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FULL PAPER

Who dominates the discourse on text-generative artificial intelligence? The presence of performative, epistemic and evaluating experts in German newspaper coverage of an emerging technology

Wer bestimmt den öffentlichen Diskurs über textgenerative Künstliche Intelligenz? Die Präsenz performativer, epistemischer und evaluierender Expert:innen in der deutschen Berichterstattung über eine aufkommende Technologie

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Abstract: The public AI discourse is shaped by visions and interpretations that influence how this emerging technology is perceived, assessed, developed and applied in society. Generating acceptance for a particular vision has thus become a central objective for various societal actors engaging with the new technology. Recently, (tech) entrepreneurs appear to have been more successful than others in advancing their visions of AI. Assuming a powerful journalism in selecting actors and presenting their statements to the public, several scholars attribute this disproportionate influence to an economically biased media coverage of AI. We propose a conceptual framework that distinguishes actors according to their AI-related expertise and apply it in a semi-automated content analysis of the media coverage of text-generative AI tools such as ChatGPT in German print media. Within the articles published between November 2022 and April 2024 in ten newspapers, scientists and entrepreneurs were the most frequently represented groups. Business-related practical expertise regarding AI development dominated the debate compared to science-related epistemic knowledge about the technology's functionality or its professional impact assessment. Our findings nuance the presumed dominance of economic actors in the mediated AI discourse by revealing a nearly balanced appearance of scientists and entrepreneurs. The results point to a shortage of independent evaluations of the technology's functionality in the form of epistemic expertise.

Keywords: Artificial Intelligence, Large Language Models, ChatGPT, experts, technology journalism

Zusammenfassung: Visionen und Deutungen über KI im öffentlichen Diskurs beeinflussen nicht nur, wie die rasant aufkommende Technologie innerhalb einer Gesellschaft wahrgenommen und beurteilt wird, sondern auch deren Weiterentwicklung und Anwendung. Gesellschaftliche Akteur:innen, die sich mit KI befassen, versuchen deshalb, öffentliche Akzeptanz für ihre Visionen zu erzeugen. Besonders erfolgreich scheinen dabei in jüngerer Vergangenheit Vertreter:innen profitorientierter Unternehmen zu sein. Nicht selten wird dem Journalismus, der diese öffentlichen Stimmen auswählt und präsentiert, eine zuguns-

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ten wirtschaftlicher Akteur:innen verzerrte KI-Berichterstattung unterstellt. In unserer Studie sollte diese Annahme mithilfe eines hierfür entwickelten Modells zur Unterscheidung verschiedener medial sichtbarer Akteur:innen – unter anderem hinsichtlich ihrer KI-bezogenen Expertise – kontextualisiert werden. Dafür untersuchten wir die Akteur:innen-strukturen in der Berichterstattung über textgenerative KI wie ChatGPT in zehn ausgewählten deutschen Zeitungen im Zuge einer halb-automatisierten Inhaltsanalyse. In den zwischen November 2022 und April 2024 veröffentlichten Artikeln kamen vor allem Repräsentant:innen wissenschaftlicher Institutionen und profitorientierter Unternehmen zu Wort. Die meisten dieser Akteur:innen wiesen praxisbezogene, oft mit KI-Firmen assoziierte Expertise in der KI-Entwicklung auf. Vorwiegend wissenschaftliches, epistemisches Wissen und professionalisierte Evaluationskompetenz hinsichtlich der Technologie waren entsprechend zweitrangig. Die hier vorgebrachten Ergebnisse perspektivieren die vermutete Dominanz wirtschaftlicher Akteur:innen im öffentlichen KI-Diskurs, indem sie eine nahezu ausgeglichene Inklusion wissenschaftlicher Stimmen herausarbeiten, jedoch auch auf fehlende unabhängige Einschätzungen der Technologie in Form epistemischer Expertise hinweisen.

Schlagwörter: Künstliche Intelligenz, Large Language Models, ChatGPT, Expert:innen, Technologieberichterstattung

1. Introduction

There is no shortage of interpretations in the AI discourse: Like Google CEO Sundar Pichai, some believe that artificial intelligence will have an enormous positive impact on the lives of modern humans, comparable to the mastery of fire (Pichai quoted by Acemoglu & Johnson, 2023, p. 30). Others, such as OpenAI's Sam Altman, express concerns that the technology's development could "go quite wrong" and cause "significant harm to the world" (Altman quoted by Zorthian, 2023). Still others foresee AI "to be either the best or worst thing to happen to humanity" (Elon Musk quoted by Harroch & Harroch, 2025), combining techno-euphoric promises of a better future with warnings about underestimating technology's dangers.

Such visions put forward by prominent (tech) entrepreneurs are common in emerging technology debates (e.g., Sun et al., 2020, p. 13). When they prevail over competing interpretations and crystallise into publicly shared "sociotechnical imaginaries," they play a significant role in shaping "the design and fulfillment of […] scientific and/or technological projects" (Jasanoff & Kim, 2009, p. 120). Utopian or dystopian AI narratives are not necessarily viewed as destructive, but rather beneficial for social and technological progress in modern societies (Roßmann, 2021) – even when articulated by profit-driven tech CEOs. Such statements made by entrepreneurs may become problematic in socio-political decision-making on AI: Firstly, they tend to depict AI as monolithic technology without reflecting the technological specificities of different forms such as generators, Large Language Models (LLMs), medical AI, or AI associated with robotics. This can mislead public perception of specific AI technology (e.g., Mustaklem, 2024) and thereby bias or obstruct citizens' engagement in or legitimation of democratic decision-making. Secondly, these sociotechnical imaginaries established by profit-oriented actors often overstate, downplay, or obscure uncertainty

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and risk inherently entangled with modern scientific and technological progress to serve self-interest purposes. Many believe that in modern risk-weighted societies, "there can only be one authority left, and that is science" (Beck 2003, p. 259), leading to calls for improved communication of scientific AI research (e.g., Hoos quoted by Henschel, 2023).

As Beck (2003, p. 259) contends, this view represents "a complete misunderstanding" of science and risk. Our study does not draw on those calls for better science communication or more frequent inclusion of scientists to the debate to drown out the voices of tech entrepreneurs. We interpret the demand for increased scientific presence in the public AI discourse as indicator of the various values at stake under post-normal conditions (Funtowicz & Ravetz, 1994, p. 1882), closely tied to emerging technology development. Assessments of AI and its application should be debated in a deliberative, hence inclusive and balanced, manner (cf., Habermas, 1998). Journalistic media organising and representing the respective public debate are urged to bring actors to the front who can provide the range of information and perspectives necessary for the (lay) public and other stakeholders to participate in societal decision-making around AI. Invited actors – particularly those introduced explicitly as experts – are expected not only to prioritise the public good over the pursuit of their partial interests, but also to possess relevant expertise.

Journalistic media "can wield considerable power in shaping the discursive expectations of AI" (Brennen et al., 2022, p. 29) by determining not only "who gets to speak in the news" (Beckers & Van Aelst, 2019, p. 886), but also making recognisable the publicly demanded and/or needed expertise(s) of the included actors. According to some scholars' reports of biased media coverage in favour of economic subjects and sources (e.g., Fischer & Puschmann, 2021, pp. 8, 22; Kieslich et al., 2022, p. 6), journalists have not lived up to this responsibility in their coverage of AI.

There is a lack of systematic analyses that could substantiate this criticism. Among the many studies on media coverage of AI (e.g., Köstler & Ossewaarde, 2022; Vergeer, 2020), most focus on technology's representation. A variety of studies describe frames and narratives surrounding AI in the media (e.g., Cools et al., 2024; Vrabič Dežman, 2024). These studies have generally found an optimistic depiction of AI in the news, emphasizing potentials in supporting human evaluations, for example, in medical contexts, or more prominently focusing on promises associated with the technology's industrial application (e.g., increase in labour efficiency & economic growth). These frame analyses predominantly extrapolate topics and evaluations (e.g., tone of the articles, risks/benefits, depiction of AI as threatening) from the news coverage, while only a few studies examine actors or sources (e.g., Brennen et al., 2018, p. 3). The few studies that have analysed actor constellations solely focus on manifest features like gender, national localisation, or institutional affiliation (e.g., Sun et al., 2020, p. 11), rather than on expertise directly.

