jones-Jang SM., 2021, *American Behavioral Scientist* [96]	Does Media Literacy Help Identification of Fake News? Information Literacy Helps, but Other Literacies Don't	Authors used a demographically diverse panel consisting of 1299 participants in an online survey administrated by Survey Sampling International (SSI).	Concerned with the media literacy of the population.
7	Su ZH., 2021, *Globalization and Health* [90]	Mental health consequences of COVID-19 media coverage: the need for effective crisis communication practices	The authors did not use data; they explained the concepts in a theoretical manner.	To study how the communication of information during a major crisis can cause mental health problems for individuals.
8	Freelon D., 2020, *Political Communication* [97]	Disinformation as Political Communication	The authors did not use data; they explained the concepts in a theoretical manner.	To present the threats of deepfake technology in the field of politics.
9	Supran G, 2017, *Environmental Research Letters* [98]	Assessing ExxonMobil's climate change communication	Authors used 36 AGW-relevant advertorials. Moreover, they used 1412 documents yielded from two Boolean ProQuest searches.	To study the case of the ExxonMobil Corporation, which is alleged to have misled society about global climate change.
10	Vaccari C, 2020, *Social Media + Society* [72]	Deepfakes and Disinformation: Exploring the Impact of Synthetic Political Video on Deception, Uncertainty, and Trust in News	The authors assessed a representative sample of 2005 respondents to three variants of the BuzzFeed Obama/Peele video (two of which were deceptive, one of which contained an educational reveal).	To explore the insecurity generated among the public by false online stories.

Bruns et al. [103] explored the dynamics of the COVID-19 pandemic's outbreak and its correlation with 5G technology in Wuhan and all around the world by performing a time series analysis combined with quantitative and qualitative investigations. The scope of the research included presenting rumors from Facebook groups. The analysis of disinformation could offer a perspective on new possibilities for mitigating the distribution of false information. The data that were used were collected from a Facebook platform called CrowdTangle. Multiple analyses had to be performed in order to create a pattern and identify specific processes that could be used to counteract the disinformation. In total, three authors from Australia contributed to the paper, which had a total of 137 citations, with an average yearly citation of 27.40 and a normalized total citation of 4.61.

Chadwick et al. [104] compared the tabloid news and disinformation and misinformation behaviors from social media platforms by taking into consideration four different datasets—17,989 web domains, 641 articles, 1,525,748 shared news, and 1313 Twitter users that responded to a survey—related to the 2017 UK election campaign. Using a novel method to investigate the data, the results obtained provided a perspective about tabloid news that is shared on social media which reflects a dysfunctional democracy, combined with disinformation and misinformation, this has a serious impact on society.

Keller et al. [105] analyzed the South Korean National Information Services (NIS) disinformation campaign that occurred during the 2012 presidential election, collecting information from Twitter. Using a methodology that had been defined during their research, the results confirmed that the NIS accounts had a limited impact on social media. The authors also developed a method that detects disinformation campaigns, identifying over 1008 Twitter accounts that were run by NIS agents. Thanks to the principal–agent framework, the accuracy of identifying disinformation campaigns increased. In total, four authors from Hong Kong, the UK, Germany, and the USA worked on the research, which obtained a total of 127 citations, with an annual citation of 25.40 and a normalized total citation of 4.27.

Ross and Rivers [106] focused on the 2016 US presidential elections, and especially on Donald Trump's Twitter usage, where a large amount of disinformation and misinformation was spread. Using the Fire Ant software tool AMD Political Twitter Discourse Corpus, the data that were collected between 9 November 2016 and 7 August 2017 confirmed that numerous pieces of disinformation and misinformation were distributed via social media platforms. The numerous times Donald Trump accuses media platforms of things in his tweets force the viewer to observe his tweets from a different perspective. In total, there were two authors from Australia that contributed to the paper, which has a total of 111 citations, with an average citations per year of 15.86 and a normalized total citation of 1.77.

Basch et al. explored the disinformation and misinformation that was spread through TikTok during the COVID-19 pandemic about vaccinations. The scope of the analysis was analyzing the content that has been published on TikTok related to COVID-19 vaccines, with the videos filtered based on hashtags such as #covidvaccine. Over 100 videos which had 35 million views were included; only 36 of them promoted the vaccine, while 38 of them discouraged people from getting the vaccination. A total of 22 videos out of 38 shared, wrongly, that a vaccine was already available, even if the scientists did not start the research, which generally affected young people. There were five authors that contributed to the research, all from the USA, leading to a total of 98 citations, with a total citations per year of 24.50 and a normalized total citation of 7.16.

Zimmerman and Kohring [107] detailed the main factors that sustain disinformation, even if the problem did not raise serious concerns. A panel survey that focused on the 2017 German parliamentary election was performed, collecting a total of 989 responses. The results show that disinformation has a significant impact, driving the voters from main governing parties such as CDU or CSU to right-wing populists' parties such as AfD. The lack of trust in politics and news means a higher trust in online disinformation. There were two authors from Germany that worked on the research, which obtained a total of 96 citations, with an average citations per year of 19.20 and a normalized total citation of 3.23.

