AN ANALYSIS OF SCIENTIFIC REQUIREMENTS ON ARTIFICIAL INTELLIGENCE GOVERNANCE

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The emergence of AI technology has prompted the need for standardization and governance due to the potential societal risks associated with its use. However, there is currently no common concept for AI standardization, that considers a broad range of social and ethical subject areas. International cooperation is necessary to address the possible threats, and various nations and organizations have already made initial efforts in this direction. Our overall research question investigates, to what extent requirements based on scientific insights have been addressed in international standards and what new insights standardization efforts can offer to science. In this paper we report the findings of an extensive systematic literature review of 482 scientific articles, using a hybrid analysis process combining manual coding with generative AI supported triangulation steps. The resulting 17 requirements will be used as a basis for a thematic analysis of the most relevant AI standards currently being developed and deployed globally.

Keywords:
artificial intelligence,
global AI governance,
AI governance components,
AI standardization,
scientific requirements

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1 Introduction

The advent of Artificial Intelligence (AI) has been a long and winding road, arguably starting with either Asimov's novel "I, robot" in 1943 or McCullogh and Pitts' scientific article "A Logical Calculus of the Ideas Immanent in Nervous Activity" in 1943, according to (Toosi et al., 2022). They describe the history of the field and in particular the "winters and summers" of AI depression and euphoria respectively and suggest, that we were already in the midst of a summer back in 2021. Since then, Microsoft, Google and Open AI launched several generative AI tools such as Dall-E in 2019 and ChatGPT in 2022, bringing AI to the attention of the general public. Whether or not this means, that we have now moved into a permanent summer, or the prelude of an AI ice-age, is yet to be seen, but it is apparent that unprecedented numbers of organizations, companies, employees and citizens are now looking for ways to make use of AI based tools.

Ethical and societal issues resulting from the adoption of AI, such as bias of training data and its resulting applications, unexplainable decisions by black-box neural networks and lack of human measure in automated decision making, have been discussed in scientific literature for decades. The generative capabilities of large language models are just one of many AI categories, but due to their exposure and availability to the general public, they are at the forefront of the public debate on AI and have raised public awareness and concerns about the ethical use of AI.

One of the consequences of this development and the societal concerns resulting from this, is that governments and other (inter)national bodies are looking to regulate and/or standardize the way AI has to be developed, implemented and used. Perhaps most prominently, the European Commission and the Parliament of the European Union have recently endorsed the EU AI Act, with the aim to "foster trustworthy AI in Europe" (European Commission, 2024). Other national and international bodies have also made initial efforts to counteract possible threats posed by AI standardization and regulation initiatives (Butcher & Beridze, 2019; Schmitt, 2022; Lorenz, 2020). The possible negative and positive impact of AI on society, organizations and individuals has such a magnitude, that it is understandable that these initiatives press on with urgency. But this also means, that unforeseen consequences may arise, due to the combination of still evolving technological capabilities and the discovery of new application domains on the one hand and the "need for speed" on the other. For instance, the classification of "emotion recognition" as a prohibited application area in the EU AI Act (European Commission, 2025) has the - probably unforeseen and undesirable - consequence, that certain applications in the medical and educational domains can no longer bring their potential benefits to society (Iren, 2025).

The standardization and regulation of AI is a young field in the IT industry (Chen, 2021) and literature describing the landscape of international AI standardization and governance activities is rare. We therefore ask ourselves, to what extent the scientific body of knowledge formulates requirements on AI governance and standardization that can help finding this balance between speed and rigor.

On the other hand, in the development of standards and regulations, it should be common practice to involve all stakeholders in the decision-making process. So even if it would be the case, that these safeguards are not always met when such processes need to be expedited, we feel it is fair to assume that the standards and regulations that are being put in place do contain a significant degree of stakeholder input, leading us to a second research question, to what extent AI standards and regulations offer relevant new contributions to the scientific body of knowledge.