We aim to provide a systematic description of the participants in this mediated public debate by using the German media discourse on text-generative AI as a case study for the broader discussions surrounding AI and emerging technolo-

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gies[1]. We analysed the constellation of active speakers focusing on who they are and how they are engaged with AI. The empirical basis for this description is a semi-automated analysis of articles about text-generative AI published in ten German newspapers between November 2022 and April 2024. We propose a new approach to categorise cited actors in technology debates by considering their AI-related expertise (referred to as (LLM/AI) expertise). After outlining the role of experts in the journalistic construction of public AI discourse and introducing the concept of expertise alongside a typology of experts as well as our methodological approach, we present the findings of our analysis. The paper concludes with a discussion of the limitations underlying our findings and their implications for future research, as well as the journalistic representation of AI discourses.

2. Theoretical framework: Experts and expertise in public discourses

Experts are actors who not only possess special knowledge in a well-defined domain, but who are also able to relate this knowledge to problems outside of the respective domain and thus serve as consultants in decision-making processes tangential to their expertise (Peters, 1994, p. 166; 2014, p. 72). Being (called) an expert usually goes hand in hand with a social responsibility that becomes particularly relevant when other societal actors (e.g., politicians, citizens, journalists) must decide on issues they cannot experience by themselves due to continual differentiation of modern societies (Schimank, 2005, pp. 79–82). Experts become highly socially relevant and powerful (Giddens, 1991, p. 27; Reed, 1996, p. 574), even though they are commonly vaguely described as "source[s] of special knowledge" (Gläser & Laudel, 2010, p. 12) representing theoretical and factual understanding ("knowing *that*") and/or practical proficiencies ("knowing *how*") (Weinstein, 1993, p. 58). While this definition seems appropriate in a macroscopic perspective, it provides some inconsistencies in terms of content and practical implementation in particular societal contexts (Bogner et al., 2014, pp. 10–11), including mediated technological debates such as the public discussion on generative AI (genAI).

2.1 Role of expertise in the journalistic construction of public discourse

Applying a broad definition of expertise, journalists covering AI topics primarily view experts as providers of information, like accurate factual explanation or contextualisation (Huber, 2014, p. 69). Given a lack of professional training or restricted resources for investigation (Brennen et al., 2018, p. 2), most of these "authors with insufficient knowledge of AI technology" (Ouchchy et al., 2020, p. 934) are reliant on their translations of knowledge to accurately report on the

1 The constraint to the discourse of text-generative AI/LLMs was necessary to examine different expert types due to the contradictoriness of the domain-specificity of expertise(s) and the variety of AI technologies featuring different characteristics, functionalities, operating modes, etc. that might be interrelated with diverse skills, experiences and knowledge, e.g., an expert on robotics might as well be an expert on AI-based robots, but not on AI-based text-generators.

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associated issues (Banholzer, 2015, p. 20) and serve as "knowledge brokers" (e.g., Meyer, 2010) for the public.

AI experts – like all members of society – hold views on different aspects of AI and are not merely neutral information sources to be passively consulted by journalists. They actively contribute to the public AI discourse (Huber, 2014, pp. 43–61). As such "public experts" (Peters, 2014, p. 70) who try to attract public attention and secure acceptance for their messages, they are evaluated by journalistic gatekeepers concerning different selection criteria, which Nölleke (2013, p. 348), drawing on the theory of news values (Galtung & Ruge, 1965), refers to as "expert factors".

For Nölleke (2009, p. 107), the so-called "expert value" is mainly derived from assigned practical (e.g., accountability, reliability) or superficial characteristics (e.g., prominence, attractiveness, linguistic conciseness). Other scholars consider their strategic usefulness to be a relevant selection criterion, for example as sources of authority (Albæk, 2011, pp. 337–338), credibility (Boyce, 2006, p. 890), and objectivity (Steele, 1995, pp. 800–801), or as "opportune witnesses" (Hagen, 1993) who help to reinforce a journalist's argumentation. In both approaches, the substance of expertise is only briefly addressed. We consider this a shortcoming, as we assume in debates surrounding the assessment of emerging technologies – where at least a basic understanding of the technology and its risks and benefits is required – factual expertise serves as an important selection criterion. This especially applies to actors lacking direct political power, whose expertise is a main source of "communicative power" (e.g., Flynn, 2014, p. 210) and therefore constitutes legitimacy for the inclusion in public debates (Gerhards & Neidhardt, 1990, p. 11).

2.2 Scientific experts in the media and newspaper coverage of AI

As it is difficult (or even impossible) to measure expertise in content analysis of media texts, many examinations of expert voices in the news (e.g., Laursen & Trapp, 2021; Peters, 1994; 2014) use a simplified operationalization of expertise. Following a narrow definition, these studies equate experts with scientific representatives and count references to scientists to quantify public presence of experts in mediated science discourses (e.g., Albæk et al., 2003; Lehmkuhl & Leidecker-Sandmann, 2019; Peters, 1994; 2014).

While there have been, to our knowledge, no attempts to explore experts' role in media coverage of AI, some scholars have distinguished sources or actors in media discourse according to societal groups commonly derived from systems theory or Habermas' centrality-periphery model (e.g., politics, economy, science). According to these studies, AI discourse is dominated by entrepreneurs, followed by scientists (e.g., Brennen et al., 2018, p. 4; Fischer & Puschmann, 2021, p. 24). Based on the narrow definition of experts as scientists, these observations might lead to an impression of lacking expertise in the mediated AI debate.

For an initial assessment of the presence of expertise in the media discourse on text-genAI, we will follow this operationalization and compare the presence of actors from different societal areas:

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RQ1: How often do scientists get to speak in German news media articles about text-generative AI compared to other societal actor groups (e.g., politicians, stakeholders of non- or for-profit organisations, cultural actors, education representatives)?

This concept of expertise has at least two weaknesses: First, it ignores the potential of actors from other societal groups to contribute substantial expertise to public discourses (e.g., Laursen & Trapp 2021). Second, it is unable to distinguish different forms or roles of expertise discussed in the literature on expertise (e.g., Collins & Evans, 2018; Priaulx et al., 2016). Analyses that use a more nuanced definition of expertise arrive at different assessments of experts' public presence. For example, Chuan et al. (2019, p. 3), who contrasted researchers (n = 116, 29.1%) and "non-science experts (e.g., scholars in ethics)" (n = 94, 23.6%) with individuals associated with companies or businesses (N = 258, 64.7%)[2] in US newspaper coverage of AI, found a nearly balanced inclusion of expert (scientists + non-science experts) and business sources.

Building on that yet (at least analytically) exceptional thought of another form of expertise complementing, counteracting or accompanying the scientific expert perspective on AI, we reconsider the concept of expertise and the role of experts in mediated public discourses to provide a more sophisticated picture of the forms of expertise present in the public discourse on LLMs. We attempt to combine different perspectives of expertise in a multi-level model of (LLM) expertise beyond the narrow attribution of expertise to scientific actors. It restricts the application of the concept to actors that either need some expertise to be invited to the public discourse or to justify their active role in the public arena[3].

2.3 Types of experts on LLMs

Following Weinstein (1993, p. 58) and Collins and Evans (2007, 2018, pp. 23–28), we understand expertise as a "social fluency" eliciting different social roles assigned to different actors within a given domain. It is generated through socialisation (expertise in the narrow sense) and externally realised through consultation by third parties (expertise in the broad sense). In the context of genAI, socialisation refers particularly to the acquisition of special knowledge and/or skills related to genAI – like understanding for scientific and technological processes, development or evaluation skills – through experience within social groups (Collins & Evans, 2018, p. 23). Third-party consultation relates to the external recognisability of acquired or presumed AI knowledge. It is linked to the aforementioned "expert factors" and their allocation to "expert values", central to the journalistic const-

2 Sum of percentages is greater than 100% because some of the 399 analysed articles included several sources, separately counted without mentioning the total number of sources identified.

3 At this state, we only want to examine expertise as an actor characteristic enabling active shaping of the discourse and not (the justification of) the shaping of the discourse by various experts, e.g., by giving specific statements, framing the subject-matter in a certain way, itself. Our approach to distinguish public actors by their expertise(s) is therefore, pending follow-up studies testing our attempt of systematisation in other contexts, e.g., by relating expertise to contents of statements, mainly to be interpreted with respect to that premise and/or limitation at the same time.

