Autonomation, not Automation: Activities and Needs of Fact-checkers as a Basis for Designing Human-Centered AI Systems

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To mitigate the negative effects of false information more effectively, the development of Artificial Intelligence (AI) systems assisting fact-checkers is needed. Nevertheless, the lack of focus on the needs of these stakeholders results in their limited acceptance and skepticism toward automating the whole fact-checking process. In this study, we conducted semi-structured in-depth interviews with Central European fact-checkers. Their activities and problems were analyzed using iterative content analysis. The most significant problems were validated with a survey of European fact-checkers, in which we collected 24 responses from 20 countries, i.e., 62% of active European signatories of the International Fact-Checking Network (IFCN).

Our contributions include an in-depth examination of the variability of fact-checking work in non-English speaking regions, which still remained largely uncovered. By aligning them with the knowledge from prior studies, we created conceptual models that help understand the fact-checking processes. Thanks to the interdisciplinary collaboration, we extend the fact-checking process in AI research by three additional stages. In addition, we mapped our findings on the fact-checkers’ activities and needs to the relevant tasks for AI research. The new opportunities identified for AI researchers and developers have implications for the focus of AI research in this domain.

CCS Concepts: • Human-centered computing → Empirical studies in collaborative and social computing; Empirical studies in HCI

Additional Key Words and Phrases: fact-checkers, misinformation, disinformation, human-centered artificial intelligence, human-information interaction

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1 Introduction

Research shows that the most effective mitigation of political misinformation in terms of lowering issue agreement and perceived accuracy is a combination of information literacy interventions and fact-checkers’ efforts [23]. Fact-checkers have an irreplaceable role in mitigating the effects of misinformation, as they successfully lower the agreement with attitudinal congruent political misinformation and can help overcome political polarization [24].

A fact-checker is “a person whose job is to make sure that the facts are correct, especially in something published” [1]. These professionals work either in larger newspaper agencies (e.g., in AFP, Deutsche Welle, Washington Post) or small or medium-sized NGOs focused just on fact-checking (e.g., Full Fact, PolitiFact.com, FactCheck.org, etc.). Many aspects of the fact-checker’s work, as well as the problems this profession faces differ across the positions (e.g., the required education), remain unclear (e.g., stages in the fact-checking process, see Fig. 3), or have not been discovered at all (e.g., geo-cultural differences – see Fig. 1).

Although growing, the number of professional fact-checkers remains low in comparison to the vast amount of misinformation. The latest census by the Duke Reporters’ Lab identified 378 active fact-checking projects worldwide. Only 88 organizations worldwide (34 in Europe) actively cooperate with social media platforms through the International Fact-checking network and in some cases, there is merely one fact-checker per country. The imbalance between the scarcity of fact-checkers and misinformation overload causes that just a fraction of potential false content is being checked. Furthermore, the work of fact-checkers is laborious and sometimes repetitive. There is, however, an opportunity to improve the balance by providing appropriate technological support for challenging or repetitive tasks.

While there is an increasing body of research on automation of the fact-checking process, especially with the utilization of Artificial Intelligence (AI) technologies, full automation of the whole fact-checking process is still viewed with skepticism by the fact-checkers as well as researchers [2, 18, 30, 36]. The main reason is that some parts of the fact-checking process require human judgments or actions. Tasks such as assessing the credibility of the sources of evidence are currently not fully automated with sufficient trustworthiness (e.g., by providing appropriate explanations), accuracy, or generability (e.g., checking complex recent claims where evidence may still be missing) [39]. The real potential of AI-based tools, therefore, currently lies in assisted fact-checking instead of pursuing to automate the whole process.

With this in mind, we reinvoke a philosophy of machine design called “autonomation”, developed in the Toyota Production System [43]. Autonomation is a blend of “autonomous” and “automation” and may be described as “intelligent automation” or “automation with a human touch”. Compared to (semi-)automation that is typically orchestrated by a centralized computer controller, autonomation separates the work of humans from machines, and thus enables the quick correction of the mistakes made by machines. Yet, autonomation relieves humans of the need to continuously judge whether the operation of the machine is right. In the “autonomated” systems, the workers are self-inspecting their work and can source-inspect the work of the machines. This is a difference from an “automatic” system (that operates without human intervention) or an “automated” system (that requires human input or monitoring but is controlled by technology). Autonomation liberates people from automatable tasks, whereas technology has to serve people and processes, not vice versa.

Although, the HCI community has significantly helped to better understand the gap between the social and technical, the existing research works on AI-assisted fact-checking are still often detached from real fact-checkers, and thus do not optimally comply with their actual needs and expectations. As Nakov et al. point out: there is a “lack of collaboration between researchers and practitioners in defining tasks and developing datasets” for automated fact-checking [39].
contributes to the skepticism of fact-checkers towards automating the entire fact-checking process, especially processes
that require human judgments [2, 36]. On the contrary, some studies, e.g. [41] mention too much trust in the system’spredictions.
In this study, we aspire to research the fact-checking procedures to design the effective and appropriate human-centered AI tools for countering false information. The role of humans is central here: the tools should empower humans instead of replacing them. This work offers the following contributions:

1. We unify the various categorizations of the fact-checking process across different computer and social science literature [2, 7, 36, 39] and we extend the process in AI research by three additional stages.
2. We investigate the activities, problems, resources and tools of under-researched European fact-checkers and examine the specifics of fact-checking work in the non-English speaking regions. We align them with the knowledge from existing studies, namely [2, 18, 36, 39], and visualize them jointly as conceptual models.
3. We identify new opportunities for research and development of AI tools that would be useful in the day-to-day work of fact-checkers following the principles of human-centered AI.

2 Related work
A lot of AI research is devoted to assisting fact-checkers by automating the individual stages of fact-checkers’ work [39, 65]. It focuses on tasks such as finding claims worth fact-checking [9, 19, 32], searching for previously fact-checked claims [25, 31, 49, 52, 60], or claim verification and evidence retrieval [33, 45, 67]. Another group of research focuses on the development of the necessary datasets [25, 40, 48, 54] and end-to-end systems or monitoring platforms [28, 55].

The NLP (natural language processing) technology capabilities and limitations for human-centered automation in fact-checking were also summarized [14]. Developing AI-based methods has also been addressed through competitions and data challenges, especially as a part of CheckThat! Labs, where tasks such as check-worthiness estimation [50] or detecting previously fact-checked claims [49] have been proposed.

Some research is also devoted to the routines and challenges of fact-checkers. The Full Fact report [2] was the first one that globally examined the practices of today’s fact-checkers. Following the semi-structured interviews with fact-checkers from 19 organizations, the report lays out the main challenges fact-checkers face, such as large amounts of potential claims to check. The report was complemented by [39] with an analysis of current technological capabilities for fact-checking automation. The recognized potential of AI-based solutions lies in multiple areas: 1) finding claims from the large information ecosystem; 2) finding previously fact-checked claims; 3) finding supporting evidence (in a form of text, audio or video), translating (for multilingual content) and summarizing relevant posts, articles, and documents if needed; and finally, 4) detecting claims that are spreading fast to slow them down.

Further research on fact-checkers’ practices was done by NORDIS (NORdic observatory for digital media and information DIOrders) and focused on the tools for some parts of the fact-checking process [18]. Semi-structured interviews with 14 respondents from Nordic countries (Norway, Sweden, Finland, Denmark), supplemented with 5 non-Nordic professional journalists and fact-checkers, were conducted. Another semi-structured interview with 21 fact-checkers from 19 countries [36] points to the motivations of fact-checkers and the reasons for the limited uptake of computational tools by these professionals. Finally, the research of [30] investigates the fact-checking infrastructures and thus expands the perception of the current fact-checkers’ work.

Although the research of fact-checkers’ practices and problems is growing, the European region as well as non-American and non-English speaking fact-checkers remain still under-explored as can be seen on the map (Fig. 1).
Secondly, the aforementioned studies did not aspire to investigate the possible geographical, language, or organizational differences in the problems of fact-checkers. Thirdly, despite existing analyses of fact-checkers’ work, there is a partial disconnection between the fact-checkers’ needs and the efforts to create (AI) tools to support their work. Their design is treated as a technical solution to a technological problem and ignores the complex social and situational context [30]. There is also a lack of collaboration between AI researchers and developers with fact-checkers [39]. For example, the stage monitoring the online space is insufficiently covered by AI research in the context of fact-checkers, although carried out routinely by these professionals and in some works [2, 30] even recognized as “the hardest part of the fact-checking process”.

This problem is not common only to fact-checkers. Although the conceptual foundations of HCAI are extensively discussed in recent literature [53, 63] and guidelines for building human-centered AI products exist (e.g. [20]), the industry practices and methods appear to lag behind [11, 26].

