Who dominates the discourse on ChatGPT? Experts on text-generative Artificial Intelligence in German newspapers

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Data can be accessed here: https://osf.io/2xp7u/?view_only=6bbab2cd62b8457f808ebdaf97a7ef90

Abstract: The public AI discourse is permeated by visions and interpretations that influence the way in which the emerging technology is perceived, evaluated, developed and applied in society. Generating acceptance for a particular vision is therefore a central goal for a variety of societal actors engaged with the new technology. Recently businesspeople like Sam Altman, Sundar Pichai or Elon Musk seem to be more successful in promoting their AI visions than others. Assuming a powerful journalism that selects actors and presents their statements publicly, various scholars explain the disproportionate influence through an economically biased media coverage of AI. To contextualise this concern, we develop a conceptual framework to differentiate actors according to their AI related expertise and examine it via 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 businesspeople were mostly identified. Commonly business-related practical expertise regarding AI development dominated the debate compared to rather science-related epistemic knowledge about the technology's functionality or its professional ethical evaluation. In summary, our findings put into perspective the assumed dominance of economic actors in the mediated AI debate by

extrapolating a nearly balanced appearance of scientists and businesspeople but indicating a shortage of independent evaluations of the technology's functionality in the form of epistemic expertise.

1 Introduction

There is no shortage of eye-catching interpretations in the AI discourse: some believe that artificial intelligence will have an enormous impact on the lives of modern humans, on a par with controlling fire. One such enthusiast is Google CEO Sundar Pichai: “AI is probably the most important thing humanity has ever worked on. I think of it as something more profound than electricity or fire” (Pichai quoted by Acemoglu & Johnson, 2023, p. 30). This can be read as a techno-euphoric promise of a better future, or as a warning of taking this technology not seriously enough. What is remarkable here is that a CEO declares a technological development driven by his company and others to be a project of humanity.

Such visions are significant in technology debates when they prevail over competing interpretations and condense into widely shared opinion. They may influence decisions about the way in which scientific knowledge translates into technologies because they specify what appears to be a desirable goal and what means are used to achieve it. They are also important in determining which alternatives are considered and how benefits and risks are weighed. And despite all the well-meaning advocates of greater participation in these debates, it has been the interpretations of influential people like Sundar Pichai that have had a disproportionate influence on what technologies are used for and how they are developed (Acemoglu & Johnson, 2023, p. 24).

However, journalistic media “can wield considerable power in shaping the discursive expectations of AI,” (Brennen, Howard & Nielsen, 2022, p. 29) if they succeed in focusing public attention on this technology. A “key event” (Kepplinger & Habermeier, 1995, p. 373) has been the public launch of OpenAI’s ChatGPT in November 2022. This chatbot is based on an LLM that “leverage[s] extensive model architectures and vast training datasets to assign probabilities to sequences of words” (Shahriar & Hayawi, 2024, p. 12) and a reinforcement learning method that depends on human evaluations of its responses. It can therefore not only generate novel content from prompts (Strobel et al., 2024, p. 4551), but also interact in human-like conversations. Thus, it can be described as a “communicative AI” (Hepp et al., 2023, pp. 47–48) that, unlike its predecessors (Chen, Grant & Weise 2023), has the potential to disrupt a variety of existing societal concepts which rely on language and communication (Esmaeilzadeh, 2023). Following its launch, OpenAI has seen a rapid increase in the number of ChatGPT users (Hu, 2023), prompting competitors to quickly respond with their own applications, such as Google’s Gemini (formerly Bard). Accompanying this was a similar growth in scientific and media coverage (e.g., Delellis et al., 2023, p. 936), which even showed signs of hype (Hepp et al., 2023; Leaver & Srdarov, 2023), culminating in promising descriptions like “the world’s first truly useful chatbot.” (Fortson, 2022)

Journalistic media exercise their power not only by covering certain topics and introducing them into the political and/or public agenda (McCombs, 2005), but also by deciding “who gets to speak in the news” (Beckers & Van Aelst, 2019, p. 886) through source selection. According to the deliberative model, this potentially attention- and opinion-shaping journalistic power is directly related to the democratic responsibility to enable a balanced public discourse to evaluate new technologies, including different perspectives, opinions, and experiences (Banholzer, 2015, pp. 10–12).

According to some scientists, journalists have not lived up to this responsibility in their coverage of AI as they have been accused of biased reporting in favour of economic subjects and sources (e.g., Fischer & Puschmann, 2021, pp. 8 & 22; Kieslich, Došenović & Marcinkowski 2022, p. 6) and therefore, spreading the “bright colours” used by economic actors to promote their AI applications (Hoos 2023 quoted by Henschel, 2023). Since citizens, in contrast, are rarely given an active voice in such a topic that is dominated by elite groups (e.g., politics, economics, science) (Kleemans, Schaap & Hermans 2017), scientist’s calls for a more diverse selection of voices in the production of AI news (Brennen, Howard & Nielsen 2018, p. 9; Sun et al., 2020, p. 14) usually aim at protecting the public.

As is often the case with emerging public issues, such judgements about journalistic selection are rarely based on systematic empirical research. Therefore, we seek to give a systematic description of the German media discourse on text-generative AI. We analysed the constellation of active speakers, focussing on who the speakers are, and how they are actually 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 way of categorising cited actors in technology debates by focusing on their AI-related expertise (hereafter referred to as (LLM/AI) expertise). After outlining the function of experts in the journalistic construction of the public AI discourse and introducing the concept of expertise and corresponding types of experts as well as our methodological approach, we provide the results of our analysis. A discussion of the findings regarding their limitations as well as implications for future research and the journalistic representation of AI discourses concludes our study.

2 Experts in the public discourse on AI

Experts are actors who not only possess special knowledge[1] in a well-defined domain or field, 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 fields of expertise (Peters, 1994, p. 166, 2014, p. 72). Consequently, 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, etc.) have to decide on issues they cannot experience by themselves, which is the "default mode" of decision-making in functionally

[1] Including theoretical and factual understanding ("knowing *that*") as well as practical proficiencies ("knowing *how*") (Weinstein, 1993, p. 58; italics in original)

differentiated modern societies (Schimank, 2005, pp. 79–82). As a result, scholars such as Gläser and Laudel (2010, p. 12) advocate a definition of the term *expert* as "source of special knowledge."[2] While this approach seems appropriate in a macroscopic perspective, it provides some inconsistencies in terms of content and practical implementation in particular societal contexts (Bogner, Littig & Menz 2014, pp. 10–11), including mediated technological debates such as the public discussion on generative AI (genAI).

2.1 The role of expertise in the journalistic construction of public discourse

Applying a broad definition of expertise, journalists covering AI topics see experts as providers of information, e.g. accurate factual explanation or contextualisation (Huber, 2014, p. 69). Thus, journalists – who are, due to their lack of personal experience, professional training or limited resources for investigation (Brennen, Howard & Nielsen, 2018, p. 2), mostly "authors with insufficient knowledge of AI technology" (Ouchchy, Coin & Dubljević 2020, p. 934) – often depend on the support of AI experts to be able to report on it (Banholzer, 2015, p. 20).

However, AI experts – as any other members of society – hold certain views regarding different aspects of AI themselves and therefore are not only "neutral" information sources to be passively consulted by journalists, but active contributors to the public AI discourse as well (Huber, 2014, pp. 43–61). As such "public experts" (Peters, 2014, p. 70) that try to generate public attention and acceptance for their messages, they are evaluated by journalistic gatekeepers with regard to different selection criteria, which Nölleke (2013, p. 348), in reminiscence of the theory of news values (Galtung & Ruge, 1965), describes as "expert factors".

[2] Translation of the original German quote "Quelle von Spezialwissen"

For Nölleke (2009, p. 107) the so-called "expert value" mainly accrues from assigned practical (e.g., accountability, reliability) or superficial characteristics (e.g., prominence/status, attractiveness, linguistic conciseness), while expertise itself is only shortly mentioned. However, we assume that in debates about the assessment of emerging technologies, which require at least a basic understanding of the technology and its potentials and risks, expertise regarding the subject-matter might be a relevant selection criterion for actors without direct political power (Gerhards & Neidhardt, 1990, p. 11). To identify the actors for whom this criterion might be of greater importance, we firstly ask:

> RQ1: Which societal actors get to speak in German news media articles about text-generative AI?

Subsequently, we focussed on the type of LLM expertise that can be attributed to different societal actors.[3]

2.2 Types of experts on LLMs

Following Weinstein (1993, p. 58) as well as Collins and Evans (2007, 2018, pp. 23–28), we understand expertise as a "social fluency" that elicits 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 enquiry by third parties (expertise in the broad sense). In the context of genAI, socialisation refers in particular to the acquisition of special knowledge and/or skills related to genAI, e.g., understanding of the scientific and technological processes, development or evaluation skills, through experience in social groups (Collins & Evans, 2018, p. 23). Third party consultation, on the other hand, is linked to the external recognisability of the acquired or assumed AI knowledge. It is therefore likely to be

[3] Not only scientists as presupposed in previous analyses of publicly visible experts (e.g., Albæk, Christiansen & Togeby 2003; Lehmkuhl & Leidecker-Sandmann, 2019)

influenced by indirect "expertise clues"[4] that are not necessarily related to actual AI expertise. Consequently, actors that do not hold AI expertise in the narrower sense, but possess information, which is otherwise intangible or unavailable to the journalists, might (misleadingly) be introduced as experts to the public as well (Fig. 1).

Taking up Bogner, Littig and Menz's (2014, p. 10) criticism of this constructivist concept of expertise ("is not then everyone an expert?"[5]), we refer to distributors of certain AI-related opinions, decisions and/or first-hand experiences (politicians and people who are confronted with AI in their everyday life e.g., through usage, by suffering, etc.) only as experts in the broad sense, but not as LLM experts. Considering the differentiated approach to expertise(s) by Weinstein (1993) and Collins and Evans (2007, 2018) and taking into account the actively discussed concept of moral expertise (e.g., Priaulx, Weinel & Wrigley 2016)[6], this seems not only more accurate, but also necessary to examine the actual expertise that is made available to the public trough the journalistic selection of actor sources. We therefore introduce an integrative model that approaches the so-called *expert status* as a combination of the societal status of an actor, his/her (journalistic) designation and the type of expertise provided in his/her statements in a stepwise manner.