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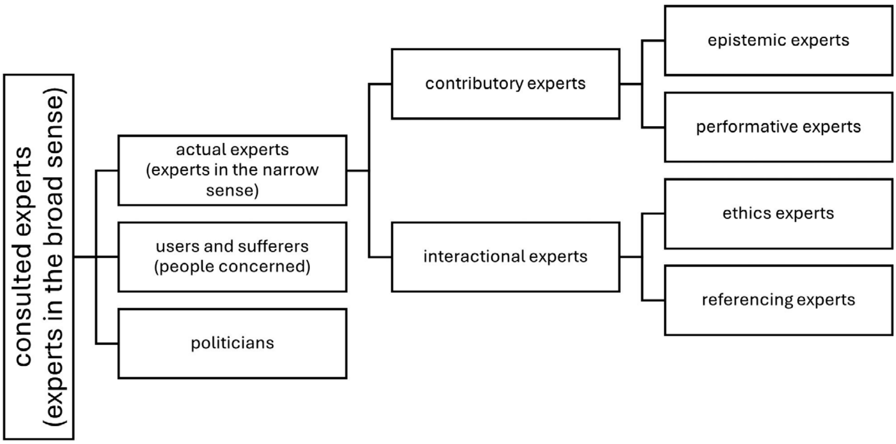
ruction of expertise in public discourse. These factors are often associated with the acquisition of expertise through socialisation, but not limited to it.

This implies subject-specific knowledge and skills of experts in public discourses are at least complemented, in some cases even replaced or predominated by other, more superficial or quantifiable traits[4] unrelated to the actual discourse subject of AI. Actors lacking AI expertise in the narrower sense may still be presented to the public as experts if they possess otherwise inaccessible or intangible information of interest to journalists. Our proposed model starts on a superordinate level (Fig. 1): Experts by designation (or experts in a broad sense) are all actors consulted by a third party (in this case, journalists) to provide information on a specific topic (e.g., LLMs).

Figure 1. Public actors in the discourse of genAI regarding their LLM expertise



Taking up Bogner et al.'s (2014, p. 10) critique of this constructivist concept of expertise ("is not then everyone an expert?"[5]), we further differentiate this broad group in the second level of our model based on the subject-related knowledge that actors can contribute to a specific debate. We distinguish distributors of certain AI-related opinions, decisions or political processes and/or first-hand experiences (politicians or people who are confronted with AI in their everyday life, e.g., through usage, by experiencing negative consequences) from subject-specific or professionalised LLM experts. Sometimes, the first form of contributions is conceptualised as subject-detached expertise such as political expertise (Weinstein, 1993, p. 57) or "anecdotal evidence" (Moore & Stilgoe, 2009, p. 654) which can be found across all sectors of society, treating a scientist not conducting AI research but using LLM-based technologies, for example, to write papers equally to a pupil using AI for homework, or a musician generating song lyrics with its help.

4 For example, reputation (Leidecker-Sandmann et al., 2022; Peters, 1994, p. 180), authenticity (Collins & Weinel, 2011, p. 404; Nölleke, 2009, p. 107), or innate characteristics like gender (Niemi & Pitkänen, 2017) and nationality (Nölleke, 2013, pp. 311–312).

5 Translation of the German original quote "sind dann nicht alle Menschen Experten?"

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Here, the differentiated approaches to expertise(s) by Weinstein (1993) and Collins and Evans (2007, 2018), as well as the still controversial concept of moral expertise (e.g., Priaulx et al., 2016) are not applicable, as they presuppose the property of subject-specific expertise through socialisation within eligible collectives (Collins & Evans, 2018, p. 23). In the third and fourth levels of our model, we focus on professionalised LLM expert types (here called *expert status*).

2.3.1 Experts in a narrow sense – Experts with professionalised and subject-specific expertise

Experts in a narrow sense have acquired domain-specific knowledge and skills through education and professional training within social groups already possessing these competencies. They can provide specialised information to the public, which can be assigned specific functionalities, particularly the promotion of techno-scientific rationality to protect the dominant knowledge order (Neuberger et al., 2019).

Following Collins and Evans (2007, p. 24, 2015, p. 119), we propose to differentiate this group into "contributory experts" and "interactional experts". "Contributory experts" are people whose knowledge enables them to actively contribute to a specific domain, promoting progress. This "ability to *do* things within the domain of expertise" (Collins & Evans, 2007, p. 24) can be realised in an epistemic or performative sense (Weinstein, 1993, p. 58). While epistemic expertise is based on theoretical knowledge, including factual understanding and the capacity to apply it to explain, justify and produce further knowledge, performative expertise is related to the mastery of a concrete skill in the respective domain without necessarily knowing how to explain it. Epistemic AI experts are actors who, while committed to scientific methods and standards, produce new knowledge or investigate, discuss, and contextualise existing knowledge about genAI technologies (e.g., how they work, effects, limitations). They can be found in university and non-academic AI research, not focussed on programming and invention of concrete technologies/applications but on the LLM/AI phenomenon and its further development as such, irrespective of whether their work is connected to pure science or company-bound. A prime example would be Kristian Kersting, who is Professor of Artificial Intelligence and Machine Learning at the Technische Universität (TU) Darmstadt.

By contrast, performative AI experts are actors with technical skills to develop concrete AI applications, not necessarily able to explain how these systems function or have evolved in detail. These are usually developers, IT specialists or similar in tech companies, but also hobby developers and "tinkerers", such as Blake Lemoine, a now freelance software engineer and former part of the Google team that developed LaMDA.

"Interactional experts" are people who act as mediators in interdisciplinary settings. In the context of AI, these experts do not contribute directly to the development or study of AI technologies, but otherwise intensively engage with it, for example, through non-scientific research, artistic examination or moral/legal as-

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sessments. This engagement enables them to understand the outputs of contributory experts in detail and communicate with them competently (Collins & Evans, 2015, p. 119). Such protracted "enculturation" (Collins & Evans, 2007, p. 30) underlies the "referencing expertise" (e.g., John Thornhill, a tech columnist and "Innovation Editor" for the Financial Times or German blogger Andre Wolf, who works for the Austrian initiative "Mimikama", specialised in the field of detecting fakes and scams on the internet) originally described by Collins and Evans (2015), and the still controversial "ethical expertise" (Weinstein, 1994, p. 61).

The latter is represented by actors with publicly accepted moral sovereignty (Priaulx et al., 2016, p. 403) who have accumulated a state of knowledge about genAI through research and discussion, which allows them to evaluate the technology and make informed moral judgements.[6] As we assume to find other non-technical evaluations of the technology and its societal consequences not exclusively linked to moral aspects, we propose broadening this concept and speaking of actors with "evaluating expertise". In this group, ethical experts are joined by other experts in technological impact assessment, including law scientists and ethicists as Sandra Wachter, a Professor of Technology and Regulation specialised on ethics of AI at the Oxford Internet Institute, Alena Buyx, a member of the German Ethics Council, or social scientists and psychologists like Peter Gerjets, a German education researcher and cognition scientist at the Leibniz-Institut für Wissensmedien who researches on the co-creation of narrative texts with LLMs and its impact on producers and recipients.

Given the absence of formal training pathways and standardised qualifications, evaluating and referencing expertise are more fluent concepts than epistemic and performative expertise. They can be acquired in greater variety of social groups depending on the final configurations of these expertises (e.g., among artists, ethicists, or journalists, within advisory boards). This type of expert status cannot be derived from an actor's societal localisation. The description of their engagement with the subject matter and the statements given by these actors usually indicate these interactional forms of expertise. For example, a comedian using ChatGPT to create jokes is no subject-specific LLM expert, whereas the German theatre writers Ulrich Greb and Sandra Höhne, who have artistically looked into the subject of LLM-based androids imitating family members and keeping them alive after death in a play for the Schlosstheater Moers, may be assigned such expertise.

6 Ethical or moral expertise refers to "the ability and capacity to exercise moral judgement" (Priaulx et al., 2016, p. 395). It is mostly debated regarding expertise of philosophers and ethicists questioning whether and how their moral considerations differ from ubiquitous moral assessments to be made by laypeople to advance in everyday life or if it is possible/justifiable to ascribe authority in moral decision-making to these (or other) actors. Since normative values are central to this debate, this concept is highly controversial in the scientific community and cannot be sufficiently addressed in this paper. The here given definition of "ethical experts" is to be considered as preliminary and shall not ultimately answer the question if moral expertise is possible. Neither shall it contribute to the normative debate on whether ethical experts are desirable in a democratic society. For further information we recommend amongst others the publications of Singer (2006) or Weinstein (1994).