The lack of end-user viewpoint in the early design-related activities is well known from the Human-centered Design (HCD) practice [26]. Specifically, while tech-savvy fact-checkers are often called for testing of developed AI tools, these often turn out to be “irrelevant” for their work [18]. This can be prevented by early inclusion of fact checkers in the tool design process. The challenge is that the capabilities of AI are unclear to users who set the end-user requirements [26]. This disproportion calls for an interdisciplinary approach, where the practices and problems of users (fact-checkers) are studied by social science and humanities (SSH) researchers and at the same time discussed with AI researchers to design powerful AI tools.

3 Methodology

Human-centered artificial intelligence (HCAI) is based on the processes that extend user experience design methods such as stakeholder engagement [53]. The goal is to create tools that augment and enhance human performance. HCAI
systems emphasize a high level of human control, while embedding high levels of automation that can be achieved by a good design [53].

Human-Centered Design (HCD) approaches are mentioned to be capable of contributing to the field of HCAI as well [5]. Specifically, Design Thinking, previously named Need-Design Response (NDR) focuses on the design and development of any tools or systems for the physical, intellectual, and emotional needs of people. It allows identifying human needs in the early phases of the design project through practices such as need finding.

Human-Centered Interaction (HCI), as an interdisciplinary field, adopts a ‘human-centered design’ approach to develop computing products that meet user needs, which makes this field a potentially strong contributor to HCAI. Nevertheless, the development of AI systems is still mainly driven by a “technology-centered design” approach [53, 63]. To respond to the challenge, a human-centered AI approach was proposed that places humans at the center of AI design as the ultimate decision makers [53, 63].

The HCAI framework [63] includes in addition to “ethically aligned design” and “technology” also “human factors design” to ensure that AI solutions are explainable, comprehensible, useful and usable. To accomplish this, they start from the needs of humans and implement the human-centered design approach advocated by the HCI community (e.g., user research and modeling) in the research and development of AI systems.

However, developers are usually less concerned on what people need in their lives or the social impact of AI [11]. These are the defining features of users’ positive experiences and need to be addressed for HCAI to be truly human-centered.

Based on the principles of HCAI and HCD, we make our research study the first stage of the HCAI design process, in which end users are constantly involved in shaping and evaluating the supporting AI tools. This is complementary to the existing human-in-the-loop approaches to fact-checking, where the human workforce is used only to train and validate models in continuous ways, usually to annotate [15] and evaluate models [64] or provide feedback [51] in order to reduce bias, increase accuracy, etc.

3.1 Research design

To analyze the activities and needs of fact-checkers, we first engaged these stakeholders individually semi-structured in-depth interviews. Using the iterative content analysis, we identified the activities — repeating routines performed by fact-checkers in the individual stages of the fact-checking process. These activities were further validated with previous research work on fact-checker practices and visualized by conceptual maps of the fact-checking process.

By proceeding from the content analysis, we also identified particular fact-checkers’ needs. Nevertheless, the needs are to some extent implicit, since they are inner motivational states to reach goals and it is possible to be unaware of one’s true needs [12]. As not all respondents were tech-savvy, they referred more often to problems instead of directly formulating their needs for specific technological support. Therefore, in this paper, we use problems of fact-checkers as a substitution of their needs (i.e., a corresponding need refers to finding a solution that can solve the problem expressed by a fact-checker). The most significant problems (and resulting needs), connected to the activities they relate to, were consequently verified by a quantitative validation survey. Finally, the implications for AI tasks and tools were derived. We illustrate this methodology (research process, methods, and terminology) in Fig. 2.

In our research, we address the following research questions:

- **RQ1**: Which information resources, procedures, and information technologies do fact-checkers use and how do they depend on local specifics?
- **RQ2**: What are the biggest problems of European fact-checkers that can be addressed by the support of artificial intelligence?
- **RQ3**: Which parts of the fact-checking processes are suitable and needed for potential autonomination?

To answer RQ1, we conducted semi-structured in-depth interviews, in which we were interested how Central European fact-checkers: 1) monitor the online space to identify potential misinformation; 2) select potential false claims/narratives; 3) communicate and avoid potential duplication; 4) verify content credibility and veracity; and finally, 5) disseminate fact-checks. We compared our findings with fact-checkers worldwide.

To answer RQ2, we quantitatively surveyed fact-checkers across Europe to assess the weight of the findings of the interviews.

Based on the findings with respect to RQ1 and RQ2 and based on current state-of-the-art research and technical possibilities in the field of AI, we identified the implications for AI development in different stages of the fact-checking process to answer RQ3.

### 3.2 Selection criteria for respondents

The in-depth interviews were conducted with nine fact-checkers from five major Central European (Slovak, Czech, and Polish) fact-checking organizations. All of the respondents performed fact-checking professionally as part of their full-time job, none of them was employed in social media. We involved both external and in-house professionals in management positions (editors in chief, project coordinator), fact-checking only positions, but also fluid and overlapping fact-checking roles with a role of a journalist, PR manager, editorial manager and senior research fellow. Our sample represents one of the low-resource language groups, under-explored in AI-research. The sample covers a variety of sizes and types of organizations – from small NGOs to large news agencies. The majority of organizations also collaborated with social media providers (e.g., Meta). Most of them were part of the IFCN network, which prohibits any kind of political connection. Two organizations were not members of the IFCN (and did not collaborate with social media). These organizations focused on the fact-checking of political discussions in mass media (mainly TV) and partisan news. The product of these two organizations was an article, summarizing the main arguments in a misleading topic of interest (not a structured fact-check of a claim).

For this work, we define Central Europe as the countries of the Visegrád Group \[57\]. While Central Europe geographically belongs to the European region, its historical and linguistic context differs from Western Europe (eastern block legacy, Slavic languages). This has many consequences on its current social and cultural setting and related issues (e.g.,
the level of Russian influence). Contextual factors affect the choices of action and the use of sources and channels in the online environment [3]. We can thus assume that some needs of Central European fact-checkers can differ from the fact-checkers elsewhere in Europe/world. In particular, we can expect differences when compared with high-resource language areas.

Nevertheless, Central European fact-checkers form a sample too small to derive conclusions about the problems of fact-checkers (not covered in existing literature). Therefore, we validated the results of the interviews with a validation survey. The survey was responded to by 24 representatives (N = 24) of 21 European fact-checking organizations, covering 20 countries. Albeit a nominally small sample, our survey respondents represent approximately 62% of active European fact-checking organizations that are IFCN signatories.

All fact-checkers participating in the survey had to be members of recognized professional groups. Therefore, organizations from CEDMO (Central European Digital Media Observatory) hub were selected for the in-depth interviews. The survey was directed at EDMO (European Digital Media Observatory) hubs members and to the International Fact-checking Network (IFCN) signatories operating in Europe. The survey respondents were recruited through contacts provided by the EDMO or LinkedIn Premium account. Both external fact-checkers and in-house professionals were involved, but none of them was employed in social media. The position names of the respondents mentioned in their LinkedIn profiles were fact-checker, verification officer, journalist, redactor, or analyst in the fact-checking parts of the organizations.

This research involved human participants. Research planning, conduct and reporting was consistent with local regulatory laws and regulations and aligned with ethical principles, such as the ACM Code of Ethics and Professional Conduct and international and national standards for such research.

3.3 Method 1: Interviews with fact-checkers

The semi-structured interviews were conducted with one organization at a time and each required between one and one and a half hours. The interviews were conducted from December 2021 to February 2022 using a video conference system using the English, Slovak, or Czech language.

When designing the interview, we faced many ambiguities in the fact-checking process. The number of stages, as well as terms used to name them, varies across the literature and tends to depend on the view that the research is dedicated to (social sciences versus AI) as shown in Fig. 3. Existing work in AI typically recognizes four core fact-checking stages, while the first study of today’s practices of fact-checkers [2] mentions three different stages. Therefore, we were obliged to redefine the stages found in the literature when designing the interview questions.

When designing the interview questions for respondents, we focused on the human-information interaction processes. Asking about information resources to identify user needs is a very common approach in information science research [12]. We also included the interview questions about problematic, time-consuming, and repetitive work, which are common in software requirements specification. The full listing of interview questions can be found in Annex A.

The interviews transcripts were read and analyzed multiple times using iterative content analysis. The techniques we have employed include open, axial, and selective coding. All codes are represented in conceptual models (Fig. 4-8).

3.4 Method 2: Validation survey

The interviews yielded many problems as well as some implicit inputs on what is desired and needed for fact-checkers to be more efficient in tackling disinformation. These inputs were discussed, using brainstorming methods, and problems that were most cognitively demanding, tedious, time demanding, and complex, as well as brought inconveniences and
uncertainty with them were selected. Finally, 13 problems were chosen for the validation survey based on the user activities and current technical feasibility, resource feasibility, and sustainability of potential AI solutions (tools) (see the validation survey questions in Annex B).

