Source Credibility Assessment in the Realm of Information Disorder: A Literature Review

Alessia Cosentino[1], Carmen De Maio[2*], Domenico Furno[1], Mariacristina Gallo[1], Vincenzo Loia[1]

[1] Department of Management & Innovation Systems, University of Salerno Fisciano (SA), 84084 (Italy)
[2] Department of Computer Science, University of Salerno Fisciano (SA), 84084 (Italy)

* Corresponding author: cdemaio@unisa.it

Received 10 August 2024 | Accepted 29 December 2024 | Published 27 January 2025

Abstract

The proliferation of information disorder in the digital age has sparked a growing concern regarding the credibility of sources disseminating information. This review examines the evolving landscape of source credibility within information disorder. The review synthesizes key findings and trends related to the factors influencing source credibility, including available tools, shared indicators, and existing methods experimented with in calculating source credibility. The analysis highlights that from a more commercial point of view, several tools are aimed at analyzing the content's credibility and studying the sources' credibility. However, from a methodological point of view, there is still something more to do. Indicators that can be used to carry out a source credibility assessment focus on the structure and design of the source, excluding others indicating how the page traffic could be. As for the techniques to be used to assess the credibility of a source, it emerged that more innovative techniques, such as deep-learning, are being developed alongside slightly more classical statistical methods. The review analyzes 23 papers from Conferences and 22 from Journals published in recent years. It also identifies avenues for future inquiry and the development of effective strategies to combat the challenges posed by misinformation in the digital era.

Keywords

Credibility Assessment, Information Disorder, Reliability, Source.

DOI: 10.9781/ijimai.2025.01.002

I. Introduction

In recent years, the rapid proliferation of social media has revolutionized the consumption of online news and content. The accessibility of information from diverse sources, ranging from traditional channels to social media platforms, has facilitated the dissemination of unverified and inaccurate content. This situation has made it increasingly difficult to evaluate the credibility of both the individual pieces of information and the sources that distribute them. While extensive research has focused on the credibility of published content (content credibility), there remains a critical need for in-depth analyses and studies concerning the sources' credibility. Cambridge dictionary defines **source credibility** as *the degree to which people believe and trust what other people and organizations tell them about a particular product or service*[1]. Similarly, scholars in *On Scalable and Robust Truth Discovery in Big Data Social Media Sensing Applications* [1] define it "*as an index which indicates how trusty a source is*". Thus, it is possible to indicate credibility as a measure of trust that an individual places in a given source.

Source credibility is a multifaceted concept influenced by various factors. These include the quality of a website, the structural features of the page [2], the presence of biases [3], the professionalism of content authors [4], and the frequency with which fake news is disseminated [5]. Despite the multitude of factors involved, establishing clear and consistent criteria for determining when a source should be labeled as unreliable remains challenging, particularly when fake news is involved. The frequency with which a source publishes fake news is a key determinant in assessing its credibility. Source credibility is evaluated not only based on the quality of current content but also by considering the source's history of disseminating misinformation. Tools like NewsGuard and MediaBias/Fact Check (described in section IV-A) utilize criteria that include the quantity and severity of fake news published to derive an overall credibility score. Thus, the threshold for classifying a source as unreliable is not fixed but is determined by the accumulation of problematic behaviors over time.

Given the exponential growth of social media and increased internet usage, addressing this issue is imperative to combat the dissemination of misleading content. The volume of research on source credibility has significantly increased from approximately 1800 papers in 2017 to over 4000 papers in 2023 (see Fig. 1), and continues to rise. Despite this considerable growth, numerous aspects remain under-explored,

[1] http://dictionary.cambridge.org/us/dictionary/english/source-credibility

Please cite this article as:
A. Cosentino, C. De Maio, D, Furno, M. Gallo, V. Loia. Source Credibility Assessment in the Realm of Information Disorder: A Literature Review, International Journal of Interactive Multimedia and Artificial Intelligence, vol. 9, no. 6, pp. 6-20, 2026, http://doi.org/10.9781/ijimai.2025.01.002.

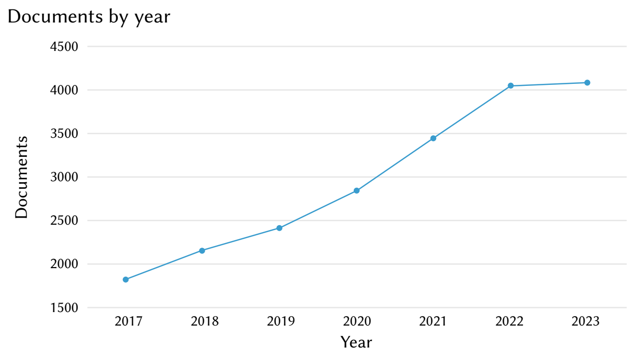

Fig. 1. The number of articles published in the field of source credibility from 2017 to 2023.

such as identifying common factors in evaluating source credibility, understanding the dependency between content and source credibility, and developing effective methods to quantify credibility.

In this context, artificial intelligence (AI) emerges as a promising solution (see Section VI). In particular, machine learning (ML) and deep learning (DL) approaches have been developed to address source credibility assessment. These advanced techniques enable automatic and scalable analysis of a source's characteristics using algorithms that learn from large volumes of data. However, adopting these techniques also raises important ethical issues, such as bias in the data used to train the models and the transparency of automated decision-making processes. These issues must be addressed to ensure that AI technologies can be used responsibly and that the credibility assessment of sources is fair and unbiased. This article will explore the role of AI technologies in improving source credibility assessment, with a focus on emerging methodologies and the ethical implications that accompany the use of these tools.

This literature review aims to analyze relevant publications in the realm of *source credibility* assessment, providing a comprehensive overview of the current state of research. Main contributions are:

- A comprehensive analysis of tools and platforms employed in assessing source credibility, distinguishing between approaches based on human evaluation, automated systems, and hybrid models (see Section IV).
- Identification of core Indicators (such as design structure, author transparency, and content quality) and methodologies for credibility scoring by synthesizing recent studies. Methodologies range from traditional statistical models to advanced machine learning and deep learning techniques (see Sections V, VI).
- Future research directions and applications, identifying research gaps and emerging trends, providing insights into potential advancements in credibility assessment (see Section IX).

This study focused on the latest articles within the last six years, starting from 2018, and about 50 articles were chosen after screening the abstract and the full-text eligibility analysis of papers resulting from a web search detailed in Section III.A. The findings reveal that various methods for assessing the credibility of information sources have emerged over the years, including data-driven, model-driven, and graph-based approaches, evolving from traditional statistical methods to innovative deep-learning techniques. Statistical approaches, for instance, utilize descriptive analysis and regression models to evaluate source credibility. Specific studies have employed multilevel regression and mixed effects logistic regression, considering variables like analytical reasoning, source credibility, and the veracity of news articles to distinguish between real and fake news. Machine learning (ML) represents another significant method, with algorithms such as Decision Trees, Support Vector Machines, and Gradient Boosting being applied to evaluate source credibility. These ML techniques analyze features, including textual content, website characteristics, and social media metrics. Furthermore, deep learning methods, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown promising in detecting fake news by analyzing large datasets and identifying complex patterns in data. Hybrid models combining CNNs and RNNs offer a robust framework for fake news analysis, demonstrating the potential of advanced computational techniques in the ongoing effort to assess and ensure information source credibility.

The paper is structured as follows:

- *Related Work.* This section navigates through a comprehensive exploration of existing literature. By synthesizing key insights from previous literature reviews on source credibility, we aim to build upon the collective knowledge in the field and identify gaps and debates within the current understanding.
- *Methodology.* Explaining the research approach, this section details the search queries, articles analyzed, tool for classification, and other methodological aspects. It also presents the research questions guiding the literature review. These questions focus on the tools available for evaluating credibility, the key indicators that should be considered, the methodologies discussed in the literature, and the availability of shared datasets.
- *Results.* Divided into three sections, this part highlights answers to the research questions. It covers platforms/tools assessing source credibility, indicators for evaluating source credibility, and methodologies for calculating credibility scores—spanning from traditional to innovative approaches.
- *Discussion.* Conducting a final analysis based on the research results, this section summarizes solutions and highlights existing issues related to the theme.
- *Conclusion and Future Research.* The concluding section summarizes key findings, offering insights and suggesting potential avenues for further research in the field.

II. Related Work

The issue of the credibility of the source of information is not recent: there have been many studies conducted in recent years on the subject, from the philosophical one to the field of communication, also passing for the scientific one. One of the first to question the issue of the credibility of the springs was Aristotle in his work *The Rethoric* [6]. Moving on to the technological/scientific field, in recent years, new approaches have emerged that aim to analyze credibility on the Web, trying to understand if there were methods and/or tools to calculate and evaluate this credibility.

Regarding existing literature reviews, a pivotal survey by Zhou and Zafarani [5] unveils various methodologies for detecting fake news, categorizing them by the conveyed false knowledge, writing style, propagation patterns, and *source credibility*. Notably, it differentiates sources based on their roles in creating, publishing, and sharing fake news, thereby offering a nuanced understanding of credibility across the information lifecycle.

Source credibility is examined by differentiating among the author, publisher, and user. Research highlights the significance of the networks formed by authors or publishers, emphasizing how these connections impact credibility. In this context, platforms like *NewsGuard*[2] or *MediaBias/Fact Check*[3] are useful tools for evaluating

[2] NewsGuard - Transparent Reliability Ratings for News and Information Sources (newsguardtech.com)

[3] Media Bias/Fact Check - Search and Learn the Bias of News Media (mediabiasfactcheck.com)

the reliability of online news publishers. From the user's perspective, the distinction between malicious spreaders of misinformation and unwitting participants highlights the complexity of news sharing dynamics. Understanding these user characteristics is crucial for developing effective strategies against the spread of fake news.

In *Fake news, rumor, information pollution in social media and web* [7] the authors recognize the role of sources in fake news detection and mitigation. In particular, through a literature review, they discuss a process for identifying the original source of information pollution. Again, in the context of fake detection, the survey *Fighting post-truth using natural language processing: A review and open challenges* [8] inspects features, resources, and systems available for credibility assessment of contents and sources.

In *A Review on Credibility Perception of Online Information* [9] the author analyzes credibility factors and methods for evaluating credibility after introducing the concept of trust and credibility. As stated in the work, some factors that influence the perception of the credibility of online information are the context, the characteristics of the platform itself, and the characteristics of the player. Moreover, looking at the methods, the author recalls statistics and machine learning methods.

