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REVIEW ARTICLE

Dominant Disciplinary and Thematic Approaches to Automated Fact-Checking: A Scoping Review and Reflection

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ABSTRACT

As artificial intelligence (AI) has become pervasive in journalistic production, the influence of algorithms on media practices has grown. We must always consider the interdisciplinary character of such sociotechnical systems. Otherwise, disciplinary discrepancies might impede the further development of these technologies. This article examines the emerging phenomenon of automated fact-checking in the context of information disorder and the growing demand for scalable solutions for information verification. Here, I identify the dominant disciplinary approaches and themes in research through a scoping review of 199 paper abstracts. My analysis shows that the literature on automated fact-checking is dominated by computer science, while the media perspective remains overlooked. Thematically, abstracts mostly concern the purpose and scope of such systems, their key components, tasks, features, and limits. Based on disciplinary and thematic analysis, I make a distinction between a computational and journalistic understanding of automated fact-checking and offer an interdisciplinary understanding of it. I argue for emphasizing the mundane use of AI technologies instead of striving for the epistemic authority of algorithms by anthropomorphizing them. This study offers the journalism research community new insights into emerging media technologies while suggesting a realistic research agenda for computer scientists by the interdisciplinary conception of automated fact-checking.

KEYWORDS

Automated fact-checking; computational fact-checking; structured journalism; information verification; scoping review; AI

Introduction

The growing disinformation problem in digitally mediated information systems—sometimes termed "information disorder"—has attracted significant scientific and industry scrutiny, empirically and conceptually (Fallis 2015; Monsees 2023; Wardle and Derakhshan 2017). Concerns from the early 1990s about the Internet becoming a "disinformation superhighway" (Floridi 1996) grew steadily along with the emergence

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of social media and the platformization of the information environment (Anderson 2021). The current hype around generative artificial intelligence (AI) aggravated concerns about the further upswing in the quantity and quality of online falsehoods (Simon et al. 2023). Against this backdrop, information verification came into the spotlight in the context of automation with the hope of scaling fact-checking (Abels 2022; Babaker and Moy 2016; Graves 2018).

Typically, fact-checking is understood as a human-led journalistic practice to determine the credibility and trustworthiness of information (Brandtzaeg et al. 2016). Currently, initiatives attempting to delegate laborious and resource-demanding routines of information checking to AI-driven technologies are proliferating (Westlund et al. 2022). One such attempt is to create automated fact-checking tools, and some AI-based prototypes have already been developed (e.g., Babaker and Moy 2016). However, to date, none of these prototypes have succeeded in becoming a technology that media professionals would widely adopt. Automated fact-checking tools seem to be more complex to develop than what the early proponents communicated when they called it "a Holy Grail of fact-checking" (Adair et al. 2017). As I will show, even after a decade since the first ideations, many uncertainties about automated fact-checking remain, including the related terminology and its definition.

As automated fact-checking is in its formative stage, such uncertainties are understandable. Emerging technologies are often stamped with ambiguity and vulnerabilities (Rotolo, Hicks, and Martin 2015), and multiple iterations of changes are expected to happen during this phase. However, I argue that these uncertainties partially stem from the fact that automated fact-checking is rarely discussed interdisciplinary, often overlooking perspectives from the media field. Tackling this disparity is especially important. As a sociotechnical system, automated fact-checking is not just a technical riddle for computer scientists: It is an endeavor that should be materialized within the world of news media production. Although there have been attempts to systematically frame knowledge about automated fact-checking, related knowledge remains somewhat scattered and guided mainly by the logic of computer science (Guo, Schlichtkrull, and Vlachos 2022; Kotonya and Toni 2020; Zeng, Abumansour, and Zubiaga 2021). Thus, it is necessary to map the automated fact-checking-related literature with a broader perspective that also encompasses journalistic perspectives.

To address this gap, I systematically searched and organized academic literature on the topic. In the analysis, inspired by the approach of Steensen et al. (2019), I identified the main disciplinary fields and prevalent themes in the abstracts of the papers concerning automated fact-checking. Through this disciplinary and thematic analysis, I documented the common approaches in research about the phenomenon, establishing an empirical basis for interdisciplinary understanding of it as a direction for future research.

Ultimately, this qualitative study clarifies the essence of automated fact-checking while recognizing its interdisciplinary character. It provides individuals interested in journalism studies with a roadmap for familiarizing themselves with and encouraging their engagement in discussions around automated fact-checking. For computer scientists, it offers a definition of the phenomenon with crucial arguments from journalism studies.

Structure-wise, this article first describes the evolution of fact-checking from a professional practice to a form of structured journalism (Caswell 2019; Graves and

Anderson 2020); this historical context is important for shifting the focus from thinking about automated fact-checking as not just a technology but also a professional practice that deals with the epistemic authority of journalists. Next, I summarize current research about automated information verification and the place automated fact-checking takes here, accompanied by two research questions. The methods section then thoroughly describes the procedures for selecting and analyzing the paper abstracts and the limitations of the study. In the findings section, I first document the dominant disciplinary and thematic approaches in the research, leading to the interdisciplinary definition of automated fact-checking. In conclusion, I propose an agenda for future research.

The Emergence of Automated Fact-Checking as Structured Journalism

The use of AI algorithms by fact-checkers has already been seen through the lens of structured journalism, which "not only uses data to generate news stories but also seeks to turn events in the world, and the stories we tell about those events, into structured data—that is, data organized in a fashion to be machine-readable—which can then be fed back into other stories" (Graves and Anderson 2020, 347). However, before moving to the realm of structured journalism, fact-checking had a rich history as an integral part of journalistic practice that turned into a separate genre of media production, aiming to protect and enrich the public discourse with factually verified information (Graves, Nyhan, and Reifler 2016). Since the early 2000s, legacy media and newly established fact-checking organizations have intensified the countering of malicious practices of spreading disinformation with so-called "ex-post" fact-checking, referring to information verification after its publication (Graves 2016). Simultaneously, the volume of misinformation and ideologically, politically, or financially motivated disinformation also grew globally—which Flroidi (1996) predicted would happen with the democratization of Internet access. Soon, it became clear that manual information verification might not be feasible and that the verification technologies might be falling short compared to the scale of information disorder (Chawla et al. 2019; Pathak 2021).

