Technological Forecasting & Social Change 212 (2025) 123971

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

# Artificial intelligence policy frameworks in China, the European Union and the United States: An analysis based on structure topic model

Shangrui Wang [a,b], Yuanmeng Zhang [a], Yiming Xiao [c], Zheng Liang [a,b,*]

[a] School of Public Policy & Management, Tsinghua University, Beijing 100084, China
[b] Institute for AI International Governance, Tsinghua University, Beijing 100084, China
[c] School of Public Administration, South China Agricultural University, Guangzhou 510642, China

ARTICLE INFO

*Keywords:*
Artificial intelligence
Structure topic model
Governance
Public policy

ABSTRACT

As artificial intelligence (AI) becomes increasingly influential, governments worldwide are developing policies to manage its multifaceted impact across sectors. This study employs the structural topic model (STM) to analyze 139 AI policies from China, the European Union (EU), and the United States (US), three key actors in global AI governance. The analysis identifies 13 primary topics within AI policy frameworks, which are categorized into "research and application" (e.g., talent education, industrial application), "social impact" (e.g., technological risk, human rights), and "government role" (e.g., government responsibility, management agency). Notably, "government role" receives the most attention, while "social impact" is the least emphasized. The findings reveal that China prioritizes "research and application," the EU emphasizes "social impact," and the US focuses on "government role," while all three demonstrate a growing emphasis on institutional systems, human rights, and scientific research. This study provides a comprehensive policy framework for AI governance, highlights the strategic priorities of China, the EU, and the US, and introduces an innovative method for policy text analysis. Moreover, it underscores the need for AI governance to balance industry development with ethical imperatives, foster comprehensive technological ecosystems, and prioritize public participation and international cooperation.

## 1. Introduction

With advancements in data accessibility, computing power, and algorithm optimization, artificial intelligence (AI) has emerged as a transformative technology with capabilities in perception, information processing, decision-making, learning, and adaptation (Haenlein and Kaplan, 2019). AI is anticipated to drive economic growth, industrial upgrades, environmental preservation, improved public administration, health advancements, and enhanced decision-making (Guenduez and Mettler, 2023; Kerr et al., 2020; Valle-Cruz et al., 2020; Margetts and Dorobantu, 2019). However, AI's inherent complexity, opacity, and unpredictability have raised significant ethical and societal concerns. Algorithmic biases, for instance, can exacerbate societal inequalities under the guise of neutrality, resulting in biased outcomes in hiring, loan approvals, and law enforcement (Desiere and Struyven, 2021). Moreover, Security flaws in AI systems pose risks ranging from data breaches to manipulation of outputs, while issues of autonomy and accountability question the locus of moral responsibility (Wu et al., 2020). In addition, privacy concerns are particularly acute, with AI's ability to conduct intrusive surveillance and profiling, disproportionately affecting vulnerable populations such as children and the elderly[1] (de Almeida et al., 2021).

Given that AI is a double-edged sword with enormous benefits and harms, there is an urgent call to govern AI in a manner that aligns with public values (Dignam, 2020; Sampath, 2021; Taeihagh, 2021; Zhang et al., 2021). Policymakers around the world have increasingly proposed

* Corresponding author at: School of Public Policy & Management, Tsinghua University, Beijing 100084, China.
*E-mail addresses:* wsr1998977@163.com (S. Wang), ym-zhang23@mails.tsinghua.edu.cn (Y. Zhang), xiaoe@scau.edu.cn (Y. Xiao), liangzheng@tsinghua.edu.cn (Z. Liang).

[1] Several illustrative instances underscore the dark side associated with AI systems across various jurisdictions. Notably, the System Risk Indication (SyRI) in the Netherlands, which was designed to identify potential welfare fraud, has drawn criticism for its discriminatory impact and privacy intrusions, leading to significant public and legal scrutiny. Similarly, in the US, the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) system, employed to inform judicial decisions in the criminal justice context, has been the subject of debate due to allegations of bias and the opaque nature of its decision-making process.

https://doi.org/10.1016/j.techfore.2025.123971
Received 22 April 2024; Received in revised form 19 November 2024; Accepted 1 January 2025
Available online 4 January 2025

pertinent policies in numerous fields, taking into account the wide-ranging impact of AI. These policy documents provide a wealth of information that not only articulates the fundamental strategies and future directions of AI governance, but also lays a solid foundation for policy evaluation and improvement (Guenduez and Mettler, 2023; Yang and Huang, 2022). Accordingly, AI policy constitutes an excellent venue for broad governance discourse and has received a booming scholarly attention. Nonetheless, a comprehensive and integrative policy framework for AI governance is still lacking, particularly in the context of the multifaceted and dynamic nature of AI policies that span multiple domains and evolve continuously (Birkstedt et al., 2023; Sigfrids et al., 2022a; Batool et al., 2023).

This study contributes to the literature by providing an in-depth analysis of AI policies in China, the EU and the US, three entities that exert the greatest global influence on AI governance. Specifically, China, the EU and the US have long been global leaders in AI talent, industry and research (Castro and Mclaughlin, 2021; Maslej et al., 2023), and they actively shape and dominate AI management and regulation, thereby influencing the future direction of international AI governance frameworks (Larsen, 2022; Sullivan and Global AI, 2023). As a result, AI governance of China, the EU and the US represent a critical focus for both academic and practical fields (Krarup and Horst, 2023; Roberts et al., 2021; Roberts et al., 2023). To this end, this study seeks to address the following research questions:

**RQs**: What are the AI policy frameworks in China, the EU and the US? How relevant and prevalent are the topics within them? And further, how do their policy frameworks differ and how have they changed over time?

To effectively address these research questions, this study employs the Structural Topic Model (STM), an advanced text analysis method particularly well-suited for the expansive and dynamic nature of AI policy documents (Guenduez and Mettler, 2023; Nowlin, 2016; Hannigan et al., 2019). STM overcomes limitations of human-coding by extracting latent patterns from extensive text corpora, enabling nuanced and systematic identification of thematic structures (Nowlin, 2016; Hollibaugh, 2019; Lee et al., 2023). Furthermore, STM facilitates cross-country comparisons and longitudinal analyses, making it a powerful tool for understanding the evolving dynamics of AI policy frameworks in diverse governance contexts. Therefore, this approach ensures a comprehensive and comparative perspective on policy framework for AI governance.

This study offers significant theoretical contributions. First, it presents a comprehensive policy framework for AI governance, identifying three critical categories—government role, research and application, and social impact—and their intrinsic elements, priority level, and mutual relationships. This framework bridges gaps in fragmented approaches by integrating multiple dimensions of AI governance into a holistic perspective (Birkstedt et al., 2023; Sigfrids et al., 2022a; Batool et al., 2023). Second, this study highlights how distinct political and cultural contexts shape the governance priorities of China, the EU, and the US, providing nuanced insights into global AI governance dynamics and laying a foundation for future international collaboration (Guenduez and Mettler, 2023; Djeffal et al., 2022). Third, it introduces the Structural Topic Model (STM) as an innovative method for text analysis. By integrating human judgment with machine learning, STM overcomes the limitations of manual analysis, ensuring both objectivity and interpretability in processing vast amounts of information (Guenduez and Mettler, 2023). This study demonstrating its effectiveness in uncovering themes, interrelationships, and trends across large datasets (Hollibaugh, 2019).

The study also provides practical implications by offering actionable insights for AI governance. First, it emphasizes the need for balanced governance frameworks that integrate diverse stakeholder perspectives, foster ethical accountability, and bridge the gap between policy intent and implementation (Ulnicane et al., 2021; Fatima et al., 2022). Second, it calls for public participation mechanisms that go beyond performative gestures to enable meaningful engagement, supported by capacity-building initiatives to empower informed contributions (Kerr et al., 2020; Wilson, 2022). Third, the study urges industry and academia to establish enforceable standards and build consensus on critical issues, such as fairness and robustness, to create a comprehensive technological ecosystem (Minkkinen et al., 2022). Lastly, it underscores the importance of international cooperation to harmonize global governance standards while respecting local contexts. Practical mechanisms, such as multilateral agreements and cross-border research collaborations, are essential for addressing transnational AI challenges and promoting ethical, inclusive, and sustainable AI governance on a global scale (Roberts et al., 2021; Roberts et al., 2023; Tuzov and Lin, 2024).

The rest of the study is structured as follows: Section 2 presents a literature review, covering existing research on AI policies and an overview of text analysis methods. Section 3 introduces the theoretical foundation, exploring the concept and framework of AI governance and analyzing the comparative governance contexts of China, the EU, and the US. Section 4 presents the data and method, including the collection of policy texts, an introduction to the STM, text pre-processing and topic number selection. Section 5 outlines the results, including the major topics in the policy texts, topic relationship and prevalence, and the covariate effect estimation of each topic. Section 6 discusses the findings, offering a comprehensive policy framework for AI governance and highlighting the diverse priorities of China, the EU, and the US. It also explores the theoretical and practical implications of the study, along with its limitations. Finally, Section 7 provides a concise conclusion.