Despite the extensive body of work, a comprehensive analysis that juxtaposes credibility-assessment tools, prevalent methods, and potential indicators remains poor. This literature review seeks to fill this gap by offering an in-depth examination of these components, thereby enriching the discourse on *source credibility*.

III. Methodology

This section delineates the systematic methodology employed to curate this literature review, encompassing the search strategy, selection criteria, and the research questions that guided our inquiry. The selection of the research questions is particularly important in understanding the role AI can play in improving the credibility assessment of sources in the realm of information disorder and whether investing in AI-based tools is worthwhile. Firstly, the search strategy will be introduced in general, indicating how the platforms or tools have been found, how the papers have been selected, on which databases they have been searched, etc.; secondly, the criteria of selection or not of the papers read will also be indicated; lastly, the research questions proposed in this review are presented. The following subsections detail each step.

A. Search Strategy

The proposed study was based on a multifaceted research strategy to comprehensively explore the domain of source credibility. Regarding the platforms/tools that allow calculating the credibility of the source, most of these have been found through the *CredCatalog*[4] site. It publishes work results of a research community of journalists, researchers, academics, students, policy-makers, technologists, and engaged non-specialists aiming to foster collaborative approaches to understanding the veracity, quality and credibility of online information. The CredCatalog site allows search among information on fact-checking groups, technology tools, academic and research institutions, and other initiatives. Entries are searchable according to geography, language, funders, and solutions categories. For the paper purposes, the search has been conducted by selecting the following categories: F*act-checking & Verification*, *Artificial Intelligence*, *Tools*, I*nfo disorder monetization*, and *Trust in media*. Moreover, Global was selected for what concerns the Location, and All for the Language. Starting from there, various tools have been reached while others, instead, emerged from studied papers or through a Google search on the following queries: "*tools for source evaluation*", "*source credibility assessment*", "*platforms for source credibility*".

These platforms and tools were then divided into three categories:

- those that use a human approach;
- those that use an automated approach and
- those that use a hybrid approach to detect whether a source is credible or not.

As for the papers, these have been searched on the academic databases *Scopus*, *DBLP*, and *Scholar*, through specific queries: "*source evaluation*", "*source credibility*", "*machine learning for source evaluation*", "*AI for source credibility evaluation*", "*information credibility*", and "*information evaluation*". The histogram in Fig. 2 shows some of the most frequent keywords among the papers analyzed for the writing of this literature review. As can be seen, the most frequent keyword is credibility with 25 occurrences, followed by fake news and sources.

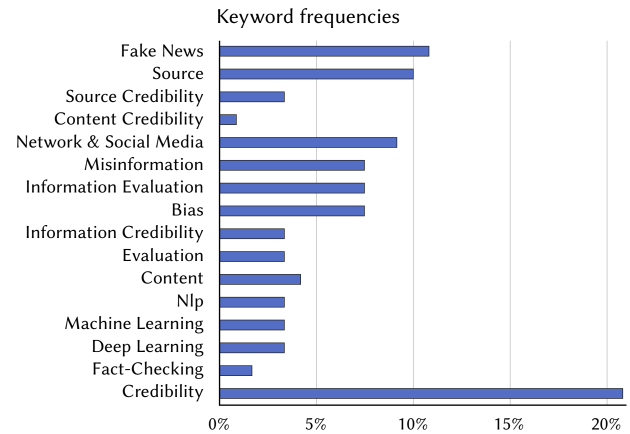

Fig. 2. Distribution of keywords per paper.

The papers have undergone different steps:

- **Preliminary research**: papers that have been found have been analyzed firstly only by looking at their title and abstract.
- **Secondary research**: papers that have passed the preliminary search have been read and then studied in order to obtain the most important information.

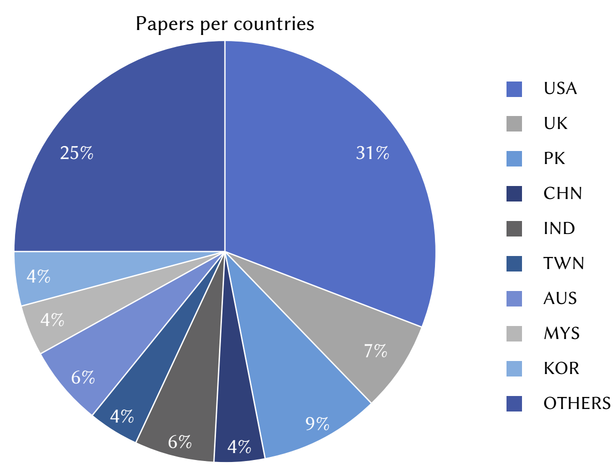

Fig. 3. Distribution of papers for the countries they refer to.

The selected papers have been written by scholars from (almost) around the globe so as to have a more open view of the issue. As the pie chart in Fig. 3 shows, most of the papers analyzed were made by

[4] CredCatalog (credibilitycoalition.org)

American authors, followed by English and Indian authors. Under the field "other" are indicated papers produced in states such as Germany, Iran, Canada, etc., that have been grouped for convenience.

In addition to considering papers written in different countries around the world, more current papers, mainly from 2017 until today, were chosen to be considered as this would provide more accurate and up-to-date information on new technological developments. In fact, in the histogram shown in Fig. 4, the data have been reported in relation to the papers analyzed and presented in this literature review. It can be observed that while the number of papers published was higher in 2020 and 2021, research on the subject has continued in the subsequent years, albeit at a slightly lower level, indicating a sustained interest in the field.

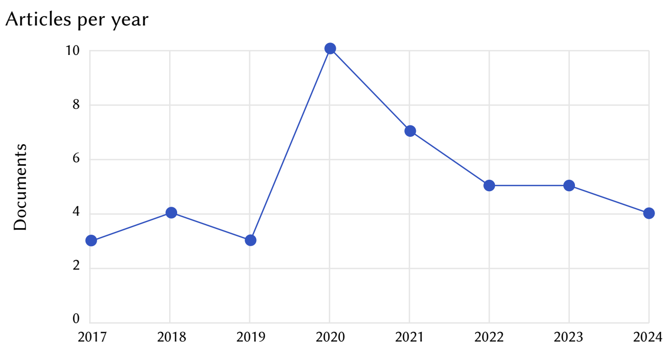

Fig. 4. Distribution of considered papers from 2017 to 2024.

B. Screening and Filtering Process

Initially, approximately 90 papers were subjected to a rigorous screening process, ultimately narrowing down to 47 papers. Editors of papers were *Elsevier*, *ACM Digital Library*, *IEEE*, *Springer*, etc., as visible from the pie chart in Fig. 5.

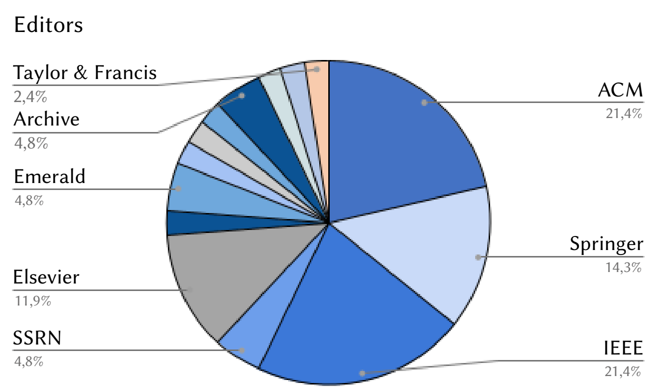

Fig. 5. Distribution of editors took into consideration.

Specific **inclusion criteria** guided the selection of papers to ensure relevance and quality for the research. First, the primary focus of these papers was on source evaluation, as this was central to the topic under investigation. Secondly, only papers written in English were included. This decision was made to maintain consistency and avoid language barriers that could complicate the synthesis and analysis of the findings. Lastly, the papers selected were published within a specific time frame, from 2017 to 2023. This period was chosen to capture recent developments and trends in the field of source evaluation.

In parallel, **exclusion criteria** were applied to ensure that only the most relevant studies were included in the analysis. First, papers that appeared to be related to the primary scope of this work but ultimately focused on other topics were excluded. This was important to ensure that the research stayed focused on the core subject. Second, works that did not contribute meaningful insights or findings to the study were excluded. This criterion ensured that only papers offering substantive content, whether in terms of methodology, theory, or empirical findings, were considered. If a paper lacked clear contributions to advancing knowledge in source evaluation—whether through insufficient data, unclear conclusions, or a lack of depth in addressing the research questions—it was deemed irrelevant and excluded from the analysis. This helped streamline the selection process, ensuring that only high-quality, impactful works were included in the review.

C. Research Questions

In order to conduct the analysis on the topic of *source credibility*, the following research questions were proposed:

1. **Are there any platforms to evaluate the credibility of the sources?** This question concerns the possibility or not of having tools and/or platforms to assist news consumers, helping them to distinguish the most credible sources from the least credible ones from which to draw information.
2. **What indicators should we consider to assess the credibility of a news source?** This question arises from the initial consideration that there are several criteria for evaluating a source, taking into account different elements that appear on websites, social networks, etc. For this reason, some studies carried out on this subject have been analyzed in order to understand which indicators and elements can be more helpful than others.
3. **What approaches should be used to assess the credibility of information sources according to relevant literature?** The objective is to understand if there were any studies in the literature that analyzed this problem in order to try to obtain concrete methods for calculating source credibility. In this regard, several methodologies have been found that allow the calculation of source credibility, and the most common ones have been repositioned into different categories.
4. **Does shared datasets exist for the source credibility assessment?** Shared available datasets adopted by analyzed papers are collected and described. Scholars generally use them to train and test models proposed in their studies. Unfortunately, it was possible to report only some of these datasets as others were no longer available.

The subsequent sections will depict the results obtained from the comprehensive analysis of the papers and platforms/tools, all of which are guided by the research questions outlined above.

IV. RQ1: Are There Any Platforms to Evaluate the Credibility of the Sources?

To date, different platforms and tools used to assess the credibility of information sources are emerging. These tools can be broadly classified based on their reliance on *human verification*, *computational evaluation*, or a *hybrid of both*. Among the human-based models, the *checklist method*, represents an early approach, but it is often criticized for being time-consuming and less adaptable to the fast pace of information flow. On the other hand, computational models are divided into two major categories: *rankings of websites*, which are computationally generated by *search engines*, and *rankings aggregated* by *user ratings*, such as *Google Pagerank* and *Alexa Rank Checker*, which leverage the opinions of a large user base to form a collective assessment of credibility. This latter approach relates closely to the concept of aggregated credibility presented by Faraon et al. [10], where the combined judgment of a diverse group of users is used to evaluate a source's trustworthiness.

