A Rapid Tertiary Review at the Fake News Domain

Juliana R. S. Gomes[1], Valdemar Vicente Graciano Neto[1],
Jacson Rodrigues Barbosa[1], Eliomar Araújo de Lima[1]

[1]Instituto de Informática – Universidade Federal de Goiás (UFG)

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juliana.resplande@discente.ufg.br,

jacson, eliomar, valdemar@inf.ufg.br
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Abstract. Context: *The spread of fake news on social media platforms has emerged as a pressing concern in recent years. Between 2018 and 2023, numerous secondary studies (SS) have explored this issue, employing diverse methodologies and approaches. Surprisingly, no tertiary study exists to summarize the state of the research.* ***Objective:*** *The aim of this paper is to provide a rapid overview of the SS on fake news research topics for researchers and practitioners.* ***Method:*** *We defined and conducted a rapid tertiary review to find SS published from 2013 to August 2023. 50 most relevant studies in a Google Scholar search were retrieved, from which 15 secondary studies were included and analyzed.* ***Results:*** *A diversity of definitions for fake news exist, often associated with the technology and content in which they are being analyzed. Various stages of fake news processing are covered in the literature. A predominance in the use of deep learning (DL) was observed and challenges still remain, including the urgent need for real-time learning and early detection of fake news.*

1. Introduction

The post-2015 period has witnessed an unprecedented use of social media, an information ecosystem that often lacks the quality criteria associated with traditional journalism. In the United Kingdom and the United States, a notable trend has emerged, with young people increasingly turning to social networks as their primary source of news, supplanting the once-dominant medium of television [Aimeur et al. 2023]. However, this digital landscape has also provided a fertile ground for the proliferation of fake news, a phenomenon that transcends mere misinformation. Fake news has evolved into a powerful tool of manipulation, capable of inflicting damage on the reputations of corporations, governments, and ethnic groups [Meel and Vishwakarma 2020, Schlicht et al. 2023].

In response to this challenge, there has been a remarkable growth in the interest in the field, as evidenced by the volume of research with a diverse array of technologies. Blockchain and natural language processing are some of the technologies being harnessed to tackle the fake news issue. Actually, the content that falls under the umbrella of "fake news" encompasses a wide spectrum, including satirical content, hoaxes, rumors, and outright misinformation [Meel and Vishwakarma 2020]. In the context of that research area, secondary studies (such as surveys, systematic mapping, or systematic research) have synthesized primary studies and approached the topic under multiple perspectives [Petersen et al. 2015], which has generated numerous publications. However, despite the abundance of secondary studies, our search for tertiary studies on fake news in Google Scholar yielded zero results.

The main contribution of this paper is the communication of results of a *rapid tertiary review*, i.e., a tertiary review conducted under the guidelines of the rapid reviews. Rapid Reviews (RR) are lightweight secondary studies focused on delivering evidence to practitioners in a short time frames when compared to traditional systematic reviews [Cartaxo et al. 2020]. RR should be conducted bounded to a practical problem, inserted into a practical context so that the results can be easily integrated in a knowledge/technology transfer initiative. Since this RR is part of a real project on technology development for fake news, the approach sounds suitable for the context. RR may use few or just one search source, more likely Scopus or Google Scholar, and may limit search by publication year, language or other criteria. Quality appraisal can be conducted by a single person, or not conducted at all. We analyzed the most relevant secondary studies in Google Scholar as a means to select them. Results reveal (i) a diversity of definitions for fake news, often associated with the technology and content in which they are being analyzed; (ii) various stages of fake news processing are covered in the literature; (iii) there is a predominance in the use of deep learning (DL) is observed in the included studies, (iv) and challenges still remain, such as user unawareness and vulnerability besides lack of media literacy, lack of cross-domain and platform approaches, and the urgent need for real-time learning and early detection of fake news.

This paper is structured as follows. Section 2 covers the related work and fake news definition; Section 3 presents the research method; Section 4 presents data extraction and results reporting; Section 5 concludes the paper and points for future work.

2. Short Background and Related Work

Fake news can be defined as fabricated content that mimics real news [Wu et al. 2022]. It is important to note that "fake news" lacks a universally accepted definition, and its interpretation can vary widely [Aimeur et al. 2023].

The main technologies related to fake news are also varied, concentrating in terms of machine learning (ML), deep learning (DL), natural language processing (NLP), fact-checking, crowdsourcing (CDS), and blockchain (BKC) [Aimeur et al. 2023]. Machine learning (ML), deep learning (DL) and natural language processing (NLP) techniques are essential for the automated discovery of patterns from textual information. For instance, traditional ML classifiers such as Logistic Regression can be paired with NLP techniques such as term frequency-inverse document frequency (TF-IDF) for text analysis. Crowdsourcing and fact-checking methods focus on journalistic agencies present on the web, which verify daily news from social media. Snopes[1] is a renowned fact-checking platform based in the United States, while Lupa[2] plays a similar role in Brazil.