2.2.1 Experts in the broad sense – Experts by designation

Politicians and people that use AI applications in their everyday life or suffer under the new technology and its consequences (users and sufferers) can have some kind of knowledge

[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?"
[6] The concept of moral expertise refers to "the ability and capacity to exercise moral judgement" (Priaulx, Weinel & Wrigley 2016, p. 395). It is therefore mostly debated regarding the 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. For further information to this concept and the debate surrounding it, we recommend amongst others the publications of Singer (2006) or Weinstein (1994).

advantage over the journalists and/or the public, for example in terms of AI regulations and laws, or everyday applications and experiences with the new technology. They can thus, despite their missing acquisition of special knowledge about AI itself (not political processes, applications, etc. around the topic), be designated as experts by journalists making it unclear if they are actually AI experts or experts for another closely related domain. To evaluate this, the statements given by these designated experts, who do not belong to a societal group that generates and transfers AI knowledge/skills, become decisive. If they point to any type of expertise described in the following section, these experts in the broad sense can become experts in the narrow sense. If this is not the case, they are continuingly considered as counterparts to the actual AI experts that are further explored through our analysis.[7]

2.2.2 Experts in the narrow sense – Experts with 'actual' expertise

In contrast to the actors described above, experts in the narrow sense have acquired domain-specific knowledge and skills through education and professional training within social groups that already possess these competences. Thus, they are able to provide specialised information to the public, which can be assigned specific functionalities, in particular 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 further differentiate this group by distinguishing between "contributory experts" and "interactional experts." "Contributory experts" refers to people whose special knowledge enables them to actively contribute to the specific domain to promote progress. This "ability to *do* things within the domain of expertise" (Collins & Evans, 2007, p. 24; italics in original) can be realised in an

[7] Nevertheless, a deepened examination of the concept of expertise in the broad sense on a theoretical and empirical basis seems insightful and is, to our knowledge, not yet provided. It may for example lead to a more differentiated analysis of the possibility and/or role of political expertise (Weinstein, 1993, p. 57) or "anecdotal evidence" (e.g., Moore & Stilgoe, 2009, p. 654) in public discourses.

epistemic or performative sense (Weinstein, 1993, p. 58). While epistemic expertise is based on theoretical knowledge that includes factual knowledge combined with the ability to apply this knowledge 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. Thus, epistemic AI experts are actors who, while being committed to scientific methods and standards, produce new knowledge or investigate, discuss and contextualise existing knowledge about genAI technologies (e.g., how they work, their effects, limitations, etc.). Conversely, performative AI experts are actors who have the skills to develop concrete AI applications without necessarily providing an explanation of how the technology works or has evolved.

Finally, "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 through their intensive engagement. This engagement enables them to understand in detail the information and products generated by contributory experts and to participate in conversations with them on an equal footing (Collins & Evans, 2015, p. 119). Such protracted "enculturation" (Collins & Evans, 2007, p. 30) underlies both the *referencing expertise* (e.g., highly specialised journalists, non-fiction writers) originally described by Collins and Evans (2015), and the still controversial "ethical expertise." (Weinstein, 1994, p. 61) This last form of expertise is represented by actors who possess a generally accepted moral sovereignty (Priaulx, Weinel & Wrigley 2016, p. 403) and have accumulated a state of knowledge about genAI through research and discussion, without having any practical experiences of their own, which allows them to evaluate the technology and to derive moral judgements from these evaluations.[8] Since moral and referencing expertise – in contrast to

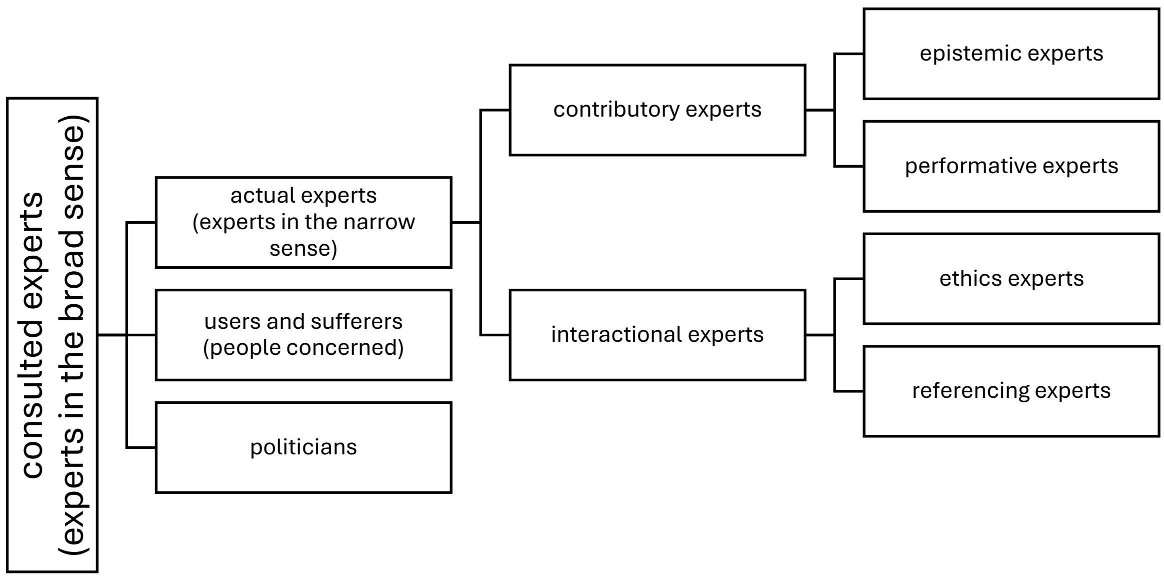
[8] As mentioned before, this concept is still controversial. The here given definition of "ethic experts" is to be considered as preliminary and shall not ultimately answer the question if moral expertise is possible or not. Neither shall it contribute to the normative debate on whether ethical experts are desirable in a democratic society.

epistemic or performative expertise – is not related to particular social groups (e.g., research institutions, AI corporations), the expert status cannot be immediately derived from the societal localisation of an actor. Instead, the statements given by actors who might eventually make such contributions to the debate (e.g., cultural actors, members of advisory boards) usually indicate these interactional forms of expertise.

2.2.3 An integrative model of public LLM experts

Assembling the expert roles described in the previous sections, the integrative model to capture and distinguish public LLM experts consists of several levels that can be assessed stepwise (Fig. 1).

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



On a superordinate level, experts in the broad sense are all actors who get consulted by a third party (in this case: journalists) to provide information on a specific topic (e.g., LLMs). These can be distinguished into the groups “politicians”, “users and sufferers” and “experts in the narrow sense” who, in turn, are further divided regarding their ability to contribute to the development of the domain into contributory and interactional experts. These two types of experts then can be again examined in more detail by distinguishing between the form of expertise they possess (knowledge vs. skill, moral assessment vs. systematic reprocessing) enabling a more differentiated analysis of publicly visible experts on LLMs. As we consider this integrative model to better capture the speaker constellation in the public LLM debate than the isolated examination of their societal origins (e.g., politics, civil society, science, etc.), 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?

With respect to the initially described rapid development and spread of the discussed AI technologies, we are also interested in the evolution of the discourse regarding the expert constellations. Since different forms of technological process can bring up various aspects that need to be assessed societally (Solomonoff, 1985), there might also be changes in the composition of the public arena observable over time. Thus, we ask:

> 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

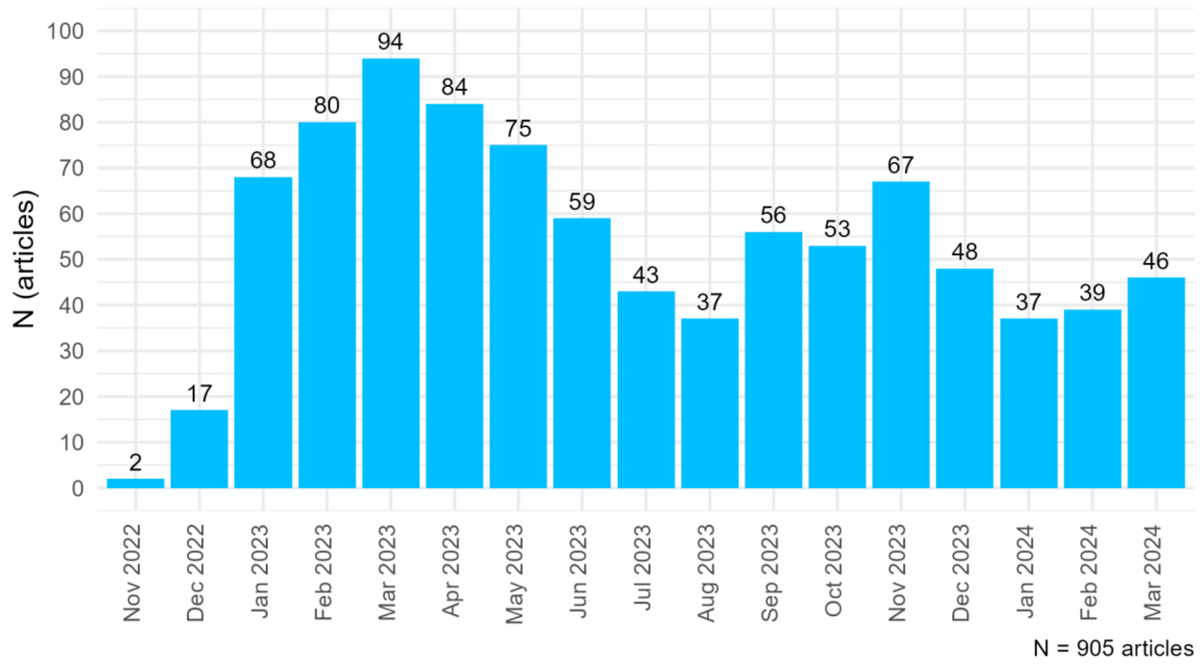
To apply our integrative model and to answer our research questions, we conducted a semi-automated quantitative content analysis of articles about text-generative AI published in ten German newspapers between November 1, 2022 and April 1, 2024. Thus, as a starting point of our inquiry period served the 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 analyzed 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 media, as well as in the regional newspapers *Nürnberger Nachrichten*, *Stuttgarter Zeitung*, *Rheinische Post*[9] and *Der Tagesspiegel*. Within this media sample, we considered every article as relevant that dealt with the topic of text-generative AI. Conversely, articles exclusively reporting on other types of AI (e.g., robotics, industrial AI, medical AI, etc.), 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. We developed several search strategies through topic modelling and systematic reviews of previous content analyses and recent media coverage on the topic and compared them using evaluation criteria for automated classifications (Scharkow, 2012, pp. 133–136)[10]. 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)"[11] (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, which account for 0.11 per cent of the whole news reporting by the ten selected German media titles in the respective time period. 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).

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

[9] Including the locally available Solinger Morgenpost, Bergische Morgenpost and Neuss Grevenbroicher Zeitung
[10] A detailed documentation of this procedure is provided as supplementary material
[11] 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)



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, Blythe & Vollgraf 2018) to extract all personal names in the analysed news coverage. This was 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 of our sample.

After excluding identified non-human entities (e.g., companies, or AI models) and persons that weren't directly or indirectly quoted at least once in an article, we further characterised each quoted actor within our article sample by manually coding nine different variables. Beneath the actors' names and institutions/organisations we recorded their genders and national localisations since these were established as potential expert factors by Nölleke (2013, pp. 307–312) and Huber (2014, pp. 113 & 120–122).