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2.3.2 Proposed systematisation of public LLM experts

Our proposed systematisation to capture and distinguish public LLM experts consists of four levels that can be assessed stepwise. At first, all actors consulted by journalists to provide information on LLMs are called experts in the broad sense. These can be distinguished into "politicians", "people concerned" and "subject-specific experts (experts in a narrow sense)". The latter are then further divided, based on their ability to contribute to the domain, into contributory and interactional experts. These two types of experts are classified according to the form of their expertise (knowledge vs. skill, assessment vs. systematic reprocessing) into epistemic, performative, evaluating, and referencing experts.

As we consider this integrative model to capture the speaker constellation in the public LLM debate rather than the isolated examination of their societal origins (e.g., politics, civil society, science), we apply this model by examining the following question:

> *RQ2: In which AI-related (expert) roles do the different actors become visible in the German media coverage of LLMs?*

Given the rapid development and spread of the AI technologies (Rotolo et al., 2015) under discussion, we expect the aspects requiring societal evaluation and bringing actors not directly devoted to technology development to the fore (e.g., "non-science experts" according to Chuan et al., 2019, p. 3) will evolve (Solomonoff, 1985). There may be observable changes in the composition of the speakers invited to the public arena, motivating our final research question:

> *RQ3: (How) Does the composition of speakers regarding their societal origin and contributed LLM expertise in the public discourse of LLMs change over time?*

3. Methods

We conducted a semi-automated quantitative content analysis of articles about text-genAI published in ten German newspapers from November 1, 2022–April 1, 2024. As a starting point of our inquiry period served the publication of the chatbot ChatGPT. We deliberately selected different German print media titles included in the database LexisNexis that can be regarded as a small extract of the German print media landscape. Namely, we analysed coverage in the national quality and tabloid newspapers and press magazines *BILD*, *Die Welt*, *Die Zeit*, *Der Spiegel*, *Stern* and *taz, die tageszeitung* which are considered as leading me-

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dia[7], as well as in the regional newspapers *Nürnberger Nachrichten*, *Stuttgarter Zeitung*, *Rheinische Post*[8] and *Der Tagesspiegel*. As we could not include regional newspapers representing all geographical regions of Germany due to resource restrictions, we chose these four high-circulation regional newspapers from the three most populated federal states and the German capital indicating a high importance of these media outlets in the regional representation of public discourses. Within this media sample, we considered every article as relevant that dealt with the topic of text-genAI. Conversely, articles exclusively reporting on other types of AI (e.g., robotics, industrial AI, medical AI), AI in general without mentioning LLMs or other genAI such as image, voice or video generators like Midjourney or DALL-E were excluded from the sample since their different or additional characteristics (e.g., different central aspects like deep fakes, purposes and potentials) might lead to other debates. We developed several search strings through systematic reviews of previous content analyses and recent media coverage on the topic and double-checked this manual identification of keywords with a computational topic modelling approach to assure that no central keywords were overlooked. This resulted in 20 different strings that were systematically compared by using evaluation criteria for automated classifications (Scharkow, 2012, pp. 133–136)[9]. As a result of this, we chose the string "LLM OR "Large Language Model" OR (Text* AND ("KI" OR "künstlich* Intelligenz") AND NOT Textil) OR ChatGPT OR (generativ* AND ("KI" OR "künstlich* Intelligenz") AND Text)"[10] (Recall = 1; F-Score = 0.78) to search for relevant articles.

3.1 Sample

After manually removing irrelevant documents and duplicates, the final article sample comprised 905 articles published between November 1, 2022, and April 1, 2024, accounting for 0.11% of the news by the ten selected German media titles. While most of the articles were published at the beginning of 2023, only a few articles (n = 19) were released before or shortly after the launch of ChatGPT in November and December 2022 (Fig. 2).

7 Due to database restrictions and limited time and personal resources (data collection in the course of a master's thesis) affecting the presented research, we could not include the national newspapers *Süddeutsche Zeitung* and *Frankfurter Allgemeine Zeitung*. As they are influential leading media, this is a limitation to our study that needs to be considered when interpretating the presented results. Nevertheless, through the inclusion of various national and regional media outlets representing different localisations within the political spectrum (e.g., Scheufele & Engelmann, 2013, p. 538), we hope to have minimised the impact of the deficiency of these two sources.

8 Including the locally available *Solinger Morgenpost*, *Bergische Morgenpost* and *Neuss Grevenbroicher Zeitung*.

9 A detailed documentation of this procedure is provided as supplementary material.

10 English translation: "LLM" OR "Large Language Model" OR (text* AND ("AI" OR "artificial intelligence") AND NOT textile) OR ChatGPT OR (generative AND ("AI" OR "artificial intelligence") AND text)

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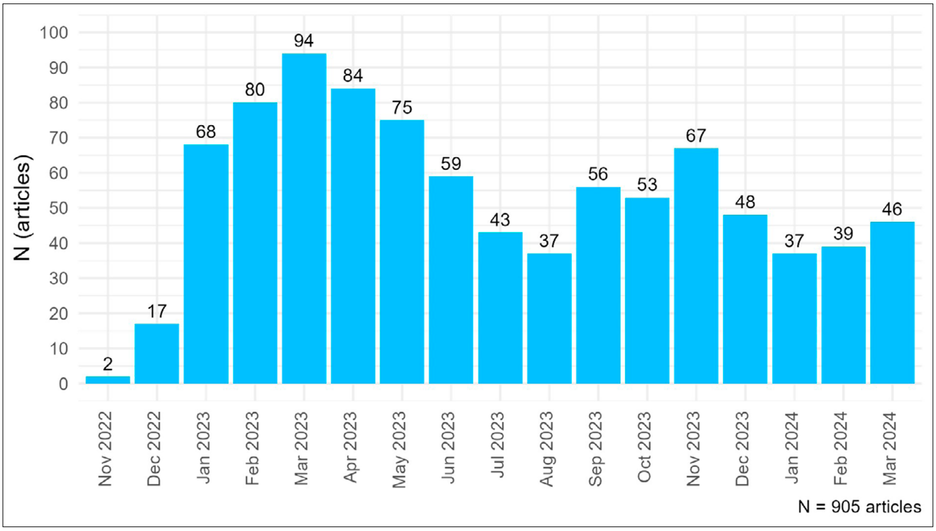
Figure 2. LLM-centred articles published between November 1, 2022, and April 1, 2024, in ten German newspapers by month of publication



3.2 Semi-automated content analysis

To identify all individual actors within the observed media coverage, we applied a Named Entity Recognition (NER) model named flair/ner-german from the Python package 'flair' (version 0.13.1; Akbik et al. 2018) to extract all personal names in the analysed news coverage validated in an earlier study (F-Score = 0.89–0.90) by Buz et al. (2021, p. 611). We automatically identified 10.422 entities in 851 articles.

After excluding identified non-human entities (e.g., companies or AI models) and persons not directly or indirectly quoted at least once, we characterised each quoted actor by manually coding nine different variables. Beneath the actors' names and institutions/organisations, we recorded gender and national localisation as established potential expert factors by Nölleke (2013, pp. 307–312) and Huber (2014, pp. 113 & 120–122).

We also captured the societal origin of the speakers (RQ1). Following the classification of social domains prevalent in systems theory (e.g., Luhmann, 1987) and the centrality-periphery model (Habermas, 1998), we distinguished different political areas (executive, administration, legislative) from peripheral domains, namely science, scientific administration, medicine, stakeholder organisations (non- and for-profit organisations) and other areas like culture, journalism, and education. For scientists, we coded whether their research was associated with organisations with partial interests (dependent research) or conducted independently (e.g., universities or independent research institutes, scientific discipline).[11]

11 Classification was adopted from the Deutsche Forschungsgemeinschaft (DFG): https://www.dfg.de/resource/blob/172316/5863ef132d178054609f74940f6a27c9/fachsystematik-2016-2019-de-grafik-data.pdf.