This paper focuses on answering the first of these two research questions. The next section provides a background from literature on AI governance and the context of standardization. Section 3 then discusses the methodological approach that we have followed for the systematic literature review. The results of the review are presented in Section 4. Finally, Section 5 discusses the results and presents the conclusions, including the limitations of this study.

2 Prior research

Butcher and Beridze (2019) give an overview about stakeholder and their kicked-off activities from the private sector, public sector, research, and multi-stakeholder organizations. The authors identify disagreements over how to effectively regulate and implement AI, challenges for legal systems, as well as regulation up-sides with incentivization or risk minimization. They name the European Union's General Data Protection Regulation as an example of an already implemented AI regulation vehicle. Butcher and Beridze (2019) conclude that AI governance is still an indeterminate for many states and that first regulation frameworks for specific use cases are needed before a global governance approach can be targeted. The authors designate aviation safety regulation as an inspiring blueprint for global AI governance.

Schmitt (2022) builds on the research of Butcher and Beridze. Schmitt divides the stakeholders in two groups based on whether the stakeholders are trying to regulate AI within existing frameworks or not. The author points out that stakeholders tend to adapt existing frameworks. Schmitt observes that an initial consolidation is taking place and that some stakeholders are increasingly aligning themselves with the Organization for Economic Co-Operation and Development (OECD). The author concludes that international cooperation is lagging legally binding agreements and actors from the public sector are effectively absent from discussions around global AI governance. Further, Schmitt sees a risk that geopolitical considerations as well as different perceptions of human-centric AI values will interfere global standardization.

In its report Lorenz (2020) gives a comprehensive overview on organizations developing AI governance standards. The report gives insights about the category, main topics, goals, and members of each identified organization. Lorenz states global governance is largely defined by political actors and standard developing organizations. Lorenz addresses the need for a mechanism to identify the most powerful international AI governance organization, to help other actors in understanding and participation.

Djeffal, Siewert and Wurster (2022) conducted a study to help understand how states approach to regulate AI. The authors identified four different approaches: Self-regulation-promotion state, market-oriented state, entrepreneurial state, and regulatory state. They identify responsibility as a crosscutting subject that runs through all four approaches.

In our observation there is limited attention in literature for AI Governance and standardization. There also seems to be a lack of literature that attempts to map current activities with a certain level of detail or that matches these with requirements from research and science. This paper's aim is to fill the first of these two gaps.

3 Research Methodology

Our aim is to derive requirements on AI governance and -standardization from the scientific body of knowledge, without putting a priori restrictions on the scientific field nor the application domain. This yields a relatively broad scope, for which we require an inductive yet systematic approach to maximize the transparency of our selection and synthesis process. We have followed the guidelines (Wolfswinkel et al., 2013), who propose a combination of a systematic selection process, combined with methods based on grounded theory. Following their structure, this chapter first discusses the definition of search, then reports about the search and select process, and concludes with a description of the analysis process, the results of which will be presented in Chapter 4.

3.1 Define

As stated before, our goal is to maintain a broad scope throughout the literature review. This requires us to deviate slightly from the guidelines offered by Wolfswinkel et al. to "efficiently perform a systematic literature review", which are aimed at narrowing both the scope of the review as well as the "fields" of research. Instead, we intend to keep our search broad, and while being precise in the definition of our search criteria and sources and the documentation of our findings, we used an alternative approach to keeping the resulting analytical work manageable, both in terms of data retrieval and the subsequent qualitative content analysis (which we will discuss in Section 3.4).

The first element for this approach is that we have chosen is to not limit the selection and thus work with a relatively large set of articles, coming from different fields and disciplines. The size of the dataset allows us to focus on the most important requirement that the respective authors present, which is typically found in the abstract of the paper. This eliminates the need to obtain and analyze the full papers, making the retrieval of the data trivial and the execution of the study feasible. From other research with large datasets, we have seen that the actual impact of the limitation to abstracts on the validity of the results only has a relatively small impact, if the number of papers analyzed is sufficiently large (Buchkremer et al., 2019).