## 2. Literature review

### 2.1. Existing scholarship on AI policies

Given the rapid and widespread integration of artificial intelligence (AI) across various domains, policymakers worldwide are facing the dual challenge of promoting AI's development while mitigating its potential risks (Guenduez and Mettler, 2023; Kerr et al., 2020; Valle-Cruz et al., 2020). AI, with its transformative capabilities, holds immense promise in driving economic growth, enhancing productivity, and solving societal challenges. However, it also raises significant concerns, such as algorithmic bias, privacy violations, and threats to human rights and democratic values (Dignam, 2020; Sampath, 2021; Taeihagh, 2021; Zhang et al., 2021). As a result, the global governance of AI has emerged as a critical policy area, with governments adopting a variety of approaches to balance innovation with regulation. For instance, the European Union (EU)'s "AI ACT"[2] adopts a risk-based approach, categorizing AI systems by their potential impact on human rights and safety and prohibiting those deemed unacceptable, such as real-time biometric identification. Similarly, China's "Ethical Norms for New Generation Artificial Intelligence" emphasize principles like fairness and transparency, aiming to align AI development with ethical guidelines. The United States' "National Artificial Intelligence Initiative Act" focuses on coordinating AI research and policy across federal agencies, balancing innovation with societal considerations. Together, these efforts reflect an international push to navigate AI's complex landscape with attention to ethical standards, economic advancement, and societal well-being.

These policy documents provide a wealth of information that not only articulates the fundamental strategies and future directions of AI governance, but also lays a solid foundation for policy evaluation and improvement (Guenduez and Mettler, 2023; Yang and Huang, 2022). Accordingly, AI policy constitutes an excellent venue for broad governance discourse and has received a booming scholarly attention. Most of

[2] European Commission, Proposal for a Regulation Laying Down Harmonized Rules on Artificial Intelligence (Artificial Intelligence Act), COM (2021) 206 final (21 April 2021)."

the relevant literature falls into five main categories: (1) Conducting in-depth analysis for influential individual policies. For example, Polyviou and Zamani (Polyviou and Zamani, 2022) analyzed the priorities in the EU White Paper on AI and the needs of stakeholders. (2) Mapping the evolution of AI policy in a particular country. For example, Yang and Huang (Yang and Huang, 2022) analyzed the distribution, targets and focus of AI policies over three decades in China. (3) Focusing on a particular aspect of AI policy. Scholars have explored the role of government (Ulnicane et al., 2021), public engagement (Wilson, 2022) and social responsibility (Krarup and Horst, 2023; Saveliev and Zhurenkov, 2021) in AI policies. (4) Tracing the formation process and influential factors of AI policies. It is found that economic competition, institutional structure, policy preferences, cultural values, research capacity and public expectations all play important roles (Af Malmborg and Trondal, 2021; Fatima et al., 2021; Filgueiras, 2022; Justo-Hanani, 2022). (5) Presenting the disconnect between reality and expectation in AI policy. AI policy suffers from many imperfections (Roberts et al., 2021) and has even been recognized as performative politics under a grand narrative (Bareis and Katzenbach, 2022; James and Whelan, 2022). It is worth noting that many of these studies have selected AI policies from different countries (or territories)[3] as source material and have taken a cross-country analytical approach, making the comparisons of AI policies across countries serve both as an important intersection of literature strands and as a useful window into the global process of AI governance. A common finding is that there are similarities as well as differences in AI policies across countries (Guenduez and Mettler, 2023; Djeffal et al., 2022; Saveliev and Zhurenkov, 2021; Cath et al., 2018; Fatima et al., 2020; Radu, 2021). However, these investigations are constrained in the following two aspects. The one is the limited policy scope. Due to the extensive impact of AI, AI policies have been developed in multiple fields, which requires analysis of comprehensive policies in a given country to discover its policy framework. The other is the limited time span. As AI evolves and policies improvement, the governance priority of AI policies shifts for each country,[4] which require the adoption of time-dynamic analysis.

### 2.2. Text analysis: Human coding and topic modelling

Text analysis is a widely utilized method in social science research, especially for scholars investigating AI policy frameworks (Ulnicane et al., 2021; Wilson, 2022; Fatima et al., 2020). One of the most established and commonly used techniques for text analysis is content analysis with human coding. This approach is considered both valid and reliable, as it often involves multiple coders working to ensure intercoder reliability and follows a predetermined codebook towards expected topics. By applying content analysis, researchers can uncover deeper structures within the data, gaining a rich understanding of social processes. This is often achieved through systematic coding and grounded theory methodology, which facilitates the discovery and development of new theories (Glaser and Strauss, 2017; Charmaz, 2015). However, content analysis with human coding has significant limitations. It is both time-consuming and resource-intensive, making it difficult to scale for large datasets. The process of developing a comprehensive codebook, training coders, and ensuring consistent application requires substantial effort and financial investment. Moreover, human coders must possess extensive contextual knowledge and expertise, adding another layer of complexity. As a result, this method is not well-suited for handling large-scale textual data, which has become increasingly prevalent in the era of AI and big data (Nowlin, 2016).

With the advancement of computing technologies, computer-assisted topic modelling approaches have emerged as powerful tools for text analysis, alleviating many of the challenges associated with human coding. Although these automated methods do not replace the need for careful reading and nuanced understanding of the texts under study, they significantly enhance researchers' ability to classify and analyze vast amounts of text across multiple categories (Nowlin, 2016). Topic modelling approach process automatedly without prior analysis or categories standard, it "analyze the words of the original texts to discover the themes that run through them, how those themes are connected to each other, and how they change over time" (Blei, 2012). The underlying principle of topic modelling is based on the distributional hypothesis in linguistics, which posits that the meaning of a word is derived from its relationship with other words. According to this hypothesis, documents are treated as "bags of words" and a word's significance is inferred from its co-occurrence patterns with other words (Tonidandel et al., 2022). These patterns reveal thematic structures that are independent of the syntax, narrative, or specific location within the documents, offering valuable insights into the latent topics. Therefore, these methods are valuable for introducing new theoretical perspectives and revisiting previously intractable problems (Hannigan et al., 2019).

When analyzing policy texts, especially global AI policies, traditional human coding faces several challenges. These include a limited perspective with potential for human bias, substantial costs associated with employing and training coders, and difficulties in interpreting diverse and specialized language (Guenduez and Mettler, 2023; Nowlin, 2016; Hannigan et al., 2019). Therefore, Manual coding often struggles to keep pace with the rapid evolution of policy documents in the dynamic AI landscape. In contrast, automated topic modelling approaches can effectively extract patterns, themes, and their interrelationships from large datasets, capturing the dynamic nature of policy development. These methods also facilitate cross-country and longitudinal comparisons, which are essential for understanding the global evolution and governance of AI policy. Topic modelling has become a widely used technique in social science (Nowlin, 2016; Hollibaugh, 2019; Lee et al., 2023), with Latent Dirichlet Allocation (LDA) being one of the most prominent methods. In this study, we utilize the STM, an advanced and extended version of LDA, which enables us to better navigate and interpret the complex landscape of AI policy frameworks. The technical characteristics and advantages of STM are detailed in the methods section.

## 3. Theoretical foundation

### 3.1. AI governance: From concept to framework

To address the dual nature of AI as both an opportunity and a risk, the concept of AI governance has garnered increasing attention from both scholars and practitioners. Building on the broader concept of governance that emphasizes the interactions of multiple actors within networks (Rhodes, 2007), AI governance refers to "the discursive processes through which different societal actors advance and contest competing visions for the appropriate development, implementation and regulation of AI" (Roberts et al., 2021; Ulnicane et al., 2021; Wilson, 2022). The goal of AI governance is to foster a collective understanding of AI across various contexts and to facilitate consensus-building among diverse stakeholders, thereby safeguarding the public interest and upholding democratic principles (Birkstedt et al., 2023; Sigfrids et al., 2022b).

National AI policies serve as a valuable platform for broader governance discourse, defining the roles and responsibilities of these various actors with the goal of generating economic and social value (Roberts et al., 2021; Ulnicane et al., 2021; Cath et al., 2018). Building upon these policies, recent studies have framed AI governance from multiple perspectives: (1) Artificial Intelligence Regulation Framework: this framework illustrates the interactions among key societal sectors involved in

[3] Hereafter referred to collectively as countries.

[4] For example, China's AI policy priorities have evolved dynamically over time, moving from a focus on technological development and application around 2010 to a more comprehensive governance approach, including ethical, legal, security, and international collaboration aspects.

AI regulation and oversight, including the legislative, executive, and judicial branches, as well as society, industry, academia, and both national and international AI governance committees. (2) AI Governance Systems: representing a multi-level governance model, this framework depicts the relationships between global, national, and subnational AI governance systems, emphasizing the hierarchical integration of governance efforts across different levels. (3) Responsible AI Framework: this approach focuses on creating AI systems that are human-cantered, trustworthy, and ethically grounded, integrating technical safeguards and ethical principles to meet societal expectations. While these frameworks share overlapping elements, such as stakeholder engagement and ethical considerations, they each approach AI governance with unique emphases. Therefore, there is a need for an integrated framework that synthesizes dimensions across technology, stakeholders, regulation, processes, institutions, and human rights, providing a comprehensive structure to guide AI governance effectively. While existing frameworks for AI governance share overlapping elements—such as stakeholder engagement and ethical considerations—each tends to emphasize specific aspects of governance, leading to gaps in overall comprehensiveness. Where these frameworks share overlappingly important elements, each tend to emphasize specific aspects of AI governance. Therefore, there is a call for a more comprehensive, inclusive, institutionalized, and actionable model of AI governance, which integrate multiple aspects including technology, stakeholder, context, regulation, processes, ethics and human right (Birkstedt et al., 2023; Sigfrids et al., 2022a; Batool et al., 2023).