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To evaluate the LLM expertise (RQ2), we developed four variables indirectly indicating the expert status of an actor. The first of these variables indicated whether a speaker voiced at least one statement about LLMs, as this is necessary to be regarded a public LLM expert, due to the domain specificity of expertise. In a second step, we measured whether an actor was explicitly labelled "expert" in the article and, if not, whether they contributed information not only accessible for insiders (e.g., corporate processes/secrets, whistleblowers[12]). If one of these requirements was fulfilled, the type of expertise provided by the regarded actor was coded. Based on the content of the expressed LLM statements[13], we differentiated between contributions to LLM development and/or research, descriptions of applications and usage experiences with genAI, or reflection of LLM contexts (e.g., ontological localisation of AI) and societal/ethical consequences. To code this indicator variable, not every single statement of an actor was analysed, but the content-related "tendency" (or majority in a non-quantitative way) of the statements served as basis for the coding decision. If actors mainly describe how they use ChatGPT to formulate answers to e-mails, the code "LLM application/usage" is chosen; if they speak mostly about the steps they took to train or program a new LLM, the code "LLM development/research" is applied, and so on. These conditional and descriptive variables were automatically aggregated with the actor's societal area to define the final expert status (performative expert, epistemic expert, evaluating expert, other expert, politician, person concerned) via a Shiny app used for the coding procedure. The codebook, including a further description of this automatic derivation of the expert status, is provided as supplementary material.

We attempt to illustrate our coding procedure with the following example from a text in our sample: "Even before Christmas, the hype was so great that the founder of OpenAI, Sam Altman, issued a warning on Twitter: 'ChatGPT is incredibly limited, but good enough at some things to create a misleading impression of greatness.'"[14]

1) As the given quote of Sam Altman clearly addresses Large Language Models (a specific application of LLMs in ChatGPT), he is recognised as an actor with an LLM statement, which makes it possible that he contributes LLM expertise to the debate.

12 Actors who only provide insider information (e.g., trade secrets) becoming public solely through their appearances (e.g., whistleblowers) are not to be considered as experts in the narrow sense as their "special knowledge" cannot be consulted by third parties because they usually do not know "how to ask for that information" or that this information exists without being tipped off by the insiders.

13 We did not further analyse the content of the statements. They served only as an indicator to assess the "expert characteristic" of an actor. What distinguishes expert from non-expert contributions on a content-level therefore remains unanswered but serves as an starting point for future studies.

14 Original quote: „Schon vor Weihnachten war der Hype so groß, dass der Gründer von OpenAI, Sam Altman, sich warnend auf Twitter zu Wort meldete: ‚ChatGPT ist noch unglaublich beschränkt, aber gut genug, um den missverständlichen Eindruck von Großartigkeit zu erwecken.'" (Tagesspiegel (25.01.2023). Wenn der Computer die Feder führt. [When the computer puts pen to paper.] *Der Tagesspiegel*, p. 26)

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2) The article is scanned for any explicit expert designations referring to Altman. If there is at least one (e.g., "AI expert Altman"), the following variable is skipped.
3) If no expert designation is identified, it is checked whether Altman provides insider information excluding him from being considered an expert by considering all his statements within the article. The presented quote does not distribute insider information, as the content expressed is (theoretically) available to other persons who have used ChatGPT. Altman is therefore still regarded as a potential expert and the coding continues.
4) Since Altman is associated with OpenAI, an AI developing company, his expert status can be derived from his societal position. He is coded as an actor with expertise in LLM research/development. If his position had not been this clear, for example, if he was a cultural actor, the content of his statement(s) would have been consulted to decide on the expertise provided. For this statement, one would probably code "other" as no other value provided seems suitable[15].

This stepwise and conditional identification of the various expert types might seem more complex than a direct coding of the expertise that an actor provides. However, it proved to be better applicable and more accurately reflecting the theory-bound model than a more straightforward option, where the coders had to directly decide on whether an actor is an expert and their domain of expertise.

Two pretests with two coders based on 200 actors each were used to refine the newly added expert variables (Krippendorff's α for expert status of 0.673 in pretest 1 and 0.897 in pretest 2). After satisfactory reliability values were achieved, manual coding was conducted by one coder from June 10–21, 2024. We checked the reliability of the codebook via tests of intercoder (same second coder as in the pretests) and intracoder reliability (second coding on June 24, 2024). Krippendorff's α ranged from 0.64 to perfect agreement for intercoder reliability[16] and 0.78 to perfect agreement for intracoder reliability. Even though the intercoder reliability for the newly developed variable "expert status" below 0.8 only allows tentative conclusions (Krippendorff, 2004, p. 429), the overall good reliability measures of the expertise indicator variables indicate our suggested systematisation and its operationalisation are practicable and provide reliable data (Tab. 1).

15 The coders were two of the authors, having basic knowledge of LLMs and being well acquainted with the public discourse on text-generative AI, but do not have in-depth technical knowledge. If actors appeared without affiliation with whom they weren't familiar, they searched the person via Google and attempted to code them accordingly.

16 We are aware that the coefficient of 0.64 lies below the generally accepted threshold for Krippendorff's α, which is why we do not analyse the variable LLM quote beneath its inclusion in the expert status. As the distribution in this variable was skewed and bound to a relatively small number of cases (n = 81), Krippendorff's coefficient might (slightly) underrate the reliability for this category (Vogelgesang & Scharkow, 2012, p. 338).

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Table 1. Overview of inter- and intracoder reliability for each variable

	intercoder reliability (2 coders)		intracoder reliability (06/10-06/21/2024 & 06/24/2024)	
	Krippendorffs alpha	Holsti	Krippendorffs alpha	Holsti
filter				
no person[1]	0.846	0.952	0.982	0.994
already coded[1]	0.992	0.996	1.000	1.000
author[1]	0.941	0.991	1.000	1.000
passive actor[1]	0.817	0.931	0.947	0.982
gender[2]	1.000	1.000	1.000	1.000
national localization[2]	0.745	0.840	0.917	0.945
societal area[2]	0.938	0.951	0.930	0.945
scientists				
scientific dependence[3]	1.000	1.000	0.778	0.952
scientific discipline[4]	0.943	0.957	0.884	0.917
LLM expertise				
LLM quote[2]	0.638	0.852	0.789	0.901
expert designation[5]	0.791	0.942	0.931	0.981
no insider[6]	1.000	1.000	1.000	1.000
LLM expert[7]	0.678	0.773	0.883	0.920
expert status[2]	0.783	0.826	0.936	0.951

coded actors per variable (intercoder | intracoder):
[1] N = 503 | 564 [2] N = 81 | 91 [3] N = 23 | 21 [4] N = 23 | 24 [5] N = 52 | 53 [6] N = 37 | 42 [7] N = 47 | 51

For data analysis and visualisation, the R (version 4.3.2; R Core Team, 2023) packages tidyverse (Wickham et al., 2019), DescTools (version 0.99.54; Signorell, 2024), patchwork (version 1.2.0; Pedersen, 2024), irr (Gamer et al., 2019), and kableExtra (version 1.3.4; Zhu, 2021) were used.

4. Results

In 689 articles, 1247 actors were identified as potential experts, having made at least one statement on LLMs. This corresponds to an average of about two actors with LLM quote (LLM actors) within an article (*SD* = 1.56). Only a few individuals (*n* = 145, 17%), such as Elon Musk (*n* = 33, 2.65%) or Sam Altman (*n* = 32, 2.57%), appeared multiple times in different articles. As these repeatedly quoted actors are outnumbered by actors appearing once (*n* = 715, 83%), this indicates a dispersed actor structure regarding individual persons quoted in LLM articles.

Taking up the assumption of an economically biased public LLM discourse (RQ1), we investigate the distribution of social domains associated with all quoted actors (*N* = 1247) in the LLM discourse. We find a dominance of actors associated with for-profit (*n* = 375, 30.07%) and science organisations (*n* = 372, 29.83%) over contributors from other sectors like education (*n* = 72, 5.77%), culture (*n* = 69, 5.53%) or politics (*n* = 149, 11.95%) (Fig. 3). This difference between scientists and for-profit actors and other groups is significant following a

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Chi^2 test against the null hypothesis of equal probabilities between scientists/for-profit actors and other groups ($Chi^2(1) = 48.93$, $p < 0.001$). There is no significant difference between scientists and for-profit actors ($Chi^2(1) = 0.01$, $p = 0.913$). If we further distinguish the group of scientists by their research depending on tech companies (e.g., research in company-associated AI labs like Google DeepMind), we see that the share of scientists independent of partial interest organisations is lowered ($n = 318$, 25.50%). If we assume the remaining 4% of scientists bound to for-profit organisations in their research, we see a bigger, significant difference between the share of for-profit ($n = 429$, 34.40%) and scientific actors ($Chi^2(1) = 16.49$, $p < 0.001$) (Fig. 4). While our initial results do not point towards an economically dominated LLM debate as entrepreneurs are nearly equally joined by researchers in the German discourse, we still see a potential overweight of economy-associated actors when we control for scientists bound to partial interests while conducting their research. This result must be interpreted with caution, as we cannot guarantee all the dependent scientists are affiliated with for-profit organisations.