Some scholars and practitioners from fields such as journalism and media studies, linguistics, and computer science proposed involving AI in fact-checking as a solution (Graves 2018; Marinho, Bastos-Filho, and Lins 2021). Consequently, ideas about involving AI in information verification practices—using approaches such as machine learning (ML), natural language processing (NLP), and knowledge graphs—became increasingly ubiquitous (Guo, Schlichtkrull, and Vlachos 2022). Thus, AI-based technologies were imagined as possible scalable solutions to disinformation.

Seeing technology as an important factor in improving journalistic practices is nothing new. This approach was concisely formulated as early as 2000 by Pavlik, who stated that "journalism has always been shaped by technology" (2000, 229), impacting both how journalists work and the news media content itself. However, automation represents a paradigm shift. It extends beyond understanding journalism evolution as tech-led while redefining the normative boundaries of the profession, rendering it challenging to draw the line between human and machine authority in journalistic production. However, as Diakopoulos (2019) notes, in the process of hybridization of newswork, where humans, algorithms, and computers come together to complement each other's labor, machines are far less likely to replace humans. Instead, algorithms can perform intellectual rule-based tasks such as information prioritization, classification, association, and filtering; however, where high-level expertise is needed for the contextual interpretation of information, where creativity is required, and algorithms need to cope with unexpected scenarios, their performance struggles (Diakopoulos 2019).

Journalism automation discourse has its early roots in Meyer's precision journalism and the datafication of news media practices—and, more generally, in the quantitative turn in news media practices (Caswell 2019; Coddington 2015; Meyer 2002). The precision turn of the 1960s advocated for adopting quantitative social scientific methods to enhance the accuracy and depth of reporting (Meyer 2002). However, this perspective did not advocate shrinking human agency in journalism practice; instead, It saw human agency as central in news media production. With the advance of data journalism and computational journalism, these boundaries became blurrier as more tasks were delegated to computation.

Computational journalism—which evolved through newsrooms' practical application of diverse technologies borrowed from external fields like computer science—lacks a clear theoretical foundation (Caswell 2022). Increasing scholarly attention on structured journalism is one approach to identifying such a theoretical framework. As Lewis (2021) notes, adding algorithms to data journalism has gradually led to an increased reliance on technological systems and the use of "semantic units" (i.e., the smallest units of journalistic knowledge, such as annotated headlines, claims, and paragraphs) to create news stories. In this process, as Caswell (2022) notes, journalistic narration is created based on structured data instead of primarily exploiting human interpretation and creativity. Structured journalism reimagines news media production as a process of deconstructing journalistic stories into structured data that machines can digest. For instance, journalistic narratives are broken down into semantic units, which are later manipulated or reused either from the editorial side of the media or by the audience to create new journalistic products (Caswell 2019; Jones and Jones 2019). However, computational or structured journalism is inherently paradoxical, as it merges two conflicting cultures—scientific and humanistic. Computing, originating from science, is "a practice of abstraction which seeks to define classes of problems and then apply generalized solutions to them" (Caswell and Anderson 2019, 6). Meanwhile, traditional journalism focuses on unique stories and human imagination and pursues improved methods within its craft. Accordingly, trying to advance computational journalism means searching for a compromise between the two somewhat clashing cultures. This distinction becomes even more important once disciplinary approaches to automated fact-checking are analyzed, and I separate papers published within the computer science domain from journalism research. Later, disciplinary distinctions to the understanding of automated fact-checking are synthesized to set interdisciplinarity as a way forward for the research agenda.

Even before the idea of automation emerged, fact-checkers were already storing their information in a structured manner. Their work practice includes identifying claims and relevant sources, making decisions about the veracity of claims, and labeling them as "true," "false," "misleading," "myth," "pants on fire," etc. (Caswell 2019). As an important side note, despite distinct job routines and somewhat distinguished professional identities, fact-checkers remain within the journalistic profession and ethical frameworks. They essentially see themselves as journalists, distancing themselves, for example, from activist identity and denouncing partisanship in their work (Mena 2019). Thus, though the birth of "ex-post" fact-checking and increased attention to storing their stories in a structured manner was a necessary premise for the emergence of automation discourse, as a phenomenon, automated fact-checking is rooted in the journalistic practice of verification within news media production.

The Quest for Interdisciplinary Understanding of Automated Fact-Checking

Automated information verification efforts in both academic and industry contexts are diverse, although still in development. One type focuses on the detection of problematic content online. They are often referred to as fake news detection, disinformation detection, deception detection, hoax detection, detection of doctored images, deepfakes and cheapfakes, multimedia verification, and so on (Afroz, Brennan, and Greenstadt 2012; Appel and Prietzel 2022; Conroy, Rubin, and Chen 2015; Hsu, Zhuang, and Lee 2020; Mezaris et al. 2019; Thota et al. 2018). Some focus on social media and user-generated content as fertile ground for creating and spreading malicious content, while others focus more on legacy or alternative media production (Aldwairi and Alwahedi 2018; Raza and Ding 2022). They target different semantic units of digitally mediated content or various characteristics inscribed in the metadata of online published information. There are text- or content-based, context-based, source- or user-credibility-based, style-based, propagation-based, and hybrid detection models, to name a few (Mahid, Manickam, and Karuppayah 2018; Qureshi et al. 2022; Swapna and Soniya 2022; Zhou and Zafarani 2021).

However, the interrelation between the detection methods mentioned above and automated fact-checking is somewhat ambiguous. According to one approach, fact-checking is at the core of "multiple applications, e.g., the discovery of fake news, rumor detection in social media, information verification in question-answering systems… It touches on many aspects, such as credibility of users and sources, information veracity, information verification, and linguistic aspects of deceptive language" (Atanasova et al. 2019, 2).