TABLE I. Summary of Platform Categories and Their Description

Platform Category	Examples	Description
Human-assessment platforms	NewsGuard, Media Bias/Fact Check, Media Monitoring Africa, AdFontesMedia, Iffy Index of Unreliable Source, and AllSides	Platforms relying on human experts to evaluate and score the credibility of sources based on predefined criteria
Automated-assessment platforms	FactStream, Factinsect, MisinfoMe	Tools that utilize algorithms and AI to assess the credibility of sources, often leveraging data like social media metrics and user behavior
Hybrid-assessment platforms	Logically	Platforms that combine human and automated methods to assess credibility, integrating multiple data sources for a comprehensive evaluation

In order to gain clarity in the field and answer our research question, we searched for tools and/or platforms that could help us better understand if a source of information is credible or not. In particular, the platforms quoted in this section have been divided into three major categories:

- *Human-assessment platforms & tools*, which utilize human experts in order to evaluate the *source credibility*.
- *Automated-assessment platforms & tools*, ones that utilize automated methods in order to assess the *source credibility*.
- *Hybrid-assessment platforms & tools*, ones that utilize both approaches mentioned before to calculate the *credibility of a source*.

Table I summarizes the platforms and tools assessed, clarifying the approach and categorizing the different methods used to evaluate source credibility.

In addition to evaluating the credibility of sources, some platforms also analyze the content being published to distinguish between true and false publications. For this reason, we have also included a separate section related to content *credibility tools* and *platforms* (see Section IV.D) in order to give a more exhaustive overview. Furthermore, to give an idea of how to use these tools or platforms, examples are provided where specific research papers indicate the use of these tools. As shown in Fig. 6, the distribution of platforms analyzed in this literature review is illustrated. The first pie chart illustrates the source credibility platforms, while the second is content credibility.

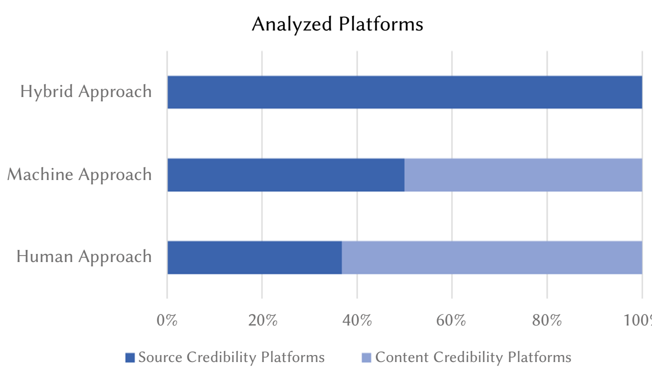

Fig. 6. Analyzed platforms based on the implemented approach.

A. Human Assessment Platforms & Tools

This section outlines the tools and platforms that utilize a human-centered methodology, predominantly rooted in traditional journalism approaches, to calculate the *credibility score* of a source. The most common ones are listed below.

NewsGuard NewsGuard[5] is a *U.S.* platform, which focuses on analyzing websites by assigning scores based on specific *criteria* and their respective *weights*. Criteria include the frequency of publishing false content, clarity in information about authors, signaled advertisements, etc.

Media Bias/Fact Check Media Bias/Fact Check (MB/FC)[6] is an independent site created in 2015, to promote awareness regarding misinformation online and the *source credibility*. The platform offers both a *source credibility* scale, as well as an additional *bias scale* of the platform analyzed by adopting a strict methodology. In particular, criteria consider the level of reliability of reported facts, the presence of biases, the quantity of traffic, and the freedom of the press in relation to countries under government control.

Media Monitoring Africa Since 1993, Media Monitoring Africa[7] deals with creating a safer Internet environment by combating the spread of *fake news* and *online disinformation*. In this regard, the platform has produced a series of tools such as *KnowNews*, a *Google Chrome* extension that allows you to check whether a website is trusted or not. Moreover, the platform indicates what factors to consider when assessing the *credibility of the source*: among these is the clarity of the source URL, the presence of a *About Us* section, in which there are possible contacts of the authors of the articles, as well as of the platform owners and information on the platform itself, etc.

Ad Fontes Media Since 2018, Ad Fontes Media[8] deals with evaluating the news spread, intending to assess the *credibility* and *reliability of sources* and also any bias, if present. To do so, it created an evaluation system with experts in different fields, especially political ones, to understand possible bias better.

Iffy Index of Unreliable Source Iffy[9] is a site that draws up a list of sources considered little or very little credible. It takes into account additional tools that assess credibility as *Alexa Traffic Rank*, the credibility mechanism of *Misinfo.me*, the presence or not of articles on *Wikipedia*.

AllSides All Sides[10] is a platform that aims to analyze online sources in order to assess how biased they are. To do so, experts use a multi-partisan analysis with six to nine right-wing, left-wing or center experts who evaluate the hidden biases in the information sources and the articles they share. *AllSides Media Bias Chart*, instead of scores, allows you to have a view of biases of platforms.

B. Machine Learning Assessment Platforms & Tools

This section presents the tools and platforms that use machine learning, and therefore an automated approach, to calculate the credibility of information sources. The following are the most widespread.

FactStream FactStream[11] is an iOS application that combines the fact-checking tools of three of the major American organizations that

[5] https://www.newsguardtech.com/it/

[6] https://mediabiasfactcheck.com/

[7] https://www.mediamonitoringafrica.org/

[8] https://adfontesmedia.com/

[9] https://iffy.news/index/

[10] https://www.allsides.com/

[11] https://apps.apple.com/us/app/factstream/id1327422405?ls=1

deal with this matter, namely, *The Washington Post*, *PolitiFact* and *FactCheck.org*. The app deals with *lie-swatting*, *claim-debunking* and *fact-checking* with the aim of blocking the growth of disinformation, providing details on why that information was considered false, possibly false, etc.

Factinsect Factinsect[12] is an online platform that uses AI to make fact-checking of content by exploiting trustworthy sources.

MisinfoMe MisinfoMe[13] analyzes Twitter account in order to identify misinformation spreaders. In particular, it considers the reliability level of pointed sources by comparing them to a fixed collection determined by fact-checking organizations. It is based on the semantic notations of *ClaimReview* in order to highlight the tweets that refer to sources and content that are credible and not credible, as stated in *Misinfome: Who's interacting with misinformation?* [11].

C. Hybrid Assessment Platforms & Tools

This section describes a platform that, combining the two aspects (*human* and *automated*), calculates the credibility score of the sources.

Logically Logically[14] is a UK fact-checking agency that offers its services to governments, public sector entities or private sector organizations. It uses several tools and methodologies to analyze the sources and content published online, including *Threat Intelligence*, *Multilingual Detection*, *Narrative Detection & Analysis* and *Network Analysis*. Areas of interest include *source credibility*, *toxic detection*, *misinformation detection*, *narrative extraction*, *name entity recognition and sentiment detection*.

Logically performs an evaluation by adopting five different scales: 1. True; 2. Misleading; 3. Unverifiable; 4. Partly True; 5. False.

D. Content Credibility Platforms & Tools

Numerous platforms and independent fact-checking groups have been established to assess the credibility of content disseminated across various information sources. In recent years, particularly in Europe, over one hundred such entities have emerged, like *Full Fact* in the UK or *Political Report* in Italy, as indicated in the work of Miriam Fernandez and Harith Alani [12]. For this reason, the current literature review has analyzed some tools and platforms that focus on content verification. This section will follow the same structure as the previous one. Most of the tools or platforms are free to use.

1. Human Assessment Tools

This subsection describes platforms that make an evaluation of content shared by web platforms using a human approach, then based on expert analysis on the subject.

Snopes Snopes[15] focuses on the analysis of content shared online by adopting a methodology consisting of several steps:

1. It entrusts news to a specific member of the staff who performs a preliminary test;
2. It contacts the source that shared the content/news to obtain more information about it. Moreover, it tries to contact individuals or organizations that may be aware of something. If the argument turns out to be complex, an additional expert will join the team.
3. The draft produced passes into the hands of the final publisher, who will review it before the official publication.

Alt News Alt News[16] is a platform that continuously monitors social media in general for dubious information. Once the claim to verify has been found, it is analyzed using different tools, such as *Google Reverse Image*, *InVid* or by contacting experts or local authorities. After this phase, the fact-check article is written and updated when some changes occur.

Politifact Since 2007, Politifact[17] is a website which fundamentally deals with *fact-checking*. In particular, by doing so, *Politifact* experts rely on some fundamental elements for the analysis, such as the *independency*, *transparency*, *honesty* and *clear writing*. The platform suggests two metrics of evaluation, namely *Truth-O-Metric* and *Flip-O-Meter*. The first metric values the accuracy of content, classifying it as true, mostly true, false, etc. The second metric, instead, values the consistency in relation to a theme, suggesting an evaluation based on 3 indicators:

1. *No flip*, when there have been no changes;
2. *Half flip*, when there has been a partial change in position taken;
3. *Full flip*, when a full change has been there in positions.

Africa Check Africa Check[18] is an African platform that deals with fact-checking. It collaborates with other bodies that deal with this matter and adheres to the *Code of Principles* disseminated by the *Poynter Institute*[19]. The platform publishes a report in which they analyze the claims they have received in relation to news and/or facts and, through a process, try to confirm whether or not the report was obtained. In particular, they ask for evidence that experts on the subject will analyze and, only at the end of this process, *Africa Check* creates the report and then publishes it.

FactCheck.bg FactCheck.bg[20] is a Bulgarian platform which does fact-checking. The team is composed of journalists who, in 2021, decided to create this platform. Once a possible false element has been found, journalists evaluate all the proofs supporting the claim and the ones refusing it, taking into account three factors:

1. *Apparent doubts on the surface.*
2. *Likely social impact.*
3. *The amount of engagement the news might have.*

The platform states that there is a need to respond to some questions to assess credibility, such as "*Who is the owner of the website?*", "*What are the editorial policies?*", "*Who are the authors?*", "*Which articles it publish?*", "*Where and when it shares the articles?*".

AFP Factcheck AFP Factcheck[21] is a French verification platform active since 2017. AFP has partnered with major global platforms such as *Google*, *Meta*, *Tik Tok*, etc. The fact-checkers of the organization use primary resources and collaborate with other agencies worldwide to transparently show the steps they took to perform the debunking process. Once the obtained news has been analyzed, the experts classify them in false content, true content, misleading content, modified photo, modified video, missing content, satire, deepfake, hoax.