Figure 3. Distribution of all quoted LLM actors according to their social domains (in %)

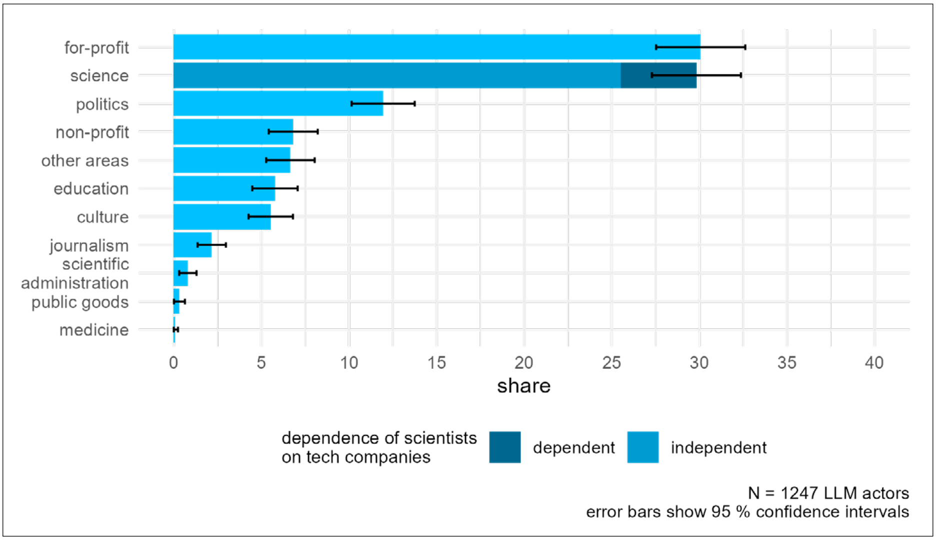

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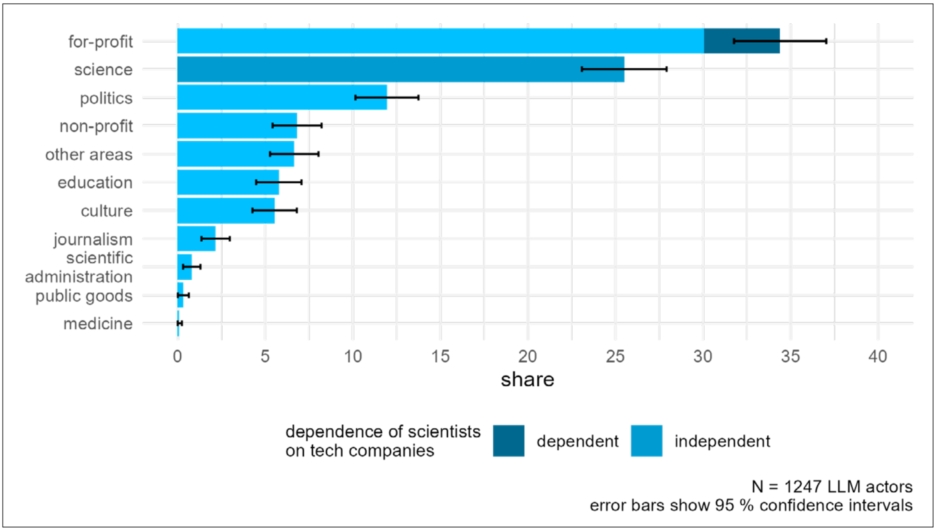
Figure 4. Distribution of all quoted LLM actors according to their social domains with respect to the (assumed) dependence on tech companies of scientific actors (in %)



In the next step, we analyse the actors' expertise based on their societal position and the content of their statements (RQ2).

Focussing on actors that can be assigned an expert status through their societal position or the content of their statements (n = 730, 58.54%), actors acquiring performative expertise, oftentimes associated with AI or software companies (n = 241, 80.97%), are the most frequently selected type of LLM expert (n = 301, 40.95%) ($Chi^2(3) = 122.79$, $p < 0.001$). Contrary to the distribution of the social domains, the commonly science-related actors (n = 147, 98%) with epistemic expertise (n = 150, 20.41%) appear less often in the public arena than speakers expressing evaluating expertise (n = 182, 24.76%) (Fig. 5), however, this difference is not significant ($Chi^2(1) = 3.08$, $p = 0.080$). As the distribution of social domains within these actors shows, the status of evaluating expert can be assigned to various societal actors (Fig. 6). While only about half of them were scientists (n = 92), cultural actors (n = 25, 13.74%; e.g., novelist John Grisham (n = 3, 1.65%)) and non-profit representatives (n = 21, 11.54%; e.g., Ramona Pop of the German consumer organisation VZBV (n = 4, 2.2%)) also played a notable role in terms of this form of expertise.

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Figure 5. Distribution of experts on LLMs according to their type of LLM-related expertise provided (in %)

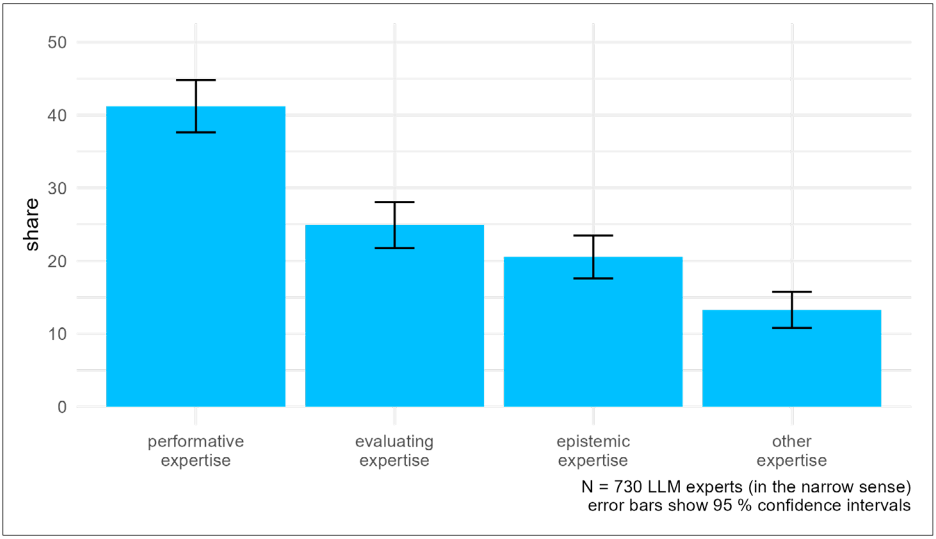
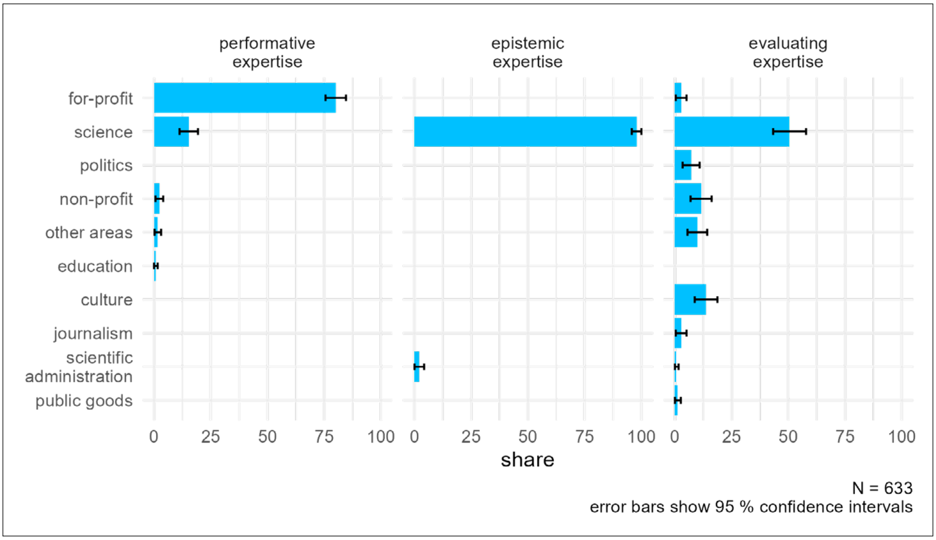