After reviewing the prior literature research documents, a keyword design was first developed based on the research question. The topic term “artificial intelligence” was set as the initial keyword. Based on the objective of the work, terms from the field of AI standardization were selected as sub-keywords (“standards”, “governance”, “principles”), which were identified during the preliminary literature research combined with forward and backward search. Further keywords during this step were used as the respective sub-categories (e. g. “policies”, “ethics” or frameworks”). From the keyword design developed, corresponding search queries for the database search were designed, considering the operators “AND” and “OR” (etc.). Preliminary searches were carried out via search tests and based on the available search options and accessibility of the publications using the following databases: IEEE Xplorer, Bielefeld Academic Search Engine, Emerald Insights and Web of Sciences. A corresponding search string was then compiled based on these test search queries (Figure 1).

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AB=(("artificial intelligence" OR "AI" ) NEAR/15 ("govern*" OR "standard*") AND ("principle*" OR "polic*" OR "ethic*" OR "framework*" OR "responsibilit*" OR "evaluation*" OR "certification*" OR "auditabilit*"))) AND TI=("artificial intelligence")
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Figure 1: Search query used in the Web of Science database
Source: Own research

We selected Web of Science (WoS) as the data source for our search, given that it is well-maintained and offers easy exporting of the raw abstract texts. (Falagas et al., 2008; Martín-Martín et al., 2018) In addition, only peer-reviewed articles that were not older than 2012 were considered.

3.2 Search and Select

The search string triggered 482 hits, which were stored in a large Microsoft Excel table for further processing. As stated before, we did not make any further reductions on this set. We made a manual analysis of the application areas for each of the articles, resulting in overview of Figure 2. The full list of articles and their labeling into application areas is available through an online appendix[1].

[1] https://github.com/rogerbons/Bled2025Goebel-Bons-Buchkremer

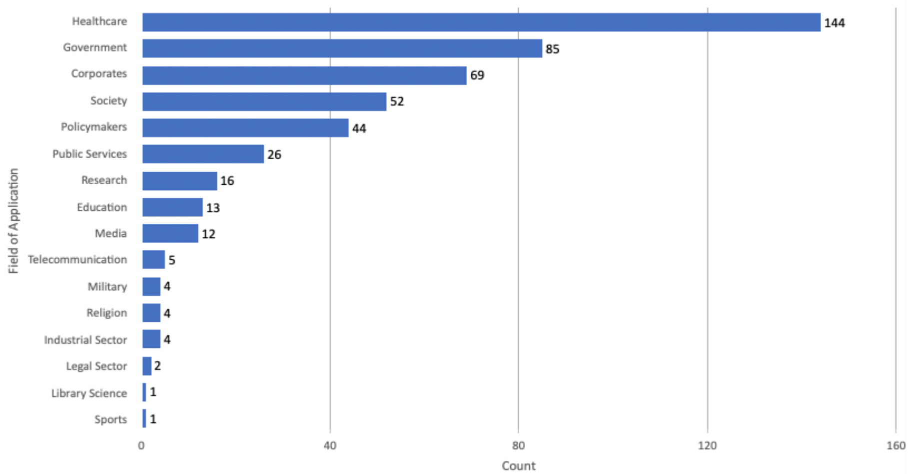

Figure 2: Distribution of the articles across application areas
Source: own research

3.3 Analyze

In the analysis stage of the process, we have made the second change to the guidelines of Wolfswinkel et al., in the way the grounded theory was applied. The inductive open coding of text is inherently subjective, when performed by a single researcher, where conscious and unconscious bias might influence the result. This is typically solved by having multiple researchers (albeit often from the same research team) execute the various steps and document the findings in a transparent way. Even after having reduced the scope of the analysis to the abstract of papers only, the set of 482 posed challenges in the feasibility of a multi-researcher full analysis.