Contrary to this, according to the other approach, automated fact-checking is part of the broader area of news content verification alongside multimedia forensics, rumor analysis, social media verification, and contextual video verification (Papadopoulou et al. 2019). Some even see automated fact-checking as a narrow task in the broader fake news detection process, alongside deception detection, stance detection, controversy and polarization identification, clickbait detection, and credibility measuring (Saquete et al. 2020).

Regardless of the place automated fact-checking will take among automated information verification systems, it faces contradictions akin to those in computational or structured journalism. On the one hand, such systems strive to create a universal, end-to-end solution that can detect a truth claim and determine the veracity of these claims based on evidence from authoritative referential sources. On the other hand, fact-checking as a journalistic practice is not as linear and clear-cut a process as computer scientists would wish. As Graves (2016) describes in one of the earlier studies on fact-checking, media professionals involved in information verification accept and appreciate the vague character of facts and the revisional nature of their resolutions about the veracity of claims. Thus, in the human world, ambiguity related to facts as semantic units is a feature, not a bug. Meanwhile, in the computer science world, uncertainties related to factual features of information can be a bug.

However, such a contradiction does not prevent different initiatives from searching for novel approaches to creating automated solutions for fact-checking. Due to the diverse approaches to and disagreements on how automated fact-checking should be implemented, it is impossible to imagine precisely what place fact-checking will take within the automated information verification field or, more generally, within the structured journalism tradition. This uncertainty is sustained due to the immaturity of automated fact-checking as a technological solution or journalistic tool. Although several papers categorized existing technologies, describing technical aspects and the related challenges, the bigger picture of automated fact-checking remains blurred (Sarr and Sall 2017). Specifically, empirical evidence is lacking on disciplinary and thematic trends about automated fact-checking, which would lay the groundwork for further investigation of the phenomenon. To address this gap, I identify prevailing disciplinary approaches and the dominant themes in the academic literature about automated fact-checking, addressing the following research question:

> RQ1. What are the dominant disciplinary approaches and themes in the research papers about automated fact-checking published between 2018 and 2023?

Answering the question lays the foundation for understanding automated fact-checking by integrating perspectives from journalism studies with the identified themes. This, then, leads to the second research question:

> RQ2. How can automated fact-checking be understood as an interdisciplinary endeavor based on the key themes identified in the existing literature?

Methodology

Scoping studies received methodological attention relatively late, compared to the other genres within "meta-studies," which refers to academic knowledge production without collecting firsthand empirical data or using primary sources (Arksey and O'Malley 2005). Scoping reviews are defined as a type of research synthesis that aims to "map the literature on a particular topic or research area and provide an opportunity to identify key concepts; gaps in the research; and types and sources of evidence to inform practice, policymaking, and research" (Daudt, van Mossel, and Scott 2013, 8). Every type of literature review has its strengths and shortcomings, and, as Arksey and O'Malley (2005) note, one "ideal type" of meta-studies does not exist (20). Scoping literature reviews are different from other, more established genres in the sense that, compared to systematic literature reviews, narrative reviews, or meta-analyses, scoping reviews allow researchers to explore topics without discriminating study designs. Moreover, unlike systematic reviews, it does not engage in discussions about the quality of arguments of the included studies (Arksey and O'Malley 2005). Thus, the scoping approach enables us to map out the existing knowledge and identify research gaps, especially in emerging topics about which knowledge remains insufficiently charted (Pham et al. 2014). I argue that automated fact-checking is one such topic. As Korkeila (2023) mentions, scoping reviews "chart concepts in emerging scientific fields or provide an overview or clarity to some research questions or aims" (1767). Considering that automated fact-checking is only just emerging, it is timely and relevant to sketch the existing knowledge about the topic with the help of a scoping approach.

Conducting a scoping review involves at least four methodological steps: identifying the research question, identifying and selecting studies, reducing and analyzing data, and reporting the study results (Arksey and O'Malley 2005). This literature review follows these steps, and the details of this process are described below.

Abstract Sampling

Finding the relevant studies for the scoping review is an iterative process that requires identifying keywords for the search, selecting databases, creating the search protocol, and collecting the results in a manageable way. As Pham et al. (2014) note, "scoping reviews share a number of the same processes as systematic reviews as they both use rigorous and transparent methods to comprehensively identify and analyze all the relevant literature pertaining to a research question" (372). Accordingly, after designing the research questions for the study, I selected databases to identify relevant studies for answering RQ1. As I am interested in automated fact-checking as the technology used by journalists, first, I selected six databases commonly used for literature searches in media and communication studies: Elsevier Science Direct Journals Complete, Taylor & Francis, Sage Journals, Communication & Mass Media Complete, Springer Link, and Web of Science.

Immediately, it was obvious that the number of papers in the selected databases was limited. Accordingly, I included more academic databases with a focus on technologies, as it was expected that automated fact-checking would be widely discussed within disciplines such as data science, computer science, and AI studies. Thus, I added ACM Digital Library and IEEEXplorer to the list of selected databases.

As automated fact-checking is still in its infancy as an empirical field, to cover the breadth of the existing scientific knowledge, I included search results from two additional databases that do not allow users to filter the results as to whether the entry is peer-reviewed: ArXiv, an openly accessible digital collection of preprints and post-prints of studies and conference papers that undergo moderation before being approved for posting without formal peer review; and Google Scholar, a search engine for scholarly literature that indexes texts or metadata from a diverse range of publishing formats and disciplines.

As an initial entry point for the literature search, I selected "automated fact-checking" as the most commonly used term for the subject of interest for this study. From the preliminary scan of the literature, I have identified three more keywords often found in the studies focusing on the automation of fact-checking practices: "automatic fact-checking," "computational fact-checking," and "algorithmic fact-checking."

I used two criteria from the beginning of the literature search to filter the results: language and the date of publishing. Papers had to have been published in the English language from January 2018 to May 2023 (i.e., within the past 5 years). Except for ArXiv and Google Scholar, in all databases, the keywords were searched indiscriminately to determine whether they appeared in titles, abstracts, and/or the text body. In the case of ArXiv and Google Scholar, to avoid contaminating the search results with excessively irrelevant literature, the keywords were searched only if they appeared in the titles or abstracts of the papers.