### *3.2. Comparative AI governance contexts: China, the EU, and the US*

The global race for AI dominance has positioned AI governance as a critical national priority, with countries striving to enhance their competitiveness and influence in the field (Filgueiras, 2022). As a result, national AI strategies across different countries often exhibit remarkably similar narrative constructions, portraying AI as a disruptive technological force capable of fundamentally transforming society and politics (Bareis and Katzenbach, 2022). This shared narrative reflects a hybrid approach, combining political will and public resources with industry interest (Radu, 2021). However, national AI policies vary significantly in their specific targets, developmental paths, and regulatory approaches, largely shaped by each country's unique cultural, political, and economic contexts (Bareis and Katzenbach, 2022). This study focuses on examining these contexts in China, the EU, and the US. While all three aim to assert global leadership in AI governance, their approaches differ considerably (Birkstedt et al., 2023).

First, China is often characterized by a government-led national system, with the central government playing a dominant role in setting strategic directions and policy objectives. While retaining authority, the central government also enables multiple departments, local governments, and policy entrepreneurs to actively contribute to policy formulation and implementation. This approach is underpinned by experimentalist governance, which allows for localized adaptation and iterative refinement within the framework of central guidelines (Mertha, 2009; Zhu and Zhao, 2021). In the context of AI governance, China has explicitly adopted an innovation-first approach, prioritizing technological development as a key driver of national competitiveness, along with the goals to enhance national security and maintain social order (Bareis and Katzenbach, 2022). More recently, ethical considerations have been integrated into China's AI governance framework, functioning primarily as utilitarian tools to support and safeguard technological advancement, rather than as constraints on development (Roberts et al., 2021; Roberts et al., 2023; Tuzov and Lin, 2024).

Second, the EU, as a supranational entity characterized by multi-level governance, aims to harmonize fragmented decision-making among member states to foster integration and enhance global competitiveness (Krarup and Horst, 2023; Justo-Hanani, 2022). Guided by "human-centred" cultural values (Robinson, 2020), the EU enforces strict market regulations that influence global standards through the "Brussels Effect", whereby non-EU entities adopt EU standards to access its extensive market (Bradford, 2020). In the context of AI governance, the EU prioritizes its regulatory power to establish ethical standards for AI, taking an incremental approach to ensure that AI systems align with citizens' rights and European values. These efforts aim to position the EU as a global leader in AI ethics, while simultaneously promoting market integration, coordinating member states, and maintaining competitiveness through a "state-market regime" (state actors recognize the necessity of establishing new regulations to reshape market framework conditions) (Krarup and Horst, 2023; Roberts et al., 2023; von Essen and Ossewaarde, 2024).

Third, the United States is often characterized by its market-oriented governance system, defined by a laissez-faire approach to regulation and a strong emphasis on market liberalism. Economic competitiveness and technological leadership are central policy priorities, with leading technology companies playing a significant role in shaping the policy landscape through extensive lobbying efforts (Dignam, 2020). In the context of AI governance, the U.S. boasts the world's most advanced AI ecosystem and prioritizes maintaining its global dominance by minimizing regulatory barriers and fostering innovation (Bareis and Katzenbach, 2022). This leadership strategy emphasizes preserving a light-touch regulatory framework, which often tempers the focus on ethical AI. Ethical considerations are primarily addressed through self-regulation, guided by voluntary frameworks. Additionally, the U.S. extends its influence by promoting open global markets and countering international competitors through a combination of formal and informal mechanism (Sampath, 2021; Roberts et al., 2021; Bareis and Katzenbach, 2022).

These analyses provide the essential context for understanding the AI policy frameworks in China, the EU and the US.

## 4. Data and method

### *4.1. Policy texts collection*

The dataset comprises AI policy texts from three leading jurisdictions: China (central government), the EU, and the US (federal government). The documents were retrieved from official and authoritative sources: "LawInfoChina" (www.pkulaw.com) for China, "EUR-Lex" (eur-lex.europa.eu) for the EU, and "GovInfo" (www.govinfo.gov) for the US. To ensure the relevance and specificity of the dataset, the selection criteria required policy documents to focus explicitly on AI rather than on broader advanced technologies. Additionally, the texts needed to be issued by national or supranational governance bodies to ensure comparability across jurisdictions and to analyze overarching governance frameworks. Data collection was finalized in June 2023. As a result, we collected a total of 139 policy texts, and the overall distribution of collected data is shown as below (Table 1).

The 139 policy texts analyzed span from 2016 to 2023. In China, the policies were primarily issued by the central government and its specialized agencies, such as the Ministry of Industry and Information Technology and the Ministry of Science and Technology. In the EU, policies were authored by institutions such as the European Commission and the European Parliament. In the US, policy texts were issued by federal entities, such as the White House Office of Science and Technology Policy, the Department of Commerce, and the Federal Trade Commission. The policy documents span diverse sectors, such as healthcare, industrial automation, education, and ethics, showcasing the multifaceted impact of AI. By encompassing strategies, legislative acts, and administrative guidelines, these policies collectively illustrate each jurisdiction's approach to addressing the challenges and opportunities of AI governance.

**Table 1**
Overall distribution of AI policy texts.

| | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | Total |
|---|---|---|---|---|---|---|---|---|---|
| China | 1 | 5 | 7 | 11 | 11 | 13 | 4 | 2 | 54 |
| The EU | 0 | 2 | 6 | 3 | 6 | 9 | 6 | 0 | 32 |
| The US | 0 | 0 | 3 | 5 | 9 | 21 | 3 | 12 | 53 |

Note: Statistics to June 2023.

### 4.2. STM approach for topic modelling

With the recent advancement of technology and software, the text-as-data methodology has been widely used in the social sciences, where it is praised for its ability to "both answer new questions as well as revisit old ones" (Hollibaugh, 2019). In line with this trend, text analytics has gained popularity in the field of public policy. In general, there are two research paths for textual analytics of public policies: one is to analyze the external (or formal) features of the policies, including their quantity, time, and sector (Yang and Huang, 2022). The other is to uncover the internal (or content) features of policies, such as semantic structure, topic classification, etc. (Lee et al., 2023). Although the aforementioned research paths are not mutually exclusive, in the absence of a unified methodological framework, it is frequently challenging for researchers to comprehensively define the landscape of the external and internal features of policies and the linkages between them.

The introduction of the Structure Topic Model (STM) provides a more efficient method for analyzing policy texts (Roberts et al., 2014). STM is a modification of the Latent Dirichlet Allocation (LDA),[5] because LDA's assumption that the prior topics distribution is the same for each document, with no correlation between topics, does not correspond to realistic policy texts (Tamakloe and Park, 2023). As a latest and sophisticated topic modelling technique, STM allows for correlation between topics and uses document-level covariates to account for topic distribution for each document and word usage within each topic (Bai et al., 2021). Therefore, STM can help researchers not only to identify the topic distribution underlying policies, but also to analyze the relationship between specific topics and other covariates (e.g., time of issuance), thus effectively connecting the external and internal features of polices (Hollibaugh, 2019; Roberts et al., 2014).

### 4.3. Text pre-processing and topic number selection

The STM analytical process is based on the "stm" package developed by Molly Roberts, Brandon Stewart and Dustin Tingley in R program.[6] Through referring to the standardized STM analytical process (Bai et al., 2021; Dwivedi et al., 2023), we pre-processed the original data before undertaking the STM topic modelling, including removing numbers and punctuations, converting words to lowercase and stemmed, and removing words appeared in less than 5 % of the documents, as well as stop words without meaningful information. The final data contains 139 documents, 1834 terms and 44,511 tokens, which were processed into a document-term matrix format, as the main input for the STM.[7]

STM requires the user to specify the number of topics (K) to be generated, a decision guided by an iterative process that combines data insights and human judgment to balance statistical fit with the substantive clarity of topics (Hollibaugh, 2019; Roberts et al., 2014). Informed by established practices in STM research, we first used a data-driven approach to select an appropriate range of topic numbers according to fit statistics, including exclusivity, held-out likelihood, semantic coherence, and residuals. Exclusivity reflects the independence between topics, semantic coherence indicates internal consistency within topics, residuals measure the degree of model fit, and held-out likelihood evaluates the model's predictive power. A robust model is expected to achieve high exclusivity, semantic coherence, and held-out likelihood, while minimizing residuals. Fig. 1 presents the fit statistics for STM models with K values ranging from 3 to 30, and we determined that models with K between 10 and 15 provided the most appropriate balance among these metrics. This range demonstrated the best trade-offs: significant increases in exclusivity and held-out likelihood, minimal residuals, and only a slight decrease in semantic coherence. These trade-offs are widely recognized in STM literature as indicative of a well-performing mode (Dwivedi et al., 2023; Choi and Woo, 2022; Sharma et al., 2021).