Table 10. Top 10 most globally cited documents covering case studies.

No.	Paper (First Author, Year, Journal, Reference)	Number of Authors	Region	Total Citations (TCs)	Total Citations Per Year (TCY)	Normalized TCs (NTCs)	Number of Self-Citations	% of Self-Citations
1	Humprecht, E., 2020, *The International Journal of Press/Politics* [67]	3	Switzerland, Belgium	158	31.60	5.31	9	5.69%
2	Farkas, J., 2018, *Javnost—The Public* [100]	2	Sweden	152	21.71	2.24	4	2.63%
3	Tandoc, EC., 2020, *Journalism*, [101]	3	Singapore	141	28.20	4.74	2	1.41%
4	Jaiswal, J., 2020, *AIDS and Behavior*, [102]	3	USA	140	28.00	4.71	4	2.85%
5	Bruns, A., 2020, *Media International Australia* [103]	3	Australia	137	27.40	4.61	4	2.91%
6	Chadwick, A., 2018, *New Media & Society* [104]	3	UK	136	19.43	2.16	10	7.35%
7	Keller, FB., 2020, *Political Communication* [105]	4	Hong Kong, UK, Germany, USA	127	25.40	4.27	1	0.78%
8	Ross, AW, 2018, *Social Media + Society* [106]	2	Australia	111	15.86	1.77	2	1.80%
9	Basch CH., 2021, *Human Vaccines & Imunotherapeutics* [108]	5	USA	98	24.50	7.16	9	9.18%
10	Zimmerman F., 2020, *Political Communication*	2	Germany	96	19.20	3.23	0	0.00%

The number of self-citations and the percentage of self-citations have also been evaluated. The highest number of self-citations was registered for the paper published by Chadwick et al. [104], with 10 self-citations, which represents only 7.35% of the paper's total citations. On the other hand, the highest percentage of self-citations was recorded for the paper authored by Basch et al. [108], where a percentage of self-citatios of 9.18% was determined. The remainder of the papers have less than 6% self-citations.

Table 11 presents the most cited papers containing case studies, together with their titles, the data that have been used, and the scope of the research.

Table 11. Brief summary of the content of top 10 most globally cited documents containing case studies.

No.	Paper (First Author, Year, Journal, Reference)	Title	Data	Purpose
1	Humprecht, E., 2020, *The International Journal of Press/Politics* [67]	Resilience to Online Disinformation: A Framework for Cross-National Comparative Research	Quantifiable indicators related to the resilience to online disinformation of 18 Western countries	To group countries based on their level of resilience to online disinformation
2	Farkas, J., 2018, *Javnost—The Public* [100]	Fake News as a Floating Signifier: Hegemony, Antagonism and the Politics of Falsehood	Social media posts that have been published between November 2016 and March 2017	To present the impact of fake information that has been spread through social media, promoting attacks or discreditation
3	Tandoc, EC., 2020, *Journalism*, [101]	Diffusion of disinformation: How social media users respond to fake news and why	Survey including 2501 respondents from Singapore	To explore social media users' activity and to understand the diffusion of disinformation
4	Jaiswal, J., 2020, *AIDS and Behavior*, [102]	Disinformation, Misinformation and Inequality-Driven Mistrust in the Time of COVID-19: Lessons Unlearned from AIDS Denialism	Opinions that were promoted during the COVID-19 pandemic	To explore the impact of disinformation during a critical period for humanity, the COVID-19 pandemic
5	Bruns, A., 2020, *Media International Australia* [103]	'Corona? 5G? or both?': the dynamics of COVID-19/5G conspiracy theories on Facebook	Facebook metrics from the CrowdTangle platform	To investigate the COVID-19 and 5G disinformation stories that had a significant impact on society
6	Chadwick, A., 2018, *New Media & Society* [104]	Do tabloids poison the well of social media? Explaining democratically dysfunctional news sharing	Twitter data related to the 2017 UK election campaign, together with domains, a survey of Twitter users, and articles	To express the consequences of disinformation from social media platforms, which led to a dysfunctional democracy
7	Keller, FB., 2020, *Political Communication* [105]	Political Astroturfing on Twitter: How to Coordinate a Disinformation Campaign	Twitter data	To evaluate the impact of disinformation on Twitter, by taking the South Korean National Information Service as an example
8	Ross, AW, 2018, *Social Media + Society* [106]	Discursive Deflection: Accusation of "Fake News" and the Spread of Mis- and Disinformation in the Tweets of President Trump	Tweets from between 9 November 2016 and 7 August 2017, all related to Donald Trump	To perform an analysis in order to extract the most used terms in Trump's tweets and to compare his tweets with typical tweets of other politicians
9	Basch CH., 2021, *Human Vaccines & Imunotherapeutics* [108]	A global pandemic in the time of viral memes: COVID-19 vaccine misinformation and disinformation on TikTok	TikTok videos	To explore the TikTok content related to the COVID-19 vaccine and to understand the impact of disinformation on young people
10	Zimmerman F., 2020, *Political Communication*	Mistrust, Disinforming News, and Vote Choice: A Panel Survey on the Origins and Consequences of Believing Disinformation in the 2017 German Parliamentary Election	Three-wave panel survey between 1st of July 2017 and 8th of August 2017	To highlight the main factors that contributed to disinformation in the 2017 German parliamentary election, while also explaining the impact of disinformation stories