After the first round of data collection, I downloaded 483 citations into the reference managing system Zotero. To clean up the data, I applied inclusion and exclusion criteria to the downloaded papers in two phases: (a) before reading the abstracts and (b) after reading the abstracts.

Prior to reading the abstracts, I excluded duplicated references, conference introductions, transcripts of invited talks, workshop tutorials, and introductions to special issues, as well as pieces from the industry press published in languages other than English. This step was taken to ensure consistency in the inclusion criteria for further data reduction. Thus, in this phase, the final inclusion criteria consisted of being a peer-reviewed article, book chapter, preprint or post-print paper, PhD thesis, or a paper published in conference proceedings in English and accompanied by an abstract. After the first phase, the number of relevant papers was reduced to 338.

During the second phase, the exclusion criterion exhibited a more evaluative nature, necessitating the interpretation of the texts in the paper abstracts. Here, I have excluded entries in which automated fact-checking was not a central topic of the study. Accordingly, in the final selection of the papers, I only included the papers that discussed automated fact-checking in general or a corresponding component. As my central interest in this article is to map out the literature that discusses automated fact-checking as a technology that is used within specific professional contexts, as well as to define automated fact-checking as an emerging media technology, it was crucial to reduce the data to the abstracts that paid sufficient attention to the automation of information verification. I ultimately selected 199 papers whose abstracts I analyzed thematically.

Data Analysis

For the analysis, I borrowed an approach from the Steensen et al. (2019) study, which analyzed article abstracts, keywords, and references from *Digital Journalism* to identify dominant disciplinary and thematic perspectives about digital journalism studies. Elsewhere, Steensen and Ahva (2015) used a similar approach to investigate theoretical trends in journalism studies based on keywords and abstracts of articles from *Journalism* and *Journalism Studies*. However, both studies analyzed articles from a discrete number of journals, with an emphasis on quantitative attributes of the acquired data. This scoping review investigated abstracts from a broad selection of publications, emphasizing the qualitative interpretation of abstract texts. Accordingly, it was necessary to modify the approach used by Steensen et al. (2019). On the one hand, the diversification of publication sources allowed me to conduct a disciplinary analysis of papers based on the scientific domain that the corresponding publishers belonged to. On the other hand, abstract texts were a suitable dataset for qualitative thematic analysis instead of collecting numerical insights about keywords and references in the articles.

Initially, I classified papers into two broad disciplinary fields—computer sciences and journalism studies—based on the scientific domains of the journals, chapters or conference proceedings where the papers were published. This division echoes the theoretical complexity of automated fact-checking as an offspring of structured journalism, which (as discussed above) juxtaposes computational and journalistic cultures (Caswell and Anderson 2019). Each of these categories can be broken down into narrower disciplinary domains. However, for this article, introducing broader field categories was a logical choice simply to demonstrate the disparity in interest toward automated fact-checking in computer science and journalism studies.

I then engaged in thematic analysis and coded the abstracts using the qualitative analysis program NVivo to identify the dominant topics discussed in the paper abstracts. The initial coding was conducted to identify prevailing themes and/or find "an abstract entity that brings meaning and identity to a recurrent [patterned] experience and its variant manifestations" (Saldaña, 2009, 139). Here, a theme serves as a means of organizing a data set by representing an underlying topic that unifies a collection of recurring ideas (Saldaña, 2009). After the initial coding, the codes were unified under broader categories. These categories represent the main themes discussed in research on automated fact-checking, and they will be described in the following chapter after I elaborate on the dominant disciplinary approaches, thus answering RQ1. In the final section, I will answer RQ2 based on the synthesis of the scoping review results and the accompanying discussion.

Study Limitations

This scoping review comes with limitations. Firstly, it excludes the literature from non-academic sources, such as trade press, public media platforms, media think tanks, research centers, or governmental and non-governmental organizations. The often-discussed gap between academic research about journalism and newsroom practices (Bélair-Gagnon and Usher 2021) results in a bulk of knowledge about journalistic production being created outside of academia due to more flexibility within the industry. This is true for automated fact-checking as well. Using Google Scholar as one of the databases for identifying relevant literature proved that organizations such as the Nieman Journalism Lab (Pogkas 2017; Schmidt 2018), the Poynter Institute (Abels 2022; Funke 2018), and Full Fact (Babaker and Moy 2016) laid the foundation for discussions about the essence of automated fact-checking.

Similarly, the Reuters Institute for the Study of Journalism and the Centre for Economics and Foreign Policy Studies has published important work about the role of AI in information verification (Graves 2018; Ünver 2023). Google Scholar, an academic search engine, usually captures not only peer-reviewed publications but also reports, white papers, and other types of "gray literature," which certainly contains valuable hands-on knowledge from the industry. However, the final dataset for this study only covers papers published through academic or semi-academic channels to ensure the necessary rigor of the selected publications. This includes research articles, book chapters, and theoretical contributions that have undergone a peer-review process.

This decision was made in combination with yet another limitation of the study - I analyzed only the abstracts of the papers. Steensen et al. (2019) note that "while abstracts do not give a full picture of articles, they will probably indicate the disciplinary, theoretical and empirical emphasis of articles" (326). As one of the main goals of this scoping review was identifying dominant themes in research about automated fact-checking, there was a risk of overlooking important topics contained within the paper but not in the abstract. However, due to the peer-reviewing standards and editorial filters, choosing academic or semi-academic databases would ensure that the selected abstracts were what the APA (2020) calls a "comprehensive summary of the contents of the paper" (73).

One more limitation of this study is the non-exhaustive nature of the selected keywords. As the abstract analysis shows, some papers also used terms such as "AI fact-checking," "AI-assisted fact-checking," and "algorithm-assisted fact-checking" to denote essentially the same concept as automated fact-checking (Lee and Bissell 2024; Neumann and Wolczynski 2023). Nevertheless, instances like these were minimal, and searching for these terms in the databases would not have significantly altered the overall outcome of the scoping process.