The survey also served to validate the individual responses, therefore for each activity, the respondents were queried on:

- how often fact-checkers need to be involved in such activity (on a six points Likert scale ranging from “more times a day”=6 to “never”=1) and
- how difficult the activity is (five points Likert scale ranging from “No problem, I like to do it”=1 to “I perceive it as a big problem. I really need help with this”=5).

To identify the most pressing problems that need automation, we calculate their importance as follows.

\[ C(a_i) = med(f_i) \times med(l_i) \]

where \( C(a_i) \) is an importance coefficient that quantifies the need for automation within activity \( i \), \( med(f_i) \) is a median score of the frequency of the fact-checkers’ involvement in activity \( i \) and \( med(l_i) \) is a median score of the level of difficulty of activity \( i \). As such, the most severe problem would get a coefficient of 30, and the least important problem a coefficient of 1.

The quantitative validation survey was conducted from March 2022 to May 2022.

### 3.5 Results presentation

The results of the interviews, i.e., the details of the fact-checking process, based on the fact-checkers’ answers in the interviews, are summarized and visualized with conceptual models using CmapTools. They are also compared with the
fact-checking process of the organizations in [36], fact-checkers’ needs in [2, 30], and utilized tools in [18]. Differences are outlined in different fonts according to the legend under each figure.

The identified problems may vary across the different tasks that fact-checkers are involved in. This may be considered a limitation of our study and prompts future research focused on complex process analyzes of individual fact-checking organizations.

4 Results and findings: Interviews with fact-checkers

In general, regarding RQ1, the results of the interviews indicate that the fact-checking process in Central Europe is similar to that in the rest of the world. However, since the fact-checking process differs in the various research studies (see Fig. 3) and some of the stages were missing according the results of our content analysis, we renamed and extended its stages from the previous works (see Fig. 3). Stage 2 (Selection of potential false claims/narratives) and Stage 4 (Verification of content credibility and veracity, in computer science labeled as evidence retrieval and claim verification) were inspired by [7, 39], but based on the interviews with fact-checkers, the names of the stages were renamed (extended) following these findings: (1) fact-checkers do not select only claims, but also narratives, (2) fact-checkers verify the sources of claims besides individual claims (collectively referred to as content).

We expanded the fact-checking process as it has been understood in previous AI research in: Stage 1 (Monitoring the online space), Stage 3 (Communication and avoiding duplication) and Stage 5 (Dissemination of fact-checks). We also extended the dissemination part of the process: no longer it means only the publication and marketing of fact-checks, but includes a novel subcategory - the identification of the other versions (i.e., other appearances in the online content) of the same misinformation. We use the term “misinformation”, as not every respondent was fact-checking at the level of claims: some of them were interested in repetitive topics (narratives), whereas their final product was a fact-checking article (not a structured fact-check of a claim). This is in accordance with two identified types of fact-checking [30]: (1) short-term claims centric, and (2) long-term advocacy centric.

As we found out, some identified problems were specific to the investigated region and connected mainly to the capacity and financial reasons (e.g. weaker collaboration with other fact-checkers or dissemination in an attractive form) and limited language capabilities of the tools (e.g. for monitoring potential misinformation or for finding the previously published fact-checks). The virtue of Central European fact-checkers was ingenuity when forced to use the freely available tools. Its manifestation could be seen in the use of personalization on social networks using fake profiles to monitor misinformation, but also in the creative use of CrowdTangle to monitor notorious liars. Below we present a detailed description of the process and problems of our respondents in comparison with the fact-checkers around the world.

4.1 Monitoring the online space

Monitoring (Fig. 4) is globally seen as one of the hardest parts of the fact-checking process. The process was illustrated, for example, by P1:

"Monitoring of online space is done in two ways: manually or automated. When authors browse media manually (the classic media such as New York Times, Washington Post), they search for topics that are interesting for our audience. Some of us also do automated monitoring in CrowdTangle... I do that every morning by coffee, where I check notorious sources - some lists have about 800 [social media] pages."

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Fig. 4. Conceptual model of the monitoring part of the fact-checking process

Monitoring is a part of the process that fact-checkers are the most open to autonomating [18]. Still, there is just a limited pool of tools that are a bit helpful for Central European as well as other non-English speaking fact-checkers on social media, such as CrowdTangle, Meta’s fact-checking tool, and Tweetdeck. These tools have many limitations; e.g. CrowdTangle was originally developed for marketing purposes. Its overemphasis on virality is not always useful for fact-checkers. This was mentioned by our respondents as well as other fact-checkers around the world [2, 18, 36]. Despite this, fact-checkers agreed on the usefulness of this tool for creating and monitoring lists of notorious liars. It is also useful for checking the popularity of misinformation, for example in cases when it was reported by regular users. Fact-checkers also reported their uncertainty about the future of the service, as Meta abandoned its active development and in August 2024 it is about to be deprecated completely without providing a sufficient alternative. TweetDeck (currently branded as X Pro) became in July 2023 a paid proprietary tool that is available only to verified and premium users of the X platform, what reduced its availability and usefulness for fact-checkers. In Norway, fact-checkers rather rely on their Storyboard tool to find problematic content [18], in other research [30] BuzzSumo, Social searcher or Influencer are mentioned.

Fact-checkers involved in Meta’s Third-Party Fact-Checking Program have access to Meta’s fact-checking tool that gathers reported data from users and their own detected potential misinformation. Although it is the only fact-checking product from social media, the fact-checkers from Central Europe mention its lower relevance for the Slavic language group. This is also similar to the experience of some other fact-checkers from non-English speaking countries [2]. Some of the Central European fact-checkers bypass the problem with Meta’s fact-checking tool by creating fake profiles that
follow suspicious groups, pages, and users. This way, they can take advantage of the sophisticated personalization of the platform to recommend other questionable sources more efficiently in contrast to the official Meta’s tool for fact-checkers.

The resources that fact-checkers monitor depend on the aims of organizations (mass media vs. social media). It usually reflects the current importance of a particular social medium in a particular country [2, 36]. However, in Central Europe, it involved only Facebook and WhatsApp for capacity reasons. The ideal monitoring requires substantial manual effort, as fact-checkers need to access information across a multitude of public and private social media channels (e.g., a lot of misinformation comes screenshots from Telegram to Facebook). Although instant messaging services are heavily used, currently there are no automates means to monitor them because of legal constraints (e.g., troll channels are still private channels), technological constraints (e.g., limited or no API is provided for this purpose), and capacity constraints (fact-checkers cannot resolve all of the user tips). User tips are nowadays the only relevant source for monitoring instant messaging services. Therefore, Central European fact-checkers still focus on open social media accounts.

4.2 Selection of potential false claims/narratives

Our participants spend considerable time filtering and prioritizing content for their audience (Fig. 5). This is in line with previous research [2, 18, 30, 36]. The selection is done either by an editorial team in larger organizations or collectively as a team in small organizations (also in[36]). In addition to that, we noticed some subjectivity in the selection of claims. None of the responding organizations had general guidelines for the misinformation selection process. However, fact-checkers agreed on some informal selection criteria for misinformation, considering the impact on their audience and society. The popularity or virality of potential misinformation was mentioned only as one of the factors for selection. Most of the respondents would appreciate early virality warnings on misinformation, as put out by one of the fact-checkers (P4):

"We need a tool that would alert us when something starts to spread before it becomes viral… At the moment, we look more at how posts on social media impact society or discussion."

Despite its importance, the impact on society was estimated only intuitively in the interviewed fact-checking organizations. Remarkably, most of them did not analyze data about the impact of their fact-checks on their audience because of the capacity constraints. Some insights based on social media engagement would therefore be helpful for a more data-based approach for filtering and selection of potential false claims/narratives. Furthermore, there are many cultural differences in the selection of claims topics [36]. Therefore, a (meta)research of the locally important narratives, enriching the data-based approach is needed.

Some Central European fact-checkers also mentioned timeliness, factuality, representativeness, controversialness of potential misinformation, or sympathy of the topic to the authors as factors for selection. All these factors are consistent with previous research [36], as well as putting more emphasis on societal impact than virality, including issues that affect minorities or disadvantaged groups. In comparison to our respondents, the volume of reader requests, verifiability, and the importance of providing a different perspective for their readers were mentioned as important factors for prioritization [36]. Some respondents in this research preferred to fact-check influencers, while others were aware of the high probability of a backlash from their followers and preferred not to check. Note that fact-checkers all over the world face legal actions. Some even reported facing personal danger, even physical attacks [2, 30]. The latter has not
been the case of our respondents, but it underlines a need for a tool that alerts fact-checkers before something goes viral.