3.6.3. Words Analysis

Table 12 contains the most frequently used keywords plus by the authors of the references cited in the selected papers. Here, it should be noted that keywords plus are a feature of the WoS platform, which extracts keywords plus (Keywords Plus® https://support.clarivate.com/ScientificandAcademicResearch/s/article/KeyWords-Plus-generation-creation-and-changes?language=en_US, accessed on 10 September 2024) from the titles of the papers cited in the references section in each paper. The most commonly used keyword plus is "*fake news*" which appeared 279 times; "*social media*" has a frequency of 235, and "*communication*" has been used in 103 papers. The next three keywords are strongly correlated, describing the process of communication and sharing data: "*information*" (96 appearances), "*misinformation*" (85 appearances), and "*disinformation*" (45 appearances). The rest of the keywords plus are less frequent; "*impact*" has 44 occurrences, "*politics*" has 41 appearances, "*trust*" has 41 occurrences, and "*science*" appeared 37 times. As can be observed, the mentioned keywords plus are related to the disinformation domain, describing the policies that should be implemented in order to stop the spread of fake news via social media, affecting, in a significant manner, our confidence in what is presented online.

Table 12. Top 10 most frequent words in keywords plus.

Words	Occurrences
Fake news	279
Social media	235
Communication	103
Information	96
Misinformation	85
Disinformation	45
Impact	44
Politics	41
Trust	41
Science	37

Table 13 explores the keywords used most frequently by authors. This is similar to the list that is presented in Table 12, which contains the most frequently used keywords plus by the authors of the cited references in the selected papers.

Table 13. Top 10 most frequent words appearing in authors' keywords.

Words	Occurrences
Disinformation	991
Fake news	339
Social media	335
Misinformation	315
COVID-19	160
Twitter	79
Fact-checking	73
Journalism	57
Infodemic	51
Propaganda	49

Table 12 was included in this table. The most common authors' keyword is *disinformation,* with 991 appearances, followed by *fake news* with 339 occurrences. Third is *social media,* with 335 occurrences, followed by *misinformation,* which appeared 315 times, and *COVID-19,* with 160 appearances. The rest of the words are less common: *Twitter* appeared 79 times, *fact-checking* 73 times, *journalism* 57 times, *infodemic* 51 times, and *propaganda* 49 times. These last words describe the environment (*Twitter*), the impact (*infodemic*, *propaganda*, *and journalism*), and the methods of combating disinformation (*fact-checking*).

Table 14 contains bigrams that are suitable for the disinformation domain, having removed those that are related to search terms and synonyms. In the first two columns are the 10 most relevant bigrams in the abstracts, while the last two contain the most important bigrams used in titles. The most common bigram found in the abstracts is "*fake news*" with 1208 appearances, followed by "*social media*" with 1199 occurrences, "*COVID-19*" with 268 appearances, "*conspiracy theories*" with 118 occurrences, "*content analysis*" with 92 occurrences, "*climate change*" with 76 occurrences, "*public opinion*" with 61 occurrences, "*hate speech*" with 47 occurrences, "*machine learning*" with 46 occurrences, and "*Artificial intelligence*" which has 40 occurrences. Regarding titles, the most used bigrams are "*Fake news*" (285 appearances), "*Social media*" (175 occurrences), "*COVID-19*" (81 occurrences), "*Conspiracy theories*" (22 occurrences), "*Artificial intelligence*" (12 occurrences), "*Machine learning*" (11 occurrences), "*Hate speech*" (10 occurrences), "*Climate change*" (9 occurrences), "*Content analysis*" (9 occurrences), and "*Disinformation detection*" (9 occurrences).

Table 14. Top 10 most frequent bigrams in abstracts and titles.

Bigrams in Abstracts	Occurrences	Bigrams in Titles	Occurrences
Fake news	1208	Fake news	285
Social media	1199	Social media	175
COVID-19	268	COVID-19	81
Conspiracy theories	118	Conspiracy theories	22
Content analysis	92	Artificial intelligence	12
Climate change	76	Machine learning	11
Public opinion	61	Hate speech	10
Hate speech	47	Climate change	9
Machine learning	46	Content analysis	9
Artificial intelligence	40	Disinformation detection	9

The bigrams found in the abstracts and titles are similar and describe the methods used to spread "*fake news*"—via "*social media*" platforms—while also presenting the various subjects that are debated: "*COVID-19*", "*conspiracy theories*" or "*climate change*". In this case, "*Artificial intelligence*" and "*Machine learning*" have both a positive and negative impact, since those two technologies facilitate the creation of fake news and disinformation, but, at the same time, are used to detect abnormal information through "*disinformation detection*" or "*content analysis*".