Beyond that, we 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 additionally coded whether their research work was associated with organisations with partial interests (dependent research) or conducted independently, e.g., in universities or independent research institutes, as well as their scientific discipline.[12]

Lastly, to evaluate the LLM expertise (RQ2), we developed four variables that indirectly indicated the expert status of an actor. The first of these variables indicated whether a speaker voiced at least one statement about LLMs. Due to the domain specificity of expertise, this is a necessity to be potentially regarded as a public LLM expert. In a second step, we measured if an actor was either explicitly labelled as an "expert" in the article and if not whether they contributed information that was not only accessible for insiders (e.g., corporate processes/secrets, whistleblowers[13]). If one of these two requirements was fulfilled, the type of expertise provided by the regarded actor was finally coded. By considering the content of the expressed LLM statements, we differentiated between contributions to the LLM development and/or research, descriptions of applications and usage experiences with genAI or the reflection of LLM contexts (e.g., the ontological localisation of AI) and (societal/ethical) consequences. These conditional and descriptive variables were aggregated together with the societal area of the regarded actor to define the expert status distinguishing politicians from performative, epistemic or moral experts as well as from people with LLM experiences (users and sufferers) or other experts (e.g., referencing experts). The whole

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

[13] Actors who only provide insider information (e.g., trade secrets) that become public solely through their appearances (e.g., whistleblowers) are explicitly not to be considered as experts in the narrow sense since 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.

codebook including a further description of this procedure is provided as supplementary material. Taking Sundar Pichai and his quote from the introduction as an example ("AI is probably the most important thing humanity has ever worked on. I think of it as something more profound than electricity or fire") the conditional coding procedure would have looked like as follows:

1) If the given quote is not Sundar Pichai's only statement and he voices at least another one with regard to LLMs, he is recognised as an actor with an LLM statement, which makes it possible that he contributes an LLM expertise to the debate.
2) The whole article is scanned for any explicit expert designations referring to Pichai. If there is at least one (e.g. "AI expert Pichai"), the following variable is skipped.
3) If no expert designation is identified, it is checked, whether Pichai provides insider information, that excludes him from being considered as an expert, by considering all of his statements within the article. The presented quote does not distribute insider information, as the content expressed is (theoretically) available to other persons. Pichai is therefore still regarded as potential expert and the coding continues.
4) Since Pichai is associated with Google, an AI developing company, his expert status can be derived from his societal position. He is therefore coded as an actor with expertise in LLM research/development. If his position wouldn't have 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.

Manual coding was conducted by one coder between June 10, 2024 and June 21, 2024. We checked the reliability of the codebook via tests of intercoder (with an additional second coder) and intracoder reliability (second coding on June 24, 2024). Krippendorff's α ranged from 0.64 to perfect agreement for intercoder reliability[14] and 0.78 to perfect agreement for intracoder reliability. It should be mentioned that the intercoder reliability for the newly developed variable "expert status" (4) below 0.8 only allows tentative conclusions (Krippendorff, 2004, p. 429).

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

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

[14] 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. Furthermore, 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).

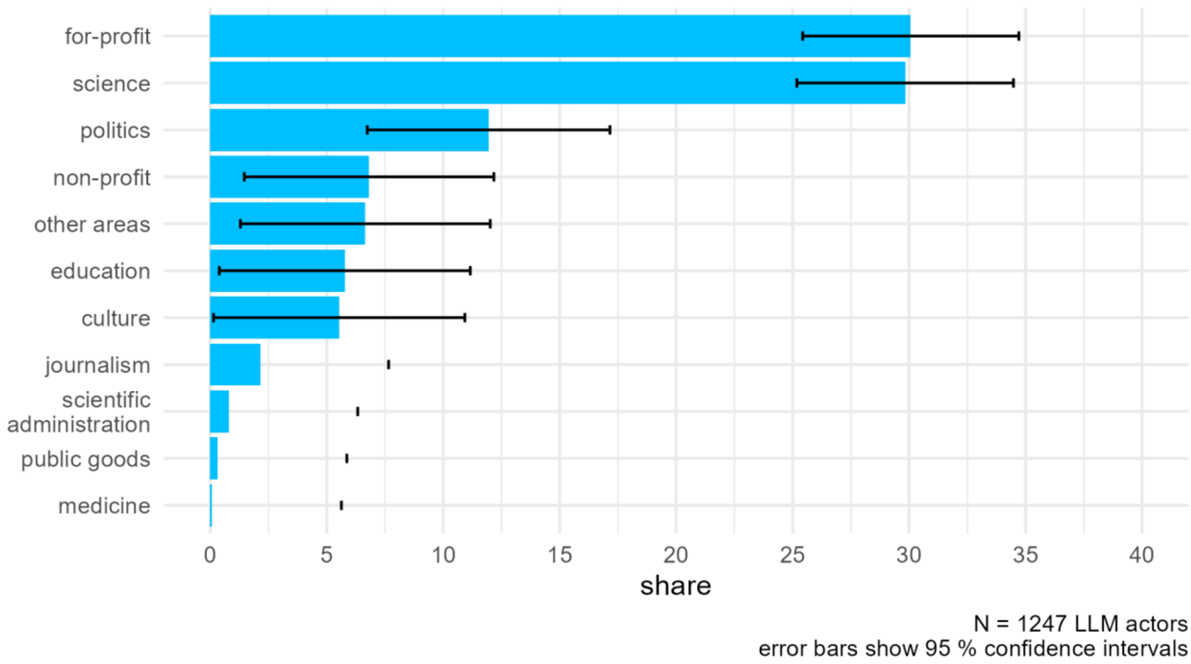
(Gamer et al., 2019), and kableExtra (version 1.3.4; Zhu, 2021) were used for data analysis and visualisation.

4 Results

In 689 articles 1247 actors were identified as having made at least one statement on LLMs and– applying our approach –being considered as potential experts. This corresponds to an average of about two actors with LLM quote (LLM actors) within an article (sd = 1.56). Only a few persons (N = 145, 17 %), such as Elon Musk (N = 33, 2.65 %) or Sam Altman (N = 32, 2.57 %), appeared multiple times in different articles. This indicates a rather 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 clear dominance of actors associated with for-profit (N = 375, 30.07 %) and science organisations (N = 372, 29.83 %) over contributors from other sectors such as education (N = 72, 5.77 %), culture (N = 69, 5.53 %) or politics (N = 149, 11.95 %) (Fig. 3). So, our initial results do not point in the direction of an economically dominated LLM debate as business is joined by academia in the German discourse.

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



In the next step, we include the expertise of these actors based on their societal position and the content of their statements in the analysis (RQ2).

Focussing exclusively on actors that can be assigned an expert status either through their societal position or the content of their statements (N = 730, 58.54 %), actors acquiring performative expertise, who are oftentimes associated with AI or software companies (N = 241, 80.97 %), are the most frequently selected type of LLM expert (N = 301, 40.95 %). 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 moral expertise (N = 182, 24.76 %) (Fig. 4). As the distribution of social domains within these actors shows, the status of a moral expert can be assigned to a variety of societal actors (Fig. 5). As 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 %)) played a notable role in terms of this form of expertise as well.

Figure 4. Distribution of experts on LLMs according to their type of LLM-related expertise provided (in %)

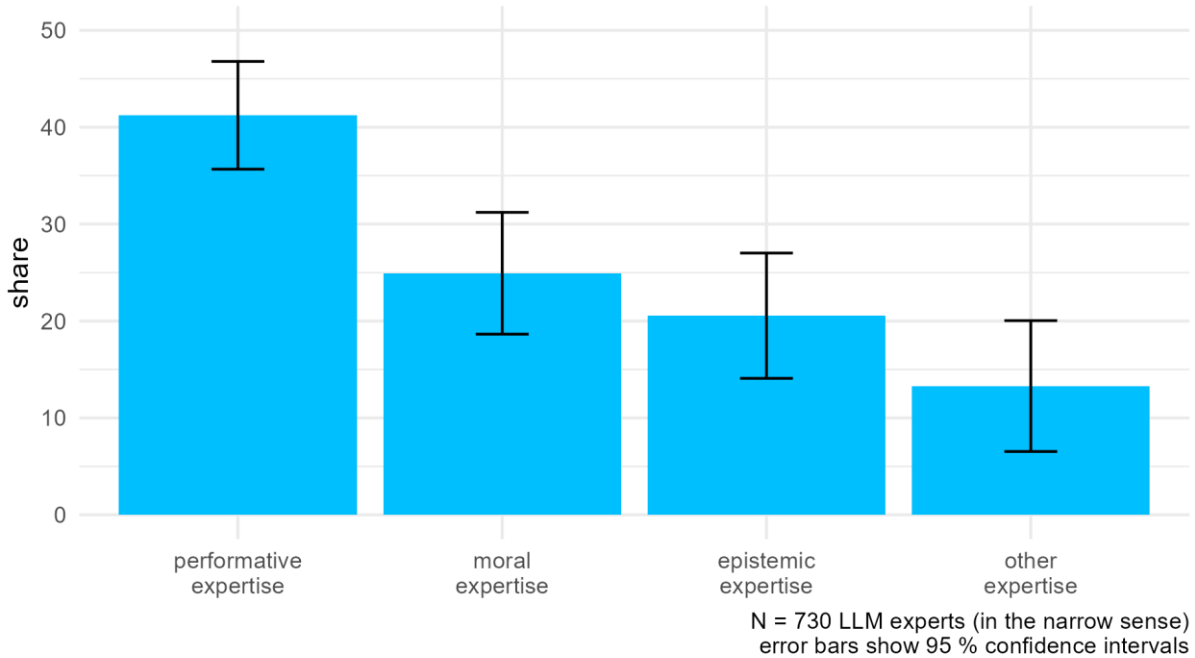
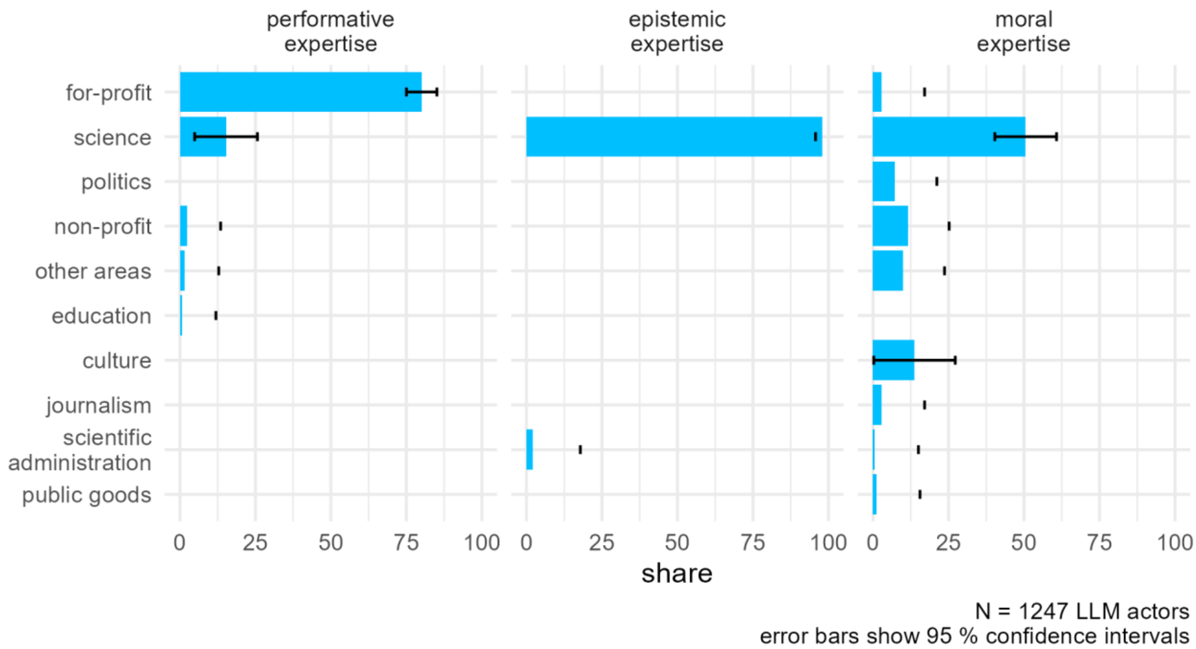
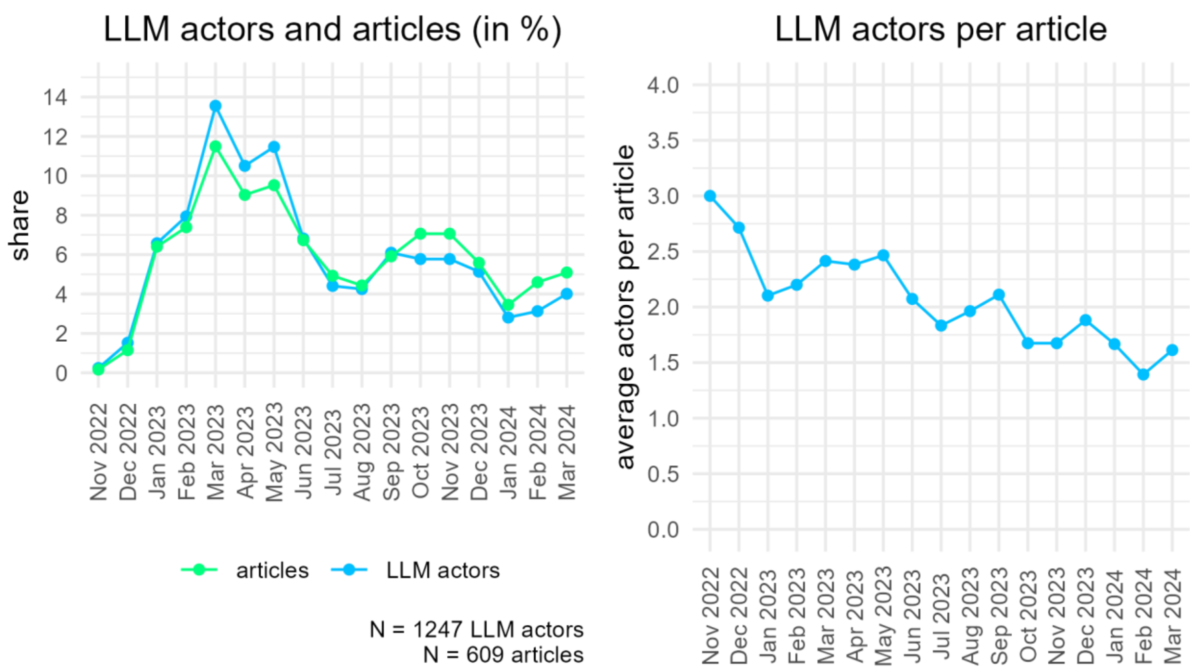