Therefore, we used a combination of manual coding with various generative AI models to triangulate the potentially subjective findings in each of the coding stages. Our methodology for analyzing abstracts, as opposed to full-text analysis, aligns with contemporary comparative studies on abstract screening that utilize large language models (LLMs), such as those conducted by Li et al. (2024) and Dennstädt et al. (2024). This approach, while efficient, also encompasses its inherent limitations. While generative AI models, particularly the large public ones, most likely will have biases of their own, it is highly unlikely that these biases are *specific* towards the prompts we ask them to execute as part of the research. By disclosing the prompts used, we can give maximum transparency of the process. In the next chapter, we will first present how we did this for each of the stages and then present the outcome of our analysis. Figure 3 summarizes the methodological steps taken, including the coding stages we will further detail in the next section.

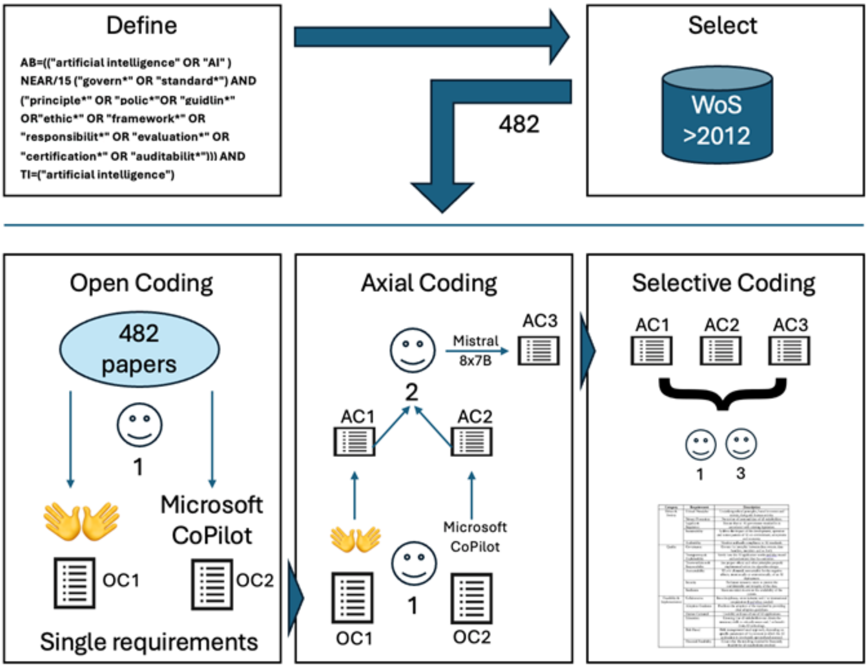

Figure 3: The qualitative content analysis stage of our study
Source: own work, adapted from Wolfswinkel et al., 2013

4 Findings

4.1 Open coding

In the first coding stage, the aim was to identify the core requirement for each of the papers in our selection. On the set of 482 abstracts, we therefore did execute a single manual inductive content analysis, following the classical coding principles defined in (Corbin, 2011), but were executed by a single researcher. This researcher first identified codes in each abstract, clustered the results and finally prioritized the most prominent components encountered. Instead of repeating this manual process with a second researcher, we then collectively deployed a Generative AI model (Microsoft

Co-Pilot version as of June 2024) on the same dataset of 482 abstracts. We prompted the GenAI to only identify a single requirement per abstract and to report back the original terms from the document. The prompts used in the process have been included in the online appendix.

4.2 Axial coding

In this stage, our aim was to reduce and harmonize the long list of requirements identified from the manual and the GenAI based process. We followed a four steps process for this part of the analysis. First, we continued with the dual approach by having a manual reduction of the list we manually created, combining similar terms into single terms wherever possible, while keeping track of the number of underlying abstracts that formed the basis of the categories. In parallel, we again prompted the GenAI we used for the open coding to combine the original set of codes coming from the GenAI open coding version, also included in the online appendix.

For the third step we involved a second researcher, who was provided with the top ranking categories from both resulting lists. He combined the terms and then performed a thematic analysis on the 482 abstracts using a different GenAI model (Mistral version 8x7B), but this time allowing for multiple requirements identified by the model as well as allowing for additional themes to be added to the list. The step confirmed the categorized codes that were specifically looked for and identified a long list of themes that were found in addition.