Then, we manually evaluated each model with K values between 10 and 15 to select the most suitable one. Specifically, the authors compared these models based on the interpretability of the keywords and documents associated with each topic and assigned a label to each topic. Discrepancies were resolved through thorough discussions, and a consensus was reached among all authors regarding the topic number and labels. After careful deliberation, we selected a model containing 13 topics, prioritizing interpretability to ensure that the identified topics provide actionable and meaningful insights. This approach aligns with best practices in STM research (Hollibaugh, 2019; Tonidandel et al., 2022; Tamakloe and Park, 2023). The consensus labels are applied consistently throughout the remainder of the manuscript.

To further validate the quality of the topics in the model with $K = 13$, we conducted maximum-a-posteriori (MAP) estimation to assess document-topic associations. The histograms generated from this analysis are presented in Fig. 2, with the dashed red line indicating the median. The results show that each topic is strongly associated with a small subset of documents, while exhibiting minimal correlation with the majority. This pattern aligns with the statistical mixed-membership hypothesis underlying the document-topic relationship in STM (Sharma et al., 2021), reinforcing the robustness of the selected model.

After text pre-processing and topic number selection, we carried out formal analysis using the STM with $K = 13$. The judgments and interpretations of the analysis were based on the STM results and their corresponding policy texts, which to some extent ensured the objectivity of the analysis.

## 5. Result

### 5.1. Major topics in the policy texts

We examined the keywords and policy documents (see Table 2) associated to each topic. Each topic is also visualized as a word cloud consisting most frequent words (see Fig. 3). Through the interpretation of these results, we identify the main elements of each topic and name them in order: industrial application, government responsibility, technology standard, research institute, impact on work, technological risk, talent education, institutional system, human right, social cooperation, policy pilot, management agency and scientific research.

[5] LDA is an unsupervised machine learning approach that automatically infers latent topics in unstructured text by assuming document-topic-vocabulary relationships and a Dirichlet prior for the topic proportions.

[6] The introduction to the "stm" package can be found at https://www.structuraltopicmodel.com, and more technical details can be found at https://cran.r-project.org/web/packages/stm/stm.pdf.

[7] For more details on the mathematical principles of STM and its implementation in R, see these references (Roberts et al., 2019; Sharma et al., 2021).

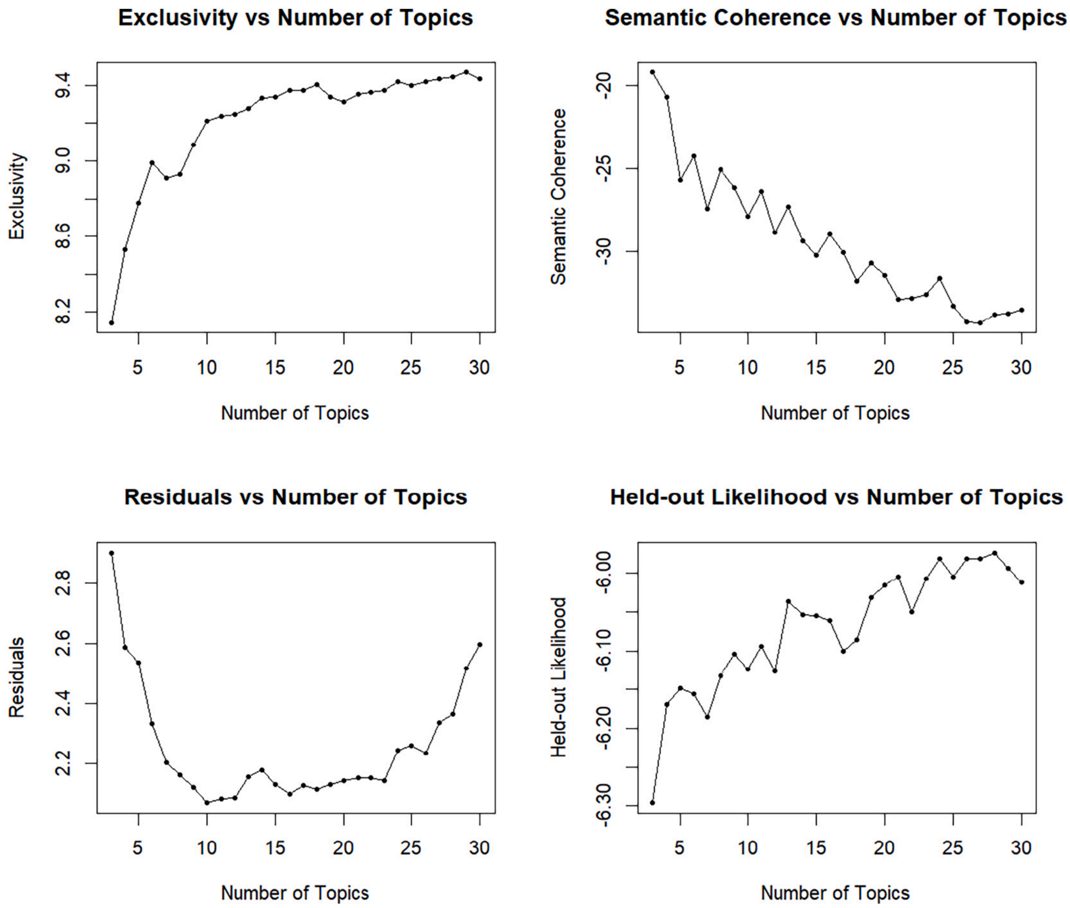


**Fig. 1.** The fit statistics for model selection.

### 5.1.1. *Industrial application*

Topic 1 focuses on the industrial application of AI, as indicated by words such as "technology," "application," and "industry." The terms "develop" and "support" highlight the significance of policy in advancing industrial AI applications, while "system" and "platform" underscore the need for robust infrastructure. Additionally, the words "robot," "product," and "service" reflect the tangible outputs of AI deployment. These findings emphasize the critical role of policy in aligning industrial AI initiatives with national strategic priorities, leveraging infrastructure development and practical outcomes to drive economic growth.

The related policy is "Work Program for Unveiling Key Tasks of the New Generation of AI Industry Innovation" issued by China's Ministry of Industry and Information Technology. The document emphasizes four aspects of industrial application: smart products such as automobiles, robots, and drones, core foundations including sensors, chips and open-source platforms, equipment for smart manufacturing, and the infrastructures and systems such as resource libraries and service platforms.

### 5.1.2. *Government responsibility*

Topic 2 addresses government responsibility in AI governance, as evidenced by terms like "commission" and "agency," which point to the roles of specialized institutions. Words such as "use," "study," "identify," and "conduct" underscore the importance of research and reporting, while "develop" and "commerce" reflect the link between governmental actions and economic growth. These findings highlight the pivotal role of governments in fostering innovation while balancing regulatory oversight, ensuring that AI contributes to societal and economic objectives.

The related policy is "American Competitiveness of a More Productive Emerging Tech Economy Act of 2020". The document states that it is necessary for the Federal Trade Commission and the Secretary of Commerce to complete a study on the state of the AI industry and its impact on the US economy, as well as a survey into the marketplace and supply chain of AI, in order to strengthen the US position globally by ensuring advances in AI and the smooth growth of the market.

### 5.1.3. *Technology standard*

Topic 3 emphasizes the development of technological standards for AI, as reflected by words such as "standard" and "technology." Terms like "risk" and "manage" suggest the need for robust frameworks to mitigate risks across the AI lifecycle, while "model," "data," and "device" highlight specific areas requiring oversight. These insights underscore the importance of integrating risk management into AI standards to ensure alignment with societal values and regulatory compliance.

The associated policy is "Guiding Principles for Defining the Classification of Medical Software Products with Artificial Intelligence" from China. The policy defines the standard for classifying AI medical software based on the maturity of the algorithms in medical application, i.e., whether the safety and efficacy have been sufficiently proven, and prescribes different management approaches for AI medical software under different classifications.