FactCheck Fact Check[22] is a nonpartisan and no-profit platform that analyzes claims and checks their truthiness, especially in the U.S. political field. The journalists, who make up the staff of FactCheck, manually select claims from different sources (such as TV, Readers, etc.) and, starting from here, try to look for information that may contradict the claims. After doing so, they publish the article on the platform.

[12] https://factinsect.com/
[13] https://misinfo.me/frontend-v2/home
[14] https://www.logically.ai/trust-and-safety
[15] https://www.snopes.com/
[16] https://www.altnews.in/
[17] https://www.politifact.com/
[18] https://africacheck.org/
[19] https://www.poynter.org/
[20] https://factcheck.bg/
[21] https://factcheck.afp.com/
[22] https://www.factcheck.org/

TABLE II. Summary of Fact-Checking Tools and Their Adoption in the Considered Literature

Tool	Citation	Brief Description of Usage
AllSides	[10]	Analyze articles for balanced political representation.
MediaBias/FactCheck (MB/FC)	[10]	Classifying news sources.
MediaBias/FactCheck (MB/FC)	[11]	Identifying biases in news.
MediaBias/FactCheck (MB/FC) & NewsGuard	[12]	Comparing their results in terms of assigned credibility scores.
NewsGuard	[13]	Collecting and comparing transparency and credibility scores of news sources.
FeedReflect	[14]	Assess user engagement and promote content credibility verification on Twitter.
PolitiFact	[15]	Evaluated fact-checks to understand challenges with complex claims and truth ratings.
Snopes	[16]	Assess article headlines and credibility indicators in the study of news sharing behavior.

TABLE III. Indicators for Source Credibility Evaluation

Indicator Category	Description	Sources
Design and Structure of the Source	Indicators related to the webpage design, such as layout, images, writing style, external links, citations, etc.	[9], [2], [13], [14],[15], [16], [17], [18]
Source Quality	Includes transparency, reliability, accuracy, and objectivity of the content and the source itself.	[9], [2], [15], [16],[19], [4], [20], [21]
Author Information	The presence of author information, such as experience and qualifications, is a key indicator of a source's credibility.	[18], [22], [23]
Published Content	Content factors such as writing style, readability, and the sentiment conveyed, which affect the credibility of a source.	[9], [2], [24], [25],[26], [27], [28]
Bias	Political bias and other forms of bias that may influence the perception of a source's credibility.	[3], [29], [30]
Ads and Traffic of the Source	The presence of advertisements and source traffic, as ads tend to reduce the perception of reliability and credibility.	[15], [18]

FactaNews FactaNews[23] is an Italian platform that deals with combating disinformation and circulating false news. In particular, they produce content of different types, such as the "Antibufale" section, dedicated to debunking articles, the "Stories" section where you can find surveys and insights, the "Articles" section where reviews and useful advice are collected on the tools to be used for correct information. After seeing the claim to analyze, the experts working there use two sources to verify whether the claim is true or not. In the case of debunking, the analyzed content is traced back to one of the following categories: False news, Out of context, Real news, Image modified, Inaccurate news, Old news, No proof, Satirical news. Once the verification phase is over, the fact-checking articles are published on the site.

Les Observateurs-France 24 Les Observateurs-France 24[24] is responsible for verifying the veracity of the information and content disseminated online following some reports by users. To do so, they use the traditional method of journalism: they take the information from the user's report by communicating with him, and then they try to get more information by searching on other sources and platforms.

The truth or the fiction? TruthOrFiction[25] is a non-partisan website where readers can quickly and easily get information about *rumours*, *fake news*, *disinformation*, etc. Firstly, they look for the source who spreads the news, and then they try to find information that may or may not confirm the statement, even by talking in person with other experts. After having done so, they publish their fact-finding report.

CheckYourfact Check Your Fact[26] deals with fact-checking, especially considering the reports made by politicians, political parties and the media. They focus on verifiable sources and not opinions. When conducting research, the platform contacts experts in the area of interest and uses only *trusted material* such as *academic sources*, *non-party agencies*, etc.

2. Machine Learning Assessment Tools

The following tool uses machine learning to assess the credibility of the content spread over a source of information.

Full Fact Full Fact[27] is a UK platform, allegedly a non-profit organization, that deals with analyzing claims that come out of the public debate, especially claims that have been exposed by politicians in the media. Their process can be divided into two steps: the first one starts with the analysis of the claims by contacting the claimant in order to understand the issue. Then, in the second step, the platform publishes the content by using an image and a headline. If necessary, experts in the field of interest are contacted to obtain more information on the matter. The platform adopts automatic tools to support fact-checking.

E. The Tools At a Glance

Some of the platforms described here have also been considered in the existing literature. Table II summarizes their adoption scope.

V. RQ2: What Indicators Should Be Considered in Order to Assess the Credibility of a News Source?

To effectively assess the credibility of information sources, it is essential to understand and evaluate key indicators that contribute to their reliability. The objective of this section is to outline the various indicators used in determining source credibility, explain their importance in the context of credibility assessment, and provide a structured analysis of the most relevant indicators. In this regard, this section analyzes some indicators, summarized in Table III.

[23] https://facta.news/

[24] https://observers.france24.com/fr/

[25] https://www.truthorfiction.com/

[26] https://checkyourfact.com/

[27] https://fullfact.org/

TABLE IV. Ranking of Indicators Considered Most Useful in Analyzing the *Credibility of the Source* [14]

Rank	Random Forest	Linear Regression	χ^2
1	Image Ratio	Grammar Errors	Existence of URL
2	Alignment	Text Ratio	Structure
3	Existence of URL	Structure	Presence of Map
4	Grammar Errors	Alignment	Number of stickers
5	Structure	Image Ratio	Font Size Conversion
6	Text Ratio	Existence of URL	Font Type Conversion
7	Number of stickers	Number of stickers	Number of tags
8	Title length	Font Size Conversion	Polarity
9		First Person Ratio	Alignment
10		Negative Ratio	Number of Media

The indicators are categorized based on their prominence in the literature: the first indicators quoted are those mentioned in more papers; as the description of the latter continues, the number of papers mentioning these indicators decreases.

A. Source Design and Structure

An indicator particularly popular for the evaluation of the source is its design and Structure, (i.e., *layout*, *the position of the images*, *the type of writing*, etc.) because they influence how users perceive the reliability and professionalism of the information being presented before they even delve into the content deeply.

Authors of *Why people trust wikipedia articles: Credibility assessment strategies used by readers* [2] extract aforementioned indicators through a survey about Wikipedia pages: the results have shown that the style used in writing the published articles, the structure of the page, the presence of external links and quotations, etc., are important indicators for assessing the source credibility of a source. Park et al. [13] also adopted these indicators in order to assess the credibility of certain articles, integrating them with other features (like the feeling they arouse). Moreover, Jo et al. [14] conducted a comprehensive study in which participants were presented with a survey with a set of indicators for assessing *source credibility*. Results demonstrated that humans consider four coherency factors when evaluating the credibility of weblog posts: structure, alignment, effort, and text/image ratios. These factors are crucial in shaping user perceptions of credibility, emphasizing the importance of not only the content itself but also its visual presentation. Moreover, survey results have also been corroborated through the application of some Machine Learning models (including Linear regression, Random Forest, and χ^2), trained to classify a blog post as credible or not. Each Machine Learning model identified its own set of influential features, as shown in Table IV.

The design of the information platform is also important in a survey [15] conducted by some of Stanford University's professors on 2500 participants. In this survey, 46.1% of them took this factor into account for the credibility assessment of sites. In addition, Shariff [9] argues that the differences in credibility that exist between different social networks are due to the design and layout of the platform interface. In the paper *Lateral Reading: Reading Less and Learning More When Evaluating Digital Information* [16], the authors consider the presence of an About Us section on the page and its graphic design as important indicators to examine when considering the *source credibility*. Moreover, S. Selva Birunda and R. Kanniga Devi [17] state that an important indicator is the presence of the publication date in the articles published on the website. Moreover, in *Assessing Google Search's New Features in Supporting Credibility judgments of Unknown Websites* [18], the authors have found that indicating the sources of funding of a platform is an important criterion to assess the credibility of the source of information.

B. Quality of Sources

Among the indicators that return most in the analyzed literature, there are some linked to the *page quality*, as *transparency*, *reliability*, *accuracy* and *objectivity of the published* content as well as the source itself. For example, Sam Winenburg and Sarah McGrew [16] asked some college students to indicate which, in their opinion, could be useful indicators to assess the trust and credibility of a news source: these have been summarized as shown in Table V.

TABLE V. Five Criteria of Web Evaluation

Criteria	Description
Accuracy	The page presents the list of authors of the published contents, their contacts, etc.
Authority	The page presents the credentials of the authors, and the source domain is well indicated (.edu, .org, .gov, etc.).
Objectivity	The page provides accurate information with limited ads and exposes the facts objectively.
Diffusion	The page is updated regularly, links are updated, etc.
Coverage	The page shows information without paying a fee, software technologies, etc.