Figure 5. Distribution of social domains of experts providing different types of LLM-related expertise (in %)



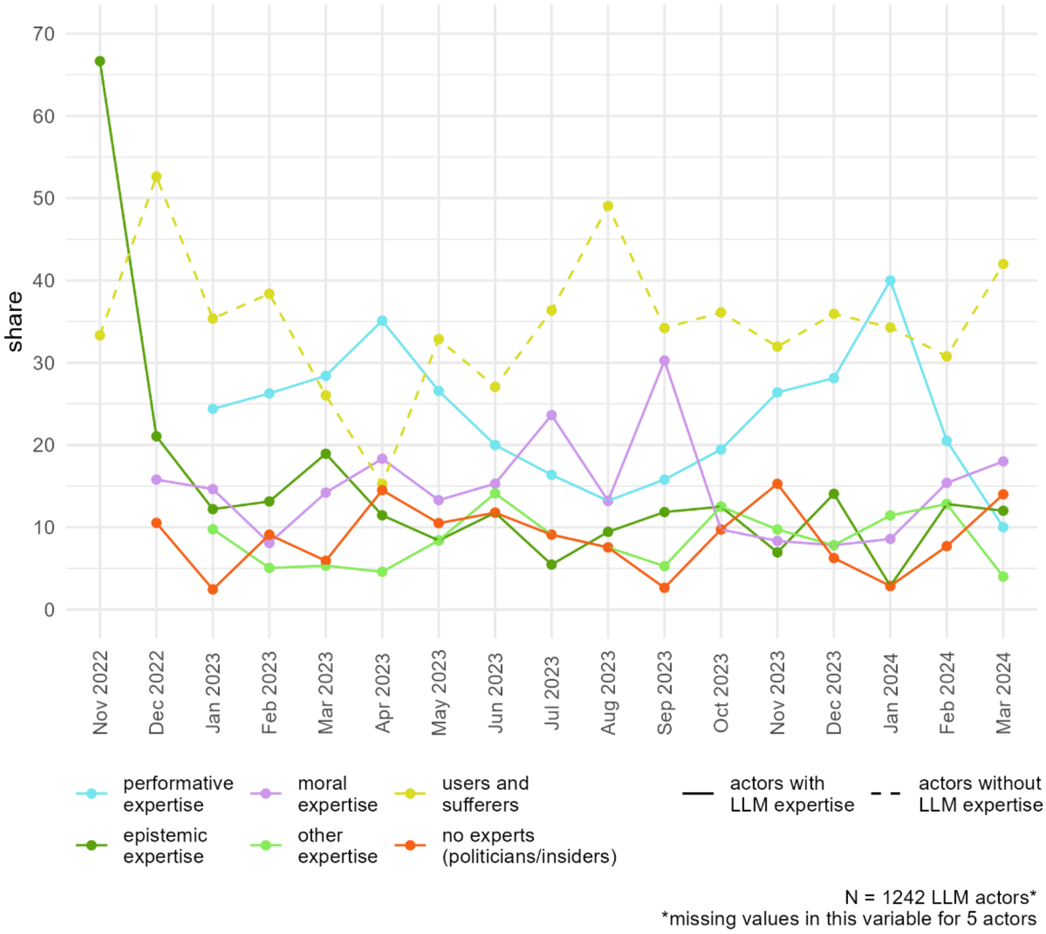
Looking at the development of the debate over time (RQ3), we find the most media coverage of LLMs and related actor citations in spring 2023 and a decline in included LLM actors per article over time (Fig. 6). In addition, there are some notable shifts in the actor constellations. At the beginning of the debate, LLMs are predominantly discussed by people who are directly concerned with the application of the technology but have not acquired any type of related expertise (users and sufferers). This changes in April 2023, as actors with performative (N = 46, 35.1 %) or moral expertise (N = 24, 18.3 %) become slightly more often visible than these users and sufferers (N = 20, 15.3 %) (Fig. 7). As both the peak in media coverage and the short-term shift in the 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 6. Distributions of identified LLM actors and articles per month



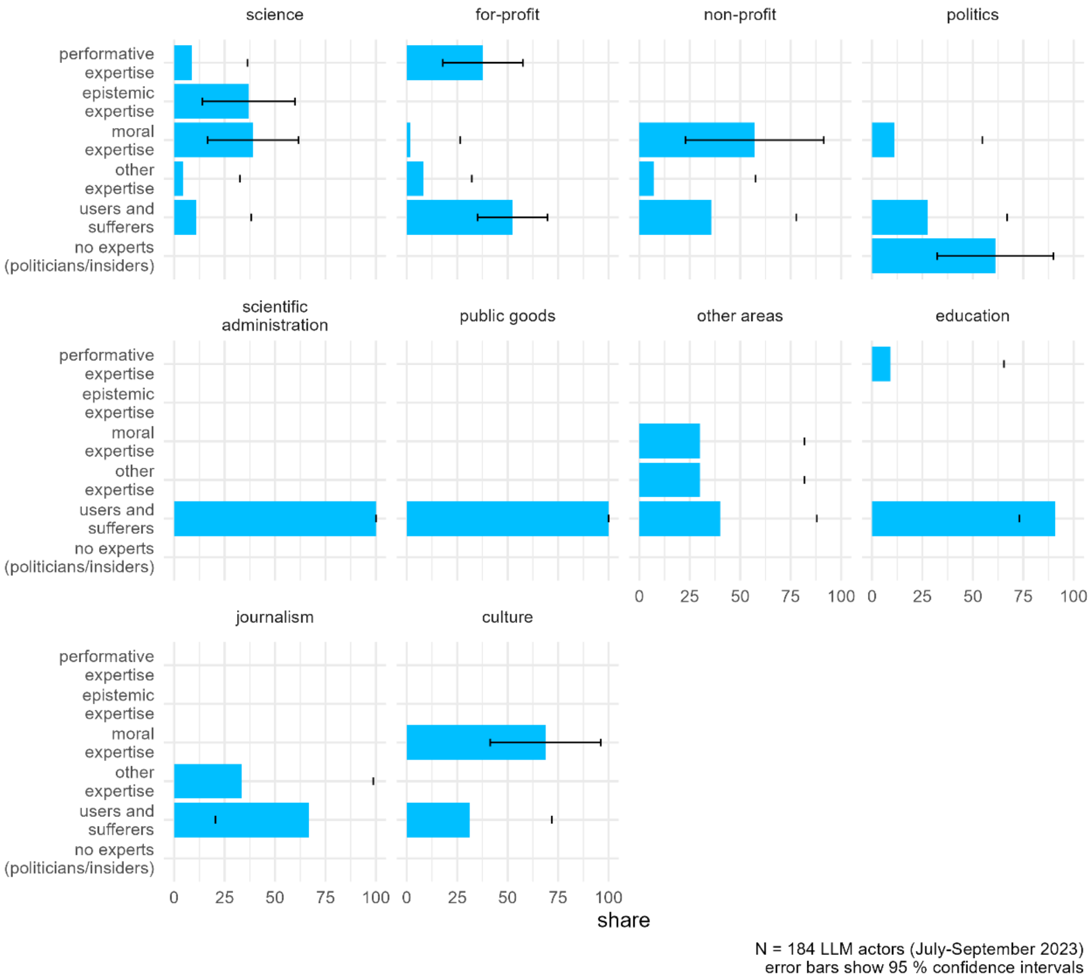
In most months, performative experts were the most frequently quoted expert group, ranging only behind users and sufferers without domain-specific expertise. But, in contrast to other expert groups and people concerned, they entered the debate not until the beginning of 2023 and were only overtaken as most dominant expert group by experts displaying moral expertise from July until September in that year (Fig. 7).

Figure 7. Distribution of LLM actors with (solid lines) and without (dashed lines) different LLM expertises per month (in %)



However, looking at the social domains of the identified LLM actors in those months, for-profit representatives were still most frequently identified even accounting for approximately half of the quoted LLM actors in August 2023 (N = 27, 50.9 %), contradicting the dominant presence of moral expertise. Distinguishing the different actors according to their contribution of expertise beforehand (Fig. 8), we see that a large share of the identified businesspeople in those months was quoted as users or sufferers (N = 32, 52.5 %) and therefore did not add any type of expertise to the discussion. Moral expertise, on the other hand, was again 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 %).

Figure 8. Distribution of contributed LLM expertise by different societal actors from July to September 2023 (in %)



5 Summary and Discussion

Combining the examined research questions under the eponymous question on who dominates the debate on text-generative AI, our results accumulate to an ambiguous answer. While people with performative expertise were significantly more present in the German news coverage than other experts in the narrow sense, their more frequent quotation did not correspond to the expected dominance of economic actors, particularly compared to visible scientists.

Dissolving this ambiguity, the public discourse on the emerging AI technology provided a third type of expertise besides knowing how and knowing that, namely moral expertise. Commonly this term refers to moral philosophers that make or advice judgements on ethically correct practices (Singer, 2006, p. 187). Therefore, it is closely connected to scientific approaches located within the humanities, such as technology assessment. Hence, depending on how scientists are concretely engaged with LLMs, they become either visible as experts on the computer sciences behind the development of AI – probably more intuitively counterbalanced to the AI developers in companies – or as experts with "follow-up knowledge" associated with the technology's contextualisation and consequences.