### 5.1.4. *Research institute*

Topic 4 focuses on the role of AI research institutes, as suggested by words like "research," "institution," and "initiative." Additional terms, such as "technology," "science," and "education," underscore their dual function as hubs of innovation and education. These findings reinforce

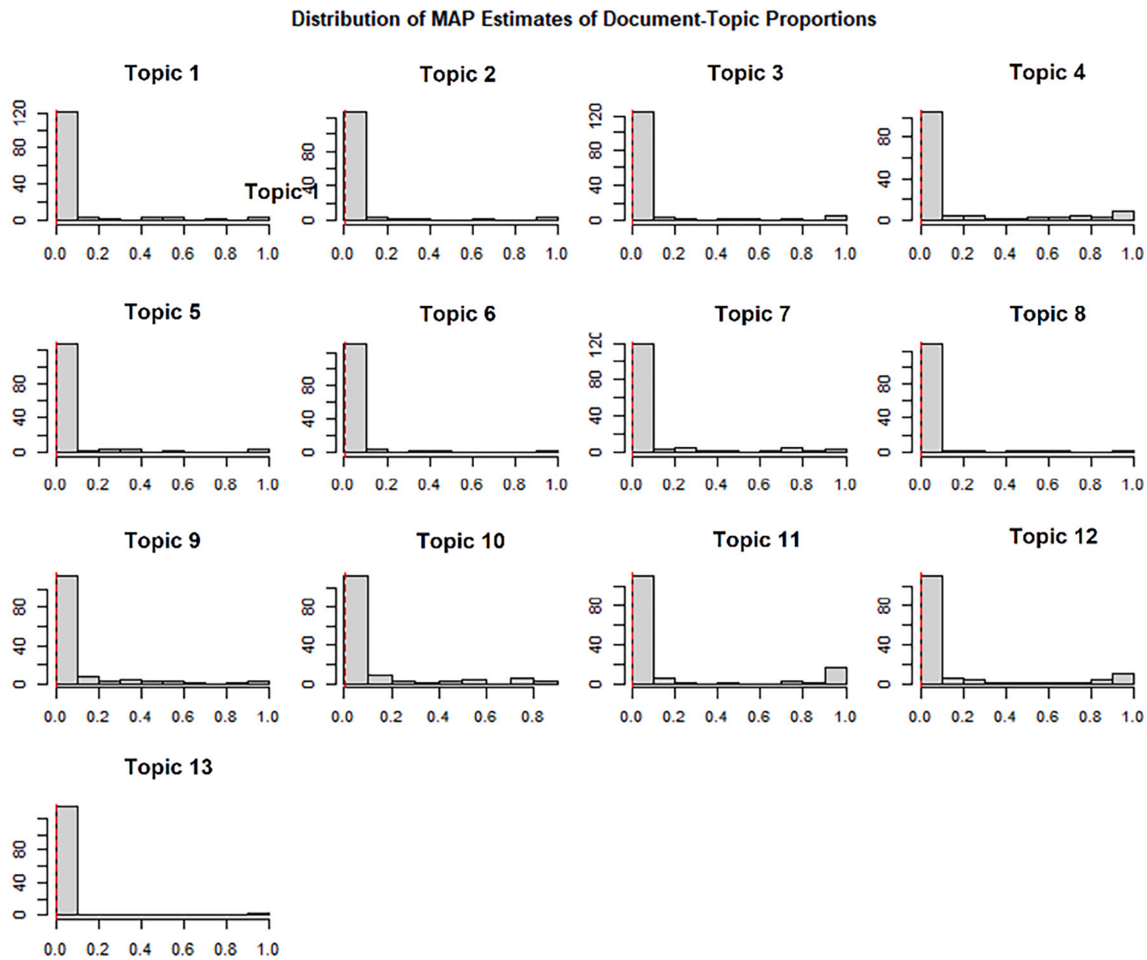


**Fig. 2.** Topic distribution within documents.

the role of research institutes in advancing robust and ethical AI systems, bridging theoretical exploration with practical applications.

The associated policy is "Growing Artificial Intelligence Through Research Act" from the US. According to the policy, the US government should set up coordination offices, advisory committees and research centers, support scientific research and educational activities through project funding, and encourage deliberation and collaboration among various institutions.

#### 5.1.5. *Impact on work*

Topic 5 explores AI's impact on the workforce, with terms like "work," "worker," and "job" indicating its transformative effects. Words such as "ethical" and "human" reflect concerns about labor ethics, while "develop" and "new" highlight opportunities for job creation. These findings stress the need for policies that balance the dual impacts of AI—creating new roles while addressing job displacement—through equitable and inclusive strategies.

The related policy is "Artificial Intelligence/impact on Work" from the EU. The policy states that AI would expand the automation of work, creating some jobs as well as eliminating others, and that social protection should be provided for the latter. In addition, ethical codes should be observed in the application of AI to work, protecting workers' autonomy, rights and freedoms.

#### 5.1.6. *Technological risk*

Topic 6 focuses on the risks associated with AI, as illustrated by terms like "risk," "safety," and "liability." Words such as "human," "user," and "application" emphasize the importance of accountability in AI deployment. These findings underline the urgency of policies that mitigate risks across the AI lifecycle, ensuring the reliability and robustness of AI systems while fostering public trust.

The associated policy is "Report on the safety and liability implications of Artificial Intelligence, the Internet of Things and robotics" from the EU. The policy argues that the opacity, autonomy and complexity of AI pose new challenges to safety and liability. Therefore, there is a need for risk assessment of AI throughout its lifecycle to improve robustness and accountability, as well as compensation in the event of physical or non-physical harm caused by AI to humans.

#### 5.1.7. *Talent education*

Topic 7 highlights the importance of talent education for AI, with words like "education," "teacher," and "talent" pointing to workforce development. Terms such as "innovation," "promote," and "develop" emphasize the role of education in driving technological progress. These findings underscore the need for robust educational programs to cultivate AI talent, ensuring a skilled workforce capable of meeting the challenges of an AI-driven future.

The related policy is "Promoting Discipline Integration and Accelerating Postgraduate Cultivation in the Field of AI in Colleges and Universities Under the Construction of 'Double First Class'" from China. The goals of this policy are innovating high-level talent training processes, expanding the pool of AI talent, and construing high-level development platforms.

#### 5.1.8. *Institutional system*

Topic 8 centers on institutional systems for AI governance, as

**Table 2**
Keywords and documents associated to each topic.

| Topics | Keywords | Documents |
|---|---|---|
| Industrial application | technology, application, industry, robot, system, develop, support, product, service, platform | Work Program for Unveiling Key Tasks of the New Generation of AI Industry Innovation (CN) |
| Government responsibility | commission, use, study, develop, identify, advance, commerce, conduct, report, agency | American Competitiveness of a More Productive Emerging Tech Economy Act of 2020 (US) |
| Technology standard | standard, manage, model, data, risk, technology, requirement, system, process, device | Guiding Principles for Defining the Classification of Medical Software Products with Artificial Intelligence (CN) |
| Research institute | research, develop, technology, science, education, unit, institution, director, program, initiative | Growing Artificial Intelligence Through Research Act (US) |
| Impact on work | eesc, social, work, worker, ethic, new, job, human, particular, develop | Artificial Intelligence/impact on Work (EU) |
| Technological risk | product, safety, copyright, work, technology, liability, application, risk, human, user | Report on the safety and liability implications of Artificial Intelligence, the Internet of Things and robotics (EU) |
| Talent education | technology, innovation, promote, develop, teacher, education, research, construct, talent, cultivation | Promoting Discipline Integration and Accelerating Postgraduate Cultivation in the Field of AI in Colleges and Universities Under the Construction of "Double First Class" (CN) |
| Institutional system | propose, liability, inform, service, person, rule, article, civil, legal, system | Provisions on Several Issues Concerning the Application of Law to the Trial of Civil Cases Involving the Use of Face Recognition Technology to Handle Personal Information (CN) |
| Human right | use, system, technology, develop, right, human, law, ethic, ensure, protect | Ethics Guidelines for Trustworthy AI (EU) |
| Social cooperation | data, digital, develop, innovation, investment, sector, use, access, public, need | Coordinated Plan on Artificial Intelligence (EU) |
| Policy pilot | develop, innovation, construct, pilot, new, generate, zone, support, area, policy | Supporting Jinan to Build a National Pilot Zone for the Innovation and Development of a New Generation of AI (CN) |
| Management agency | agency, use, defense, department, office, secretary, director, program, chief, term | AI Leadership to Enable Accountable Deployment Act (US) |
| Scientific research | method, research, develop, project, learn, innovation, risk, problem, secure, knowledge | Union Support for the Implementation of a Project "Promoting Responsible Innovation in Artificial Intelligence for Peace and Security" (EU) |

reflected by terms like "system," "legal," and "rule." Words such as "liability" and "civil" suggest the need for structured frameworks to address complex challenges. These findings highlight the importance of comprehensive institutional systems to ensure ethical and legal oversight in AI governance.

The associated policy is "Provisions on Several Issues Concerning the Application of Law to the Trial of Civil Cases Involving the Use of Face Recognition Technology to Handle Personal Information" from China. This policy determines the lawful scope of face recognition in terms of information collection, storage, processing, transmission, provision and disclosure, preventing the face recognition from infringing on the personality right of citizens.

#### 5.1.9. Human right

Topic 9 addresses the protection of human rights in AI applications, as shown by words like "right," "ethic," and "protect." Additional terms such as "law," "ensure," and "develop" indicate the systems needed to uphold these rights. These findings reinforce the imperative of embedding human rights protections in AI governance, ensuring fairness, accountability, and societal well-being.

The related policy is "Ethics Guidelines for Trustworthy AI" from the EU. This policy states that AI systems should be developed, deployed and applied in accordance with human right and ethical rules, especially for socially vulnerable groups. Therefore, there are seven key requirements for Trustworthy AI:(1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) environmental and societal well-being and (7) accountability.

#### 5.1.10. Social cooperation

Topic 10 emphasizes social cooperation in AI governance, as indicated by terms like "sector," "public," and "data." Words such as "develop" and "innovation" suggest the importance of collaborative efforts to advance AI. These findings underscore the value of multi-sector cooperation, integrating diverse perspectives to guide inclusive and effective AI policymaking.

The related policy is "Coordinated Plan on Artificial Intelligence" from the EU. The policy proposes to maximize investment through partnerships, facilitate the transfer of research results to industry, promote data sharing between the public and private sectors and strengthen international cooperation.