These technologies can be classified based on their purpose: Content-Based, Social context-based, Temporal-Based, and Credibility-Based [Ali et al. 2022, Kondamudi et al. 2023]. Content-based technologies assess the text and images, either with or without consulting external knowledge. Text linguistic and image patterns can be analyzed to detect emotion, bias, written mistakes, and contractions. When external knowledge sources are consulted, the process is often referred to as manual or automatic fact-checking, which involves cross-referencing claims with informa-

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[1]https://www.snopes.com/
[2]https://lupa.uol.com.br/

tion from trusted sources. In-social context techniques, the environment reaction, such as comments, replies, and reposts, makes a network architecture which can be analyzed, such as blockchain and graphs. The temporal considerate that rumors resurface, and credibility based analyzed the credibility of the news source [Ali et al. 2022, Kondamudi et al. 2023].

While there is a lack of dedicated tertiary studies specifically focused on the phenomenon of fake news, the closest existing tertiary research pertains to sentiment analysis [Ligthart et al. 2021]. Notably, sentiment analysis techniques hold relevance in the context of fake news detection, as they can be harnessed to identify emotional cues, biases, and hate speech, all of which may indicate the presence of fake news. The findings from this research indicate several key trends and challenges in sentiment analysis, including a growing preference for complex Deep Learning techniques capable of detecting intricate patterns, the necessity for adapting techniques to different domains, and the persistent challenges associated with domain and language dependencies.

3. Research Method

In this section, we outline our research method for raising the state-of-the-art and common practices about fake news in the context of social networks, addressing various technologies including blockchain, natural language processing (NLP), and deep learning (DL).

Research questions. To guide our investigation across different stages of the fake news lifecycle, we formulated the following research questions (RQ):

RQ1 How is fake news defined in the peer-reviewed literature?
RQ2 What techniques, tools, and methods have been reported in the literature?
RQ3 What are the main challenges in the detection, blocking, and explanation of fake news?

Search process. We defined our tertiary study search process analogously to prior others [Rios et al. 2018]. The search string was created using population and intervention (PI). The population is the study area, which comprises `fake news`, and the intervention is the method intended to be applied in the population, which are `secondary studies`, as follows.

- Population: fake news, misinformation, rumor, disinformation
- Intervention: systematic review, systematic mapping, literature review, survey

We conducted this search on Google Scholar[3] on August 29, 2023, using the following query:

> ("fake news" OR misinformation OR rumor OR disinformation) AND ("systematic review" OR "systematic mapping" OR "literature review" OR "survey")

Study selection. From the 17300 results obtained in our search on Google Scholar, we selected the first 50 results for a rapid review. Among these, we identified 15 relevant secondary studies that align with the objectives outlined in Section 3.

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[3]https://scholar.google.com.br/

The selected studies are listed in References, identified by an S and a study number, for example, [S13]. The year of the studies ranged from 2020 to 2023, with four studies in 2020, 2021, and 2022, and three studies in 2023. Among the 15 results, 8 (53.3%) were systematic, with an average of 65.5 primary studies being analyzed. Six studies were conducted in the area of social networks, four in the field of deep learning, two in the realm of health, and one in the realm of news creation and consumption.

Table 1. Research questions in reported systematic secondary studies.

Research question	Systematic secondary study
Definition	[S2, S6, S7]
Techniques, tools, and methods	[S1, S2, S6, S10, S13]
Main challenges/Future	[S1, S2, S6]
Research Methods	[S10]

Eight systematic studies were identified, five of which explicitly stated their research questions ([S1, S2, S6, S7, S10, S13]). Research questions were grouped into categories, as presented in Table 1. Most of the studies included similar research questions to those raised herein. [S10] was the only study to include an additional research question, "What research methods did the literature use?".

Data extraction. We extracted pertinent data from each secondary study, capturing the following variables as outlined in Table 2:

4. Data Analysis

The findings of our study on the research questions of this tertiary study are presented in this section.

4.1. RQ1: How is fake news defined in the peer-reviewed literature?

Generalist fake news studies tend to define fake news approaches according to its technology and content, as explained in Section 2 [S2, S3, S4, S9, S11, S15]. However, fake news issues are often examined in the literature in terms of social networks, health, and deep learning techniques.

Within the domain of deep learning (DL), [S6] analyzes the advantages and disadvantages of each approach. Meanwhile, [S5] classifies fake news based on characteristics such as news content, social context, and external knowledge, categorizing DL techniques into supervised, weakly supervised, and unsupervised methods. [S13] assess DL techniques in terms of the pre- and post-COVID-19 pandemic.