Findings

In the next two sections, I answer the first research question: *What are the dominant disciplinary approaches and themes in the research papers about automated fact-checking published between 2018 and 2023?*

Dominant Disciplinary Approaches

Out of 199 studies, only 12 are published in journals, books, or conference proceedings relating to journalism studies (such as Adair et al. 2019; Graves 2018; Johnson 2023; Rubin 2022). For the most part, the studies are published in the computer science domain, and only an insignificant number of papers are published on academic platforms focusing on health science or business studies. This disparity was obvious even during the initial literature search when the results from the first six databases did not yield significant results. Consequently, to grasp the thematic characteristics of research about automated fact-checking, it was necessary to add papers from databases specifically focused on computer sciences: ACM Digital Library, IEEEXplorer, and ArXiv. Adding literature from such databases affected the disproportionality of results regarding disciplinary domains.

Except for the selected databases, the other cause of disciplinarily uneven results may be that automated fact-checking as a sociomaterial phenomenon has not yet matured. Studies that document media practitioners' experiences engaging with automated fact-checking tools are lacking. Moreover, researchers see automated fact-checking primarily as a technological product. This was apparent in my analysis, especially regarding the limits of automated fact-checking, as papers usually focus on technical barriers impeding AI systems from fulfilling the information verification task: for example, the quality of the data set, system scalability and integrity, issues with annotating data, system bias, multimodality of information, and the ability of AI to grasp the contextual or common sense information (Nakov et al. 2021; Zeng, Abumansour, and Zubiaga 2021). Despite some attempts to use the journalistic lens, such disciplinary disparity leaves large areas of automated fact-checking underresearched (e.g., De Haan et al. 2022; Johnson 2023; Thomson et al. 2022). Following the thematic analysis of the abstracts, I discuss the issue of interdisciplinary understanding of automated fact-checking as a means of addressing such blind spots.

Dominant Themes in Automated Fact-Checking Research

The abstract analysis shows that most of the papers about automated fact-checking center around three broad thematic categories: the purpose and scope of automated fact-checking systems, key components and tasks of automated fact-checking, and key features and the limits of automated fact-checking. Though these thematic categories are interpretative, they cover most of the range of the topics discussed within the selected abstracts.

The Purpose and Scope of Automated Fact-Checking

In the selected abstracts, the overall purpose and scope of the automated fact-checking systems are often discussed. The purpose of automated fact-checking tools is often determined by isolating a specific angle of the disinformation problem, and it is motivated by the impossibility of fact-checkers to cope with the abundance of information requiring verification. Naturally, this also affects the scope of the implied tools. By scope, I refer to the goal of the tool developers regarding what should be automatized in the fact-checking process, what type of information should be checked, and to what extent.

The purpose of suggested automated fact-checking tools is mostly concerned with the quality of digitally mediated information and determining the positive or negative agenda for automated tools. By negative agenda, I mean targeting problematic modes of information, such as disinformation (Ghosal, Deepak, and Jurek-Loughrey 2020), misinformation (Barve and Saini 2023), fake news (Wang et al. 2023), and false or misleading claims (Santos and Pardo 2020). Meanwhile, automated tools with a positive agenda to assess the credibility of media content generally (Wild, Ciortea, and Mayer 2020) or specifically in claims relevant for fact-checking (Botnevik, Sakariassen, and Setty 2020); to estimate truthiness or trustworthiness (Primiero, Ceolin, and Doneda 2023; Thirumuruganathan, Simpson, and Lakshmanan 2021); and to determine qualitative characteristics of information, such as correctness, factuality, veracity, and authenticity (Wang, Deng, and Wu 2019; Fairbanks et al. 2020; Brand et al. 2023).

When describing the existing research in terms of what should be automatized, some researchers seek to automate the entire information verification cycle, i.e., creating an end-to-end automated fact-checking system (Aloshban 2020; Pathak and Srihari 2021;). Researchers usually refer to automated fact-checking systems as end-to-end when they are "not only capable of searching different sources, but also predicting the factuality of claims, and presenting a set of evidence with explanations to support the prediction" (Ahmed, Hinkelmann, and Corradini 2022, 356). However, on a more detailed level, there is no agreement on what such an end-to-end system should contain. The so-called "pipelines" for end-to-end systems vary from paper to paper, depending on the approach to information verification.

The other group of researchers focuses on the automation of singular or multiple tasks (e.g., claim detection, data annotation, evidence retrieval, and claim verification), about which I will elaborate in the subsequent discussion on automated fact-checking tasks (Botnevik, Sakariassen, and Setty 2020; Meel and Vishwakarma 2021).

Moreover, some publications discuss automated fact-checking systems in the context of verifying information about one or several specific domains—such as public health issues, politics, migration, climate (Barve and Saini 2022; Cao, Manolescu, and Tannier 2019; Hu et al. 2022), or events (Nikiforos et al. 2020)—while other initiatives aim to create, what I call, universal systems, to automatize fact-checking without differentiating between the topics (Fang 2021; Pathak 2021). Domain-specific automated fact-checking can be considered a more manageable alternative to universal systems, as they are less ambitious and framed by requiring less data to train the algorithms. However, domain specificity does not mean that, within the domain, new data do not emerge and that, in real-world scenarios, such systems will not have problems with accuracy.

The other major dimensions in the scope of automated fact-checking tools are the modality of information, language, and the temporal dimension. Research papers discuss whether such systems should aim to verify textual claims, which is the case for most studies (Ullrich et al. 2023), or if the system should have multimodal verification features (Svahn and Perfumi 2021). Moreover, as expected, most of the research focuses on checking facts in English; however, one can also notice the growing interest in designing automated fact-checking systems for so-called "low resource languages," such as French, Arabic, and Czech, or in multilingual models (Gupta and Srikumar 2021; Sarr and Sall 2017; Ullrich et al. 2023).