Table 15 presents the trigrams most often used in abstracts and titles, excluding related search terms and synonyms in the field of disinformation. Taking a look at first column, the most frequently used trigrams are "*Social media disinformation*" (137 occurrences), "*disinformation fake news*" (36 occurrences), "*Internet research agency*" (30 occurrences), "*Artificial intelligence ai*" (16 occurrences), "*European union eu*" (13 occurrences), "*social networks analysis*" (12 occurrences), "*Fake news detection*" (12 occurrences), "*COVID-19 theories*" (10 occurrences), "*climate change communications*" (9 occurrences), and "*Critical discourse analysis*" (8 occurrences).

The 10 trigrams most used in titles are presented in the second column. The most used trigrams here are "*Disinformation fake news*" (18 appearances), "*Social media disinformation*" (18 appearances), "*COVID-19 theories*" (11 appearances), "*Internet research agency*" (9 appearances), "*Media literacy education*" (5 appearances), "*Fake news detection*" (4 appearances), "*Climate change communications*" (4 appearances), "*Machine learning techniques*" (2 appearances), "*strengthening scientific credibility*" (2 appearances), and "*Social media analytics*" (2 appearances).

The trigrams describe, in general, the disinformation domain and fake news, presenting the most important platforms which help to spread the information and how researchers are trying to detect fake news. Exploring existing papers, Sandu et al. [109] and Sandu et al. [55] found similar trigrams to those in our research, such as "fake news

detection", "social media disinformation", and "machine learning algorithms", but we also found trigrams that describe the COVID-19 pandemic.

Table 15. Top 10 most frequent trigrams in abstracts and titles.

Trigrams in Abstracts	Occurrences	Trigrams in Titles	Occurrences
Social media disinformation	137	Disinformation fake news	18
Disinformation fake news	36	Social media disinformation	14
Internet research agency	30	COVID-19 theories	11
Artificial intelligence ai	16	Internet research agency	9
European union eu	13	Media literacy education	5
Fake news detection	12	Fake news detection	4
Social network analysis	12	Climate change communications	4
COVID-19 theories	10	Machine learning techniques	2
Climate change communications	9	Strengthening scientific credibility	2
Critical discourse analysis	8	Social situation analytics	2

Figure 14 combines two Word Clouds, one for the 50 most used keywords plus (A) and the second one for the most used authors' keywords (B). A Word Cloud is a graphical representation of the most common words in an area, with the size of the text correlated to the number of appearances of the word. The most frequently used keyword plus is *fake news*, which appeared 170 times; *media* is second, with a total number of 122 appearances; *social media* appeared 109 times; and *news* appeared 103 times. *Information* has a frequency of 96, *misinformation* appeared 85 times, and *disinformation* appeared 45 times, while *impact* and *politics* have 44 and 41 appearances.



(**A**) Top 50 words based on keywords plus (**B**) Top 50 words based on authors' keywords

Figure 14. Top 50 words based on keywords plus (**A**) and authors' keywords (**B**).

As for the authors' keywords, the most common word is *disinformation*, which appeared 991 times; *fake news* has a frequency of 325, and *misinformation* 315, while *social media* and *COVID-19* appeared 234 and 160 times. The remaining words appeared rarely but are still relevant for this research: *Twitter* has a frequency of 79, *fact-checking* appeared 73 times, and *media literacy* appeared 61 times, while *journalism* and *infodemic* have frequencies of 57 and 51.

Figure 15 groups the 200 most frequently used keywords plus into nine categories. The minimum frequency per thousand documents is five.

The cluster with largest impact is in the bottom right and contains "*fake news*" and "*media*", describing the tool that spreads disinformation. The second most important cluster is shown in pink, on the right side, and contains "*science*" and "*credibility*". Thanks to scientific advances, the credibility of news is seriously affected, making public opinion more susceptible to information on the internet. Other relevant clusters include the possibility of "*propaganda*" using disinformation, affecting "*elections*" and increasing the power of fake news, reducing the "*belief*" in online mass media news. The subject of "*climate-change*" is highly debated and numerous fake news exists in this area.

In Figure 16 there are 10 clusters describing different crucial topics in the field of disinformation. The same parameters that have been presented in Figure 15 have been used, but the focus was, in this case, on authors keywords rather than keywords plus.