Thus, as the news 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 last-mentioned scientific experts may eventually not be perceived as equal counterparts to the people representing performative expertise in the public eye. This could lead to the fear of "[a]n Industry-Led Debate" (Brennen, Howard & Nielsen 2018, p. 1) which is not supported by our results. However, except for Brantner and Saurwein (2021, p. 5091) who analysed the Austrian media coverage of AI, previous content analyses focusing on topics, rather than actors, prevalently come to other conclusions (e.g., Fischer & Puschmann, 2021, p. 18; Zhai et al., 2020, p. 146). Our results regarding the actor constellation should therefore be critically reflected and further investigated in combined topic- and actor-bound approaches to avoid either over- or underestimating the role of economic voices within the debate.

Nevertheless, connecting our observations of the actor constellation over time to genuine AI-related events that are independent of media coverage indicates that we are able to capture and extrapolate actor-related characteristics of the LLM debate that might be linked to such developments. For example, the noticed short-term shift in the arrangement of experts compared to the beforehand and afterwards dominant group of users and sufferers in spring 2023 could be linked to the publication of the AI moratorium in March 2023. As performative and moral experts stepped into the place of users and sufferers, one can suppose that the open letter calling "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) accounted for a change in the public assessment of LLMs. Their perception changed from being an application designed to support the day-to-day practices of different societal actors to that of a transformative, yet potentially dangerous technology that requires sophisticated evaluations calling for AI expertise – although this does not seem to be long lasting. Moral expertise came again to the front in summer 2023, this time replacing the perspective brought into the debate by performative experts. Since we are not aware of any AI events that could explain this shift, it might be possible that social and ethical aspects of the technology also become relevant when there is no urgent need for decision-making. As this insight is based on a limited and rather small sample of German print media coverage observed over a relatively short period of time, it can primarily serve as a starting point for further analysis of this or other technology debates.

Another rather surprising result that should be examined in follow-up studies concerns the presence of actors from different social domains. Inconsistent with the increasing importance of the so-called "Leadership frame" observed by Ryazanov, Öhman and Björklund (2024, p. 11) and in contrast to other scientific topics that require political and/or societal decisions such as Covid-19 (e.g., Hart et al., 2020, pp. 685–687; Leidecker-Sandmann & Lehmkuhl, 2022, pp. 356–358) or climate change (e.g., Gärtner, 2023, pp. 121–124), we found relatively little involvement of political actors in the debate on LLMs. This finding could be a consequence of the LLM debate being an emerging technology debate that is (so far) mostly driven by technological fascination, (playful) trial (Zhai et al., 2020, p. 146), and novelty

(Rotolo, Hicks & Martin, 2015, pp. 1835–1836). Furthermore, the global interconnectivity of the technology and a resulting need for international political decision-making which goes along with uncertainties regarding regulative responsibilities (Cath et al., 2017) might also explain the reticence of politicians. Likewise, the role of citizen voices and anecdotal evidence (e.g., Kleemans, Schaap & Hermans, 2017; Moore & Stilgoe, 2009) in these kinds of public debates might be worthy of further investigation. From a normative perspective, these voices are especially important in debates that can be interpreted as public technology assessments as they, following Grunwald (2019, pp. 704–705), only fulfil the normative ideals underlying deliberative democracies when they are participatory and inclusive. Lastly, it would also be interesting to focus on the interplay and connectivity of the observed actors in the debate to deepen the understanding of the interactivity inherently underlying such communicative processes (van Dijk, 2009, pp. 2–3). Therefore, it seems promising or even necessary to include more context conditions, e.g., the content and composition of the voiced statements itself.

Although the results of our explorative quantitative study cannot be transferred to the entire news coverage of genAI due to sample-based restrictions, we hope to have opened up a new perspective on the ongoing public AI debate through our study. By providing a deepened insight into the role of speakers with different societal backgrounds, we revisited the warnings of an economically biased discourse to motivate further discussion on the identification, function and forms of expertise on an emerging technological issue. With new topics arising, novel actors attracting attention, and, as Bartsch et al. (2024, p. 7) have pointed out recently, not everyone immediately putting their cards on the table we expect this to remain an interesting, yet increasingly complex object of research.

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Supplemental material

A. Development and evaluation of the search string

For the development of an adequate search string to identify relevant articles about text-generative AI/LLMs, we inductively extrapolated various keywords from different sources and combined them in multiple strings, which were then quantitatively evaluated based on their precision, recall and F-Score.

Generation of strings

Firstly, we scanned a small sample of articles found through the search term “ChatGPT” for commonly used synonyms for the chatbot:

- Bot
- Chatbot
- Textroboter
- Künstliche Intelligenz
- KI
- Text-KI
- KI-Programm
- Intelligenzbestie
- Dr. Allwissend
- Schreibprogramm
- Textgenerator
- Algorithmus
- Chatsoftware
- Sprachsoftware
- Software
- Textautomat

We summarised them in five central “characteristics” of text-generative AI that should be represented in the search string:

- Automatisation
- Text production
- Chatfunction
- Computer software/application
- Artificial intelligence (umbrella term)

In a next step, we gathered the search strings used in 21 published content analyses of AI related contents:

source	search string
Brantner/Saurwein 2021	Automatisierung, Roboter, Robotik, Algorithmen, künstliche Intelligenz, Artificial Intelligence
Brennen/Howard/Nielsen 2022	“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural network”
Brennen/Howard/Nielsen 2018	“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural network”
Bunz/Braghieri 2022	“artificial intelligence medicine”

Chuan/Tsai/Cho 2019	“artificial intelligence”
Crépel et al. 2021	“artificial intelligence” OR “AI” OR “algorithm*” OR “machine learning” OR “deep learning” OR “neural network*” NOT (“amnesty international” OR “weiwei” OR “air india”)
Curran/Sun/Hong 2020	“AlphaGo”
Delellis et al. 2023	“ChatGPT”
Duberry/Hamidi 2021	artificial intelligence, AI, artificial intelligence algorithm, machine learning, neural, neural network, deep, deep learning, bot, robot
Fast/Horvitz 2017	“artifical intelligence” OR “AI” OR robot
Frost/Carter 2020	(“AI” OR “artificial intelligence” OR “machine learning”) AND (“screening test” OR “screening for” OR “diagnosis of” OR diagnosing OR “test for” OR “testing for”) AND (health OR healthcare)
Garvey/Maskal 2020	“A. I.” OR “artificial intelligence”
Kieslich/Dosenovic/Marchinkowski 2022	“AI” OR “Artificial Intelligence”
Korneeva et al. 2023	Artificial Intelligence, Machine Learning, Deep Learning, Reinforcement Learning, Supervised Learning, Unsupervised Learning, Neural Network
Köstler/Ossewaarde 2022	(competition OR participation OR innovation) AND “artificial intelligence”
Moran/Shaikh 2022	(journalism OR reporter OR journalist) AND (algorithm OR bot OR robot OR “AI” OR “artificial intelligence” OR automation OR automated OR “OpenAI” OR “machine learning” OR “GPT-3”)
Nguyen/Hekman 2022	“A. I.” OR “AI” OR “artificial intelligence”
Ouchchy/Coin/Dubljevic 2020	“Artificial Intelligence” OR “Computational Intelligence” OR “Computer Reasoning” OR “Computer Vision Systems” OR “Computer Knowledge Acquisition” OR “Computer Knowledge Representation” OR “Machine Intelligence” OR “Machine Learning” OR “Artificial Neural Networks” AND (Morals OR Moral OR Morality OR Ethic* OR Metaethics)
Sun et al. 2020	“artificial intelligence” OR “AI” OR “machine learning” OR robot
Vergeer 2020	“kunstmatige intelligentie” OR “AI”
Zhai et al. 2020	“AI” OR “artificial intelligence” OR “A. I.”

We concluded from that that the umbrella terms “AI” and “Artificial Intelligence” are useful, but alone not sufficient to extrapolate relevant articles.

Additionally, we quantified and expanded the impressions from these steps by generating a document-feature matrix (DFM) (and topic models, which weren’t helpful in the end) from 996 articles found via the search term “ChatGPT” and published between November, 1st 2022 and November, 1st 2023 in the newspapers *BILD*, *Nürnberger Nachrichten*, *Rheinische Post*, *Der Spiegel*, *Stern*, *Tagesspiegel*, *taz, die tageszeitung*, and *Die Zeit*. After lower-casing, tokenisation, stemming, and exclusion of stopwords, we received the following DFM:

```
      ki     chatgpt intelligenz   kunstlich        frag   unternehm
    4054        2460        2244        2194        1204        1070
 prozent        welt        nutz      arbeit
     940         847         820         819
```

Lastly, we researched via Google for other LLMs beneath ChatGPT. From three sources, we found the following (potentially relevant) competitors:

- Bard / Gemini (Google)
- Claude (Anthropic)
- LLaMa2 (Meta)
- MPT (MosaicML)
- BLOOM (BigScience Large Open-science Open-access Multilingual Language Model)
- WuDao 2.0 (Beijing Academy of Artificial Intelligence)
- MT-NLG (Megatron-Turing Natural Language Generation; Nvidia/Microsoft)
- LaMDA (Google)
- PaLM 2 (Google)
- Bing / GitHub Copilot (Microsoft)

These various keywords were combined into 20 different search strings and the six most promising strings regarding the number of results in the ten aforementioned newspapers between November 1st, 2022 and April, 1st 2024 (bold) were finally systematically evaluated. To approach the true recall, we compared the articles found via the string to a manually coded reference sample, that included all published articles in nine media titles (aforementioned, without the *Rheinische Post*) on three days that were associated with AI relevant events (02/09/2023 = Publication of Bard; 03/30/2023 = AI moratorium; 11/30/23 = 1st birthday of ChatGPT):

	string	results	precision	recall	F-Score
1	ChatGPT	2027			
2	ChatGPT OR “Large Language Model*” OR LLM	2027			
3	**ChatGPT OR Bard OR ((Copilot OR Gemini OR Claude OR Llama OR Bloom OR MPT OR PaLM) AND (“künstlich* Intelligenz” OR “KI”))**	**2134**	**0.696**	**1.000**	**0.821**
4	LLM OR “Large Language Model” OR *bot	7203			
5	LLM OR “Large Language Model” OR Chatbot	926			
6	LLM OR “Large Language Model” OR Textbot	27			
7	LLM OR “Large Language Model” OR Textbot OR Chatbot	928			
8	**LLM OR “Large Language Model” OR Textbot OR Chatbot OR ChatGPT**	**2277**	**0.727**	**1.000**	**0.842**
9	LLM OR “Large Language Model” OR Textgenerator OR “Text-KI”	70			
10	**LLM OR “Large Language Model” OR Textbot OR Chatbot OR Textgenerator OR “Text-KI” OR ChatGPT**	**2285**	**0.727**	**1.000**	**0.842**
11	Text* AND (“KI” OR “künstlich* Intelligenz”)	1614			

12	Text AND (“KI” OR “künstlich* Intelligenz”)	564			
13	Text* AND (“KI” OR “künstlich* Intelligenz”) AND NOT Textil	1588			
14	LLM OR “Large Language Model” OR (Text* AND (“KI” OR “künstlich* Intelligenz”) AND NOT Textil) OR ChatGPT	2770			
15	generativ* AND (“KI” OR “künstlich* Intelligenz”)	319			
16	generativ* AND (“KI” OR “künstlich* Intelligenz”) AND Text	75			
17	**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)**	**2771**	**0.696**	**1.000**	**0.821**
18	ChatGPT OR LLM OR “Large Language Model” OR Textgenerator OR (Text* AND (“KI” OR “künstlich* Intelligenz”) AND NOT Textil) OR (generativ* AND (“KI” OR “künstlich* Intelligenz”) AND Text)	2771			
19	**ChatGPT OR LLM OR “Large Language Model” OR Chatbot OR (Text* AND (“KI” OR “künstlich* Intelligenz”) AND NOT Textil) OR (generativ* AND (“KI” OR “künstlich* Intelligenz”) AND Text)**	**2974**	**0.667**	**1.000**	**0.800**
20	**ChatGPT OR BARD OR ((Copilot OR Gemini OR Claude OR Llama OR Bloom OR MPT OR PaLM) AND (“künstlich* Intelligenz” OR “KI”)) OR LLM OR “Large Language Model” OR Chatbot OR (Text* AND (“KI” OR “künstlich* Intelligenz”) AND NOT Textil) OR (generativ* AND (“KI” OR “künstlich* Intelligenz”) AND Text)**	**3047**	**0.640**	**1.000**	**0.780**

To lastly decide between the strings 10 and 19, we expanded the reference sample with two more days at the beginning (12/15/2022) and the end (03/14/2024) of the targeted period of investigation. Through that, the recall of string 10 declined from 1.000 to 0.913 (precision = 0.656; F-Score = 0.763), while the recall of string 19 remained perfect (precision = 0.639; F-Score = 0.780). As irrelevant articles could be removed later in the coding process, we tolerated the slightly lower precision and decided to use string 19 for generating our article sample.