Fogg et al. [15] quote these indicators after a survey submitted to some students, from which it emerges that for 14.3% of them aspects such as *authority*, *credibility*, *expertise*, *trustworthiness*, etc., of a source influence the credibility of a source of information. Moreover, Hamid Keshavarz and Mohammadreza Esmaeili Givi [19] think that expertise and trustworthiness have a significant role in source credibility. But, there are other relevant factors for doing so, such as *safety*, *qualification*, *dynamism*, *goodwill*, *agreeableness*, *extroversion*, and *professionalism*. Furthermore, Houda Elmimouni et al. [2] asked some participants to express what kind of indicators they take into account when evaluating online sources. Some of them state that an important indicator is the *reputation of webpages*, as the popularity. In summary, it is possible to synthesize these indicators in a formula, as indicated by Shah et al. [4]:

$$\mathrm{Score}(p) = \frac{1}{7}(\mathrm{Acc}(p) + \mathrm{Auth}(p) + \mathrm{Curr}(p) + \mathrm{Prof}(p) + \mathrm{Pop}(p) + \mathrm{Imp}(p) + \mathrm{Qual}(p)) \tag{1}$$

where *Acc* stands for Accuracy, *Auth* for Authority, *Curr* for Currency, P_{rof} for Professionalism, P_{op} for Popularity, *Imp* for Impartiality and *Qual* for Quality. To obtain the Accuracy (Acc) of a source, the TF-IDF and

TABLE VI. Criteria and Metrics for Source Credibility

Criteria	Metrics
Source Verification	Ease in the identification of the source or publisher of the information Ease in the verification of the dataset on the source's website Ability to contact the source for support or clarification
Source Reliability	Number of years of experience in the corresponding information domain Credit rating of the source: lookup; features Prior experience or trusted reviews about the source Public and media sentiment on source's reputation Consequences of previous market decisions taken based on data provided by the source Susceptibility of the source to political propaganda and similar possibilities of misinformation Alignment of aims, goals, and objectives between the source organization and the decision-makers Probability of bias due to the nature of funding of the source organization
Site access and usability	Credibility based on site URL (edu, org, gov, private) Stability and compatibility of the URL on computer and phone Specified rules for data access and sharing Frequency of updating data Cost of data to the user Commercial advertisements on site Security of online payments

the Google search result rank are used. As for the Authority (Auth) the presence of the author's name and links to the latter's profile (or any contacts) are considered. For the calculation of the Currency (*Curr*), the date of creation of the content and the date of the last update using, for example, the Diffbot API. In addition, for Professionalism (*Prof*), some factors are used, such as the source domain type, Alexa median load time percentage, Google speed score, Mozscape domain authority, child safety users' ratings, etc. For the calculation of Popularity (*Pop*), five credibility factors are taken into account, such as the popularity rank or the traffic rank of the Web page. The Impartiality (*Imp*) is analyzed instead of the tone of the diffused content. To conclude, the Quality (*Qual*) of the source is calculated considering the content's readability, using the Flesch-Kincaid reading ease tests, the Flesch-Kincaid grade-level tests and the Dale-Chall readability formula. The reputation as an indicator of source credibility is recalled in the paper A Review on Credibility Perception of Online Information [9], where the trustworthiness is considered another indicator of the importance of a source, too. In the paper proposed by Zehra Ece Serman and Julian Sims [20], the authors research what factors influence the credibility of online news, referring in particular to blogs and the SMEs (Small-Medium sized Enterprises) in the hospital sector. The authors developed a research model to investigate these factors, which is illustrated in Fig. 7. The figure presents a comprehensive framework showing the relationships between various constructs that influence the credibility of blogs shared by SMEs during the COVID-19 pandemic. Specifically, the model includes several hypothesized factors, such as trustworthiness, expertise, promotional incentives, and reputation, and examines their impact on perceived credibility. Trustworthiness and reputation are found to significantly enhance the credibility of the blog content, while expertise and promotional incentives do not demonstrate a significant impact.

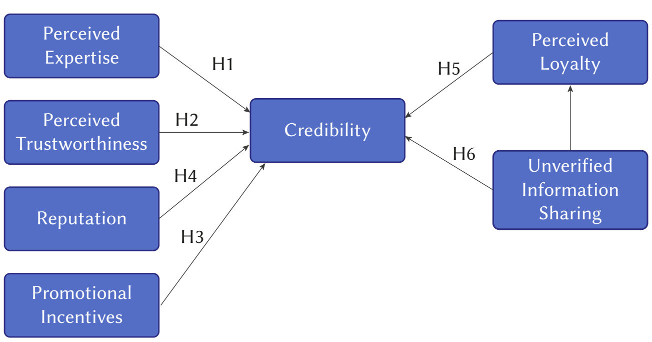

Fig. 7. Research model proposed by Zehra Ece Serman and Julian Sims in their work.

Suyash Padhye and Makarand Hastak proposed a framework to assess source credibility in their paper [21]. In particular, the authors considered three different criteria with 18 evaluation metrics as can be seen in Table VI. The three criteria are:

- source verification, with 3 reference metrics;
- source reliability with 8 reference metrics;
- site access and usability with 7 reference metrics.

C. Authors' Information

Another indicator found while performing the analysis on the matter is the presence of authors' information on the sources. In fact, different papers focused on the importance of having this information. For example, Gorodishchev et al. [22] analyzed the credibility of the Web 3.0 source, focusing on principles for ranking media sources. They stated that attributes such as the *content creators' expertise*, their *experience*, and *ability in writing* significantly enhance the credibility of the information. The study shows authors with high credibility are more likely to publish accurate and truthful news. Therefore, user information is seen as a key element in assessing the overall reliability of news, contributing significantly to the improvement of fake news detection. Similarly, Ace Wang et al. [18], assess the presence of author information as one of the most useful elements in judging the credibility of an unknown source, along with other information such as citations and third-party reviews. In particular, during a user study involving 25 participants, seven of them identified the presence of information about the author as a critical factor for evaluating the credibility of unknown sources by Google. The findings suggested that such author-based credibility signals play a significant role in how users perceive the reliability of online information. H. Liu et al. [23] propose a framework, the *Fake News Detector Based on Multi-Source Scoring* (*FNDMS*), to evaluate the credibility of multiple information sources by using a *Dempster-Shafer Theory* (*DST*). This framework used a combination of author-based features — including the certification status, average number of likes, and number of followers — and content-based features — such as audience activity, the use of "shocked-style" phrases in the title, and statistical features in the abstract. The framework demonstrated the effectiveness of integrating these features to provide a more objective credibility assessment compared to single-source analysis, underscoring the importance of author information in credibility evaluation.

D. Published Content

The *published content* considerably impacts the source credibility, as highlighted in various studies. In this literature review, the published content is analyzed in relation to its style (so, how it is written), its readability, and the sentiment it transmits to readers. H. Elmimouni et al. [2] discuss how published content affects the credibility of sources, with a particular focus on Wikipedia. In particular, readers focus on aspects such as the clarity and professionalism of the writing, the structure of the article, and the accuracy of the information provided. The presence of an authoritative and neutral tone, along with the inclusion of external sources, was found to be critical in judging credibility. In general, the quality of the content is one of the most influential aspects in determining the level of trust toward an article. Fayaz et al. [24] further explored specific aspects of content style, such as word count, the uppercase and lowercase characters, the TF-IDF (uni, bi and tri-gram types), etc. They employed an ML algorithm to distinguish between fake and real news on Twitter, demonstrating that these textual features play a critical role in determining credibility.

Ahmad et al. [25] propose a framework based on several Machine Learning algorithms, such as K-nearest neighbors (KNN), the Support Vector Machine (SVM), the Decision Tree, etc., in order to evaluate the performance of fake news detection classifiers. The authors use textual features to test ML algorithms: in particular, the features concerned some textual characteristics converted into numerical form: among these are the percentage of words that transmit negative or positive emotions, the percentage of stop words present, punctuation marks, etc., leveraging the LIWC[28] tool, highlighting the relevance of emotional tone and linguistic markers in credibility assessment. Another key indicator linked to the published content is the *readability*, which means the presence (or absence) of *grammatical errors*, the *length of the text*, etc. In this regard, Shariff [9] cites this factor referring to the level of affinity of information with the theme, the language used, etc. The results showed that, when evaluating language as a factor of credibility, the more formal it seems, the more credible the source is considered. In the study by Michal Karol et al. [26], the authors aimed to predict the credibility of web content using the Content Credibility Corpus[29] . They found that readability, quality of language, and completeness of information significantly impact credibility evaluations. Specifically, individuals assess whether the content is well-written, free of slang, and comprehensive. The study also considered the type of source—for example, whether it is a blog, forum, news site, or scientific publication—as well as whether the information provided is verifiable and objective. These factors all contribute to how credible the content is perceived to be.

In the study proposed by Sitaula et al., [27], on the detection of fake news based on the analysis of the credibility of the article, it emerged that writing some content by using grammar appropriate to the style of the source increases the credibility of the platform and the news itself. Moreover, news with fewer words is considered less credible than news with more words. In the same paper, the authors introduce another factor that affects the published content: the sentiment that the published article conveys to readers. In fact, Sitaula et al. include sentiment that is drawn from the text as one of the factors that indicate the credibility of a text. However, the authors consider it to be a weak indicator for that purpose.

Zhao and Zhang et al. [28]. highlight that the quality of the published content was a key element in evaluating the credibility of health-related information sources. They found that factors such as content quality, source trustworthiness, and style of language all influence perceived credibility. Notably, they reported a strong positive correlation between content quality and perceived credibility ($r = 0.6414$), indicating that higher quality content leads to greater trust in the source. This coefficient underlines the quantitative relationship between content quality and credibility, supporting the overall argument that enhancing content quality is critical for building trust.

[28] https://www.liwc.app/

[29] https://rawgit.com/s8811/reconcile-tags/master/describe_ data.nb.html

E. Bias

Biases are distortions inherent in the human mind that come out in the case of an evaluation or a judgment. In the majority of the cases, the *bias* is linked to the political affiliation of an individual, which can influence his way of seeing things. The paper *Computational Approaches to Developing the Implicit Media Bias Dataset: Assessing Political Orientations of Nonpolitical News Articles* [3] cites political orientation as an indicator of *page credibility*. Following the analysis of 24576 articles, it has been shown that the political vision that emerges from the contents published on a source makes it more or less credible. In particular, articles considered conservative have been seen as more objective, honest and with less bias than progressive ones. Political affiliation returns also in the paper *NudgeCred: Supporting News Credibility Assessment on Social Media Through Nudges* [29] who considered this factor in reference to nudges (treated as a communication strategy). The authors considered how *partisanship*, *attitude towards politics*, and *attitude towards the media* can influence users in evaluating the credibility of the sources (in this case, the tweets published on *Twitter*). Furthermore, looking at the effects and the consequences of the biases on people, in the work *Featured Snippets and their Influence on Users' Credibility Judgements* [30], the authors state that users tend to overestimate the credibility of snippet information in the foreground. This is because users show a tendency to implicitly trust the information that is in the foreground, considering these more reliable than the following.

F. Advertisements and Traffic of the Source

Although few papers mention this indicator, it is right to mention it among the possible factors that affect the credibility of a source. In fact, C. Soohoo et al. [15] consider the presence of ads on the source as a credibility factor: many ads induce low credibility. Furthermore, the presence of advertisements and the *traffic* on the source is also quoted in *Accessing Google Search's New Features in Supporting Credibility Judgements of Unknown Website* [18].

VI. RQ3: What Approaches Should Be Used to Assess the Credibility of Information Sources?

According to Viviani and Pasi [31], in recent years, different methods have emerged for source credibility assessment: data-driven, model-driven, graph-based approaches, and so on. As reported in the following subsections, emerging research goes from the traditional statistical ones to the slightly more innovative ones, such as *deep learning*. Table VII summarizes these approaches used to assess the credibility of information sources.