Checking whether a claim is verifiable is one of the tasks that the fact-checkers are open to automating the most [18]. In some countries, it is performed by a simple Google search or by using freely available tools like ClaimBuster [28], BSDetector [36] or Full Fact tool [18]. There are also open-source tools developed and used by fact-checking organizations in Latin America that: 1) differentiate between the opinion and factual statements [8]; and 2) optimize the process of collecting and responding to WhatsApp reader requests [10]. None of these tools was mentioned or utilized by our interviewees. [18] mentions five reasons for not adopting AI tools by fact-checkers: 1) lack of knowledge about the existence of such tools; 2) lack of time to learn the tool; 3) lack of resources to pay for the tool; 4) lack of knowledge of how the AI tool works; and 5) difficulty in integrating the tool into the organization’s workflow. Keeping fact-checkers in the design process of the AI tools and appropriate training may help overcome these barriers [18].

4.3 Communication and avoiding duplication

Communication within the teams in fact-checking organizations (Fig. 6) is not usually considered an issue, whereas fact-checkers utilize traditional communication channels together with freely available tools (e.g. Google Docs, instant messaging services). Nevertheless, inter-organizational and preferably international communication is very important for fact-checkers as they need 1) to be aware of the fact-checks that are being verified or published, and 2) for the coordination with other fact-checkers worldwide.

And it is the coordination of fact-checkers with other organizations globally (Fig. 6) that our respondents considered problematic. Even though fact-checkers search for fact-checks from other organizations, they have been aware of just
about some of the published fact-checks. Communication or some automated identification of misinformation among the fact-checking and journalistic organizations globally is also important to identify local misinformation in one’s country quicker, as this fact-checker (P2) responded:

“As an international team, we [can internally] share information [about misinformation in individual countries]. [In this way], we can predict that the same misinformation will appear [in our country as well]. It can originate on the opposite side of the world, or many times the fake news comes from Germany; we know that there is a probability that it will appear to us, too, and mostly we are right.”

Collaboration between fact-checking organizations is recognized as essential throughout the world to share tips and technical knowledge [36]. However, Central-European fact-checkers working in small NGOs do not share such tips. In some regions such as, for example, the Balkan region or Latin America, it is common practice to actively share such tips in mailing lists, regional forums, or WhatsApp groups related to fact-checking [30, 36]. Some, like Factify, even set up e-learning platforms with video tutorials just for fact-checkers [36]. Collaboration, building coalitions with other fact-checkers and shared training are the fields that need to be improved in the region to strengthen the positions of fact-checkers.

4.4 Verification of content credibility and veracity

The evaluation of the claims is considered an activity that requires human judgment. In our region as well as throughout the world [2, 30, 36], this activity requires communication with people. Fact-checkers regard domain experts as important
sources of information. Sometimes, fact-checkers confront authors of the checked content, asking them to back up their claims or respond to fact-checks. Communication also involves requesting or clarifying data from government officials and press agencies, which slows down the process significantly as these officials are very careful about their statements. The complexity of the task can be considered as an obstacle to automation.

Nevertheless, another time and labor-intensive stage, viewed by fact-checkers as a potential candidate for automation, is evidence retrieval. Basically, it involves the acquisition of primary sources to achieve the maximum possible objectivity (Fig. 7). Our focus on human-information interaction enabled us to go deeper into the specific resources that the fact-checkers use. The textual sources involve mostly official data (as statistics), official information on the websites of governments, private companies, and NGOs, or original research studies. A fact-checker (P3) describes the process:

,"We have to find the right source for the data, such as in the Polish statistical bureau, central controller’s office, Eurostat… If the claim is not about data, we try to find facts or proof since as journalists, we can be sued for everything we write… It is not just debunking whether [the claim] is true or not… Lots of claims are manipulative or partially true, … Very often we use experts (such as in finance, energy, or climate) to evaluate information in statements - including implicit ones... The media is not our sources, they are good for background or if someone said something in the media.”

The official data are hard to retrieve as they are not usually in easily accessible formats or are not publicly available. Fact-checkers in all regions experience different difficulties in reaching primary and official data sources, depending on the level of development of a country [36]. However, not being able to verify a claim is one of the biggest frustrations of fact-checkers [18].

Fact-checkers often work with audiovisual evidence, such as parliamentary speeches or recorded interviews to check whether a person mentioned the claim that someone else accuses him or her of saying. The fact-checkers frequently require watching hours of videos, many times without any result. Therefore, most of the Central European respondents would appreciate having searchable transcripts of the videos in local languages.

Secondary sources such as mass media are rarely used for verification of claims. They were mentioned (if at all) rather as illustrative than reliable. Sources like Wikipedia were never used or considered credible for verification during fact-checking, as confirmed also by [18]. Nevertheless, according to [21], textual sources, such as news articles, academic papers, and Wikipedia documents, have been one of the most commonly used types of evidence for automated fact-checking. As the above mentioned sources are not utilized by fact-checkers, verification tools trained or tested just on Wikipedia and mass media datasets will never be sufficient for the work of these professionals.

The largest exception to the non-usage of secondary sources are existing fact-checks of other fact-checking organizations. These are seen as the most credible secondary source of evidence for central European fact-checkers. Existing fact-checks within the same organization are considered good sources of information, as politicians and other actors often repeat themselves. However, previously existing fact-checks (regardless of their relative provenience) are often hard to retrieve as P3 continues:

,"The most cumbersome is to find, if a claim or statement has already been fact-checked or if fake news was verified by someone else. Most of the fact-checks come from abroad. We have to check if English, French, Italian, German fact-checkers did it… If yes, we sometimes use it so that we can prove the history of spreading, then we quote these fact-checking websites.”
Another reason is, that many fact-checks are not created with the necessary structure or metadata and are thus difficult to search through services such as Google Fact-Check Explorer. Adhering to the most common fact-check schema, the ClaimReview, is rather cumbersome for fact-checkers under their present technological conditions.

According to our respondents (Fig. 7), few search engines are helpful for fact-checkers. They mention mostly the Google Reverse Image Search that can identify similar images. Ordinary Google Search is not sufficient for the needs of Central European fact-checkers as it does not retrieve the most credible and hard-to-search textual sources of evidence. This is in accordance with [36] as well as [27], who studied the effectiveness of commercial web search engines for fact-checking. They found out that the engine’s performance in retrieving relevant evidence was weakly correlated with the retrieval of topically relevant pages.

InVid tool in the WeVerify plugin was seen as very relevant for our respondents as it decomposes the videos into keyframes (images) that are possible to be reverse-searched. Nevertheless, as some misinformation is very complex, fact-checkers need to do more than reverse-search the images. Interestingly, participants in the study of [36], who reside mostly outside of Europe, do not report being aware of these tools.

Claim verification is seen by our respondents as an “intuitive process” that results from the long-term practice of fact-checkers, often journalists. Fact-checkers prevailingingly stated that they notice questionable sources “at first sight”. However, one respondent shared his credibility indicators for the evaluation of sources, namely: non-existent
A “contextualization stage” was mentioned [36], where most fact-checkers of their study looked into the evolution of the claim from its origin to the present state to help readers understand their conclusions. Nonetheless, this process is very challenging, especially in foreign languages. One of our interviewees mentioned the problematic tracing of such a history, particularly on social media, where the search capabilities are very limited.

The verification process is considered very transparent, as the websites of fact-checking organizations often explain how the judgment was reached, attaching the sources as well (often their archived versions). Besides that, it is very rigorous. As reported, none of the fact-checks is published without consulting it with at least one editor. Participants from Africa and Oceania have even longer peer review processes than Western countries [36].

4.5 Dissemination of fact-checks

Because of capacity reasons, dissemination of fact-checks mostly takes place where the misinformation spreads - on social media, mostly Facebook (Fig. 8). Fact-checks are published on the websites of the organizations. In connection to web publishing, Central European fact-checkers frequently report limited technological capabilities in their organizations (unlike some fact-checkers throughout the world [2, 36]). These prevent them from full exploitation of search engine optimization (SEO), ClaimReview, appearing in Google News, or paid ads on Google as noted by P5:

“We thought of using the ClaimReview format, we tried it on fifteen claims in the Google Search Console. But as there are many fact-checks, we would need a process that would fill it automatically. It was very time consuming to fill all those fields.”
Our respondents from small NGOs also struggle with personal (marketing and design) capacities to be able to make their fact-checks more appealing and popular by including visuals (e.g. infographics, videos, comic stripes). This is a common practice for copy editors in some fact-checking organizations [30]. Nevertheless, fact-checkers communicate with the media, as P6 claimed:

"Sometimes the media notice that we fact-checked something, sometimes we reach the media ourselves, sometimes we have a project with them to fact-check something."

Fact-checkers around the world pointed out that they communicate with their audience through instant messaging services, particularly WhatsApp [2, 30, 36]. Nevertheless, this communication is more cumbersome, and Central European fact-checkers do not utilize these channels.

Some of our fact-checkers, as well as the respondents in the study of [36] and [18] revealed concerns about the limited reach and potential of their outcomes. The collaboration with social media platforms achieved some success. Nonetheless, fact-checking is a long process, and carrying out all its stages allows misinformation to spread in the meantime. Unlike our respondents, some fact-checking institutions also reach out to policy makers and civil organizations or organize literacy campaigns to strengthen the dissemination of facts.