4.3 Selective coding

In the first step we generated a list of clustered themes present in at least two of the three sets we found in the previous stage, keeping track of how originating concepts of the three sets were collided into the encompassing term. After that, themes that exclusively occurred in only a single set were added to the cluster list for transparency reasons, but without assigning a term to them. To conclude the selective coding, the 19 resulting requirements were critically reviewed by Researchers 1 and 3 on their usefulness. We eliminated the category "Standardization & Guidelines" as a separate requirement, as we consider their appearance in the results primarily as a confirmation that they are indeed needed, but not as a requirement on the process to define them. The resulting list is depicted in Table 1.

Table 1: Requirements on AI Governance Standardization

Category	Requirement	Description
Ethics & Society	Ethical Principles	Underlying ethical principles, based in norms and morals, that guide human activity.
	Privacy Protection	Protection of personal data of all stakeholders.
	Legality & Regulation	Ensure that an AI governance standard is in accordance with existing legislation.
	Sustainability	Address the impact of the development, operation and consequences of AI on ecology, society and economy.
	Auditability	Monitor and audit compliance to AI standards.
Quality	Governance	Govern the interplay between data owners, data handlers, modelers and so forth.
	Transparency & Explainability	Verify how the AI application works. Trace and understand the outcomes.
	Trustworthiness & Responsibility	Are proper ethical and other principles properly implemented within the algorithm design.
	Accountability	Who is ultimately accountable for the negative effects, intentionally or unintentionally, of an AI deployment.
	Security	Technical measures taken to protect the confidentiality and integrity of the data.
	Resilience	Measures taken to ensure the availability of the system.
Feasibility & Implementation	Collaborative	Interdisciplinary, cross-industry and / or international cooperation if and when needed.
	Adoption Guidance	Facilitate the adoption of the standard by providing clear adoption guidelines.
	Human Centered	Useability and ease of use of AI applications.
	Education	Ensuring that all stakeholders can obtain the skills to critically assess and / or benefit from AI technology.
	Risk-Based	Risk-management based approach, depending on specific parameters of the context in which the AI application is developed, operated and assessed.
	Financial Feasibility	Ensure that the resulting standard is financially feasible for all stakeholders involved.

4.4 Discussion on the requirements

We conclude our section on findings with a brief review of each of the resulting requirements and our interpretation thereof. It is not our aim to define the resulting concepts, that is left to the developers of the standards, regulations and legislations. For readability and easy access, we have clustered the requirements into four main categories: Ethics & Society, Quality, Feasibility & Implementation.

In the "Ethics & Society" cluster, we have combined the requirements that stem from addressing ethical / societal demands on AI applications, which may or may not have been also captured by other legislation. The "ethical principles" are the first requirements in this category, which we interpret to be the underlying ethical principles, based in norms and morals, that guide human activity. These principles can yield a range of specific requirements, for instance aiming at safeguarding human rights, fairness and non-discrimination, or put negatively, aiming at avoiding gender bias, age bias and so forth. "Privacy protection" can be seen as a result of addressing the ethical principles, but has such profound impact on citizens, that we use it as a separate requirement, referring to the protection of personal data of all stakeholders of the AI application. To ensure that a standard developed for AI governance can work in harmony with existing legislation, we have added "legality and regulation" as a requirement on such standards as well. The realization of the UN's Sustainable Development Goals is another important dimension of the ethics and society cluster and the "sustainability" requirement reflects the need to explicitly address the impact of the development, operation and consequences of AI applications on environment, ecosystems and economy. In order to achieve all these goals, it must also be possible to monitor and audit the compliance of any standard in use, which is why the "auditability" requirement has been included in this category as well.