A. Statistical Models

Statistical approaches represent the foundation for early research in source credibility assessment. These methods leverage traditional statistical models and metrics, such as correlation coefficients, regression analysis, and probabilistic models, to quantify relationships between credibility indicators.

One of the methods particularly common in the papers analyzed concerns the use of statistical methods, from simple *descriptive analysis* to the use of *regression models*, to verify whether a source is credible. For example, in the paper *The Role of Analytical Reasoning and Source Credibility on the Evaluation of Real and Fake Full-Length News Articles* [32], the authors' aim is to determine the role of analytical reasoning and news source credibility in evaluating real and fake news story articles. In order to do so, they have offered participants 6 real and 6 fake news articles from credible authors to evaluate, selected from the "junk news" taken from *Snopes.com*. The analysis leverages multilevel random intercept models: the *multilevel regression* for accuracy and the

TABLE VII. Approaches for Assessing Source Credibility

Approach Type	Description	Sources
Statistical Models	Traditional statistical methods, such as descriptive analysis and regression models, are commonly used for source credibility evaluation. These models often analyze source features like veracity and credibility scores.	[32], [33], [34], [35]
Machine Learning	Uses algorithms like decision trees and support vector machines to predict and assess the credibility of sources based on data features. Machine learning automates the credibility assessment process.	[9], [17], [36]
Deep Learning	Models using deep learning for fake news detection and complex pattern recognition across large datasets .	[3], [33], [37] [38],[39], [40], [41]

mixed effects logistic regression for perceived credibility. The models considered the fixed effects of the news article's veracity (0 = real, 1 = fake), the source's credibility (0 = credible, 1 = non-credible), and each participant's continuous variable, or CRT score, as predictors. In each model, the interactions between these independent variables are also evaluated. Results demonstrated that higher analytical reasoning was associated with greater accuracy and reduced perceived credibility for fake news, while analytical reasoning ability did not moderate the accuracy and perceived credibility of real news.

The regression models also return in *Explainable AI-assisted Multimodal Credibility Assessment System* [33] for the analysis of a blog's overall web credibility score considering source, author and images. In particular, for the source credibility assessment, authors consider features such as Internal Links, Meta Tags Page Titles, URL-Format, Amount of Content, Popularity, Freshness, Images, Printability, Server Behavior, Popularity, Accessibility, Security, etc. Features are extracted by SEO testing tools, Nibbler[30], and Google Search Index, based on their characteristics.

A. Aker et al. [34] have correlated credibility scores evaluated by NewsGuard with manually collected features, such as credibility and transparency scores, and some automatic features, such as:

- *CheckPageRank*, studying the Google Page Rank, the cPR Score, the Citation Flow and Trust Flow, etc.;
- *Facebook*, analyzing the number of likes and followers of a page;
- *Twitter*, taking into consideration the number of followers and the listed count.

After this phase, the authors first performed a *Pearson correlation* with a *logarithmic substitution* and the *Spearman and Kendall Tau correlations*. The authors realized that there are six features that did not meet their expectations, which are *EDU Domain*, *Trust Metric*, *Trust Flow*, *Topic Value*, *Citation Flow*, *Page Authority* and *Alexa USA*. In contrast, some indicators, such as back-links and referring domains from government and educational sites, are good indicators of credible sources.

Also, Shin et al., in the paper *News Credibility Scoring: Suggestion of Research Methodology to Determine the Reliability of News Distribution in SNS* [35], employ a logistic regression model as a method of source evaluation. The authors used two heuristics, taking into account the credibility score for each document they analyzed, which included expertise and unbiasedness. Moreover, for the estimation of the credibility score, they adopt a regression method by using some features extracted from Facebook. The features considered are linked to the creator of the content, the distributor and the follower. Furthermore, they offer a viable formula for the logistic regression model to convert a feature vector x of a document d to a credibility score between 0 and 1. The formula is the following:

$$t = w * x$$
$$f(t) = \frac{\exp(t)}{\exp(t)+1} \tag{2}$$

where w is a vector of weight per each feature in x, and $f(t)$ represents the probability that the document d is credible.

B. Machine Learning

A second pattern among the methods of evaluating the credibility score of the sources regards machine learning. Machine learning approaches have become increasingly popular due to their ability to learn complex patterns from data without explicit programming. These techniques often involve using algorithms like Support Vector Machines (SVM), Random Forests, or Naive Bayes to classify the credibility of sources based on a set of features.

The authors of *A Review of Credibility Perception of Online Information* [9] conduct an analysis of some machine learning algorithms to perform *source evaluation*, considering the Twitter account that published the content as the source of information. To do so, these algorithms take in input the *tweet messages*, *the tweet authors*, *the tweet topics* or a collection of tweets and the propagation of retweets as features for *Decision Tree* or *Support Vector Machine* (SVM).

S. Birunda and Devi [17] use the *Gradient Boosting* to perform some evaluation on *source credibility*. In particular, they have analyzed news articles through TF-IDF (for *Text* and *Title*), taken from a dataset on *Kaggle*, and considered additional features regarding *Site_Url* (e.g., domain, contained text, etc.). The authors have used NLP (Natural Language Processing) in order to extract some textual features from the news. Then, the *Gradient Boosting* has been applied which recorded an accuracy of 99.5%.

Furthermore, in the paper *Machine Learning for the peer assessment credibility* [36], the authors collected data from an online *peer assessment* (PA system) held at the University of Tasmania. They then moved on to the labeling phase, in which the Mechanical Turk human evaluators intervened to indicate the level of each peer assessment. As a last step, the authors trained a classifier to estimate the level of credibility of the students' peer assessment, trying different machine learning algorithms. The best algorithm turns out to be the C*5.0 decision tree*.

C. Deep Learning

Deep learning approaches represent the most advanced techniques for source credibility assessment. Utilizing architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or Transformer-based models like BERT, deep learning techniques can automatically extract relevant features from text for assessing credibility in complex, multimodal contexts.

In *Explainable ai for multimodal credibility analysis: Case study of online beauty health (mis)-information* [33], authors utilize Convolutional Neural Networks (CNN) and Transfer Learning methods to analyze images, as well as Natural Language Processing (NLP) techniques to evaluate the text content for credibility. The study integrates deep learning models to classify images as credible or not and also uses a regression model to evaluate the credibility of the blogs based on several features. Moreover, the use of Explainable AI (XAI) techniques provides transparency by highlighting how

[30] https://nibbler.insites.com/

different features contribute to credibility scores, making the system interpretable for end users. The authors effectively apply these models to assess multiple modalities—platform credibility, author credibility, and image authenticity—to ensure a comprehensive evaluation of misinformation in the beauty and health domains.

Authors of *Computational Approaches to Developing the Implicit Media Bias Dataset: Assessing Political Orientations of Non-Political News Articles* [3], utilize a combination of machine learning and deep learning techniques to compare human and automated approaches for credibility analysis. Specifically, they evaluate the performance of a traditional method, the Naive Bayes classifier, against three deep learning algorithms: the Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and BERT. The authors used these models to analyze a dataset containing non-political news articles, aiming to assess media bias and political orientation. The Naive Bayes classifier, being a simpler probabilistic model, provided solid performance in terms of precision (94.12%), particularly effective in minimizing false positives. However, it demonstrated limitations in recall, which was lower compared to the deep learning models, indicating a lesser ability to correctly identify relevant instances of media bias. On the other hand, deep learning models such as CNN, BiLSTM, and BERT showed significantly higher accuracy, with KoBERT achieving an accuracy of 98.50%. This comparative analysis highlights the strengths and weaknesses of each approach: while Naive Bayes offers strong precision, deep learning models demonstrate superior performance in terms of recall and overall accuracy, making them more suitable for nuanced bias detection.

In the paper *Research on Information Source Detection Based on Machine Learning Algorithm* [37], the authors implement a system based on the *neural network* divided into four levels that investigate the subject. These layers include the *conventional layer*, the *pooling layer*, the *rectified linear unit* (*ReLU*) *layer* and the *full connected layer*. The conventional layer extracts features, followed by pooling to reduce dimensionality, ReLU for non-linearity, and the fully connected layer for classifying sources as positive or negative. The study, using the Gemsec-Deezer and Emergent datasets, achieved high accuracy (80%-85%) in identifying information sources, demonstrating the effectiveness of machine learning in assessing source credibility in social media.

In *Investigating the difference of fake news source credibility recognition between ann and bert algorithms in artificial intelligence* [38], the study compares the performance of two different approaches: *Artificial Neural Networks* (*ANN*) and *BERT* (*Bidirectional Encoder Representations from Transformers*). The authors utilize ANN as a traditional neural network model to analyze and classify fake news, while BERT, a transformer-based model, is employed for its advanced language understanding capabilities. The comparison focuses on evaluating the accuracy and reliability of these models in identifying credible versus non-credible news sources. Results demonstrate that the BERT system presents a higher and more stable overall source credibility recognition rate than the ANN system (BERT 91.2%, ANN 82.75%).

BERT was also used in another paper by Arash Amini et al. [41] to conduct a credibility analysis on the Reddit platform. In this paper, the authors proposed a further model based on BERT, the so called CREDiBERT, which was applied to a Siamese network. The model was trained on a news dataset published on Reddit from 2016 to 2022. CREDiBERT has been compared to other models, such as word2vec, embedding model, BERT text standard, classification model and S-BERT embedding model. The authors' analysis showed that the model they proposed obtained an accuracy of 0.851 and an F1 score of 0.796.

In the paper [39] the authors evaluate three different types of models based on deep learning, namely MLP, RNN and BERT, used to carry out a credibility assessment on Twitter. The authors consider four different types of features: metadata, text features, user features and timeline features. Initially, they used a perception multilayer (MLP) that features an input layer composed of 192 neurons. Next, they focused on the textual context and sentiments of a tweet with a recurrent neural network (RNN). Finally, they added BERT embeddings. After evaluating the models, the authors believe that the MLP and RNN models have shown lower quality but better performance for real-time applications.

Another paper that deals with the use of deep learning methodologies is [40]. The authors present a solution for detecting fake news. The proposed model is a hybrid that combines *Convolutional Neural Network* (CNN) and the *Recurrent Neural Networks* (RNN). This model, as shown in Fig. 8, is structured as follows:

- a first layer is based on a Keras embedding layer;
- the second layer is the one-dimensional CNN layer (Conv1D);
- then, the other layer is composed of large feature vectors generated by the previous layer, which are given to the MaxPooling1d layer;
- after, there is the RNN (LSTM) layer, which receives the output of the previous layer;
- finally, the vectors are classified using the Dense layer.