5 Results and findings: Validation survey

5.1 The problems of European fact-checkers

In general, we can conclude that the validation survey supports and extends the findings of the in-depth interviews. Regarding the differences, the survey showed a higher urgency to autonomize alerts and user tips from instant messaging services and filtering the monitored outlets. The coordination with other fact-checkers and the analysis of the impact of the fact-checks was perceived as an issue with a lower urgency than it seemed from the interviews. Thus, these problems are considered specific to the region and need to be addressed locally.

Addressing RQ2, our results (Fig. 9) indicate that the biggest problems of European fact-checkers lie in the monitoring as well as in the verification parts of the process. The interviewed fact-checkers are overloaded with potentially false content, which requires better filtering (beyond virality measures).

According to the results from interviews, the verification of the truthfulness of the claim is not perceived as an issue. However, some parts of the verification process take most of the valuable time of fact-checkers and would urgently need some AI support. The validation survey confirmed that one of the biggest problems relates to searching for the sources of evidence for verification, particularly in hard-to-find official documents, videos, and statistics. This is especially true for cases where data needs to be integrated, as one fact-checker (P10) noted:

"[I] hardly believe that machine recognition of misinterpretation of scientific studies/statistics is possible."

Even when misinformation is verified, its numerous versions exist and are shared on the internet. Therefore, the tools that would be able to identify other versions of the same misinformation would be crucial for misinformation mitigation. One fact-checker (P8) illustrated some parts of this process as follows:

"The content on Facebook is very hard to find. We have to use some tricks, but still, there is a lot of manual work. It is very hard to identify, given a text query, all the places and URL addresses where the content exists (external pages, Facebook posts... images, and videos are even harder). No tool would do this and this consumes about half of our time... I think the technology to automate searching the source of misinformation already exist and with them, we would be able to do much more fact-checking."

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Fig. 9. The biggest problems of European fact-checkers identified by the proposed coefficient of the perceived importance of the problem (scale of the coefficient ranges from 1 to 30)

Additionally, two ideas were mentioned frequently by our respondents (10 times each):

- a tool to monitor trending YouTube claims and/or topics, and
- a tool connected to WhatsApp’s API which collects and prioritizes reader tips.

We further investigated the differences between the fact-checkers’ problems according to the location, language group affiliation, and size of their organization.

5.2 Differences between the fact-checkers’ problems

The fact-checking organizations that were respondents of our validation survey have been split into two groups: 12 Eastern (including Central) European organizations (from these countries: Czech Republic, Slovakia, Hungary, Poland, Lithuania, Latvia, Estonia, Croatia, Slovenia), and 10 Western European organizations (from these countries: Belgium, Italy, Ireland, France, Spain, Germany, Switzerland, Austria, Denmark). We further distinguish 12 organizations from countries using low-resource languages (from Slavic and Ugro-Finnish language groups), and 10 organizations from countries with high-resource languages (from Germanic and Romance language groups). Finally, the size of organizations varied as follows: 3 large (250 and more employees), 3 medium (50 to 249 employees), 6 small (10 to 49 employees) and 9 micro-sized (less than 10 employees).

5.2.1 Differences between the problems of Eastern and Western European fact-checkers. The data do not show many differences between the problems of Eastern and Western European fact-checkers (Fig. 10). However, searching within the existing fact-checks (both their own and from other fact-checking organizations and in potentially different languages) is considered a more urgent problem to solve by Eastern European fact-checkers. This identified need is relevant to address, as the existing fact-checks are an important source of evidence for these professionals. The need for a tool that would help to autonamate this part of the process was confirmed by a fact-checker (P9) in a comment of the survey.
Fig. 10. Differences in the coefficients of the most important problems depending on the location of the fact-checkers (Eastern vs. Western Europe)

"Would totally be a great help. Compiling all the IFCN signatories' outputs into one big (keyword-driven) database? A fact-checker’s dream. Although, it is fair to say that Google Search supplements a lot of this proposition - although it's always difficult with other languages than English - relevant now for Ukrainian."

The first explanation of different perceptions of this difficulty is a better coverage of fact-checks in bigger language groups by Google Fact-Check Explorer. The lack of experience and/or resources to invest in ClaimReview markup was mentioned both by Eastern as well as some Western European fact-checkers.

The second explanation of this difference is that Eastern European fact-checkers need to check first the Western European fact-checks (which seems not to be the other way around). For example, a fact-checker (P7) revealed in the interview that:

"Russian trolls know that in order to be successful, they have to go through the west (Germany, for example), because Poles do not like Russian sources... Also, sometimes what is popular abroad - mostly in Czech or English, such as vaccines - is popular in Poland as well."

In contrast, western European fact checkers focus more on misinformation modalities beyond text and platforms beyond Facebook. This is demonstrated by their pressing need to automate alerts from instant messaging services, such as WhatsApp, possibly Telegram, and a more urgent need to search for image manipulations. The less perceived urgency of these needs by Eastern European respondents can be explained by the lack of capacity that allows them to focus mainly on text and Facebook, as mentioned during some of the interviews.

5.2.2 Differences between the problems of European fact-checkers according to their language affiliation. Regarding the various language groups of the fact-checkers, we can see (Fig. 11) that there are some differences in the perceived problems, but they are not always language-related. Nevertheless, the perceived urgency level stands out in the Ugro-Finnish group that is the smallest language group of participants. According to the results of the survey, these professionals are much less involved in the coordination of actions of other fact-checkers. Generally, fact-checkers from
the low resource languages, such as Hungarian, Slovak or Czech perceive more urgently the language-related problems in searching for the other versions of misinformation or in searching within the existing fact-checks. This is also in line with the NORDIS report [18].

We can hypothesize that misinformation in dialects would be even harder to detect by machines than small language groups. This puts the people communicating in dialects in a more vulnerable position. A fact-checker (P10) supports this hypothesis:

“Machine does not recognise the dialect…A tool which recognizes the dialect would help to simplify my work.”

5.2.3 Differences between the problems of European fact-checkers according to the size of their organization. If we divide the results according to the size of the fact-checking organizations (Fig. 12), we can see that large organizations perceive the tasks connected with: 1) image and video analysis; 2) monitoring of instant messaging services; as well as 3) searching for the other versions of misinformation as more difficult than smaller organizations do. The reason lies again in the higher capacities of these organizations to focus on more tasks that require more time, as confirmed during interviews. This finding points out that these tasks are not of little importance, but of little personal capacities to involve in such responsibilities. The automation of such tasks by artificial intelligence would help bigger organizations in the first place, but in the end also the smaller organizations, as the process of disinformation detection would be much easier and possible to complete with less capacity.

The other problems that were identified in our research include marketing issues (insights analysis, ClaimReview) that are just partially relevant for AI research. The reasons for these problems of both types of organizations are different: the small ones face capacity issues or lack of knowledge in terms of technology or marketing support; the fact-checkers of the largest organizations face complicated processes of the big media concerns that prevent fact-checkers to edit or monitor any content on the website that is common for all parts of the organization. Nevertheless, filling out
ClaimReview would help AI researchers to collect better datasets of the previous fact-checks and insights analysis would provide more information about the topics that are important for users.

6 Implications for AI research and AI-based tools

To answer RQ3, we identified implications and opportunities for research and development of AI tools that would support fact-checkers in fulfilling their tasks. For clarity, we mapped the stages of fact-checking process, the most urgent problems of fact-checkers (resulting from our validation survey) with the corresponding implications for AI support (Fig. 13).

Our proposed implications for AI support come from the current state-of-the-art research and technical possibilities in the area of AI – machine learning (ML) and NLP (including the latest development of generative large language models), and also from available datasets and tools and are consistent with the work by [39]. Compared to [39], we add three more AI tasks: (1) check-worthy document detection, (2) mapping of the existing fact-checks to additional (newly appearing) online content, and (3) fact-check summarization and personalization.

At the same time, we recognize that some of the most important problems do not require AI-based solutions. In such cases, the implementation of suitable tools represents mainly an engineering challenge (e.g., how to implement a tool that fact-checkers can use to insert ClaimReview schema into their fact-checks), which is out of the scope of this work.