In contrast to other works, [S7] conducts a meticulous analysis of the terminology of fake news, focusing primarily on taxonomy. While other studies may also mention taxonomy as a secondary objective, it assumes a central role in [S7]. [S11], [S12], and [S14] also touch upon taxonomy, but it does not constitute their primary research focus. In a distinct vein, [S8] investigates the creation and consumption of news, particularly within the domains of computer and social sciences, while [S14] centers its attention on approaches aimed at minimizing the spread of misinformation in social networks, post-detection.

Table 2. Data collection variables and their purpose. Each collection variable is aimed at whether a research variable or to provide an overview of secondary studies.

Data collection variable	Purpose
V1 - Year	Overview
V2 - Complete reference	Overview
V3 - Research questions of the study	Overview
V4 - Is it systematic?	Overview
V5 - If it is, systematic, number of primary studies	Overview
V6 - Focus of the study	RQ1
V7 - Aspects of the ecosystem and information lifecycle covered	RQ1
V8 - Tasks covered	RQ1
V9 - Covered techniques	RQ2
V10 - Architectural solutions (and technologies) mentioned	RQ2
V11 - Mentioned techniques, tools, and methods	RQ2
V12 - Public datasets	RQ2
V13 - Public models	RQ2
V15 - Explicit research gaps	RQ3
V16 - Implicit research gaps	RQ3

Comparative analysis of fake news research reveals a multifaceted perspective, wherein considerations span aspects of the Ecosystem and Information Life Cycle, along with the various stages of the task, as encapsulated by data collection variables V8 and V9, as presented in Table 2. The information cycle of fake news is distributed across key phases: Propagation (37%), Creation (33. 3%) and Consumption (29. 6%) (V8). In particular, fake news creation receives more in-depth scrutiny compared to other phases, while consumption is comparatively less explored, as underscored by [S8]. Furthermore, content-based technologies, as expounded in Section 2, feature more prominently in the literature concerning the creation of fake news materials.

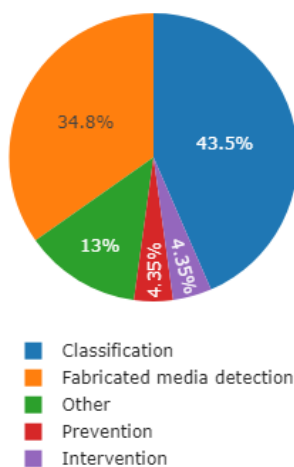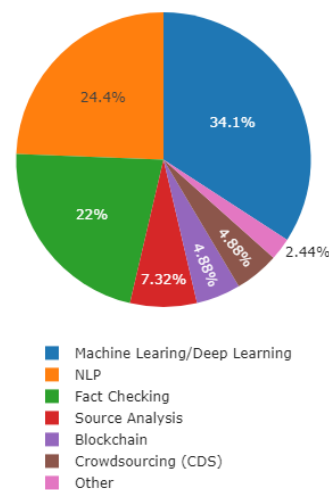**Figure 1. Fake news task stage covered**

Figure 2. Mentioned technologies in literature

As shown in Figure 1, the most mentioned fake news task stage (V9) is the content classification whether is real or not. Fabricated media detection such as fake images

is called *Fauxtography* [Zlatkova et al. 2019]. However, proposing technologies to deal with this task is rarely mentioned [S11]. Intervention and prevention of fake news are less mention in the literature.

4.2. RQ2: What techniques, tools, and methods have been reported in the literature?

Figure 2 illustrates the most mentioned technologies reported in the literature. Deep Learning emerges as the most frequently mentioned technology. Post the COVID-19 pandemic, research endeavors focused on detecting fake news related to health have gained prominence. [S1] and [S13] represent two studies that exclusively concentrate on COVID-19. The former offers a comprehensive examination of misinformation concerning COVID-19-related news on social media, while the latter juxtaposes pre- and post-pandemic scenarios using deep learning techniques. Similarly, [S12] targets health misinformation in a broader sense, with a specific aim of identifying analogies and distinctions between COVID-19 datasets and datasets associated with other health domains.

Recent advancements in fake news detection include applications such as SemiNext, a web search engine misinformation notifier extension [Shams et al. 2021], and Coverifi, a web application utilizing machine learning and human feedback to assess the credibility of COVID-19 news [Kolluri and Murthy 2021]. Additionally, there is ClaimKG, which is a knowledge graph of fact-checked claims [Tchechmedjiev et al. 2019].