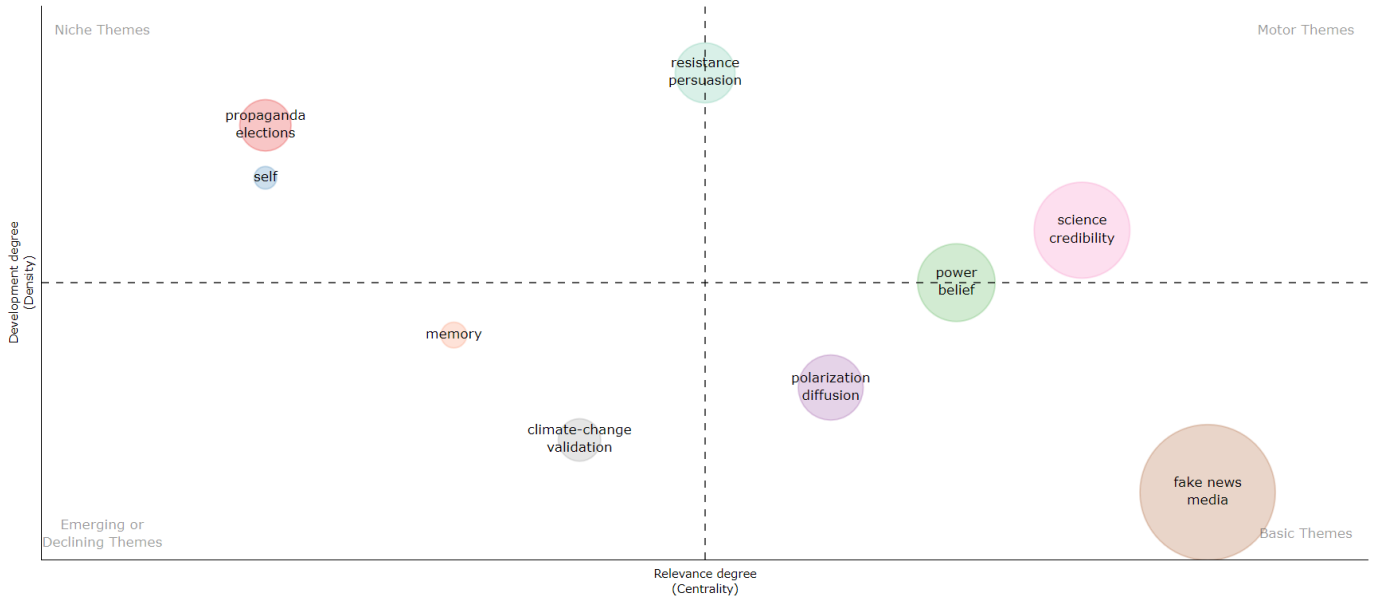

Figure 15. Thematic map of keywords plus.

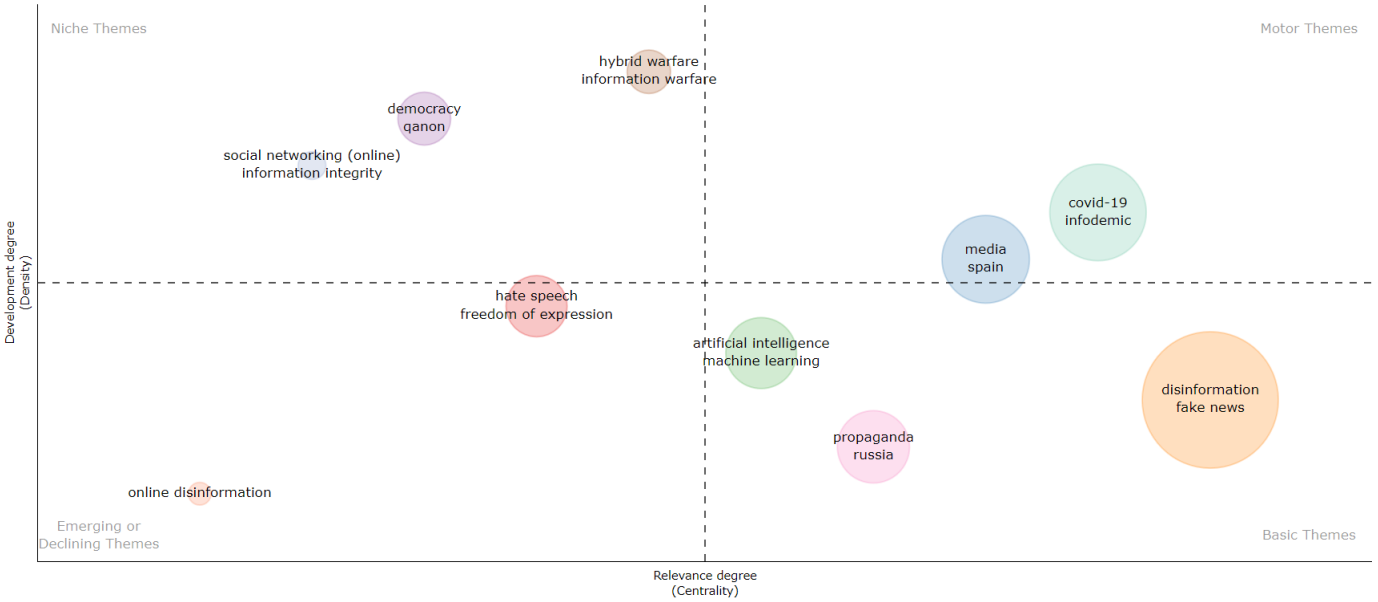

Figure 16. Thematic map of authors keywords.