Figure 6. Distribution of social domains of experts providing different types of LLM-related expertise (in %)



Looking at the development of the debate over time (RQ3), we find most media coverage of LLMs and related actor citations in spring 2023, and a decline in included LLM actors per article over time (Fig. 7). There are notable shifts in the actor constellations. At the beginning of the debate, LLMs are predominantly

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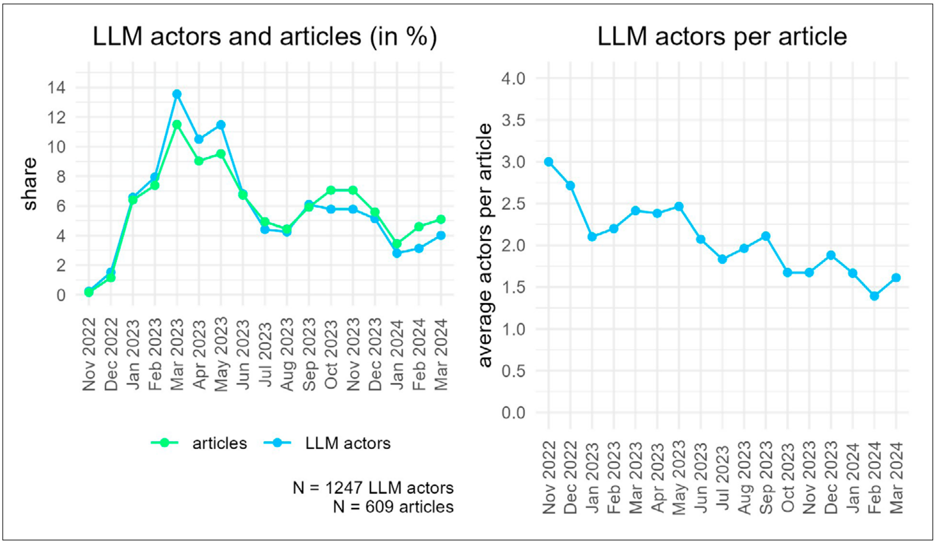
discussed by people directly concerned with the application of the technology but have not acquired any type of related expertise (people concerned). This changes in April 2023, as actors with performative (n = 46, 35.1%) or evaluating expertise (n = 24, 18.3%) become slightly more often visible than these people concerned (n = 20, 15.3%) (Fig. 8). As the peak in media coverage and the short-term shift in expert constellation go along with the publication of the so-called AI moratorium in March 2023, this might point to a more sophisticated public debate on the assessment of the technology.

Figure 7. Distributions of identified LLM actors and articles per month



In most months, performative experts were the most frequently quoted expert group, ranging only behind people concerned without domain-specific expertise. In contrast to other expert groups and people concerned, they did not enter the debate until the beginning of 2023 and were overtaken as most dominant expert group only by experts displaying evaluating expertise from July until September in that year (Fig. 8).

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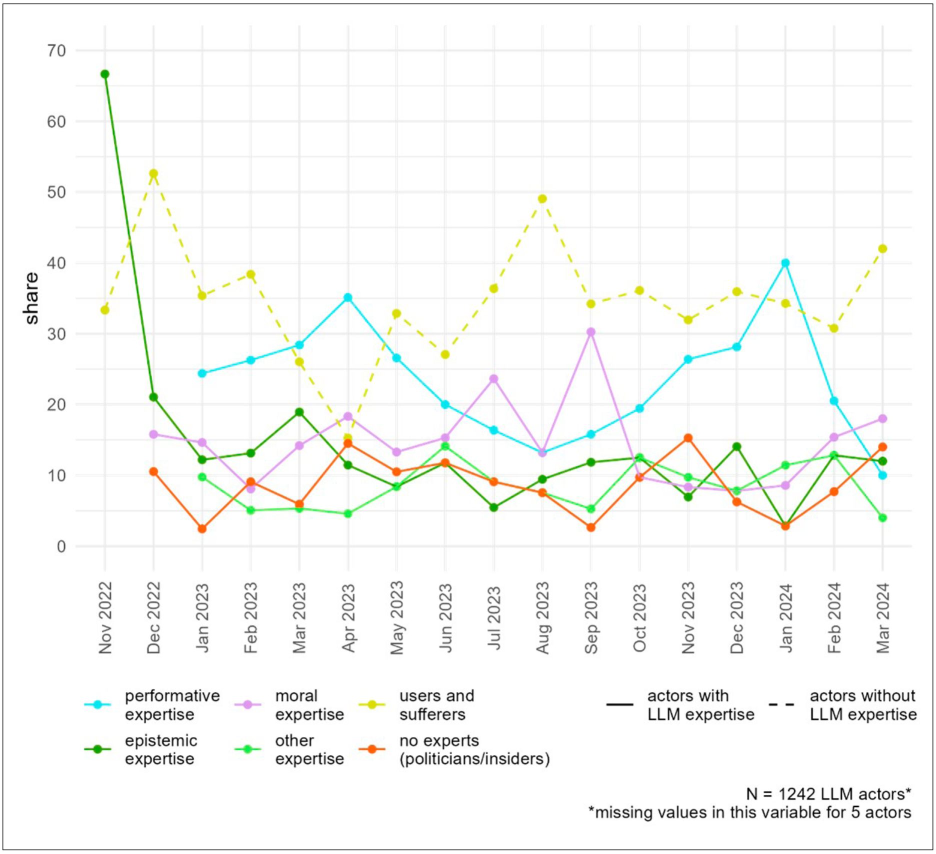
Figure 8. Distribution of LLM actors with (solid lines) and without (dashed lines) different LLM expertise per month (in %)



Looking at the social domains of the identified LLM actors in those months, for-profit representatives were still most frequently identified, accounting for half the quoted LLM actors in August 2023 (*n* = 27, 50.9%) and contradicting the dominant presence of evaluating expertise. Distinguishing the different actors according to their contribution of expertise beforehand (Fig. 9), we see a large share of the identified entrepreneurs in those months quoted as people concerned (*n* = 32, 52.5%) and therefore not adding any type of professionalised LLM expertise to the discussion. Evaluating expertise was particularly included through the selection of scientists (*n* = 18, 39.1%), non-profit ambassadors (*n* = 8, 57.1%) and cultural actors (*n* = 11, 68.8%).

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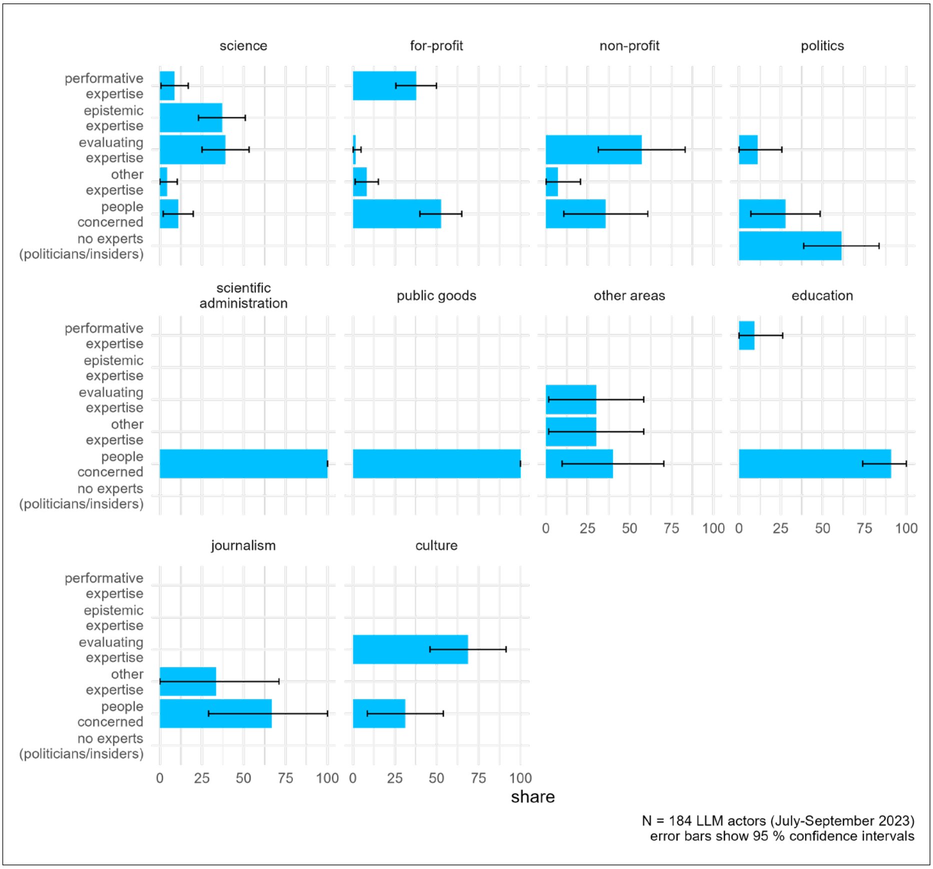
Figure 9. Distribution of contributed LLM expertise by different societal actors from July to September 2023 (in %)



5. Summary and discussion

While people with performative expertise were significantly more present in German news coverage than other experts in the narrow sense, their more frequent quotation did not align with the expected dominance of economic actors, especially in comparison to visible scientists.