6.1 Implications for Check-worthy document detection

The first AI task aims to support filtering the check-worthy documents (that is, news articles, blog posts, or even posts on social media) from monitored sources. It can be defined as follows: given an input set of documents, detect such documents that are worth fact-checking, and thus they should receive fact-checkers’ attention (e.g., they contain factual claims, they are potentially impactful and harmful to society, etc.). This task can be addressed either as a classification (a document is or is not check-worthy) or a ranking problem (prioritizing the most check-worthy documents). It should be addressed with information available at document creation time (i.e., without relying on user feedback that appears later). Given that false information spreads faster than true information [61], the impact of a fact-check can be limited
Fig. 13. Mapping of the top 10 most important problems of fact-checkers with the corresponding stages of the fact-checking process and implications for AI support

| Stages of fact-checking process | Problems of fact-checkers | Implications for AI support |
|---------------------------------|--------------------------|-----------------------------|
| **Stage 1** Monitoring the online space | **Problem 4** Filtering from monitored outlets | **Implications for** Check-worthy document detection |
| **Stage 2** Selection of potential false claims/ narratives | **Problem 3** Late alerts from instant messaging services | **AI support is not needed** |
| **Stage 3** Communication and avoiding duplicity | **Problem 7** Seeking factual claims suitable for fact checking | **Implications for** Check-worthy claim detection |
| **Stage 4** Verification of content credibility and veracity | **Problem 8** Searching within existing fact-checks | **Implications for** Previously fact-checked claim retrieval |
| **Stage 5** Dissemination of fact-checks | **Problem 1** Searching for the source of evidence for verification | **AI support is not needed** |
| | **Problem 5** Searching for the source of evidence in videos | **Implications for** Evidence retrieval |
| | **Problem 2** Searching for other versions of misinformation | **Implications for** Mapping to additional content |
| | **Problem 6** Low visibility of fact-checks | **Implications for** Fact-check summarization and personalization |
| | **Problem 10** Measurement of the impact of fact-checks | **AI support is not needed** |

once the post has already become viral. On the other hand, early fact-checks can limit the spread of false information and can thus serve as a way of pre-bunking, which has already been shown to be effective in existing studies [47].

We argue that this task should generally precede the task of check-worthy claims detection (extraction) to limit and prioritize the amount of potential misinformation content the fact-checkers need to examine. Current systems (e.g., a fact-checking tool used within Meta’s Third-Party Fact-Checking Program) often prioritize the virality of a post as noted by the fact-checkers in our as well as in the previous studies [2, 18, 36]. In research work, check-worthiness detection is originally related to claims (i.e., identification of particular sentences, typically in political debates). Nevertheless, starting in 2020, the CheckThat! Lab introduced the detection of check-worthy tweets [27]. Similarly, [4] introduced a
holistic approach to annotate 7 features reflecting the check-worthiness of COVID-19 related tweets. Although tweets are natively short texts containing just a few sentences, we would like to emphasize distinction with check-worthy claim detection (see below) and we consider this as the first step towards check-worthy document detection. At the moment, we are not aware of any works on check-worthiness detection for longer pieces of text (e.g., for social media posts from other platforms that do not pose such strict length limitations, or even for whole news articles/blogs) or for multimodal content. Such extension of current research works and construction of a suitable dataset represents the possible next step.

Check-worthy document detection may be considered as related to a more generic task of credibility indicators assessment. Credibility indicators (e.g., credibility signals proposed by W3C Credible Web Community Group) would similarly help fact-checkers (as well as other media professionals) to pre-screen the document and decide whether to proceed with the manual in-depth investigation to determine the necessity to fact-check it. Such a tool would speed up fact-checkers’ comprehension of the online content. To detect such indicators, a wide variety of techniques may be used, from a simple lookup in whitelists/blacklists, through the automatic check of pre-defined credibility criteria (e.g., presence of an author’s name, the known editorial board of a newspaper, etc.) up to advanced ML/NLP models. These would, for example, classify typographical and stylistic characteristics reflecting psychological features influencing the reader’s sentiment, detect the use of logical fallacies, or classify the leaning (bias) of the text [17, 35].

The detected check-worthiness of documents can serve as one of the indicators if the detection also considers their potential harmfulness or their expected impact on society (see, e.g., [4]), which are the aspects usually considered by the fact-checkers (see Fig. 5).

6.2 Implications for Check-worthy claims detection
While the task of check-worthy document detection (and the related task of credibility signals extraction) has attracted researchers’ attention only recently, the check-worthy claims detection has been addressed by the researchers for a longer period and several established approaches, as well as datasets, already exist (see, e.g., [28]). This task can be defined as follows: given an input sentence (or a set of multiple sentences, for example, from a political debate), detect such sentences that are worthy of fact-checking. Most of the existing approaches have so far focused on text using transformer-based language models, such as BERT [16]. However, there is a growing need for multimodal approaches, since claims can be accompanied by images, they can themselves appear in images (e.g., a screenshot of a social media post) or images can modify/change their meanings. There are already the first multimodal datasets for claim detection (see, e.g., [13, 69]).

6.3 Implications for Previously fact-checked claims retrieval
The previously fact-checked claims retrieval has also attracted the researchers’ attention lately, see e.g., [25, 29, 34, 38, 49]. It is typically defined as a ranking problem, where, given an input claim and a set of verified claims (fact-checks), the goal is to retrieve a ranked list of previously fact-checked claims [48]. However, the existing datasets and consequently, most of the existing approaches focus on retrieval in a single language - mostly English - although there are also datasets in other languages, namely Arabic [49] as well as Hindi, Bengali, Malayalam, and Tamil [31]. To the best of our knowledge, only [31] used multilingual embeddings and provided a preliminary proof-of-concept of multilingual previously fact-checked claims retrieval. Additionally, the existing datasets are relatively small (e.g., the English dataset

1While the definition of a check-worthy claim differs across literature, it is usually a factual statement, that the general public would be interested in knowing, whether it is true or not.
by [38] contains 1,610 pairs of input claims and fact-checks), they draw input claims from a single social medium (Twitter in the case of [38], WhatsApp in the case of [31]) and fact-checks from a limited number of fact-checking organizations (mostly Snopes or PolitiFact except of [31], who use a mixture of sources). The missing cross-lingual links between fact-checks and social media posts in the existing datasets limit their practical applicability since the claims can spread across borders and languages. The research on multilingual and cross-lingual approaches to this task is currently largely missing. This is especially problematic given the results of our study which suggest that searching for other versions of misinformation and searching in existing fact-checks is one of the most important problems among Central and Eastern European fact-checkers and fact-checkers from low-resource languages. The fact-checkers themselves could help foster this type of research by the more widespread use of ClaimReview and especially by providing more appearances of the fact-checked claim (using the ItemReviewed field of the schema). However, this would require better supporting tools and/or training for fact-checkers as discussed in the sections above.

Within this specific AI task, we already did AI research to provide a novel tool for fact-checkers. We collected so far the most extensive and the most linguistically diverse dataset of fact-check to social media post pairs, experimented with and selected the best-performing text embedding models, and built the tool on top of them [44]. The whole AI research and tool development process was done in a co-creation manner, in which the identification of fact-checkers’ problems covered by this study played the important first step.

6.4 Implications for Evidence retrieval
Tools supporting evidence retrieval that would be explainable and trustworthy represent one of the most challenging, but also one of the most urgent needs of fact-checkers. Such tools would need to operate beyond Google searches on websites or extractions from Wikipedia. However, it is exactly these two that are often used when constructing datasets for claim verification; e.g., Wikipedia was used to construct FEVER dataset and its variants [42, 56, 59] and Google search was used to retrieve evidence in the case of MultiFC [6] or X-Fact datasets [22]. Therefore, a more demanding data collection would be crucial for usable and credible verification tools for fact-checkers. One such attempt can be considered the dataset CTKFacts [59] which extracted evidence from the articles of the Czech Press Agency (CTK), but databases containing (and combining) the most important sources for fact-checkers, such as the existing fact-checks, official statistics and other official data and the transcriptions of audio-visual content are largely missing. Nevertheless, the introduction of OpenAI’s automatic speech recognition system Whisper has a promising potential for multilingual audio-to-text transcriptions [46].

6.5 Implications for Claim verification and justification production
The claim verification and justification production, which require a human judgment, was not perceived as problematic by fact-checkers. These professionals enjoyed such challenging tasks requiring higher cognitive load and creativity. Therefore there is no urgency in developing tools that would directly aim to autonamate this stage, and thus support or even replace the fact-checkers. However, the claim verification approaches can be used indirectly as supporting tools to rate or rerank the retrieved evidence and distinguish between sources that support or reject the claim under review [37].

6.6 Implications for Mapping to additional online content
In the mapping to an additional online content task, the veracity, or knowledge of already fact-checked claims, is automatically disseminated to additional content (already existing or new, constantly emerging). This task is similar to
the previously fact-checked retrieval, but, in this case, the input is an already fact-checked claim and the output is a list of claim appearances, i.e., a list of social media posts or news articles, in which the fact-checked claim is present and at the same time, which has a positive stance (they support the claim; see [54]). Alternatively, the task can be defined as a combination of previous fact-checked claim retrieval and stance classification. Such an additional step is not usually done in the manual fact-checking process as it is impossible for the fact-checkers to manually find all existing relevant articles or routinely update their list as they continuously appear [62]. Meta performs this task to some extent – when a new post shares an image that has been previously fact-checked, it propagates the original fact-check to that post. Nevertheless, having an automaton method that would be able to work also with text in multilingual and cross-lingual settings would further help the fact-checkers increase the impact of their work.