The most representative cluster is at the bottom right and contains "*disinformation*" and "*fake news*", which are the main factors which contribute to instability and concerns on social media. Another important cluster is at the top right and includes "*COVID-19*", "*infodemic*", "*media*", and "*Spain*", which describes the lack of confidence in the Spanish media, which began during COVID-19 when numerous pieces of fake news were shared. "*artificial intelligence*" and "*machine learning*" represent the software tools that facilitate the appearance of fake news and disinformation, but they are also used for its detection, in order to minimize its negative impact. Furthermore, "*hate speech*" and "*freedom of expression*" are promoted more and more on social media, with freedom of expression representing one

of the major rights of citizens who live in a democracy, while hate speech is more frequently present in online messages, promoting violent activity, especially in politics.

3.7. Mixed Analysis

In this section, the focus is on understanding the connections between journals, authors, countries, and keywords in order to extract patterns.

Figure 17 explores the connections between the most relevant countries (AU_CO), authors (AU), and journals (SO). The width of the colored bar in each of the mentioned columns represents the volume of publications originating from that country, author, or journal. Notably, the Netherlands and the United Kingdom display the widest bars, signifying their substantial contributions to the field. In terms of authors, as expected, the most prominent author is Hameleers M.

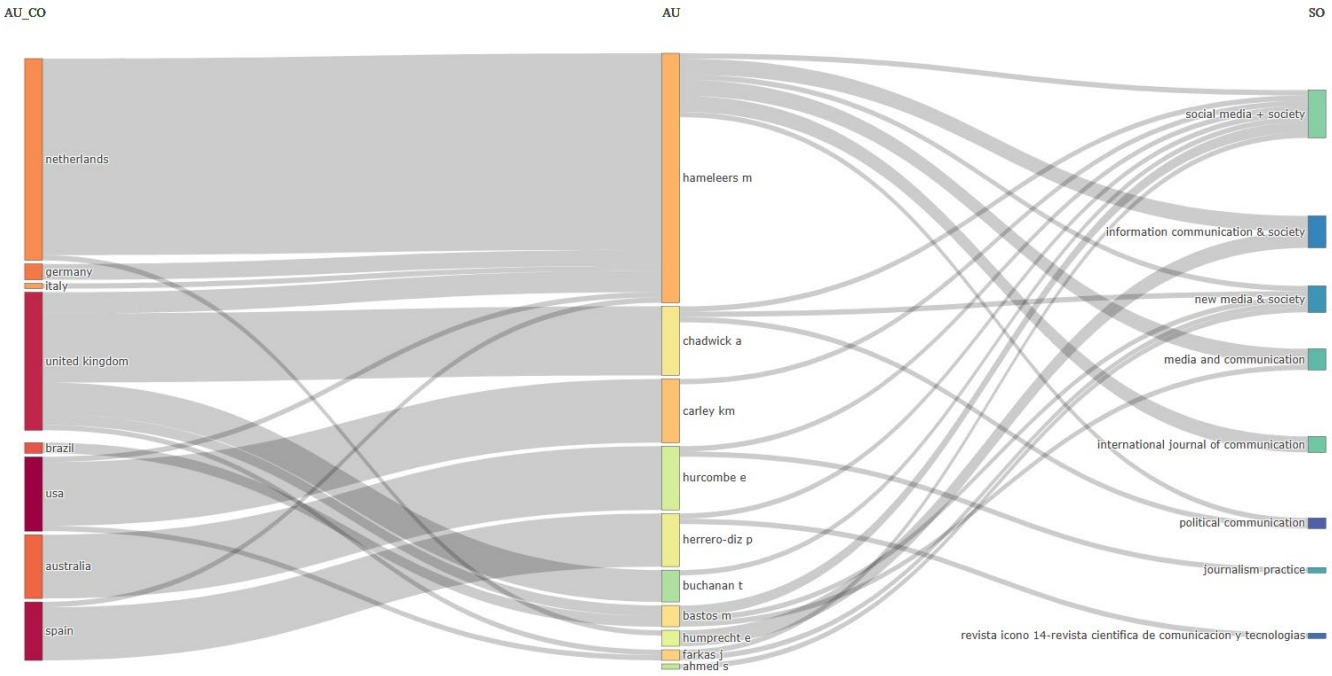

Figure 17. Three-field plot: countries (**left**), authors (**middle**), and journals (**right**).

Furthermore, the thickness of the lines connecting each section reflects the strength or frequency of contributions from each country to specific authors and from each author to specific journals.

The purpose of the diagram is to provide an overview of the scholarly landscape by connecting leading countries, influential authors, and key journals that shape the field.

Figure 18 combines the cited sources (CR_SO), most important authors (AU), and keywords used (DE) in order to create a pattern between them. As in the previous case, the width of the colored bar in each of the mentioned columns represents the relative volume of the elements included in each column, while the thickness of the lines connecting each column reflects the strength or the frequency of the connection. As expected, most of the keywords used are related to disinformation and other associated forms of information (e.g., misinformation, fake news), while other keywords refer to social media in general, Twitter in particular, and the disinformation associated with the COVID-19 pandemic.