The most mentioned public datasets are LIAR [S2, S5, S3, S6, S11, S15], FakeNewsNet [S2, S3, S5, S6, S11, S10, S15], CREDBANK [S3, S5, S6, S11, S15], and FacebookHoax [S3, S5, S6, S11, S15]. LIAR composes 12,8K human labeled short statements from fact-checking website PolitiFact[4] [Wang 2017]. Each news is labeled with six-grade truthfulness: true, false, half-true, part-true, barely-true, and mostly-true. FakeNewsNet contains 23K GossipCop[5] and PolitiFact fact-checking websites [Shu et al. 2018]. CREDBANK is a large crowd-sourced dataset of 6M tweets over 96 days starting from October 2015 [Mitra and Gilbert 2021]. FacebookHoax contains information about the posts from Facebook pages associated with scientific news (nonhoax) and conspiracy pages (hoax), gathered using the Facebook API. The data collection includes 15.5K postings from 32 pages [Tacchini et al. 2017].

It is worth noting that only [S12, S5] list six datasets more recent than 2018, all of which are related to COVID-19. Among these datasets, four are in English and have more than 100 citations as of October 10th, 2023: CoAID, FakeCovid, FakeHealth, and Re-COVery [Cui and Lee 2020, Shahi and Nandini 2020, Dai et al. 2020, Zhou et al. 2020].

4.3. RQ3: What are the main challenges, difficulties, and technological limitations in the detection, blocking, and explanation of fake news?

The main challenges approached in the literature are as follows:

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[4] https://www.politifact.com/
[5] https://web.archive.org/web/20190807002653/https://www.gossipcop.com/about/

Bridging echo chambers [S1, S2, S8, S11]: Addressing fake news and misinformation proves challenging due to public vulnerability and user unawareness, as highlighted by [S2]. A critical issue is the lack of media literacy, the ability to critically evaluate online content [S8]. Individuals often gravitate towards information that aligns with their pre-existing beliefs, while dismissing contradictory information [S1]. This behavior contributes to the formation of information bubbles, or echo chambers [S11].

Cross-domain, cross-platform datasets and frameworks: Fake news exhibits a dynamic and ever-evolving nature, characterized by diverse content, themes, publishing techniques, and sources, often designed to appear genuine [S2, S11]. It frequently incorporates a blend of "partially" true facts with false or misleading information, including inaccuracies in temporal data [S15]. However, many existing detection approaches focus on only one aspect, such as content, propagation, or style [S2, S11, S15]. In the context of health misinformation, most datasets are sourced from Twitter, yet misinformation also spreads through instant messaging apps and platforms like Quora [S12]. Furthermore, while the majority of available datasets are in English, fake news circulates in multiple languages. Propagation of misinformation from one country to another, resulting in new trends, is a noteworthy challenge [S11, S12, S15]. [S2, S11, S12, S15]

Real-time learning and Early detection of fake news [S2, S11, S15]: The social networks allow fast spread of content, and fake news, due to its structure and social bots, hence there is a need for early detection [S2]. Furthermore, the consequences of health misinformation could be harmful to individuals or public health [S12]. A potential search direction is user profiling, in which the capture of contextual information on user behavior derived from social media users and the network can provide additional useful information to increase detection accuracy [S2, S12]. Another direction is real-time detection, utilizing web applications for fact-checking that can continuously learn from newly fact-checked articles, providing real-time identification of fraudulent information [S11].

5. Final Remarks

The main contribution of this paper is the communication of results of a rapid tertiary study with the objective of raising the state of the art and common practices about fake news with respect to a variety of tasks and technologies in the context of social networks. 50 most relevant secondary studies in Google Scholar were analyzed, and 15 were included. Results revealed that, besides the expected diversity of definitions for fake news, various stages of fake news processing are covered in the literature, with a predominance in the use of deep learning (DL), and gaps still exist to be explored, including the urgent need for real-time learning and early detection of fake news.

Threats to Validity, Limitations and Future Work. Once this is a rapid review, with few secondary studies analyzed, relevant secondary studies were likely not included. This threat is alleviated because we considered the most relevant secondary studies ranked by Google Scholar algorithm. Moreover, the number of primary studies considered in the included secondary studies is high, which give us a reasonable panorama of the area and satisfies the premise and goal of a rapid review: support practitioners in their decision-making and delivering evidence in a timely manner [Cartaxo et al. 2020] (and the study

was actually effective for the team under that perspective). The other recurrent threats to conventional systematic reviewers are also smoothed here, since quality appraisal is often not conducted at all in rapid reviews and other concerns have their impact reduced in that context. However, we remark the importance of the results communicated here, not only for our team but also for the community, besides the novelty nature of our study, not only being (maybe) the first tertiary study about fake news but also by combining rapid reviews technique with tertiary studies conduction, which can also be a novelty and an advance in the state-of-the-practice for evidence-based research. Future work include (i) the refinement of the procedures for the conduction of rapid reviews in the context of tertiary studies, (ii) the replication of this study with a larger number of secondary studies, with a refinement in the the search string to reduce non-relevant results and including more scientific databases.

Acknowledgement

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