#### 5.1.11. Policy pilot

Topic 11 focuses on policy pilots for AI, as reflected by terms like "pilot" and "policy." Words such as "construct" and "support" suggest their role as localized experiments to test governance strategies. These findings highlight the importance of government-backed pilot programs as testing grounds for scalable innovations in AI policy.

The related policy is "Supporting Jinan to Build a National Pilot Zone for the Innovation and Development of a New Generation of AI" from China. The policy states that policy pilot zones should integrate resources to enhance AI innovation capabilities and explore new models of AI governance, resulting in replicable and transferable experiences.

#### 5.1.12. Management agency

Topic 12 addresses the need for specialized management agencies in AI governance, as suggested by terms like "agency," "department," and "office." Words such as "coordinate" and "program" emphasize their role in oversight and cross-sector collaboration. These findings highlight the necessity of centralized governance bodies to enhance administrative efficiency and ensure effective AI management.

The associated policy is "AI Leadership to Enable Accountable Deployment Act" from the US. The policy calls for the establishment of AI governance boards with a chief officer in each agency, as well as a Chief AI Officers Council, and defines the structure and responsibilities of these governance bodies.

#### 5.1.13. Scientific research

Topic 13 focuses on scientific research in AI, as indicated by terms like "research," "project," and "innovation." Words such as "risk" and "secure" reflect its role in advancing safe and ethical AI. These findings affirm the critical role of scientific research in driving innovation while informing evidence-based policymaking for AI governance.

The related policy is "Union Support for the Implementation of a Project "Promoting Responsible Innovation in Artificial Intelligence for Peace and Security" from the EU. This policy calls for the joint participation of academia, industry and other stakeholders to advance the capacity building of AI practitioners, and promote responsible AI innovation and long-term sustainable development through project support.


**Fig. 3.** Word cloud for keywords in each topic.

## 5.2. *Topic relationships and prevalence*

STM enables the analysis of topic correlations to explore their interrelationships, as shown in Fig. 4 (detailed correlation coefficients are provided in Fig. A1 in the Appendix), where edges between topics represent positive correlations (Bai et al., 2021). To examine and refine the results, we conducted a bottom-up clustering of topics based on their substantive meanings, assigning each cluster a category name (Minkkinen et al., 2022). This approach combines data-driven insights with contextual interpretation to ensure conceptual clarity.

As a result, we identified three main categories from the 13 topics: **(1) Research and application**: This category includes topic 1 (industrial application), topic 3 (technology standard), topic 7 (talent education), and topic 13 (scientific research). Data shows that Topic 1 serves as the pivot, with correlation coefficients of 0.07, 0.04, and 0.02 with Topics 3, 7, and 13, respectively. This grouping reflects the interconnected topics of industrial applications, technical standards, talent training, and scientific research of AI, all of which contribute to advancing AI research and application. Accordingly, we named this category "research and application". **(2) Social impact:** This category includes topic 5 (impact on work), topic 6 (technological risk), topic 8 (institutional system), topic 9 (human right) and topic 10 (social cooperation). The correlation coefficients between Topic 9 and Topic 6, Topic 8 and Topic 10, and Topic 10 and Topic 5 are 0.02, 0.06, and 0.14, respectively. These topics collectively highlight the societal challenges posed by AI technologies, such as ethical concerns, workforce

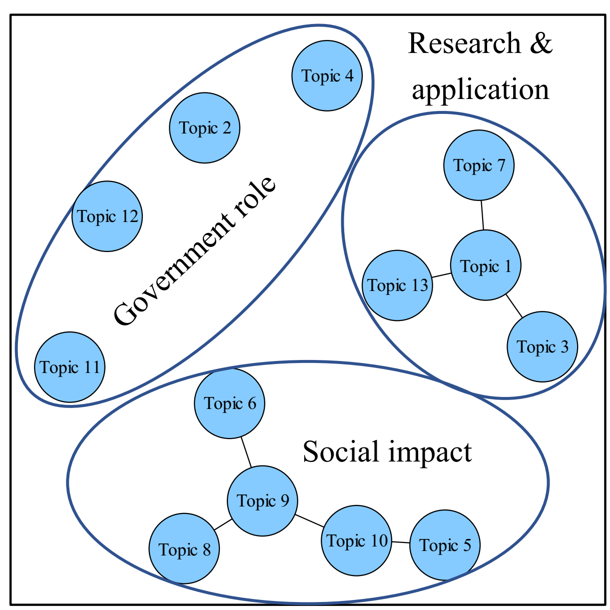


**Fig. 4.** The relationships between different topics.

disruptions, and the need for institutional and cooperative governance. Based on these shared themes, this category is named "social impact". **(3) Government role:** This category includes topic 2 (government responsibility), topic 4 (research institute), topic 11 (policy pilot) and topic 12 (management agency). While these topics are not directly correlated at the data level (i.e., the correlation coefficients are not positive), we carefully deliberated and concluded that they all pertain to various aspects of government involvement, such as establishing new agencies, assigning new responsibilities, and implementing policy pilots. Thus, we grouped these topics under the "government role" category.

The topic prevalence is also inverestigated through the propotions of each topic in the entire policy texts, as shown in Fig. 5. As can be seen, topic 11 (policy pilot), topic 4 (research institute), topic 12 (management agency) are the most important topics in the policy texts, each accounting for more than 10 % of the total, while topic 6 (technological risk), topic 13 (scientific research), topic 8 (institutional system) and topic 5 (impact on work) received the least attention in the policy text, with the proportion less than 5 % each. Taken together with the relationships between the different topics, it can be inferred that the topics under "government role" are mentioned most frequently in the policy texts, while the topics under "social impact" receive relatively the least attention.

### 5.3. Covariate effect estimation of each topic

STM allows the effect of covariates on topic prevalence to be estimated. In this study, we expected the year and region in which the policy was issued to have an effect on topic prevalence, and the corresponding results are shown in Fig. 6, which displays the change in the prevalence of each topic in China, the EU, and the US over time.

#### 5.3.1. Industrial application

In the early stages, China highly focused much more on the industrial application of AI than the EU and the US. From the overall trend, the topic prevalence has decreased significantly in both China and the EU, with the exception of a slight increase in the US. This shift in focus could reflect a growing awareness among policymakers that AI is more than a technological advance with industrial applications, but has far-reaching implications for all facets of society. As a result, there may be a deliberate shift in policy priorities towards developing a more holistic approach to AI governance, encompassing not only economic benefits but also social, ethical and regulatory dimensions.

#### 5.3.2. Government responsibility

While governments undoubtedly play an important role in AI governance, the topic of government responsibility has only been widely mentioned in the US's AI policy, with little attention paid to it in China and the EU. This result suggests that the US prefers to clarify the various aspects of government responsibility in the AI era. This focus in the US may be indicative of a proactive strategy to deal with the regulatory and accountability challenges raised by AI, clarifying government roles and management boundaries to improve AI research and its impact on society.

#### 5.3.3. Technology standard

The topic prevalence of technology standard in China's AI policy is higher than in the EU and the US, as China has set standards for AI software in the medical industry. In three regions, the topic has become more prevalent over time, indicating a concerted desire to regulate AI through standards. However, the increase of topic prevalence is rather minimal, reflecting the challenges in balancing the need for standardization with the complexity of AI and the diversity of its application scenarios. In this regard, there should be ongoing discussions among stakeholders to develop comprehensive, flexible and adaptable standards.

#### 5.3.4. Research institute

Compared to China and the EU, the US places more emphasis on the research institute in its AI policy. Although the prevalence of this topic has declined over time, it remains relatively high. This finding suggests that the US prefers top-down initiatives to establish AI research institutes, building strong ties and partnerships between politics and academia. It underscores the significance of research institute as catalysts for technological progress and as centers for cultivating the talent to propel AI, which is integral to maintaining a competitive edge in the global AI space.

#### 5.3.5. Impact on work

In the early stages, the EU was highly concerned about the impact of AI on work, for which it introduced a targeted policy. This topic is also partially mentioned in the US's AI policy. Overall, however, the topic prevalence has declined significantly over time, perhaps as a result of policies that prioritize other societal effects of AI rather than just its effects on the workplace. This pattern also points to a maturing viewpoint on AI, with initial concerns about employment displacement are part of a more comprehensive dialogue about integrating AI into society responsibly and ethically.

#### 5.3.6. Technological risk

The EU was the first to pay attention to the technological risks of AI, followed by an increasing trend of AI policies in China and the US mentioning technological risks. This progression underscores a growing global recognition of the technological risk in AI deployment, including security vulnerabilities, ethical dilemmas, algorithmic biases. Therefore, global AI governance is increasingly focused on proactive measures to identify, assess, and mitigate potential risks, ensuring that AI is deployed in a manner that is consistent with societal values.

#### 5.3.7. Talent education

Compared to other countries, China's AI uniquely prioritizes talent education, with several targeted initiatives aimed at reshaping educational frameworks to meet the needs of the AI era. This distinct approach highlights China's strategic investment in cultivating skilled AI workforces, viewing talent development as a crucial component of its long-term AI strategy. This emphasis on education indicates a top-down, policy-driven commitment to building a strong foundation in AI expertise and research.