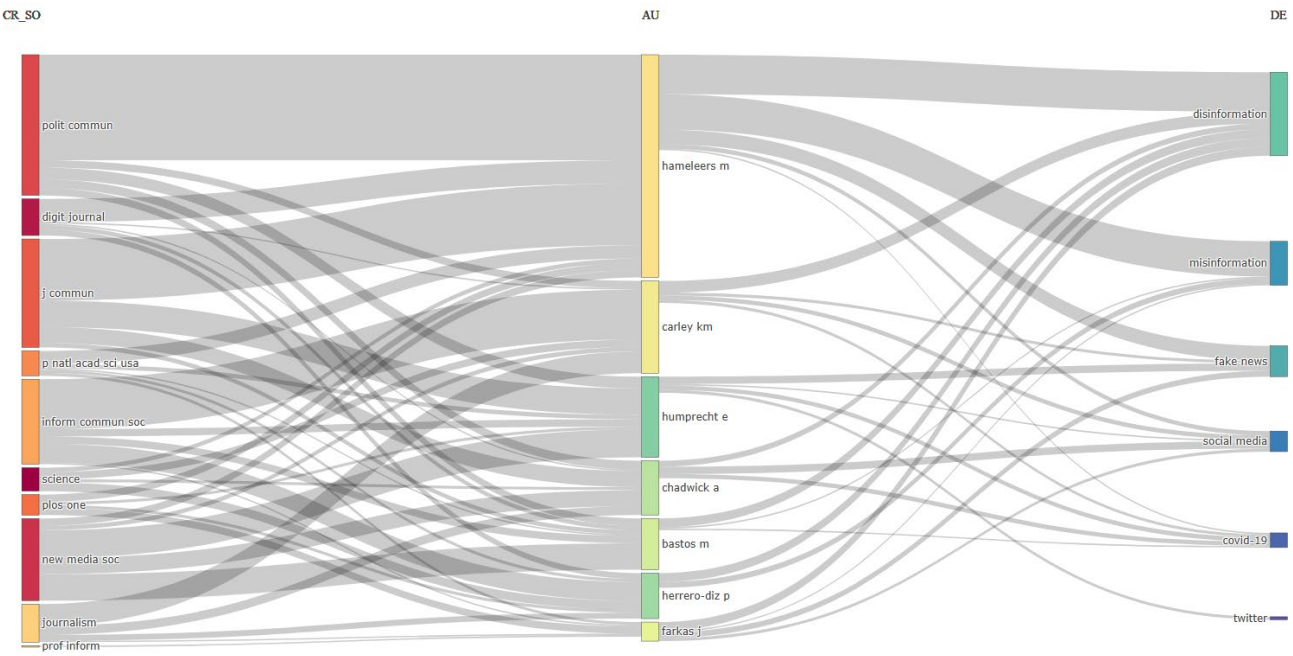

Figure 18. Three-field plot: cited sources (**left**), authors (**middle**), and keywords (**right**).

4. Discussion and Limitations

This bibliometric research offered a comprehensive evaluation of the disinformation domain, with its exploration starting with 1980, when the first paper was published, which had a very small impact. However, thanks to the evolution of technology, this area has evolved and grown exponentially in the last few years of the analysis, with a maximum of 429 papers being published in 2023. Over the 42 years that have been investigated, a positive trend was observed, which highlights the increasing interest of researchers, thanks to technological evolution.

Disinformation has a significant impact on society, especially in politics, and in order to reduce its spread, it is important that the government adopt laws which block the distribution of fake information, together with achieving better control over the information that is presented in the news. Pherson et al. [110] detailed what measures should be adopted in order to minimze disinformation: create a safe space in the cloud where information should be validated by real sources, adopt tools that combat online disinformation such as bot and spam detection—Botometer, FakerFact, and many others.

The domain of disinformation became more and more interesting to researchers. The most relevant country in terms of the number of papers it has published is the USA, which has published 313 papers which have 6758 citations. The impact of the USA is accentuated by the four universities which are in the top 10 most important affiliations: the University of Texas Austin, University of Washington, Harvard University, and the University of California System, which have together published 164 articles.

Journals play a crucial role in the evolution of a domain, and the most important ones in the disinformation domain are *Profesional de la Informacion*, *Social Media + Society*, *International Journal of Communication*, *Media and Communication*, *Journalism Practice*, *New Media & Society*, *Information Communication & Society*, *Revista Icono 14-Revista Cientifica de Comunicacio*, *Political Communication*, and *Revista Latina de Comunicacion Social*.

In terms of limitations, the most significant limitation is the database that has been chosen for extracting papers, as we have taken into consideration only papers indexed in the WoS database. Singh et al. [111] explained the differences between the Scopus and WoS databases, and the major difference is the coverability level, which has improved massively since 1990 for the WoS, which has the most cases papers written in English. The WoS had indexed around 13,610 journals with over 13 million articles as of June 2020, offering a

higher impact for WoS publications. Scopus indexed a larger variety of journals, containing, in total, approximately 40,385 journals with over 18 million publications as of June 2020, but its impact is much lower compared to that of the WoS. The decision to exclude Scopus documents from this research could have altered the results but has provided interested readers with more papers with a well-respected database within the research domain.