The final important aspect of the automated fact-checking scope is the degree to which such systems are autonomous: namely, the role of manual supervision in the functioning of automated tools and the degree and points of human interference in validating the automated fact-checking results—often portrayed as "a human-in-the-loop" approach or "semi-automated" fact-checking systems (Nguyen et al. 2018; Wild, Ciortea, and Mayer 2020). This approach is often also manifested in discussing "human–AI partnership" (Nguyen et al. 2018) or conceptualizing automated fact-checking as a technology assisting humans in decision-making about informational features of news content (Lin et al. 2022; Nakov et al. 2021). On the opposite side of the autonomy scale are the studies pursuing end-to-end automated fact-checking systems designed to reduce the burden on manual fact-checkers for verifying facts (Pathak and Srihari 2021). However, such tools have not yet materialized, unlike semi-automated fact-checking tools that are already in use in several organizations, such as the British fact-checking organization Full Fact.

Key Components and Tasks of Automated Fact-Checking

Apart from the purpose and scope, a vast amount of research focuses on the material components of automated systems for fact-checking. Here, the word "material" is applied in its broadest meaning, usually referring to the digital components of the systems, such as data, algorithms, or the outputs of the fact-checking systems. Despite diverging opinions about the precise elements of automated fact-checking pipelines, the abstract analysis allows us to sketch the constituent parts of such systems. At its most basic, automated fact-checking systems are imagined as mathematical models composed of multiple underlying algorithms trained with the human-produced data of previously checked information, mostly textual claims. The result or output should be the resolution concerning the factual veracity of claims and the explanation for such a resolution. Accordingly, the often-discussed key components of automated fact-checking systems are as follows:

- Data refers to the previously annotated and stored information in databases used for either training algorithms to identify relevant claims and matching them to the previous fact-checks or for cross-checking them with reference sources containing credible, institutionalized information (Bondielli and Marcelloni 2019; Meel and Vishwakarma 2021).
- Algorithms are the mathematical calculations or rules upon which automated tools rely to determine the relevance of the claim and evidence for fact-checking, retrieve them, and predict the veracity value of the claim based on such evidence (Huynh and Papotti 2019; Primiero, Ceolin, and Doneda 2023).
- The output component refers to the algorithm's decision concerning where the relevant claim lands on the veracity value range from true to false. It is usually marked with labels and often accompanied by explanations or automatically generated reasoning for such a decision (Rani et al. 2023; Ullrich et al. 2023).

Apart from the material components of automated fact-checking technologies, the literature also focuses on the semantic units involved in the functioning of such systems. Semantic units, which refer to the building blocks of the journalistic information arranged as structured data of annotated textemes (Caswell 2019), typically involved in automated fact-checking systems are as follows:

- A claim is a bit of information that must satisfy the criteria of checkability and checkworthiness to merit fact-checking; it also refers to sources or claimants as entities from whom the claim originates (Chen et al. 2023; Dong et al. 2021).
- Evidence refers to the information against which the claim is weighed and evaluated to determine how and why it can be regarded as true, false, or anything in between. Such evidence can be previous fact-checks or information stored in a reputable database (Glockner, Hou, and Gurevych 2022; Mohr, Wührl, and Klinger 2022).
- Context—or additional information related to the information conveyed via a claim or the evidence—also determines the veracity value of the information that must be checked and is particularly difficult for automated systems to grasp as structured data (Aloshban 2020; Atanasova et al. 2019)

According to the literature, the abovementioned components are part of the multiple procedures that fact-checking technologies must perform. Various automated fact-checking pipelines, which could also be seen as a chain of information processing stages, conceive this verification process differently—though Figure 1 shows the four core steps often discussed in the selected abstracts:

These procedures are discussed either in the framework of the end-to-end system or as a single step or multiple steps that must be developed before creating the entire system. Claim detection as a step refers to the process of singling out a specific type of information that can be factually verified or refuted and is often discussed in the context of checkworthiness or checkability (Allein, Augenstein, and Moens 2021; Atanasova et al. 2019; Farinha and Carvalho 2018; Hansen et al. 2019). As Wright and Augenstein note (2020), "claim check-worthiness detection is a critical component of fact-checking systems" as the initial step for automated fact-checking (p. 1). Some argue that it has received less attention than the verification step, as automated systems seem far from yielding satisfactory results even in this first task. However, Sheikhi, Touileb, and Khan (2023) argue that "large language models could be successfully employed to solve the automated claim detection problem" (1).

Furthermore, automated fact-checking systems should be able to assess whether the information stored in referential databases and repositories matches the identified claims, which corresponds to the verification step. However, before verification, the major step is evidence retrieval from the databases. Evidence retrieval might also include processes such as evidence ranking, sentiment analysis, and stance detection (Lin, Song, et al. 2019; Mongiovì and Gangemi 2022). Eventually, the algorithm should be able to determine the veracity value of the claim based on the comparison to the retrieved evidence, decide to label the claim as factually correct or incorrect and generate an explanation that humans understand.

The other important procedures discussed in the context of automation and fact-checking involve annotating the data or so-called tagging (Mohr, Wührl, and Klinger 2022), referring to breaking down journalistic information into structured textemes, digestible by the computer (Casswel 2019). This is a necessary step that precedes even the claim identification step, as the algorithm should be pre-trained based on such structured data to identify checkworthy claims and/or manage claims related to the evidence. Annotations are usually done manually. However, some studies discuss the automatization of this process, as manually annotating data is laborious and time-consuming (Xu, Mohtarami, and Glass 2019).

Key Features and Limits of Automated Fact-Checking Systems

The idea of automating fact-checking is often rationalized by stating the need for technological solutions for information verification that can be scaled and efficient while countering disinformation flooding the digital information ecosystems (Boididou et al. 2018). Thus, automated systems' scalability and efficiency are often discussed in research as key features that would ease the burden of manual fact-checkers and

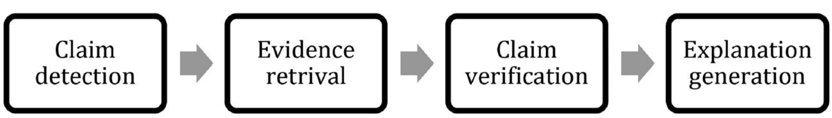

Figure 1. Core steps in automated fact-checking pipelines.

effectively identify problematic online content (Lin, Song, et al. 2019). However, scalability and efficiency are not the only features that would determine the viability of automated fact-checking systems. Such technologies are also often discussed in the context of robustness in real-life scenarios or generalizability (Glockner et al. 2023; Schiller, Daxenberger, and Gurevych 2021). Automated systems trained on data to verify claims about one topic, such as election debates, COVID-19, climate, etc., most likely will not work when applied to other subject matters.