To resolve this ambiguity, public discourse on the emerging AI technology included a third type of expertise besides "knowing how" and "knowing that": evaluating expertise. Broadening the concept of moral or ethical expertise – typically associated with philosophers who make or advise judgements on ethically correct practices (Singer, 2006, p. 187) – this type of expertise is tied to scientific approaches within the humanities and social sciences, like technology assessment or psychological research. Depending on their specific engagement with LLMs, scientists emerge either as experts on technical details of AI development – probably more intuitively counterbalanced to corporate AI developers – or as experts

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offering "follow-up knowledge" concerning the technology's contextualisation and consequences.

As media coverage of AI "shift[s] from portraying the technology as a concept or research subject … to focusing on the concrete economic, social, cultural, and political impacts," (Nguyen & Hekman, 2022, p. 12), the latter scientific experts may not always be perceived as equal counterweight to those with performative expertise by the public. This might give rise to concerns about "[a]n Industry-Led Debate" (Brennen et al., 2018, p. 1), only partially supported by our results, as we observe no differences in the presence of scientists and entrepreneurs until we control for the (in)dependence of scientists from partial interest organisations. Except for Brantner and Saurwein (2021, p. 5091), who examined Austrian media coverage of AI, prior content analyses focusing on topics, rather than actors, prevalently arrive at less ambiguous conclusions (e.g., Fischer & Puschmann, 2021, p. 18; Zhai et al., 2020, p. 146). Our findings on the actor constellation would benefit from further investigation using combined topic- and actor-based approaches, to avoid overstating or underestimating the industry's role in the discourse. The handling of researchers and scientific advances bound to partial interests and (other) actors contributing performative expertise, mainly associated with industrial stakeholders, deserves reconsideration if we are to critically assess claims of economic bias in the debate.

The question remains whether the mere (greater) presence of industry-linked actors is leading to an economically biased discourse, or if it rather reflects the specificity of technology development and expertise allocated to various people in charge. This seems plausible when comparing the presence of scientists and economic actors in this technological discourse to other science-related debates, where scientists are typically the most frequently identified group such as those concerning genome sequencing and cloning (e.g., Gerhards & Schäfer, 2009), molecular medicine (e.g., Milde & Ruhrmann, 2006), stem cell research (Schäfer, 2009), infectious diseases (Leidecker-Sandmann & Lehmkuhl, 2022) or genetic causes of certain behavioural patterns and disorders (Conrad, 1999). Scientists also feature prominently in techno-scientific discourses on nano- (e.g., Hauser, 2013) or biotechnology (e.g., Nisbet & Lewenstein, 2002), suggesting that technological development does not inherently entail an increasing importance of (emerging) industries. As soon as technologies are expected to be economically beneficial or disadvantageous, economic actors appear to assume a more central role in public debates, evident when comparing the AI discourse to media coverage of Carbon Capture and Storage (CCS) technologies (e.g., Schneider, 2019). Across various analyses of climate change and global warming discourse, second to politicians, scientific (e.g., Gärtner, 2023; Takahashi, 2011) or economic actors are more present (e.g., Boykoff, 2012; Tavares et al., 2022). This may reflect a shift in topical discourse focus, for example, from a more scientific search for causes to technology-supported adaptation (Carvalho & Burgess, 2005).

Expecting a similar dynamic in the still-emerging LLM discourse, we analysed how actor constellations evolved. Connecting these results to genuine LLM events outside media coverage indicates that we successfully captured and extrapolated actor-related characteristics of the LLM debate that might be linked to these de-

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velopments. For instance, the short-term shift in spring 2023, during which performative and evaluating experts displaced the previously and afterwards dominant group of people concerned, could be associated with the release of the AI moratorium in March 2023. The open letter urging "all AI labs to immediately pause for at least 6 months the training of AI systems more powerful than GPT-4 … that no one – not even their creators – can understand, predict, or reliably control" (Bengio et al., 2023) may have triggered increased public or laypeople attention for ethical and social aspects of the technology. This would signal a shift in public perception of the technology from a tool to support day-to-day practices of different societal actors to a transformative and possibly hazardous technology requiring sophisticated evaluations calling for AI expertise. Even if the AI moratorium had (co-)prompted this shift, it does not seem to have had a lasting impact. By summer 2023, evaluating expertise again came to the fore, replacing performative experts. Since we are not aware of any AI-related events explaining this shift, social and ethical aspects of the technology might gain relevance in the absence of immediate need for decision-making. Given the limited sample of German print media coverage observed over a short period, this insight primarily serves as a starting point for broader investigations into technology debates.

Another unexpected finding is the presence of actors from different social domains. Inconsistent with the increasing importance of the so-called "Leadership frame" (Ryazanov et al., 2024, p. 11) and in contrast to other scientific topics necessitating political decisions – like COVID-19 (e.g., Hart et al., 2020, pp. 685–687) or climate change (e.g., Gärtner, 2023, pp. 121–124) – we found little involvement of political actors in the LLM debate. This may be due to the LLM debate being an emerging technology debate that is (so far) shaped by technological fascination, (playful) experimentation (Zhai et al., 2020, p. 146), and novelty (Rotolo et al., 2015, pp. 1835–1836). As Bareis and Katzenbach (2022, pp. 875–876) argue, internal political narratives tend to be relatively "closed" in an uncritical or even hyped sense that "AI is established as a key sociotechnical institution; […] taken for granted and inevitable across many sectors already". This strategically useful narrative may explain why politicians are rather reluctant in the more controversial public AI discourse (Marcinkowski & Flaßhoff, 2024, p. 129). Another possible reason could lie in the technology's global interconnectivity and need for international political decision-making, accompanied by uncertainties regarding regulatory responsibilities (Cath et al., 2017).

The role of citizen voices and anecdotal evidence (e.g., Kleemans et al., 2017; Moore & Stilgoe, 2009) in such public debates might be worthy of further investigation, for example, as "non-professionalised expertise" existing alongside formally trained experts. From a normative perspective, such voices are essential in public technology assessments, which, following Grunwald (2019, pp. 704–705), can only fulfil the normative ideals of deliberative democracy if they are participatory and inclusive. Lastly, it would be valuable to explore the interplay and interconnections among the observed actors in the debate to gain deeper insights into the interactive nature of such communicative processes (van Dijk, 2009, pp. 2–3). It seems promising or even necessary to include more context conditions (e.g., content and composition of voiced statements).

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Although the results of our explorative quantitative study cannot be generalised to the entirety of genAI news coverage due to limitations of our sample, we hope to have offered a novel perspective on the ongoing public AI debate. By shedding light on the role of speakers from diverse societal backgrounds, we revisited concerns about an economically biased discourse to motivate further discussion of the identification, functions, and forms of expertise in an emerging technological issue. With new topics arising and, as Bartsch et al. (2024, p. 7) noted, novel actors who may not reveal their agendas straightaway, we expect this will remain an interesting yet increasingly complex research object.

Generative AI declaration

The authors used ChatGPT-5o to assist with language refinement. Afterwards, the proposed content was carefully reviewed and edited by the authors, who take full responsibility for the final publication.

Supplementary material

The supplementary material can be accessed here: https://osf.io/2xp7u

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