B. Extract of the codebook

Conceptual categories – actor level

…

2.6. Social domain (aktbez)

This variable records the social domain with that an actor is associated. This area needs to be coded as specific as possible in the given subcategories. Only if no such specification is possible, the toplevel categories should be coded. The social domain is derived from the institutional affiliation of the actor, e.g., spokesperson of the German Umweltbundesamt = scientific administration.

ATTENTION: If one actor is introduced with more than one social area (e.g., “x is an AI expert and journalist for the Stuttgarter Zeitung.”), the description that is more precise needs to be consulted to derive the societal area (in this example: journalist), unless the person is explicitly giving the statement in his/her other societal function.

ATTENTION II: Organisers or hosts of fairs, symposia etc. are coded accordingly to the societal localisation of the organised event if there are no further information to their field of activity. If it is apparent that an actor works as an event manager, event planer or similar and therefore predominantly organises such events without being involved with regards to their contents, he/she is to be coded with “900 = other”.
Example: The organiser of an industrial fair is coded with “522 = For-profit organisation” if he/she (probably) has an direct link to the industry. Usually, this can be retraced by looking at the statements given by the actor.

100 Science
The category of science captures researchers without political or social functions. “Scientist”, „researcher“ or „biologist“ are clearly scientific actors as well as actors of the German Deutsche Forschungsgemeinschaft (DFG). Members of the IPCC are scientists too. A definition criterion for scientific actors is their independent and objective work that is “only committed to the truth”. Therefore, scientists are not motivated by partial interests in the narrower sense.
ATTENTION: If a medic gives a statement in the societal role of a researcher (which means that he researches and does not practise), he/she is to be coded with “100 = Science”. If this is not clearly recognizable, he/she is coded with “400 = Medicine”. The staff of university hospitals (except for nursing or administrative staff), like head physicians or deputies, are coded as scientific actors with the corresponding discipline “Medicine”.
ATTENTION II: Members of private research institutions are scientific actors as well, but staff of economically oriented corporations or members of NGOs, that also research beneath their main interests, have to be coded with “522 = For-profit organisation” respectively “510 = Interest group 1” or “521 = Non-profit organisation”. An exception are actors for which through the given position within a company or interest group that also researches is clearly identifiable that they are exclusively researching inside this organisation. These actors are coded as scientists with the corresponding value “1 = Research bound to partial interests” in category 2.7 as well as with the fitting scientific discipline (e.g., researchers from Google’s X, DeepMind/Google Brain). If it is uncertain/unclear, whether a person is employed as researcher or other staff, there needs to be coded a subcategory of “500 = Interest groups”. The same procedure is to be applied for members of thinktanks or (technical development) networks like the Cyber Valley.
ATTENTION III: Staff of botanical gardens are coded as scientists.
ATTENTION IV: Information scientists, IT specialists, (AI) developers, AI experts and similar actors, that are not linked to a particular institution inside

the article/commonly known, and for whom it remains unclear whether the research or practice inside the field of AI development, are coded with “100 = Science” and “1 = Research bound to partial interests”.

200 Politics
Members of governmental institutions, political administrations (e.g., governmental departments) as well as political parties belong to the political area. “Members of the CDU” or “deputies of the EU“ are political actors. **ATTENTION**: Former politicians (no actual political function, e.g., as secretary or similar, but also no other societal roles, e.g., stakeholder with partial interests) are coded with the toplevel category “200 = Politics”.
We further distinguish between:

210 Political executive
Political executive actors are members of the government (EU commission, federal, federal state or communal government). If an actor holds multiple political positions (e.g., Gröhe was German Health Secretary as well as member of the CDU), the role in which he/she speaks in the respective context has to be coded. If this remains unclear, for executive actors are always coded as such. Also members of the United Nations (UN) are political executive actors.

220 Political administration (governmental departments, agencies)
ATTENTION: If an actor is Secretary of a governmental department (in Germany: Minister:in), he/she needs to be coded as member of the government with “210 = Political executive”. Beginning at the level of a minister (in Germany: “Staatssekräter:in”), actors are coded as political administrates. Members of the FAO (body of the UN), the UNESCO or similar also belong to the political administration.

230 Political legislative
Political legislatives are members of the parliaments on different levels (EU, nation, federal state, county, community). They are – if possible – distinguished with respect to their party affiliation:
231 CDU
232 SPD
233 Grüne
234 FDP
235 AfD
236 Linke
237 Other

300 Scientific adminstration
This subcategory captures the narrower group of members from scientific institutions that also fulfil administrative functions. Particularly departmental research institutions (in Germany so-called „Ressortforschungseinrichtung“) that are subordinated to federal or federal state departments are counted among those, e.g., the Robert-Koch-Institut (RKI), the Paul-Ehrlich-Institut (PEI), the Umweltbundesamt (UBA) or the Bundesamt für Verbraucherschutz und

Lebensmittelsicherheit (BVL). The Weizenbaum-Institut is an example for such an institution in the area of digital developments. In the case of uncertainty this list (https://www.ressortforschung.de/de/ueber_uns/mitglieder/index.htm) can be consulted (ATTENTION: not necessarily complete!). On the international level, for example, members of the WHO belong to the scientific administration. On the European level, organisations such as the European Space Agency (ESA), the European Centre for Disease Prevention and Control (ECDC) or the European Environment Agency (EUA) can be considered as such scientific administrations. The Defense Advanced Research Projects Agency (DARPA), the NASA, the Defense Technical Information Center (DTIC), the National Institutes of Standards and Technology (NIST) or the Environmental Protection Agency (EPA) are examples from the USA. This list of US-American institutions (https://www.usa.gov/agency-index) can be considered for further information (ATTENTION: In this list are particularly agencies belonging to the political administration! Therefore, it needs to be double-checked in an additional step if an agency is a political or scientific administrative organ). Example: "Experts of the WHO" are coded with "300 = Scientific administration".

400 Medicine
The subcategory is referring to medical specialists (physicians) and not to other hospital staff (these are coded with "900 = other area).
ATTENTION: If a person is solely introduced as "medic", he/she is coded as medical actor (and *not* as scientific actor).

500 Stakeholder organisations
For the stakeholder organisations we differentiate between organisations that advocate public goods, such as the protection of the environment, nature or animals, the protection of human rights and peace, humanitarian aid or child-welfare (Stakeholder organisations 1), and collectives which advocate partial interests of (smaller/more restricted) social groups (Stakeholder organisations 2). Here, we do not distinguish national from international groups.

510 Stakeholder organisations 1 (public goods)
This category captures actors who advocate so-called public goods, which are interests of "the general public". These are issues that concern many people, usually the whole population of the world or a nation, but at least big parts of these total populations (e.g., all children, all teenagers…). For example, the protection of the environment, nature and animals, the protection of human rights and peace as well as humanitarian aid, child-welfare or disaster control.

520 Stakeholder organisations 2 (partial interests)
Among those are actors who advocate the interests of particular, "exclusive" societal groups (generally the interests of their own members). We further differentiate between:

521 Non-profit organisations (self-serving clubs/associations/unions/initiatives)

Actors, who represent organisations, that exclusively advocate the interests of gated societal groups (e.g., their members) are captured under this category. Among those are, for example, churches and other religious communities, sports and other hobby clubs, and trusts (even if they fund „collective systems“ like „the” science or “the” culture), citizen lobbies (e.g., patient organisations, consumer protection associations) and initiatives, trade or professional associations (e.g., worker’s compensation boards) as well as (trade/labour) unions.

ATTENTION: Citizen initiatives usually act locally (partially even limited to particular neighbourhoods, districts or similar). For that reason, they usually have to be coded with “521 = Non-profit organisations”. If it becomes definitely clear that an initiative is a larger movement, the individual case has to be re-evaluated with respect to an eventually more fitting capturing under “510 = Stakeholder organisation 1 (public goods)”. Nationwide movements and initiatives are often more accurately described as “510 = Stakeholder organisations 1 (public goods)”. Groups that act across one or more German federal states, but not in the whole nation, are edge cases for whom the concrete interests that are advocated, need to be double-checked: If these only concern the local populations of the German parts in which the association becomes active (e.g., solely South Germans, solely former citizens of the GDR…), they have to be coded with “521”. If the initiative speaks up for matters that concern the general public, but hasn’t further (locally) spreaded yet (“developing movement”), the subcategory “510” is more suitable.

522 For-profit organisations (corporations)

This category captures members of private corporations that primarily pursue economic success. The industrial sector of the profiting corporation, its legal form (GmbH, KG, …) and the position of the actor within the company (leader, staff member, founder…) are irrelevant for the coding.

ATTENTION: Also, charitable corporations (gGmbH, gAG) have to be coded with “522 = For-profit organisations”.

Note: Actors who are solely associated with the Silicon Valley (no other societal localisation), need to be coded with “522 = For-profit organisations”.

900 Other area

If the societal area of an actor is not identifiable (e.g., if only “experts” are quoted), the actors are coded as „others“. Also, when none of the available options seems suitable and other – in the words of Habermas – ‘peripheral’ societal areas are represented (e.g., zoos), this value has to be chosen. Furthermore, representatives of the judiciary (e.g., judges) are captured under this category. In addition, three peripheral areas are captured in separate subcategories:

910 Education

Employees in the education sector, in the narrower sense teachers (inclusive lecturers, principals), are localized in this area. Administrative staff in this sector (e.g., school secretaries) and actors with administrative functions in education agencies and departments *must not* be coded with this value. The former are coded with the toplevel category "900 = Other area", while members of education agencies and departments are captured as „220 = Political administration". Pupils, students, parent representatives or similar actors who make use of the educational supply or who enrich it through extracurricular offers/functions, are coded with "900 = Other area".