Apart from the characteristics of the entire system, literature also determines the key features of the automated fact-checking components or tasks. Concerning claims, checkworthiness and checkability constitute two central features that stand out in the abstracts. Checkworthiness can be understood as a qualitative feature of information bits that determines the relevance of a specific claim for a verification task. However, a claim's checkworthiness does not necessarily mean that the automated system will move to the verification step, as its checkability plays a central role in determining whether the verification can be performed. For the claim to be deemed checkable, it should satisfy certain criteria: It should not express someone's judgment, and it should not be speculative or concerned with future scenarios.

For the evidence retrieval and claim verification tasks, the key feature is accuracy: Automated fact-checking algorithms should be able to determine the relevant piece of evidence from the database and define the relationship between the claim and the evidence to label it correctly. Without a proper degree of accuracy in these steps, the entire system risks becoming irrelevant. However, it is also noticeable that a growing number of studies pay particular attention to features such as the transparency and interpretability of automated fact-checking results (Augenstein 2021; Nguyen et al. 2018). These features can be seen through the explainability potential of automated systems, as they play a central role in creating trust among end users of information toward the decisions made by AI-based technologies (Augenstein 2021; Brand et al. 2023; Kotonya and Toni 2020).

Importantly, the key features of automated fact-checking systems and their components are also often the reason those systems have not yet achieved widespread adoption, especially concerning the features of the automated fact-checking components and tasks. For instance, determining the checkability and checkworthiness of claims, guaranteeing the retrieval of relevant evidence, and establishing an accurate relation between the two are still unattainable goals for algorithms. As Glockner et al. note (2023), "the retrieved evidence may not unambiguously support or refute the claim," while "existing fact-checking datasets necessitate that models predict a single veracity label for each claim and lack the ability to manage such ambiguity" (p. 1). Ambiguity becomes particularly problematic when automated fact-checking capabilities must be tested in real-world scenarios, where contextual information exerts even greater influence on the claim's meaning (Liu and Zhou 2022; Mansour, Elsayed, and Al-Ali 2023). Although there have been efforts to translate the contextual and discursive information into machine-readable structured data (e.g., Atanasova et al. 2019), Graves (2018) highlights that "much of the terrain covered by human fact-checkers requires a kind of judgment and sensitivity to context that remains far out of reach for fully automated verification" (1). In addition to challenges arising from real-life scenarios and difficulties in structuring contextual information, the other limits of automated fact-checking systems denoted in the selected abstracts include managing bias in data sets used to train the algorithms or for verification (Schlichtkrull, Ousidhoum, et al. 2023); accessibility to data (Hardalov et al. 2022); "relying on artificial claims, lacking annotations for evidence and intermediate reasoning, or including evidence published after the claim" (Schlichtkrull, Guo, et al. 2023, 1); and vulnerability to disinformation campaigns, as they might become targets of attacks from "fact-saboteurs" and fed unreliable data that could negatively affect their functionality (Abdelnabi and Fritz 2023). Moreover, as Neumann, De-Arteaga, and Fazelpour (2022) write, "the ethical and societal risks associated with algorithmic misinformation detection are not well-understood" (1), as algorithms might be problematic in terms of fairness, disproportionately benefiting certain societal groups over others (Neumann and Wolczynski 2023).

Towards an Interdisciplinary Understanding of Automated Fact-Checking

Responding to RQ2—*How can automated fact-checking be understood as an interdisciplinary endeavor based on the key themes identified in the existing literature?*—requires simplifications given the discrepancies in computer science literature and journalism research and the interpretative thematic categories from the qualitatively analyzed abstracts. Abstracts from both disciplines discuss core tasks of automated fact-checking, be it claim identification, evidence retrieval, verification, and generating explanations or semantic units such as claims or explanations. However, where the two disciplines diverge most is the scope and features of automated fact-checking systems, which, as I discussed above, are also often seen as limitations for such systems. Below, I discuss the distinctions between computer science and journalism research understandings of automated fact-checking and how the interdisciplinary understanding of the phenomenon can inform future research.

Computational Understanding of Automated Fact-Checking

Due to the disciplinary disparity, much of the literature seems to emphasize automated fact-checking as a product or a technological assemblage that should function autonomously from humans and achieve a high degree of authority in the information verification process. Thus, in this body of literature, more material aspects of automated fact-checking pipelines, such as data, algorithms, and system outputs, receive significant scientific attention.

As Das et al. (2023) note, "The core idea behind automated fact-checking is enabling AI to reason over available information to determine the truthfulness of a claim" (3). According to the other definitions, in the fact-checking pipeline, "first, the input document is analyzed to identify sentences containing check-worthy claims, then these claims are extracted and normalized, and finally, they are fact-checked" (Atanasova et al. 2019, 2), while Torabi Asr and Taboada (2019) claim that "computational fact-checking attempts to find unverified claims in a story or rumor and check them against reliable sources" (4). Thus, papers published within the computer science field often describe automated fact-checking tools as potent for high-level intellectual tasks. However, when researchers from computer science formulate the goal of automated fact-checking to determine the credibility or truthiness of media content, they anthropomorphize the machine by ascribing to them the human ability to reason. Realistically, machines can only determine whether one structured element of information (the claim) matches the other (the evidence). By determining the goal of automated fact-checking as making decisions about the correctness, factuality, veracity, fakeness, authenticity, integrity, etc. of information, the bar is set too high, as AI cannot reason, at least for now. It can only calculate and make predictions about the matchability of the claim and the evidence.