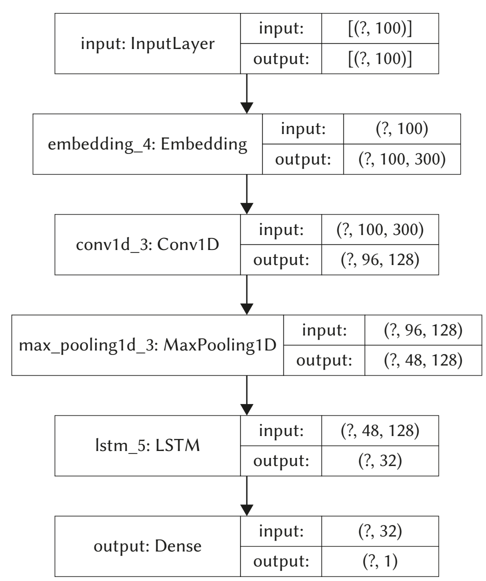

Fig. 8. The Hybrid CNN-RNN Model proposed by Jamal Abdul Nasir, *Osama Subhani Khanb and Iraklis Varlamis* [40] with permission.

Overall, it would seem that the use of models like this is promising in the analysis and tracing of fake news. The results obtained through experiments on benchmark datasets show that the hybrid model achieves high accuracy and improved robustness compared to models that use only CNN or RNN individually, demonstrating the effectiveness of integrating multiple deep learning techniques for credibility assessment.

VII. RQ4: Which Available Datasets for Source Credibility Assessment?

This section describes the most important and adopted datasets in calculating the credibility of the information sources, preferring available ones. To enhance clarity, a summary table (i.e., Table VIII) listing the four mentioned datasets is also included.

TABLE VIII. Available Datasets

Dataset Name	Features
Explainable-AI-Analysis-for-Multimodal-Credibility-of-Online-Beauty-Health-MisInformation [33]	As part of a framework for evaluating the credibility of platforms hosting blogs, it offers multiple datasets consisting of blog pages, their contents, authors' details, PageRank scores, etc.
Corpus Korean Dataset [3]	It contains over 3 million Korean news articles, specifically titles, authors, news content, publishers, and publication dates.
ISOT Dataset [24]	Thousands of fake news articles and real articles, divided into two datasets composed of more than 12 thousand items. Titles, texts, types, and publication dates characterized the items.
Kaggle's Fake News Dataset [25]	It contains the news article's title, content, and author.
Kaggle's Fake News Detection [25]	It contains the URL of the news article, the headline, and the body.
Reddit Dataset [41]	It contains text, author IDs, source domains, submission times, associated subreddits, overall submission scores, and comment counts collected from 2016 to 2022.

The *Explainable-AI-for-Multimodal-Credibility-Analysis-of-Online-Beauty-Health-MisInformation*[31] project [33] contains data linked to the authors' credibility scores, PageRank, and images included in platforms hosting blogs.

The *Fake News*[32] dataset by Kaggle [42] contains titles and body text of about 20 thousand news articles.

The *FakeNewsNet*[33] dataset [43] contains fake and real news collected from *PolitiFact* and fake and real news collected from *GossipCop*. For each article, there is a title, URL, and tweet IDs of tweets sharing the news.

The *FakeNewsCorpus*[34] dataset [44] contains over 9 million news items with contents of domain's web pages and information about authors.

The *News Credibility*[35] dataset [45] contains features of news according to seven information identification categories (e.g., reputation, readability, etc.).

The *Reddit dataset*[36] [41] contains some news published on five major political subreddits such as r/politics, r/Conservative, r/Libertarian, r/Republican, and r/democrats containing information about text, author IDs, source domains, submission times, associated subreddits, overall submission scores, and comment counts.

VIII. Discussion

In the analysis carried out in this *literature review*, a series of articles dealing with the issue of *source credibility* have been analyzed. In particular, a series of tools/platforms have been subjected to analysis, as well as a series of papers, in order to obtain factors and/or methodologies to carry out a source *credibility assessment*.

Firstly, a number of indicators have been identified which can be used to understand whether a source can be considered credible or not. It emerged that, although many of them are almost subjective, a common line on which to use seems to exist. Moving the analysis to the platforms and/or tools analyzed, several projects active in the field were listed, different by objective and technology used: some, in fact, employed human experts to carry out the analysis; others used an automated approach instead; still, others combined the two aspects, thus adopting a hybrid approach. As for the last part of the present work, we focused on the analysis of a series of papers in order to understand the methods/methodologies most used to calculate a score of credibility of information sources. As has been noted, there has been a growth in the publication of studies in recent years, showing a growing interest in this field. Nevertheless, a number of considerations should be made downstream of the whole analysis, as there are a few points that it seems appropriate to clarify. First of all, analyzing the indicators that the relevant literature identifies as useful for the purpose of a credibility analysis of the sources, it would seem that few address the issue of source traffic. Among the papers analyzed, in fact, few argue it is interesting to treat the analysis of page traffic as a means for the evaluation of news sources, focusing instead on more 'visible' indicators. In fact, most of them take into account the design of the page, followed by the qualities of the latter (such as correctness, transparency, professionalism, etc.) that might seem more abstract indicators. Secondly, with regard to the platforms and tools analyzed, as can be deduced from this paper, the majority of these are commercial and focus mostly on content analysis rather than *source analysis* itself (16 out of 18). This shows two important aspects that need to be clarified. First, that to date it would seem almost impossible to separate the analysis of the credibility of the source related to that of the content, indicating a strong link between both. Secondly, it is also possible to see how large companies have understood the importance of this analysis (and the fight against *disinformation*) and are investing in this field by proposing useful platforms and tools. Unfortunately, many of these have decided to do so in a limited way by guaranteeing the services exclusively through the request of a demo or registration. Lastly, regarding the papers dealing with the methodologies used, it was necessary to distinguish in this case (as well as for platforms) between the methods used for *content credibility* and those for *source credibility* indicated in this literature review. Moreover, the analysis shows an increasing interest in new approaches for source *credibility assessment* in terms of deep learning.

IX. Conclusion and Future Research

The current study aimed to analyze the current state of the art in the field of source credibility assessment, focusing on the platforms, indicators, and methods used to evaluate the *credibility score* of the different sources of information. First of all, tools providing users with insights into the credibility of sources have been analyzed, making a small digression even on platforms that calculate the credibility of the published content and project on *source credibility assessment*. Subsequently, an in-depth review of relevant literature listed indicators crucial for assessing source credibility. From this analysis, it was possible to understand how, although the choice of possible indicators is very subjective, some factors are often repeated, such as the presence of the structure of the Web page the contact information of the publisher and authors of the articles. As a last step, some methodologies already established and used in the field have been summarized, offering a valuable resource for evaluating

[31] http://github.com/vidsssw/Explainable-AI-for-Multimodal-Credibility-Analysis-of-Online-Beauty-Health-MisInformation/tree/maste

[32] https://kaggle.com/competitions/fake-news

[33] https://github.com/KaiDMML/FakeNewsNet

[34] http://github.com/several27/FakeNewsCorpus

[35] https://dx.doi.org/10.21227/xjkz-c814

[36] https://pushshift.io/signup

source credibility. Despite the existence of numerous platforms and tools for credibility assessment, our analysis suggests that there is significant potential for methodological advancements. Future research in the field of source credibility assessment is expected to move towards more comprehensive and systematic approaches that integrate advanced technologies, cross-domain applicability, and ethical considerations. A key trend involves the development of robust frameworks for systematically evaluating source credibility, especially in high-risk sectors such as health information, where misinformation can have significant consequences. There is also a strong need for meta-analytical studies to standardize the factors influencing credibility, enabling consistent and reliable metrics across different research contexts. Moreover, the integration of advanced natural language processing (NLP) and deep learning models, such as transformer-based architectures, is gaining prominence for real-time credibility assessment in dynamic environments like social media. These models increasingly employ semi-supervised learning and leverage community-based data to enhance their adaptability and accuracy. Ethical considerations, including user privacy in automated credibility assessments, are also becoming a central focus, emphasizing the need for balanced frameworks that ensure both efficacy and ethical responsibility. Finally, expanding the applicability of credibility assessment models across multiple platforms and domains—ranging from political discourse to health and business contexts—will be crucial for developing versatile and context-aware tools capable of addressing the diverse challenges posed by misinformation.

Acknowledgment

This work was partially supported by project SERICS (PE00000014) under the MUR National Recovery and Resilience Plan funded by the European Union -NextGenerationEU.

References

[1] D. Zhang, D. Wang, N. Vance, Y. Zhang, S. Mike, "On scalable and robust truth discovery in big data social media sensing applications," *IEEE Transactions on Big Data*, vol. 5, no. 2, pp. 195–208, 2018.

[2] H. Elmimouni, A. Forte, J. Morgan, "Why people trust wikipedia articles: Credibility assessment strategies used by readers," in *Proceedings of the 18th International Symposium on Open Collaboration*, 2022, pp. 1–10.

[3] S. Lee, J. Kim, D. Kim, K. J. Kim, E. Park, "Computational approaches to developing the implicit media bias dataset: Assessing political orientations of nonpolitical news articles," *Applied Mathematics and Computation*, vol. 458, p. 128219, 2023.

[4] A. A. Shah, S. D. Ravana, S. Hamid, M. A. Ismail, "Web pages credibility scores for improving accuracy of answers in web-based question answering systems," *IEEE Access*, vol. 8, pp. 141456–141471, 2020.

[5] X. Zhou, R. Zafarani, "A survey of fake news: Fundamental theories, detection methods, and opportunities," *ACM Computing Surveys (CSUR)*, vol. 53, no. 5, pp. 1–40, 2020.

[6] B. Umeogu, "Source credibility: A philosophical analysis," *Open Journal of Philosophy*, vol. 2, no. 2, pp. 112–115, 2012.

[7] P. Meel, D. K. Vishwakarma, "Fake news, rumor, information pollution in social media and web: A contemporary survey of state-of-the-arts, challenges and opportunities," *Expert Systems with Applications*, vol. 153, p. 112986, 2020.

[8] E. Saquete, D. Tomás, P. Moreda, P. Martínez- Barco, M. Palomar, "Fighting post-truth using natural language processing: A review and open challenges," *Expert Systems with Applications*, vol. 141, p. 112943, 2020.

[9] S. M. Shariff, "A review on credibility perception of online information," in *2020 14th International Conference on Ubiquitous Information Management and Communication (IMCOM)*, 2020, pp. 1–7, IEEE.