920 Journalism

Actors who denominate themselves or are denominated by others as journalists are – irrespective of the journalistic quality of their contributions as well as the used media (broadcast, print or online) – captured under this value. This subcategory is, indeed, only related to journalists, that appear within an article and not to the authors of the articles. Journalists who only appear as authors have to be filtered by chosing the value „3 = The person is the author of the article" in the filter variable (2.3).

ATTENTION: Other members of media corporations who are in charge of corporative or administrative tasks, which means that they are not (primarily) journalistically active (e.g., publishers, directorates, artistic directors…) are captured as stakeholders (business operators) by chosing the value „522 = For-profit organisations".

930 Culture

This category describes actors who are quoted in terms of their artistic, musical or literary engagements (among those: theatre, dance, cabaret and similar "aesthetic/artistic forms"). Their prominence as well as the quality and impact of their work is irrelevant in that term. If an actor is introduced as, for example, "artist" (in the literal sense), "person engaged in the cultural sector" or "(book/screenplay/script) author", he/she has to be coded with "930 = Culture". Additionally, actors who become active in museums are also captured under that value.

ATTENTION: If the German term "Künstler:in" is used figuratively (e.g., Überlebenskünstler:in (= survivalist), Künstler:in der Lüfte (= highly-talented pilot)…), the actor has to be coded regarding his field of activity.

ATTENTION II: Actors who produce media products, but are no journalists (e.g., influencers, bloggers, prosumers…) have to be coded with "930 = Culture". Among those are also „media artists" like, for example, photographers or designers, who present media products with an „artistic aspiration" on media platforms, as long as they don't do this professionally in order to

mandates from third parties (e.g., corporations), like graphic designers or PR staff (they have to be coded with the toplevel category “900 = Other area”).
ATTENTION III: Only authors in the narrower sense are to be captured under this subcategory. This means that they have to write cultural goods as books, poems or similar. Actors who are introduced as „author of the study xy“, „author of the text xy“ etc. have to be evaluated regarding their primary role (e.g., as scientist, journalist…) that enables them to become “authors” and therefore choose the suitable value for this variable. Authors of non-fiction books are coded with “930 = Culture” too, if they appear primarily in that role. If a scientist who also has published a non-fiction book appears, he/she still has to be coded with “200 = Science”. The same procedure has to be applied for other societal actors, e.g., politicians or stakeholders, who have also become visible as authors of, for example, biographies, guidebooks and so on. Therefore, authors are only coded with “930 = Culture”, if they appear exclusively or at least predominantly in that role in an article.

2.7. Scientific dependence (scidepend)

Note: This variable is only coded, if “100 = Science” has been selected in category 2.6.

Through this category, we distinguish scientists of university and private research organisations (= research organisations without sales or similar self-interests) from researchers that are bound to partial interests through their association with corporations, NGOs or other stakeholder organisations (e.g., thinktanks, technology development networks…). Actors whose research takes place within or in close association with a stakeholder organisation, e.g., information scientists from Google’s DeepMind/X, are coded with “1 = Research bound to partial interests”. Other scientific actors of independent research institutions, such as universities, colleges or private research consortia (e.g., Fraunhofer-Institutes, Helmholtz-Centres, Leibniz-Institute…) are, on the contrary, coded with “0 = Independent research”.

0	Independent research
1	Research bound to partial interests

2.8. Scientific discipline (discipline)

Note: This variable is only coded, if “100 = Science” or “300 = Scientific administration” has been selected in category 2.6.

This category captures the (predominant) discipline of quoted scientists and actors from the scientific administration. The categorisation of the discipline is derived from the classification of the DFG (see this list (https://www.dfg.de/resource/blob/172316/5863ef132d178054609f74940f6a27c9/fachsystematik-2016-2019-de-grafik-data.pdf)).

Only the subordinate disciplines (humanities, social sciences etc.) are coded – the subcategories (pre- and ancient history, classical philology etc.) serve as points of orientation to correctly assign the scientific fields to the discipline.

ATTENTION: If multiple disciplines with a similar level of detail are mentioned (e.g., physicist and information scientist), the first mentioned discipline is coded. If the information differs regarding its precision (e.g., AI researcher and physicist), the more specific discipline has to be coded (in the example: physicist).

1	Liberal arts and humanities
2	Social sciences
3	Biology
4	Medicine
5	Agricultural science, forestry, veterinary medicine
6	Chemistry
7	Physics
8	Mathematics
9	Geoscience
10	Informatics, systems and electrical engineering
11	Engineering
12	Actor is no scientist (e.g., spokesperson)
99	Not identifiable

ATTENTION II: In individual cases, the disciplinary localisation can be difficult or unclear. Research into artificial intelligence can be pursued from numerous, possibly interlinked disciplines (interdisciplinary branches of research). Nevertheless, an attempt should be made to extract the discipline as precisely as possible from the article content. For example, of a "psychologist" is mentioned in an article, "2 = Social sciences" has to be coded according to the DFG classification. If an "ergonomist" is mentioned, "10 = Informatics, systems and electrical engineering" has to be coded according to the DFG classification.

Eventually, the terms used to describe the disciplines will not always be clearly recognisable. In these cases, it should then be inferred from the context of the actor quotation whether an "AI expert" or "researcher" is, for example, a computer scientist, a social scientist or a humanities scholar. For example, if an article is focussed on the technical creation of neural networks, "10 = Informatics, systems and electrical engineering" is probably the suitable discipline, whereas if it is more about the question of in how far AI can become human and develop consciousness, "1 = Liberal arts and humanities" is probably more appropriate, etc. When it comes to the training of large language models, „10 = Informatics, systems and electrical engineering" is likely to be the best option – but when it comes to social aspects (e.g., discrimination, legal issues, effects on human behaviour…) of the use of trained models, "2 = Social sciences" if often the more appropriate choice.

Moreover, we specify:

If an actor is described unspecifically as a "climate researcher", we code "9 = Geosciences" according to the DFG classification.

"Neuroscientists" are coded under "4 = Medicine" according to the DFG classification.

"Meteorology" is coded under "9 = Geosciences".

If an actor is described unspecifically as “AI researcher” and it is not clear from the context in which disciplinary environment he/she is active, he/she is coded with “10 = Informatics, systems and electrical engineering”.

Actors who take on university policy and/or administrative functions within the science system after having conducted research in a specific scientific branch (e.g., university presidents) are code das “12 = Actor is no scientist” if they appear exclusively or predominantly in this (non-researching) function.

2.9. National localisation (aktort)

This category captures whether an actor becomes active/works (predominantly) in Germany or in another country respectively a transnational institution.

ATTENTION: This variable is *not* about the nationality (citizenship) of a person, but about his/her current institutional affiliation/place of work. For example, in the case of scientists, whether they are researching at a German university or not, and in the case of politicians, whether they are members of the German Bundestag or not.

Only information within the article is used for coding. If it is not clear from the article information in which country an actor is active, “99 = Not identifiable” is coded.

1	Germany
2	Other country in the EU
3	USA
4	Other country
5	Supranational (multiple countries, e.g., if an actor is a member of an international organisation like the WHO or the EU (e.g., commissioner of the EU) or of an international scientific group)
99	Not identifiable

ATTENTION II: The United Kingdom is coded as country in the EU, as it was still a member state of the EU in periods of analysis of other studies for which this codebook was initially designed.

2.10. LLM quote (llm_quote)

For the present research project, it seems appropriate – despite the lack of an in-depth statement analysis – to analyse whether actors comment on the object of investigation in the narrower sense, i.e., on text-generative Ais such as ChatGPT or similar large language models (e.g., Bard, Llama, Gemini, Claude…). If this is the case at least once in a whole article, “1 = Quote about LLMs” is coded. Therefore, all statements made by the actor within an article must be considered, which is why the entire article can be displayed by using the “complete text”-button (the name of the actor to be coded is highlighted throughout the text). To be coded as a LLM statement, a LLM does not have to be explicitly mentioned in it. Instead, it is sufficient if it becomes clear in the overall context that the respective statement is related to such an AI (e.g., a teacher states in an article discussing a grade reform due to the publication of ChatGPT: “We can no longer initially assume that a student wrote a text by his/herself.”) If direct or indirect quotations of the person refer solely to other topics in the whole article, the category is not coded or left at the default value.

NOTE: Chatbots, e.g., Eliza, A.L.I.C.E., Mitsuku, Artemis or similar, are treated as LLMs in the coding. The same applies to software for automated translation, provided it is discussed in the context of LLMs and it is not clear from the article that the programme in question is NOT based on a LLM.

ATTENTION: If an actor comments on AI in general, but not explicitly on text-generative AI such as chatbots or other text generators (e.g., translators, “search engines”), he/she should be coded with “0 = No quote about LLMs”. This also applies if an actor only comments on other generative AI such as image, voice or video generators. Since, in practice, the boundaries between different AI technologies are often blurred and/or not taken into account, there may appear “mixed forms” in the statements (e.g., an actor explains how machine learning works (= AI in general) and mentions ChatGPT as an example (= text-generative AI)). In the edge cases, “1 = Quote about LLMs” is coded. Even in cases where it remains unclear which form of generative AI an actor is referring to (e.g., when talking about data protection concerns), “1 = Quote about LLMs” should be coded. If actors who speak for an organisation that deals with LLMs among other things make “general” AI statements that go beyond LLMs and for which it is therefore unclear whether they are considered to be a LLM statement or not, it should be coded “1 = Quote about LLMs”. The same applies to general AI statements in articles that refer (almost) exclusively to LLMs and statements about AI technologies in which LLMs are integrated.
ATTENTION II: If unspecified AI applications in industries in which LLMs could play a role (i.e. in which an AI could potentially be used for text processing/production) are mentioned, “1 = Quote about LLMs” is coded.
Example: An actor associated with the tourism industry says that AI will change his/her everyday working life without going into further detail about how. (Justification: text-generative AI could be used, for example, to answer customer enquiries, facilitate hotel searches, create travel plans…).

0	No quote about LLMs
1	Quote about LLMs

2.14. Expert status (expert_status)

Note: This variable is only coded, if “1 = Quote about LLMs” has been selected in category 2.10.

In order to determine whether an actor is introduced as an expert for the object under investigation (here: LLMs/text-generative AI) in an article, several variables on the basis of which the expert status of an actor can be inferred are combined. The single variables are derived from an inductively and deductively developed stage model for the description of visible experts in the media (cf. Bogner 2014: 12-13; Huber 2014: 20, 31 & 62-72; Weinstein 1993: 58 & 71)

…

The coding to be carried out here starts at the 3rd level (which actors are presented as experts by the journalists?) and then differentiates this form of journalistically constructed expertise (cf. Nölleke 2009: 98) with regard to 1) the domain of expertise (which actors are presented as experts for LLMs?) and 2) the form of the declared expertise (cf. Weinstein 1993). In addition, experts are distinguished from insiders (cf. Bogner 2014: 14). In order to arrive at such a classification, three new variables are coded at this point and summarised (automatically via the app used for coding) to the following values:

0	Actor is no expert
1	Actor is a performative expert
2	Actor is an epistemic expert
3	Actor is a moral expert
4	Actor is a LLM user
9	Actor is another expert
99	Not identifiable

2.11. Expert designation (expbez)

Note: This variable is only coded, if "1 = Quote about LLMs" has been selected in category 2.10.