#### 5.3.8. Institutional system

Early AI policies in China, the EU and the US did not include much content on the institutional system, as institutional building lagged behind technological development. However, over time, there has been a notable shift towards emphasizing the institutional system in policymaking, especially in the EU. This trend indicates a collective recognition of the importance of establishing robust institutional structures for AI governance. This move towards institutionalization represents an effort to align technological innovation with structured governance, ensuring that AI advances in a controlled, ethical, and socially beneficial manner.

#### 5.3.9. Human right

The ideas of human rights initially featured prominently in the EU's AI policy, followed by the gradual recognition of its importance by China and the United States. This evolution signifies a pivotal shift in AI governance, moving from a focus primarily on technological advancement to a more people-centric approach. Therefore, there is an acknowledgment that AI, while a powerful tool for progress, must be managed in a way that prioritizes individual rights and freedoms, thereby aligning technological growth with the fundamental values of human society.

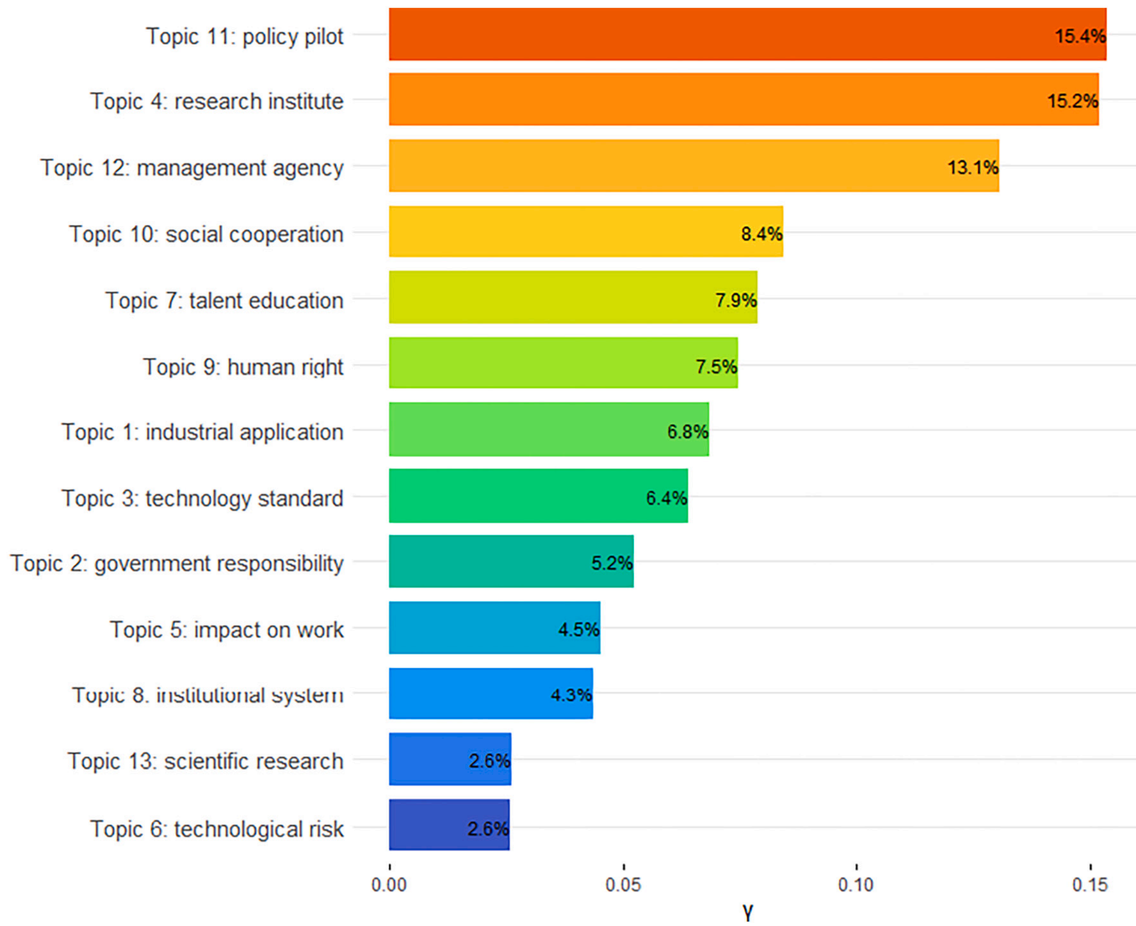


**Fig. 5.** Topic prevalence in the policy texts.

### 5.3.10. *Social cooperation*

The EU's AI policy strongly advocates for the advancement of AI through widespread societal collaboration, encompassing member states, governments, academic institutions, and industry sectors. This policy stance is rooted in the belief that AI's success hinges on a unified effort and a collective approach, thereby leveraging diverse expertise and resources to create an inclusive, innovative AI ecosystem.

### 5.3.11. *Policy pilot*

As a tool for policy experimentation and innovation, policy pilots have attracted considerable attention, particularly in China's AI policy. China has initiated several AI policy pilot zones, aiming to address the intricate governance challenges presented by AI. These zones, authorized by the central government, allow local governments a great deal of autonomy in execution and adaptation. This pragmatic and flexible approach enables a diverse range of governance models to be tested, providing valuable insights into effective AI policy strategies that can be scaled or adapted based on local experiences and outcomes.

### 5.3.12. *Management agency*

The topic of management agency received little attention in China or the EU's AI policies and has predominantly been a focus in the US, where it demonstrates a clear upward trend. This pattern suggests that the US is actively adapting its management structures to accommodate the swift and transformative changes brought about by AI technologies, aiming to ensure that AI governance keeps pace with the rapid advancements in the field.

### 5.3.13. *Scientific research*

The prominence of scientific research in AI policies has been on the rise across China, the EU, and the US, reflecting a collective recognition of its critical role in driving AI development and innovation. Specifically, the success and ethical integrity of AI advancements are deeply rooted in scientific research, as it not only accelerates the breadth and depth of AI applications, but also promotes trustworthy and responsible AI systems.

In summary, from a regional perspective, China's AI policy prioritizes topics under the "research and application" category, such as industrial application, technological standard, talent education, with the exception of policy pilot topic; the EU's AI policy emphasizes topics under the "social impact" category, including impact on work, technological risks, institutional system, human rights and social cooperation; and the US's AI policy pays more attention to topics under the "government role" category, including government responsibility, research institution and management agency.

From the temporal standpoint, the topics of institutional system, human right and scientific research have gradually taken their place in AI policy in both China, the EU, and the US, indicates a potential paradigm shift in AI governance. Despite their current relatively low prevalence, as depicted in Fig. 6, the growing focus on these topics suggests an evolving understanding of the complex dimensions of AI. This trend may portend a more holistic approach to future AI governance, incorporating not just technological advancements but also ethical, legal, and institutional considerations, thus promoting the integration of AI into society in a way that is both innovative and consistent with human values and institutional structures.