The "quality" cluster contains properties of the standards, that are needed for stakeholders to assess the quality of the AI applications satisfying those requirements. Many of them are direct consequences from ethical and legal considerations, but the difference with that category is that the "quality" requirements aim at properties of the resulting standards themselves, rather than the considerations that have to be safeguarded in the standardization process. Firstly, one of the key areas to be addressed in the standards is the "Governance" aspect. The interplay between data owners, data handlers, modelers and so forth makes the governance of data, algorithms, access and so forth an important aspect to be addressed in the standards. "Transparency and Explainability" refers to the possibility that stakeholders can verify how the AI application works and that outcomes of them can be traced and understood. "Trustworthiness & Responsible AI" on the other hand refers to the intentions behind the AI application and whether they are proper implementations of the ethical and other principles at the foundation of the development. In other words, the question whether these properties have been taken account already during the design stage of the application. "Accountability" follows these requirements by looking at the question, if there is somebody ultimately accountable for the negative effects, intentionally or unintentionally, of an AI deployment. Given the increasing dependence that society will have on these systems, the requirements "security" and "resilient" close this category, with the former referring to the technical measures taken to protect the confidentiality and integrity of the data and the latter to the measures taken to ensure the availability of the system, even in case of unforeseen errors or acts of God.

In the cluster "feasibility & implementation" we have combined those requirements that aim to ensure the societal and financial feasibility of the standards that are to be developed. A first requirement in this category is the need for a "collaborative" approach, where various stakeholders work together on defining the standard. This includes the requirement for interdisciplinary, cross-industry and / or international cooperation if and when needed. The "adoption guidance" requirements refers to the need to facilitate the adoption of the standard by providing clear adoption guidelines. The feasibility of an implementation is also strongly connected to the useability and ease of use of the AI application under consideration, which we cover with the "human centered" requirement. We have also put "Education" in this category, which we interpret as ensuring that all stakeholders can obtain the necessary skills to critically assess and / or benefit from AI technology. With the requirement "Risk-based approach" we refer to a type of standardization that allows for a risk-management based approach, which allows for a diversified approach depending on specific parameters of the context in which the AI application is developed, operated and assessed. Ensuring that the standards are based on and fed into scientific research and the innovation agenda of companies helps with the efficiency of the standard development process. A final element in this category is the "financial feasibility", covering all financial aspects that might be covered to ensure that the resulting standard is financially feasible for all stakeholders involved.

5 Conclusion

This study addressed the question, to what extent the scientific body of knowledge formulates requirements on AI governance and standardization that can help finding a balance between speed and rigor. We have identified 17 requirements, which we derived from analyzing 482 scientific sources, using an approach that combined manual and AI-supported coding technique and was designed to be able to analyze a broad body of literature.

The practical relevance of this paper is twofold. Firstly, even though this was not our original aim for the research, we believe that our results can also help organizations that are preparing to develop and/or implement AI applications in identifying key areas for the governance they need to address as part of their implementation process. The areas we identified might serve as guidance for those activities, but of course more empirical research would be needed to verify this claim. Secondly, it enables us to investigate to what extent these requirements are reflected in standards and guidelines that are currently available and thus possibly contribute to their continuous improvement and applicability in practice.

The validity of our results may have been impacted by the decision to just use abstracts, in lieu of being able to take a wide perspective on the field. The impact is determined largely by how mature the field of research is and 482 results, based on fairly broad search terms suggest, that the field is indeed not yet very mature. Also, the resulting selection of the primary requirement per article might have an limiting impact. We think that the size of our sample has a mitigating effect on both these aspect, but our analysis of standards used in practice should provide a more precise estimate of the impact, perhaps leading additional requirements. In parallel we are evaluating options to perform an AI-supported full-text analysis, to enhance the depth and reliability of the research approach.

We are acutely aware of the potential risks and limitations associated with employing generative AI tools such as CoPilot and Mistral, therefore we documented the use and output of the tools according to best practices to maintain transparency and accountability insofar as possible. Our upcoming analysis of current standards will be a first indication of the practical relevance of our findings.

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The references to the 482 scientific articles analyzed are accessible via:
https://github.com/rogerbons/Bled2025Goebel-Bons-Buchkremer

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