To put it simply, computational understanding of automated fact-checking

- Focuses on automated fact-checking as a product or technological assemblage.
- Inclines towards the autonomy from humans.
- Focuses on claim identification and verification potential of technologies.
- Strives for a higher degree of epistemic authority in deciding the truth value of claims.
- Has an anthropomorphic conception of AI.

However, some articles from computer science do mention the "human-in-the-loop" approach and assisting function of AI-based technologies, which come closer to the journalistic conception of automated fact-checking, discussed next.

Journalistic Understanding of Automated Fact-Checking

Arguments from the field of journalism studies, along with discussions within the trade press, the fact-checking industry, media think tanks, and research centers, prove that automated fact-checking is not just a technological advancement (Babaker and Moy 2016; Graves 2018). It also refers to a new journalistic practice based on a different philosophy. This philosophy somewhat contradicts the idea that automated fact-checking is a primarily technological product that should function autonomously from humans. Instead, it acknowledges the role and the function AI could acquire in the process of fact-checking without giving away too much journalistic authority. Such functions can be aforementioned rule-based intellectual tasks, such as prioritization of claims and evidence, their classification, associating claims with evidence, and filtering information (Diakopoulos 2019). However, fact-checking also involves dealing with ambiguities, context-dependent modifications of information, and sophisticated expert knowledge that should be adaptable and creative in certain scenarios, for example, when it comes to interpreting visual cues or tacit knowledge. Accordingly, perspectives from the field of journalism studies can help us to understand the phenomenon interdisciplinarily and more realistically.

In one of the early attempts at conceptualizing automated fact-checking, Graves (2018) notes that "primary approaches to automatic verification are matching statements to previous fact-checks or consulting authoritative sources" (4). Emphasizing the matching feature of the technology deflates the overly exaggerated expectations from automated fact-checking. Such deflation not only spares AI systems from adharing to ambitious, as yet unachievable epistemic goals but also creates an effective basis for the industry to welcome such technologies. As Johnson's (2023) study found, with regard to meta-journalistic discourse in terms of boundary work around the automation of fact-checking, two forms were present: expansion and protection. This means that media professionals were open to expanding their toolkits with AI-powered technologies as an assisting, mundane extension of their skills. However, they remain protective in terms of giving up their epistemic authority in favor of machines. In the context of fact-checking, this can be translated into the mantra of "Automate what computers do best, let people do the rest" (Diakopoulos 2019, 13), meaning letting AI accelerate data processing by translating journalistic knowledge into semantic units and associating the claim units with evidence ones. Yet, making decisions about the veracity of the claim and the qualitative coherence of matching claims with the evidence would remain within the human domain.

Thus, the journalistic understanding of automated fact-checking:

- Focuses more on automated fact-checking as a practice.
- Adheres to a human-in-the-loop approach.
- Focuses on claim-evidence matching capabilities of sociotechnical systems.
- Leaves epistemic authority to humans.
- Has a mundane conception of AI.

Interdisciplinary Understanding of Automated Fact-Checking

Both understandings of automated fact-checking offer important clarifications regarding the potential of AI for information verification. Moreover, automated fact-checking as a sociomaterial endeavor does not fit into a single disciplinary domain, as it uses AI techniques (such as ML and NLP) to replicate actions typically performed by humans. Simultaneously, as structured journalism, it relies on human input, is often targeted at a particular professional group (media practitioners), and attempts to merge computational and journalistic cultures (Caswell and Anderson 2019). Accordingly, it should be imperative to study automated fact-checking as an interdisciplinary phenomenon both as a technology and as a practice.

Synthesizing the above-discussed two understandings, automated fact-checking, as an interdisciplinary endeavor, *should be understood as a sociotechnical tool and a practice that seeks autonomy in information verification tasks with limited epistemic authority. Such tasks are processing data to translate journalistic knowledge into semantic units – claim, evidence, and resolution/explanation - and calculating the compatibility of semantic units with each other to enhance and speed up the human ability to verify information.*

This definition offers a reorientation toward mundane tasks, such as matching claims to evidence, rather than anthropomorphizing AI technologies and setting high expectations for their epistemic potential. It spares the technology from the burden of determining the truthfulness or falseness of information and, instead, emphasizes the value of matching information bits to authoritative sources. More importantly, this reorientation leaves space for humans to have the final say in the intricate process of information verification.

Conclusion

Though automated fact-checking emerged as an idea and a practical determination among computer scientists and journalism communities almost a decade ago, it has yet to materialize as an actual tool or a viable journalistic practice. As the literature on the topic has mounted over the years, the necessity of sketching out academic knowledge about the automation of fact-checking more systematically is apparent. In this study, I addressed this need by scoping the disciplinary and thematic characteristics of 199 academic paper abstracts. Although knowledge about automated fact-checking has been summarized previously, this study, for the first time, mapped out the academic knowledge on the topic while placing the phenomenon within the structured journalism tradition (Caswell 2019) and conceptualizing it both as a sociotechnical tool and a practice.

Importantly, I found a significant disciplinary gap in the literature about automated fact-checking. Although automated fact-checking is an inherently interdisciplinary phenomenon where computational and journalism traditions (Caswell and Anderson 2019) join forces to create a new type of technology for a new journalistic practice, so far, academic research on the topic stems mostly from computer science. Perspectives from journalistic research are thus overlooked, resulting in a lack of a truly interdisciplinary understanding of the phenomenon.

By defining automated fact-checking as technology that should calculate the matching potential of semantic units of information instead of autonomously deciding what is true or false and striving towards epistemic authority, I argue for diverging from the anthropomorphic perception of AI in future research. Doing this is possible by reemphasizing the mundane function of AI technologies to help human fact-checkers. Though several studies have addressed the automated fact-checking application (or the lack thereof) within journalism (De Haan et al. 2022; Graves 2018; Johnson 2023), the definition I offered opens up discussion about the practical use of AI tools for fact-checking without burdening the technology with a high degree of epistemic authority. This approach can be used as a reference point in future research while reducing the anxieties within automation discourses (Barbour et al. 2023) that can sometimes cloud the real opportunities of AI for journalistic practice.

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No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are openly available in "figshare" at http://doi.org/10.6084/m9.figshare.25305199.

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