Another important limitation that might have altered the results of this research is related to the process of selecting which articles are included in the database. In our case, the papers marked as "Article" by the WoS database were included in the analysis, which also included conference and journal publications. The filters that were used to extract the database limited the number of publications since specific words were included as filters. A restriction was added to the languages used; keeping only English publications and excluding the year 2024 are two other limitations that reduced the size of the database and altered the results.

5. Conclusions

The purpose of this paper was to offer a comprehensive analysis of the disinformation domain in order to understand the evolution and potential development of the area. Using a bibliometric approach, this research offered a clear perspective on the main authors, the main topics of disinformation, what the collaboration network looks like, the most important journals, and the most relevant countries. Based on the findings discovered during this research, we can highlight the following results:

- SQ1 response: Based on the number of publications, most of the papers were published by universities in the USA, such as the *University of Texas Austin*, *University of Washington*, *Harvard University*, and the *University of California System,* with a total of 164 papers published by these institiutions. There are also important universities from the Netherlands (*University of Amsterdam)*, the UK (*University of Oxford*, *University of London)*, Spain (*University of Navarra*, *Complutense University of Madrid),* and China (*Nanyang Technological University)*.
- SQ2 response: The first paper was published in 1980 and had a very small impact, but during the timespan of this research, the trend was positive, and in the last few years the domain has grown rapidly, especially since 2018. The largest number of papers were published in 2023, at more than 429 documents.
- SQ3 response: The collaboration network between authors in the disinformation domain is complex and in the majority of cases it involves authors from same countries, based on the SCP values seen. The SCP value for the top 10 most important countries ranges between 63.1% and 90.2%, with the UK having the smallest value for SCPs and Spain having the highest value for SCPs. Regarding the collaboration between countries, the most fruitful collaboration was between the USA and UK, who have published 20 articles together. Another important collaboration between countries is that of the UK–Germany, with 15 documents published, and the USA–China with 14 articles, the USA–Australia with 12 articles, the USA–Germany with 12 articles, the UK–Australia with 11 articles, the USA–Canada with 10 articles, the UK–Canada with 9 articles, the UK–Netherlands with 9 articles, and the UK–South Africa with 8 articles.
- SQ4 response: Regarding authors, the most relevant author in the disinformation domain, based on their number of publications, is *Hameleers M.*, who has 29 papers published. The second author, *Carley KM.*, has only published 9 documents, which shows how important *Hameleers M.* is in the analyzed area. Other important authors include *Farkas J.*, *Bastos M.*, *Chadwick A.*, *Herrero-Diz P.*, *Humprecht E.*, *Hurcombe E.*, *Ahmed S.*, and *Buchanan T.*
- SQ5 response: The most important journals that publish scientific papers on the disinformation domain are *Profesional de la Informacion (36 papers)*, *Social Media + Society (35 papers)*, *International Journal of Communication (32 papers)*, *Media and Communication (26 papers)*, *Journalism Practice (19 papers)*, *New Media & Society (16 papers)*, *Information*

Communication & Society (15 papers), and *Revista Icono 14-Revista Cientifica de Comunicacio (15 papers)*.

- SQ6 response: Keywords are a crucial part of a bibliometric approach since they provide a clear perspective as to what each author is focusing on. The most used keywords plus in the disinformation domain are *fake news (279 appearances)*, *social media (235 appearances)*, *communication (103 appearances)*, *information (96 appearances)*, *misinformation (85 appearances)*, *disinformation (45 appearances)*, *impact (44 appearances)*, *politics (41 appearances)*, *trust (41 appearances)*, and *science (37 appearances)*. Regarding the keywords used by authors, the most relevant words are *disinformation (991 occurrences)*, *fake news (339 occurrences)*, *social media (335 occurrences)*, *misinformation (315 occurrences)*, *COVID-19 (160 occurrences)*, *Twitter (79 occurrences)*, *fact-checking (73 occurrences)*, *journalism (57 occurrences)*, *infodemic (51 occurrences)*, and *propaganda (49 occurrences)*. These terms represent the disinformation domain, the platforms that are helping to share information rapidly, the impact on politics, and the challenges faced by journalists in verifying information.

These results offer a complete overview of the disinformation domain, how it evolved, and what the consequnces are if fake information continues to be distributed. Several examples of methods that mitigates disinformation have been presented during this research. Providing the most important universities, the collaboration networks between authors, the most relevant authors and journals, the yearly number of papers that have been published, and the main keywords that authors have used, together with an investigation into the collaboration between countries, the number of SCPs and MCPs, and the top 10 most cited documents that present the theorical and practical aspects of this field of research creates a foundation for researchers and governments to start to take into consideration the dangers of disinformation, promoting methods that mitigate the spread of fake information.

Future research could include more documents from other databases, analyzing non-English articles and papers that are not marked as "Article" in the WoS.

Last but not least, an evaluation of the impact of technology on the disinformation domain and the policies that should be adopted could represent other future approaches.

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