6.7 Implications for Fact-check summarization and personalization

To the best of our knowledge, this last AI task has not been addressed by existing works so far. The recent emergence and consequent rapid development of generative AI, particularly large language models (LLMs), such as ChatGPT, provides an opportunity to support fact-check dissemination and tackle with fact-checks’ low visibility. Namely, LLMs excel in summarization [66], paraphrasing [58] and translation [68] of the textual content. Therefore, we argue that LLMs can be in the future employed to help fact-checkers process fact-checking articles to shorter and/or more comprehensive forms, such as fact-checking briefs that are suitable to be posted as a social media post. Furthermore, we recognize potential to prepare such LLMs’ prompts that will personalize the fact-checking article for the specific social media platform and target audience.

In this way, fact-checkers can effectively generate a scaffold of the text that can be further manually adjusted (e.g., to clarify potential incomplete information caused by automatic summarization).

7 Discussion and study limitations

In this study, we first studied the fact-checkers’ activities, needs, and problems. We transformed the findings into practical implications for AI research, AI tasks and AI-based tools. We have presented design implications, which have not yet been used to design and evaluate an AI tool. We defined the stages of the process in a natural setting, the most urgent user needs to autonomize and rejections to do so. Obtaining such results was possible due to the interdisciplinary collaboration (information and computer scientists) as well as due to the involvement of users in the first stages of autonomation. The necessity of such a human-centric AI approach was further demonstrated in the case of the tool for previously fact-checked claim retrieval [44]. Our research study was the first stage of the HCAI design process, in which end-users are constantly involved in shaping and evaluating the supporting AI tools. Later on, fact-checkers should be actively involved in training AI models by applying a human-in-the-loop approach.

The implications may be valuable not only for AI researchers but also practitioners from technological companies and social media platforms. In general, we recognized that AI has a tremendous potential to help fact-checkers across the whole fact-checking process. Nevertheless, considering the current technical maturity, we suggest using its potential especially in providing support in filtering the monitored content, searching within the existing fact-checks, and evidence retrieval.

Providing multiplatform, multilingual, and multimodal solutions for fact-checkers would be the most useful help for this target group. Our findings extend the implications of [36] that propose personalized multiplatform solutions, including crowdsourcing of user tips; as well as of [39] who discuss what the technology currently has to offer as well as current major challenges, such as multilingualism and multimodality. The results of our research also pointed
to the scenarios that would be ideal, but currently not feasible to automatize. First, filtering from monitored outlets based on the impact on society would be a task that requires long-term research on how misinformation affects society. Secondly, a tool that would be used globally by fact-checkers would be an ultimate goal for the multinational collaboration and exchange of misinformation narratives, but such a tool would be resource and sustainability heavy as well as context-specific. Thirdly, the ideal content verification would require the availability of (structured) data from governments, which is still not a reality. Fourthly, mapping to additional content to disseminate fact-checks would be impossible without the hands-on cooperation of fact-checkers with social media.

We would also like to acknowledge other limitations of our study. While we aimed to focus specifically on European fact-checkers and complement the existing works, we would like to encourage future researchers to investigate the processes and problems/needs of fact-checkers from the remaining underexplored regions in Asia and Africa. Covering these regions would be beneficial to get a comprehensive global picture of fact-checkers’ routines and problems.

Although the research of the fact-checking activities and problems was directed to the European region, only minor differences were found when comparing these activities and problems with the findings about the fact-checkers from other non-English speaking regions. The implications are also not anyhow specific to individual countries and can be generalized to other contexts with similar attributes (e.g., countries where fact-checkers face the disinformation spread in other languages transmitting from the neighboring countries). This gives the implications a very broad applicability.

8 Conclusions

In this study, we analyze the activities, processes, and problems of fact-checkers. We focused on European fact-checking space and through this, covered many regions outside of the scope of the existing studies. We compared the details of our research with the findings of existing studies. We have extended the stages of the fact-checking process as it is understood in the current AI research. The hitherto known processes and common problems of this profession were summarized in conceptual models. The fact-checkers’ needs inferred from problems served to inform future AI research on assisting fact-checkers. This is in accordance with the necessity to eliminate the recognized gap between current AI research and fact-checkers’ requirements on and consequent utilization of AI-based tools.

We noted that monitoring the online space to find potential misinformation is one of the most time-consuming and difficult parts of the fact-checking process. As this stage in the fact-checking process is often overlooked in AI research (e.g., [7, 36, 39], it is lacking the appropriate support from AI-based information technologies. Besides that, we postulate that without the AI-assisted additional step in the manual fact-checking process mapping to additional online content, any effective mitigation of misinformation is impossible with such a scarce number of fact-checkers.

The biggest problems of European fact-checkers relate to searching for the sources of evidence for verification. We examined the information resources that the fact-checkers use, and our results show that the mass media are rarely used by fact-checkers and Wikipedia is never used and considered credible for fact-checking. Nevertheless, textual sources, such as news articles, academic papers, and Wikipedia documents, are one of the most commonly used types of evidence for automated fact-checking [21]. Although Wikipedia may be useful for some tasks, verification tools trained or tested just on Wikipedia and mass media datasets will never be sufficient for these professionals. This calls both for the creation of new datasets built on primary sources (official statistics, governmental reports, etc.) and for new methods and systems of supporting evidence retrieval that can tap into these hard-to-access resources.

Fact-checkers do not think that AI can automate their whole work, neither they want it. Fact-checking often requires evaluating complex statements, talking to experts, or determining the truth which are processes inherent to
human judgment. Nonetheless, fact-checkers are open and need assistance from AI-based tools, and in this paper, we summarized the possibilities that are offered by the current AI technologies.

Our findings confirm that the identified problems and activities of the target groups can and should serve as potential cases for automation to empower, not replace people.

9 Research ethical considerations

All ideas and content presented in this research are the authors’ own. This study involved human participants and adhered to national and international regulatory laws and ethical standards relevant to such research. Participants were informed that their participation was voluntary and that they could withdraw at any time or request deletion of their data. They were briefed on the research objectives and the use of their data exclusively for research purposes. Additionally, participants were assured that their data would be anonymized, securely stored in the institutional repository, and deleted after publication. While approval from the Institutional Review Board/Ethics Committee was not obtained due to the absence of such a committee at our institution at the time of research design, every effort was made to ensure ethical conduct throughout the study.

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### A Semi-structured in-depth interview questions

**Shortened introduction**

We would like to talk with you about the process of your fact-checking and about the problems it brings to you. Our aim is to identify how the appropriate AI support to fact-checkers can be provided.

| Category                          | Question                                                                                     |
|-----------------------------------|---------------------------------------------------------------------------------------------|
| **Basic information**             | Institution                                                                                 |
|                                   | Position                                                                                     |
|                                   | What kind of false information do you check?                                                 |
| **Problem and needs to automatize**| What do you miss the most when fact-checking?                                                |
|                                   | What is the most hard/ cumbersome when fact-checking?                                        |
|                                   | What are the most repetitive works when fact-checking that could be automatized?             |
|                                   | What are the most time consuming issues?                                                     |
|                                   | What and how would you suggest improving the information systems that you use?               |
| **Monitoring and selection of potential misinformation** | How do you spot news that need to be checked?                                               |
|                                   | Do you also check the popularity of the claims before fact-checking? How do you check it? When is the right time for you to fact-check? |
|                                   | Where do you spot false information? Do you use any kind of resource management tools?      |
|                                   | Would it be beneficial to you if you had the (possibly most popular) check-worthy claims prepared by an AI system? |
| **Verifying the content credibility and veracity** | How do you verify whether the claim/news are false or manipulated?                          |
|                                   | What kind of resources do you use to fact-check the news? Do you mention them in the fact-check? |
|                                   | Which criteria do you use to verify the credibility of content?                              |
|                                   | Who verifies your fact-checks?                                                               |
|                                   | What does your evaluation look like? Is it a scale or textual evaluation?                   |
|                                   | Would it be beneficial to you, if AI identifies some credibility criteria for you in the news (like e.g., missing author or sources, hateful sentiment, spell check errors etc.?) |
|                                   | What else would help you in verifying the content?                                          |
| **Communication and avoiding duplication** | Which channels do you use for communication with other fact-checkers? Do you have a platform for communication? |
|                                   | What type of communication is there? Do you also exchange some know-how there?              |
|                                   | How do you organize your work between your colleagues?                                       |
|                                   | Do you have any kind of system that you use in your organization to organize your workflow? |
|                                   | How do you organize your work across fact-checkers in other organizations? Do you check whether the claim is already fact-checked? |
|                                   | Does it happen, there are duplications in fact-checking?                                     |

*continues on next page*
Would it be beneficial to you, if the information technology that you use checks whether the content is already fact-checked?