[10] M. Faraon, A. Jaff, L. P. Nepomuceno, V. Villavicencio, "Fake news and aggregated credibility: Conceptualizing a co-creative medium for evaluation of sources online," *International Journal of Ambient Computing and Intelligence (IJACI)*, vol. 11, no. 4, pp. 93–117, 2020.

[11] M. Mensio, H. Alani, "Misinfome: Who's interacting with misinformation?," in *Proceedings of the 18th International Semantic Web Conference (ISWC 2019): Posters & Demonstrations, Industry and Outrageous Ideas Tracks*, CEUR WS, October 2019, CEUR Workshop Proceedings.

[12] M. Fernandez, H. Alani, "Online misinformation: Challenges and future directions," in *Companion Proceedings of the Web Conference 2018*, 2018, pp. 595–602.

[13] J. Park, R. D. Ellezhuthil, J. Isaac, C. Mergerson, L. Feldman, V. Singh, "Misinformation detection algorithms and fairness across political ideologies: The impact of article level labeling," in *Proceedings of the 15th ACM Web Science Conference 2023*, 2023, pp. 107–116.

[14] Y. Jo, M. Kim, K. Han, "How do humans assess the credibility on web blogs: Qualifying and verifying human factors with machine learning," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 2019, pp. 1–12.

[15] C. Soohoo, D. R. Danielson, L. Marable, J. Stanford, E. R. Tauber, "How do users evaluate the credibility of web sites? a study with over 2,500 participants," in *Proceedings of the 2003 Conference on Designing for User Experiences*, 2003, pp. 1–15.

[16] S. Wineburg, S. McGrew, "Lateral reading: Reading less and learning more when evaluating digital information," 2017.

[17] S. S. Birunda, R. K. Devi, "A novel score-based multi- source fake news detection using gradient boosting algorithm," in *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, 2021, pp. 406– 414, IEEE.

[18] A. Wang, L. M. De Jesus Sanchez, A. Wintner, Y. Zhu, E. Mustafaraj, "Assessing google search's new features in supporting credibility judgments of unknown websites," in *Proceedings of the 2023 Conference on Human Information Interaction and Retrieval*, 2023, pp. 303–307.

[19] H. Keshavarz, M. E. Givi, "Website evaluation frameworks: Is oriented vs. business oriented models," in *2020 6th International Conference on Web Research (ICWR)*, 2020, pp. 223–228, IEEE.

[20] Z. E. Serman, J. Sims, "Source credibility theory: Sme hospitality sector blog posting during the covid-19 pandemic," *Information Systems Frontiers*, vol. 25, no. 6, pp. 2317–2334, 2023.

[21] S. Padhye, M. Hastak, "A framework to evaluate information and source credibility: International construction decision-making," *Journal of Management in Engineering*, vol. 40, no. 1, p. 04023046, 2024.

[22] A. V. Gorodishchev, A. N. Gorodishcheva, D. O. Baigozhina, G. P. Kovalev, "Web 3.0 credibility: Principles for ranking media sources," in *2023 Communication Strategies in Digital Society Seminar (ComSDS)*, 2023, pp. 184–188, IEEE.

[23] H. Liu, L. Wang, X. Han, W. Zhang, X. He, "Detecting fake news on social media: A multi-source scoring framework," in *2020 IEEE 5th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, 2020, pp. 524–531, IEEE.

[24] M. Fayaz, A. Khan, M. Bilal, S. U. Khan, "Machine learning for fake news classification with optimal feature selection," *Soft Computing*, vol. 26, no. 16, pp. 7763–7771, 2022.

[25] I. Ahmad, M. Yousaf, S. Yousaf, M. O. Ahmad, "Fake news detection using machine learning ensemble methods," *Complexity*, vol. 2020, pp. 1–11, 2020.

[26] M. Kakol, R. Nielek, A. Wierzbicki, "Understanding and predicting web content credibility using the content credibility corpus," *Information Processing & Management*, vol. 53, no. 5, pp. 1043–1061, 2017.

[27] N. Sitaula, C. K. Mohan, J. Grygiel, X. Zhou, R. Zafarani, "Credibility-based fake news detection," *Disinformation, Misinformation, and Fake News in Social Media: Emerging Research Challenges and Opportunities*, pp. 163–182, 2020.

[28] Y. Zhao, L. Zhang, C. Zeng, Y. Chen, W. Lu, N. Song, "Factors influencing online health information credibility: a meta-analysis," *Aslib Journal of Information Management*, 2024.

[29] M. M. Bhuiyan, M. Horning, S. W. Lee, T. Mitra, "Nudgecred: Supporting news credibility assessment on social media through nudges," *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW2, pp. 1–30, 2021.

[30] M. Bink, S. Zimmerman, D. Elsweiler, "Featured snippets and their influence on users' credibility judgements," in *Proceedings of the 2022 Conference on Human Information Interaction and Retrieval*, 2022, pp. 113–122.

[31] M. Viviani, G. Pasi, "Credibility in social media: opinions, news, and health information—a survey," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 7, no. 5, p. e1209, 2017.

[32] D. Pehlivanoglu, T. Lin, F. Deceus, A. Heemskerk, N. C. Ebner, B. S. Cahill, "The role of analytical reasoning and source credibility on the evaluation of real and fake full-length news articles," *Cognitive Research: Principles and Implications*, vol. 6, no. 1, pp. 1–12, 2021.

[33] V. Wagle, K. Kaur, P. Kamat, S. Patil, K. Kotecha, "Explainable ai for multimodal credibility analysis: Case study of online beauty health (mis)-information," *IEEE Access*, vol. 9, pp. 127985–128022, 2021.

[34] A. Aker, K. Vincentius, K. Bontcheva, "Credibility and transparency of news sources: Data collection and feature analysis.," in *NewsIR@ SIGIR*, 2019, pp. 15–20.

[35] K.-Y. Shin, W. Song, J. Kim, J.-H. Lee, "News credibility scroing: Suggestion of research methodology to determine the reliability of news distributed in sns," in *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 2019, pp. 737–740.

[36] Y. Lin, S. C. Han, B. H. Kang, "Machine learning for the peer assessment credibility," in *Companion Proceedings of the The Web Conference 2018*, 2018, pp. 117–118.

[37] G. Hu, H. Liu, J. Wang, J. Ye, W. Gong, S. Song, "Research on information source detection based on machine learning algorithm," in *2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP)*, 2022, pp. 1507–1510, IEEE.

[38] T. H. Chiang, C.-S. Liao, W.-C. Wang, "Investigating the difference of fake news source credibility recognition between ann and bert algorithms in artificial intelligence," *Applied Sciences*, vol. 12, no. 15, p. 7725, 2022.

[39] M.-A. Kaufhold, M. Bayer, D. Hartung, C. Reuter, "Design and evaluation of deep learning models for real-time credibility assessment in twitter," in *Artificial Neural Networks and Machine Learning–ICANN 2021: 30th International Conference on Artificial Neural Networks, Bratislava, Slovakia, September 14–17, 2021, Proceedings, Part V 30*, 2021, pp. 396–408, Springer.

[40] J. A. Nasir, O. S. Khan, I. Varlamis, "Fake news detection: A hybrid cnn-rnn based deep learning approach," *International Journal of Information Management Data Insights*, vol. 1, no. 1, p. 100007, 2021.

[41] A. Amini, Y. E. Bayiz, A. Ram, R. Marculescu, U. Topcu, "News source credibility assessment: A reddit case study," *arXiv preprint arXiv:2402.10938*, 2024.

[42] W. Lifferth, "Fake News. Kaggle," 2018. [Online]. Available: https://kaggle.com/competitions/fake-news.

[43] K. Shu, D. Mahudeswaran, S. Wang, D. Lee, H. Liu, "Fakenewsnet: A data repository with news content, social context and dynamic information for studying fake news on social media," *arXiv preprint arXiv:1809.01286*, 2018.

[44] M. Szpakowski, "FakeNewsCorpus," 2020. [Online]. Available: http://github.com/several27/FakeNewsCorpus.

[45] M. Zainab, "News credibility dataset," 2021. [Online]. Available: https://dx.doi.org/10.21227/xjkz-c814.

Alessia Cosentino

She received a bachelor's degree in diplomatic, international, and global security studies from the University of Salerno, Italy, in 2022. She is currently a data science and innovation management student at the same university.

Carmen De Maio

She graduated and received a Ph.D. degree in Computer Sciences, both from the University of Salerno, Italy, in 2008 and 2011, respectively. The research activity has focused mainly on the definition and experimentation of Knowledge Extraction methodologies adopting Conceptual Data Analysis techniques and processes relying on Fuzzy Logic and Computational Intelligence theories. She has over 50 publications in Fuzzy Decision Making, Knowledge Extraction and Management, Situation and Context Awareness, Semantic Information Retrieval, and Ontology Learning. More recently, she has been working on the definition of Time Aware Knowledge Extraction, Process Mining, and Social Media Analytics methodologies. She is currently an Associate Professor in Computer Science at the University of Salerno.

Mariacristina Gallo

She earned a master's degree in computer science at the University of Salerno, Italy, in 2009. In 2021, she obtained a Ph.D. degree in Big Data Management at the same University. Research interests mainly focus on Computational Intelligence methods to support semantic-enabled solutions and decision making. Research activities regard Knowledge Extraction and Management, Context Awareness, Semantic Information Retrieval, Ontology Learning. She is currently a research fellow at the University of Salerno.

Domenico Furno

He received master's degree cum laude and PhD with evaluation excellent from University of Salerno, respectively, in 2007 and 2013. He has publications in Situation/Context Awareness, Soft Computing, Intelligent agents, Data Mining, Semantic Web and Knowledge Representation. He started his research career by defining and testing hybrid approaches based on Computational Intelligence and Semantic Web methodologies and techniques for distributed Situation and Context Awareness scenarios. He is currently a researcher at University of Salerno, and his research interests include Information Disorder Awareness.

Vincenzo Loia

Graduated in Computer Science at the University of Salerno, Italy, in 1985 and received his Ph.D. in Computer Science in 1989 at the Universite' Pierre and Marie Curie Paris VI, France. He is currently a Computer Science Full Professor at the University of Salerno, where he served as a researcher from 1989 to 2000 and as an associate professor from 2000 to 2004. Dr. Loia is the Co-Editor-in-Chief of Soft Computing and the Editor-in-Chief of Ambient Intelligence and Humanized Computing. He serves as an Editor for 14 other international journals.