This category is intended to answer the question of whether an actor is literally or by using a synonym (e.g., Koryphäe (= luminary), Spezialist:in (= specialist), Sachkundige:r (= professional), Ass (= dab hand), Kenner:in (= connoisseur)) designated as an expert in an article. Strict coding should be applied so that only unambiguous designations are coded. Edge cases are labelled with "0 = Actor is not designated as an expert". As a consequence, they will automatically undergo the process for the indirect determination of the expert status. Descriptions, which clearly indicate that an actor enjoys a high reputation or can demonstrate great success in his/her activity/field of expertise, such as "Actor x is one of the most cited voices/most successful …", also count as explicit expert designations and are coded accordingly with "1 = Actor is designated as an expert".

0	Actor is not designated as an expert
1	Actor is designated as an expert

ATTENTION: Depending on the context, the German terms "Fachmann:frau" (= professional) or "Meister:in" (= master) can either be used as a synonym for "expert" or represent an alternative description of a professional level/profession. The meaning of the synonym must therefore be double-checked on a case-by-case basis to select the appropriate value.

ATTENTION II: In some journalistic texts, experts are not initially introduced, but clearly referred to as such in generic statements, such as "However, all experts agree that…". While coding inside the app, these generic statements are often not immediately identifiable. Therefore, before selecting „0 = Actor is not designated as an expert", it must be carefully checked whether the actor under investigation is somewhere in the entire text (can be displayed via the "Complete text"-button) described as an expert. As an aid, the words/word fragments "Expert", "Spezial", „Fachmann/-frau/-leute", "Sachkundige" and "Koryphäe" are highlighted in colour inside the coding app. However, if these word fragments are identified by the app, it must be again checked whether the term is related to the actor to be coded or not.

2.12. No insider (no_insider)

Note: This variable is only coded, if "0 = Actor is not designated as an expert" is coded in 2.11 and neither "210 = Political executive" nor "230 = Political legislative" (or subcategories) are selected in category 2.8.

This category excludes so-called insiders, who possess specialised knowledge that is, indeed, not accessible to laymen, but only relates to the organisation/institution of the actor. Thus, this specialised knowledge is not generalisable to the object of the media reporting (here: LLMs/text-generative AI). Therefore, insiders are not considered to be experts. Accordingly, it should be decided whether an actor speaks solely about "interal matters" (e.g., company secrets, workflows, etc.) based on his/her statements. If this is the case, the actor is considered to be an insider and coded with "0 = Actor is an insider". Insiders exclusively talk about organisational secrets, that are characterised by their high specificity and non-transferability to other contexts, e.g., operational workflows, staff matters, specific interal applications/codes… Statements about organisation-specific AI applications or implementations, that are (potentially) transferable to other organisations and/or can be observed by external actors, or plans/projects, that will be made visible/available to the public at a later date (i.e. with their implementation/realisation) are no internal matters. Consequently, actors voicing such statements are coded with „1 = Actor is no insider". In cases of doubt, actors should be also coded with "1 = Actor is no insider".

0 Actor is an insider
1 Actor is no insider

2.13. LLM expert (llm_expert)

Note: This variable is only coded, if either 1) "1 = Actor is designated as an expert" in category 2.11 or 2) "1 = Actor is no insider" in category 2.12 has been selected.

The purpose of this category is to determine in what way the expertise of an actor is related to the object of media reporting (here: LLMs/text-generative AI). Therefore, the institutional affiliation (societal area)/job title or similar characteristics of the actor are used to derive a so-called "expert domain", which means the field in which the actor is predominantly active/known. By this, it can be further determined whether the actor to be coded is directly involved in the development of or research on LLMs/LLM applications ("1 = LLM development/research"), handles with already established LLM applications respectively is confronted with their handling by third parties within his/her domain ("2 = LLM application/usage") or if he/she investigates LLMs/LLM applications with regard to their social, legal or ethical consequences and/or localises those models epistemologically or in relation to humans ("3 = LLM consequences/contexutalisation"). If none of these descriptions seem suitable, the expert is coded with "9 = Other". **Only if the institutional affiliation/societal area or other characteristics of the actor are not sufficient to decide on the value to be coded**, the statements of the actor can be consulted. If afterwards no value can be selected, the actor has to be coded with "99 = Not identifiable".

1 LLM development/research
Actors who are engaged with the research on and/or the development of LLMs/text-generative AI
Note: Actors who are associated with the Silicon Valley and not localised

otherwise (respectively coded with “522 = For-profit organisations” in category 2.6) have to be coded as experts for LLM development.

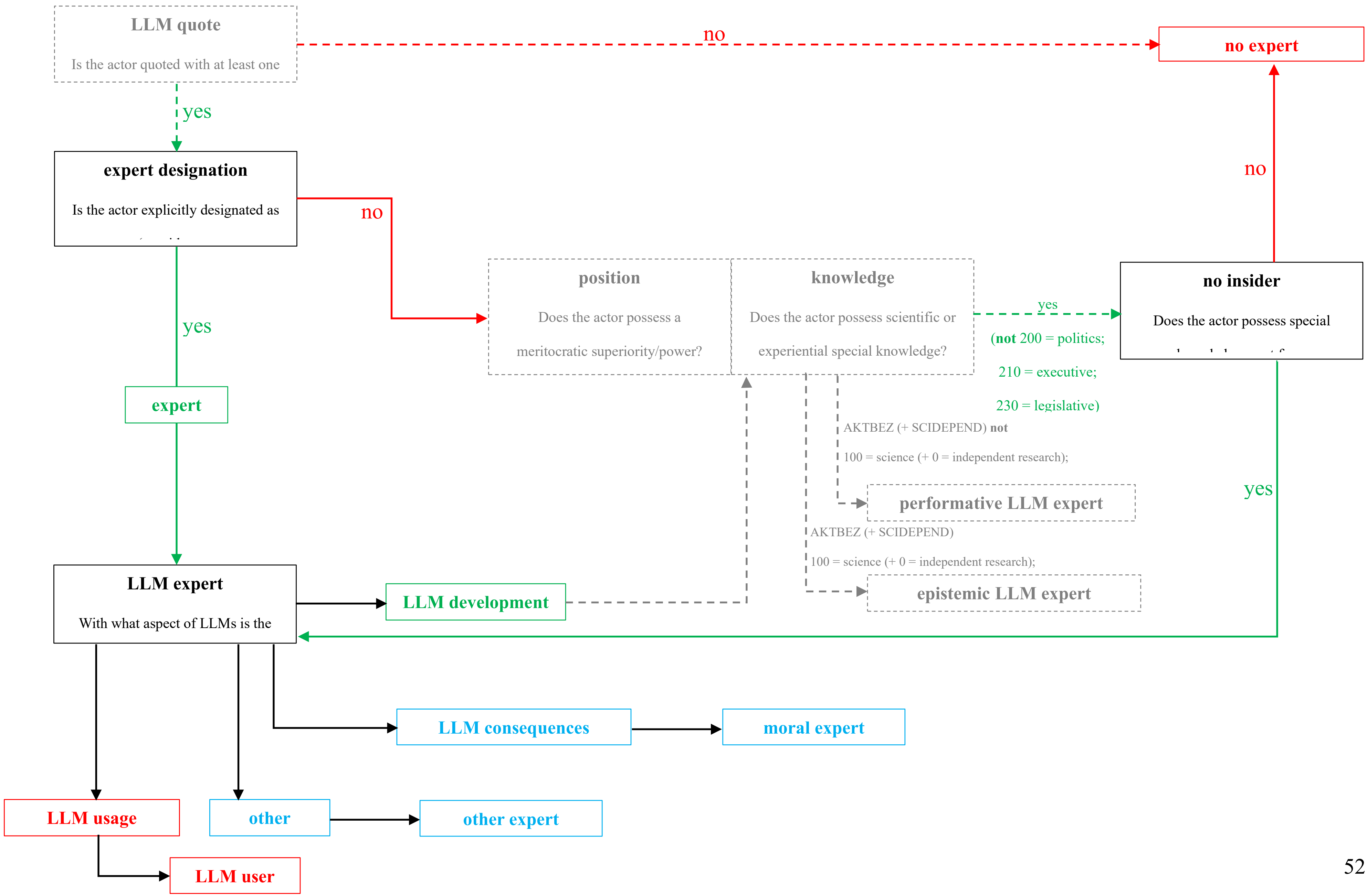
2 LLM application/usage
Actors who narrate personal experiences during the usage of LLMs with regard to different tasks (e.g., to support teaching, as translator, as source of inspiration, for entertainment, etc.) or who talk about the exposure to LLM applications within their domain (e.g., teachers who describe their treatment of AI generated homeworks or musicians who evaluate the quality of LLM-generated songs…)

3 LLM consequences/contextualisation
Actors who consider LLMs exclusively with regard to ethical, moral, legal, philosophical or other ideational aspects. Among those are both actors who describe or assess societal consequences of the technology (e.g., technology assessors, members of an ethics committee) and actors who ideationally localise it, for example, in contrast to human intelligence (e.g., psychologists who distinguish human cognitions from artificial intelligences or people engaged in the cultural sector who artistically reflect on the distinction of humans and AI etc.)

9 Other
All actors for whom the other options are not appliable. Experts, who have acquired their expertise through the persistent reception of informational material about LLMs (e.g., journalists who have gathered information about the topic for years and now write non-fiction books about it) are also collected under this category

99 Not identifiable

ATTENTION: Politicians who are explicitly designated as experts usually have to be coded with “9 = Other”, UNLESS it is unambiguous that they use LLMs/LLM applications. In this case, “2 = LLM usage/application” is the appropriate choice.
ATTENTION II: Scientists who are engaged with “AI decisions” or “AI decision-making” have to be coded with “1 = LLM development/research”, “2 = LLM usage/application” or “3 = LLM consequences/contextualisation” considering the disciplinary perspective from which they approach the topic. In the fields of informatics, robotics, etc. (“10 = Informatics, systems and electrical engineering” in category 2.7), the term “AI decisions/decision-making” is usually used to describe decisions made by the AI technology itself. Consequently, for scientists engaged with that, “1 = LLM development/research” has to be selected. In other scientific disciplines external to informatics, “AI decisions/decision-making” might also refer to decisions about the AI technology or its (societal) handling. In that case, “2 = LLM usage/application” is the more suitable option. If “AI decisions/decision-making” is mentioned while debating the (social) consequences of a LLM invention/application or its implementation, “3 = LLM consequences/contextualisation” must be coded.
ATTENTION III: Leaders of software or technical development companies are invariably coded with “1 = LLM development/research”, unless it is doubtlessly ascertainable that they are “only” managers with administrative functions (only the case if a training or career path that is exclusively focused on administrative tasks (e.g., business administration) is described within an article). Similarly, directors of AI-related research associations, thinktanks etc. (e.g., the German Cyber Valley) are coded with “1 = LLM development/research” if there is no further information to their tasks or career path given inside the article.



LLM quote
Is the actor quoted with at least one
no
no expert
yes
expert designation
Is the actor explicitly designated as
no
yes
expert
position
Does the actor possess a
meritocratic superiority/power?
knowledge
Does the actor possess scientific or
experiential special knowledge?
yes
(not 200 = politics;
210 = executive;
230 = legislative)
no insider
Does the actor possess special
no
AKTBEZ (+ SCIDEPEND) not
100 = science (+ 0 = independent research);
performative LLM expert
yes
AKTBEZ (+ SCIDEPEND)
100 = science (+ 0 = independent research);
epistemic LLM expert
LLM expert
With what aspect of LLMs is the
LLM development
LLM consequences
moral expert
LLM usage
other
other expert
LLM user

Coding process