Do you publish your fact-checks just on your website or do you communicate them more widely?

Do you also contact the person who made the misleading claim and ask them to correct or withdraw the claim?

How is your fact-check structured? Do you also use semantics (like tags) to help search engines identify the claims? Which tools do you use to make the semantic markup?

Do you cooperate with social media? How? Which languages do you cover?

What would be helpful in dissemination of your fact-checks?

Unstructured discussion

B Quantitative validation survey questions

Introduction

Dear fact-checker, dear editor,

We have collected the most serious problems that were mentioned during our interviews with Central European fact-checkers, operating in Slavic languages. This survey is meant to collect the answers of the fact-checkers of the rest of Europe to become a more complex picture of the needs and problems of fact-checkers. As we plan to publish the results as a research paper, your answers may serve as important inputs for the AI research community to research and develop better solutions for you and to help your processes be smarter and smoother. Therefore, please, indicate the level and frequency of problem felt during your fact-checking process, as well as the perceived priority of support needed by a tool / tech. assistant for your work tasks that take you the most of the time or are most repetitive. Thank you very much for your valuable answers as well as for your important work.

Table 2. Quantitative validation survey questions

| # | Question | Answer options |
|---|---|---|
| I. | Institution | Free text answer |
| II. | How big is your institution? | 1) micro (fewer than 10 employees) 2) small (10 to 49 employees) 3) medium-sized (50 to 249 employees) 4) large (250 and more employees) |
| III. | How often do you need to filter from monitored outlets manually to decide what to focus on? Example: You are overloaded with potential disinformation from e.g., Crowd Tangle. You need to filter them to see just the results „this looks suspicious“, „this might be important“...) | 1) More times a day 2) About once a day 3) About once a week 4) About once a month 5) Less than once a month 6) Never |

continues on next page
IV. If it was the case, how seriously do you suffer from manual filtering from monitored outlets? Would you appreciate some tech. support (tools) for this work? 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

V. How often would you need to have any alerts about potential disinformation from instant messaging services? Example: You noticed that there are many screenshots from Telegram that are shared on Facebook and you would like to have a quicker alert before it is shared heavily on Facebook 1) More times a day 2) About once a day 3) About once a week 4) About once a month 5) Less than once a month 6) Never

VI. If it was the case, how seriously do you suffer from the late alerts about potential disinformation from instant messaging services? Would you appreciate some tech. support (tools) for this work? 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

VII. How often do you need to seek factual claims suitable for fact-checking in a selected article? Example: You are overloaded by potential disinformation and you need to filter out just the factual claims that need/can be fact-checked 1) More times a day 2) About once a day 3) About once a week 4) About once a month 5) Less than once a month 6) Never

VIII. If it was the case, how seriously do you suffer from seeking factual claims suitable for fact-checking in a selected article? Would you appreciate some tech. support (tools) for this work? 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

IX. How often would you need to coordinate with other fact-checking organizations to avoid duplicates of your work? Example: You want to be aware, who is doing what, not to do the duplicate fact-checks. Better coordination with the other fact-checking organizations is needed 1) More times a day 2) About once a day 3) About once a week 4) About once a month 5) Less than once a month 6) Never

X. If it was the case, how seriously do you suffer from duplicates of your work with other fact-checking organizations? Would you appreciate some tech. support for better coordination with the other fact-checking organizations? 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

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Manuscript submitted to ACM
| S. No. | Question                                                                                                                                                                                                 | Options                                                                                           |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
| XI.   | How often do you need to search for the source of evidence for verification of the potential disinformation? Example: You need to find the relevant proof that the information you are fact-checking is manipulated, not true etc. You need a better search in the official statistics, media etc...to fulfill this task. | 1) More times a day  2) About once a day  3) About once a week  4) About once a month  5) Less than once a month  6) Never |
| XII.  | If it was the case, how seriously do you suffer from searching for the source of evidence for verification of the potential disinformation? Would you appreciate some tech. support (tools) for this work?                          | 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this |
| XIII. | How often do you need to search for the source of evidence in videos? Example: You need to verify a very toxic rumor about a politician and you know, you will find the proof in parliamentary speeches. But it is very hard to search within these materials (videos without appropriate metadata). You would need a searchable textual transcript of the video. | 1) More times a day  2) About once a day  3) About once a week  4) About once a month  5) Less than once a month  6) Never |
| XIV.  | If it was the case, how seriously do you suffer from searching for the source of evidence in videos? Would you appreciate some tech. support (tools) for this work?                          | 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this |
| XV.   | How often do you need to seek the debunking comments of common users under videos? Example: Some comments under manipulative Youtube videos (e.g., with links) debunk false information that the video contains. You need to quickly find the potential debunking comments to be able to assess the videos faster. | 1) More times a day  2) About once a day  3) About once a week  4) About once a month  5) Less than once a month  6) Never |
| XVI.  | If it was the case, how seriously do you suffer from seeking the debunking comments of common users under videos? Would you appreciate some tech. support (tools) for this work?                          | 5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this |
XVII. How often do you need to reverse-search the image with a low resolution?

Example: A lot of disinformation in your country is shared on images with low resolution that Google reverse-search doesn’t capture. You need a textual explanation, what is there to be able to search within them.

1) More times a day
2) About once a day
3) About once a week
4) About once a month
5) Less than once a month
6) Never

XVIII. If it was the case, how seriously do you suffer from searching for an image with a low resolution? Would you appreciate some tech. support (tools) for this work?

5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

XIX. How often do you need to search for the image manipulations within the images?

Example: A lot of filters on manipulated images were identified by a tool for filter detection. But many filters are just used for aesthetic reasons. You need to find the ones that are relevant for more serious manipulations detections

1) More times a day
2) About once a day
3) About once a week
4) About once a month
5) Less than once a month
6) Never

XX. If it was the case, how seriously do you suffer from searching for the image manipulations within the images? Would you appreciate some tech. support (tools) for this work?

5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

XXI. How often do you need to search within the existing fact-checks (your own and/ or of the other organizations)?

Example: The politician, whose speech you are fact-checking, made the same misleading claim as a month ago. You need to search in your previous fact-checks to find the same sources of evidence.

1) More times a day
2) About once a day
3) About once a week
4) About once a month
5) Less than once a month
6) Never

XXII. If it was the case, how seriously do you suffer from searching within the existing fact-checks (your own and/ or of the other organizations)? Would you appreciate some tech. support (tools) for this work?

5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

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XXIII. How often do you need to search for the other versions of the same disinformation to debunk them all/ to have a better outreach?

Example: You have debunked a disinformation, but you are aware that it is shared in slightly different forms on other websites or social media. You want to find as much similar disinformation as possible to connect it with your debunk.

1) More times a day
2) About once a day
3) About once a week
4) About once a month
5) Less than once a month
6) Never

XXIV. If it was the case, how seriously do you suffer from searching for the other versions of the same disinformation to debunk them all/ to have a better outreach? Would you appreciate some tech. support (tools) for your work?

5 point Likert scale: 1 = No problem, I like to do it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

XXV. How often do you analyze the insights/ impact of your fact-checks?

Example 1: You need to learn which of your debunks do your users read.

Example 2: You wish to seek duplicates of your fact-checks (post hoc)

1) More times a day
2) About once a day
3) About once a week
4) About once a month
5) Less than once a month
6) Never

XXVI. If you don’t analyze, how seriously do you suffer from the lack of information about the impact of your fact-checks? Would you appreciate some help with the assessment of the impact of your fact-checks?

5 point Likert scale: 1 = No problem, we don’t need it; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

XXVII. Do you wish to make your fact-checks more visible in Google search results or in Google Fact Check Explorer?

Example: You would like to use the structure in Schema/ Claim review on your website, but you don’t have any technical capacities or possibilities to do it (even in the Wordpress plugin from Fullfact - Claim review schema)

1) More times a day
2) About once a day
3) About once a week
4) About once a month
5) Less than once a month
6) Never

XXVIII. Would you appreciate some tech. support to make your fact-checks more visible in Google search results or in Google Fact Check Explorer?

5 point Likert scale: 1 = No, I want to do it on my own; 5 = I perceive it as a big problem. I really need a help with this

Please, provide us comments, if you have any Free text answer

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| XXIX. | Do you have any ideas about other tools that would help to simplify your work? Please don’t feel limited by these examples and fill in all your ideas. | Multiple choice answer:  
1) A tool to monitor trending Youtube claims and/or topics  
2) A tool connected to WhatsApp’s API which collects and prioritizes reader tips  
3) No, the above-mentioned needs covered everything that I can think of  
4) Other (free text answer) |
| XXX. | Are you interested in receiving the results of this research? | 1) yes, as a preprint  
2) yes, as a final paper  
3) no, thanks |