## 6. Discussion

This study addresses key questions in the theory and practice of AI

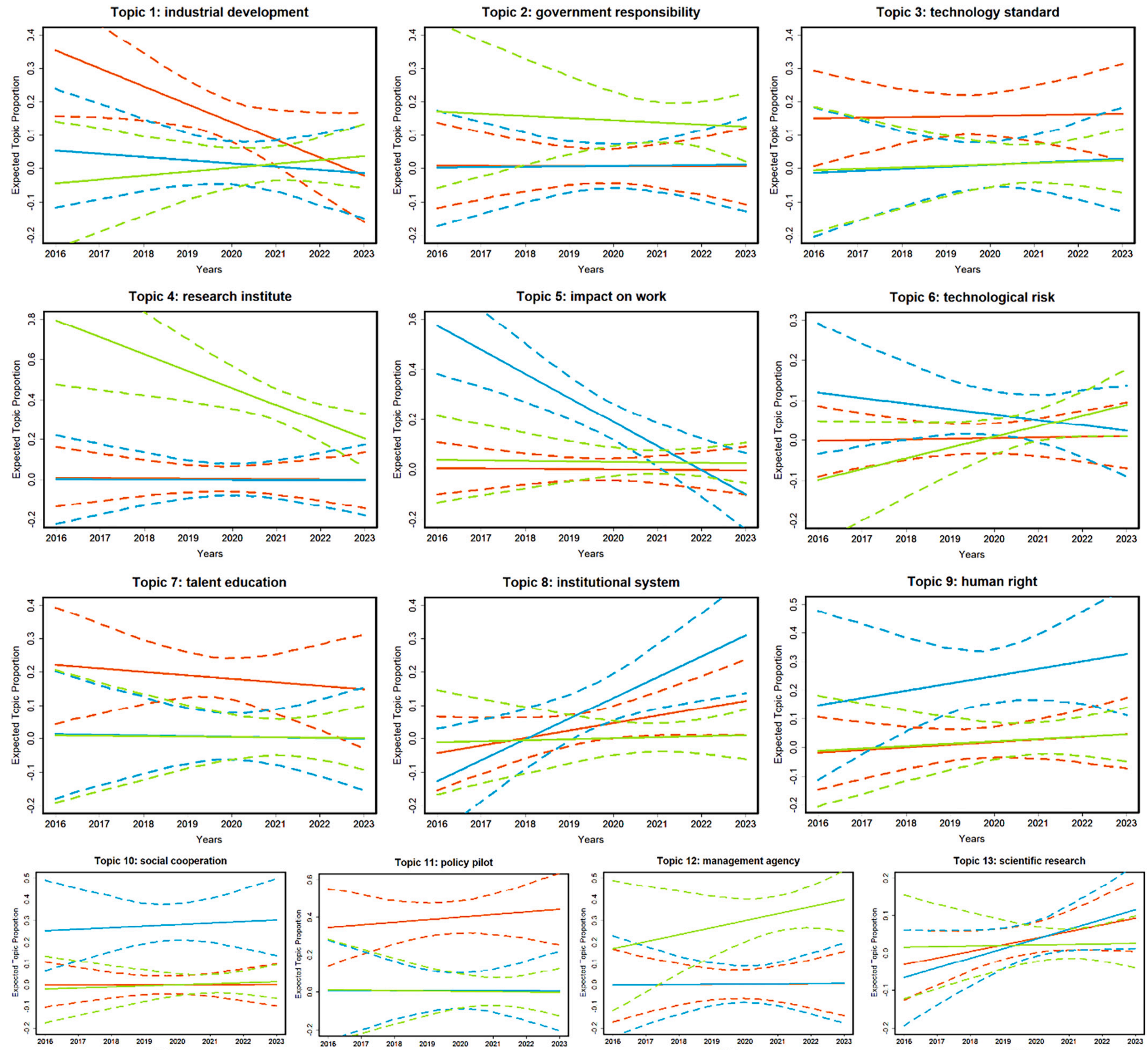


**Fig. 6.** Covariate effect estimation of topic prevalence
Note: Red represents China, blue represents the EU, and green represents the US, with the solid line representing the fitted line and the dashed line representing the 95 % confidence interval (CI). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

governance, focusing on the structure and diversity of AI policy frameworks. By applying STM to 139 AI policy texts from China, the EU, and the US, the study offers novel insights into policy framework for AI governance, making explicit contributions to both scholarship and practice.

### 6.1. Main findings

The findings from our analysis provide a comprehensive policy framework for AI governance, as shown in Fig. 7. It identifies three key categories: government role, research and application, and social impact, which align with the concept of AI governance by emphasizing the interaction of multiple actors within networks to appropriately develop, implement, and regulate AI (Roberts et al., 2021; Ulnicane et al., 2021; Wilson, 2022).

This figure extends AI governance by exploring the inherent elements and bidirectional interactions within and between each category. Firstly, the top left of the figure illustrates the relationship between the government role and research & application. Governments play a pivotal role in enabling AI research and application by setting strategic priorities, making macro-level judgments, and establishing specialized agencies. These initiatives are supported by policy experimentation and resource allocation. Conversely, advancements in AI research and application contribute not only to industry development and policy input but also introduce governance challenges, requiring governments to assume new responsibilities. These dynamics foster public-private partnerships, ensuring alignment between innovation and governance. Secondly, the bottom of the figure highlights the interaction between research & application and social impact. Technological advancements in AI drive profound social changes, including standard spillovers and

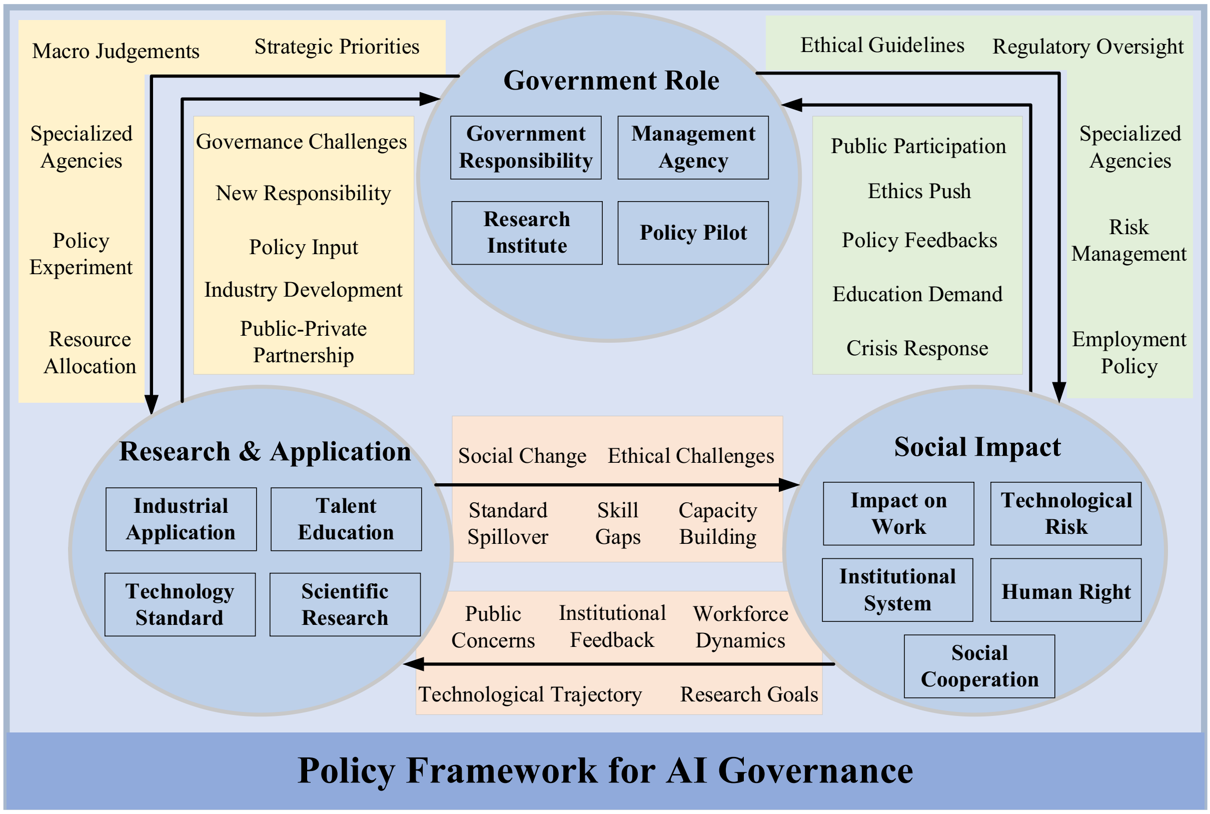


**Fig. 7.** Policy framework for AI governance.

capability building through education and training. However, they also raise challenges, such as ethical dilemmas and skill gaps, necessitating adaptive societal responses. Simultaneously, social responses—such as public concerns, institutional feedback, and workforce dynamics—shape the technological trajectory and research goals of AI. This reciprocal relationship underscores the role of societal actors, as end-users of AI technologies, in influencing innovation to meet public expectations and values. Thirdly, the top right of the figure focuses on the interaction between the government role and social impact. Governments uphold public values by issuing ethical guidelines, conducting regulatory oversight, and implementing risk management strategies. These efforts are supported by the creation of specialized agencies to monitor AI developments and employment policies to mitigate labor market disruptions. Furthermore, societal actors actively shape governance by making ethics pushes, providing policy feedback, and engaging in public discourse. These activities not only prompt governments to integrate ethical considerations into AI governance but also call for public investments in education and crisis responses, ensuring societal needs are adequately addressed.

Among them, the government role is highlighted as the most frequently mentioned and influential actor. Therefore, the network of multiple actors is centralized and integrated by the government, which is responsible on promoting industry and scientific research, as well as preventing technological risks and safeguarding ethical considerations to ensure effective governance of AI systems (Provan and Milward, 1995). However, the limited emphasis on social impact suggests an imbalance between development-driven priorities and broader societal considerations in AI governance. This underrepresentation suggests that current frameworks may inadequately address ethical concerns, public engagement, and the societal trust needed to ensure AI systems align with public interests alongside innovation goals (Wilson, 2022; James and Whelan, 2022; Cath et al., 2018).

Our analysis further explores how the policy frameworks for AI governance differ among China, the EU, and the US. While there are overlapping elements in AI governance, China prioritizes “research and application”, the EU emphasizes social impact, and the US focuses on the government role. In China, the government adopts a distinct approach by operating under a government-led governance model while granting a great deal of autonomy to the AI industry and academic research (Mertha, 2009; Zhu and Zhao, 2021). The central government formulates broad supportive policies and establishes policy pilots to create a permissive environment for AI development. It actively promotes talent training, encourages innovation, and allows for trial and error, reflecting its political tradition of “crossing the river by feeling the stones” (Roberts et al., 2023; Tuzov and Lin, 2024). This approach underscores China’s view of AI as a critical tool for economic growth and national competitiveness (Bareis and Katzenbach, 2022). For the EU, its focus on “social impact” in AI governance reflects a cautious stance on high technology and a strong regulatory tradition. By leveraging AI to uphold fundamental rights and promote public welfare, the EU fosters public trust and unifies member states around human-centered values, thereby legitimizing the EU’s role as a supranational political and administrative entity (Roberts et al., 2023; Robinson, 2020; von Essen and Ossewaarde, 2024). This regulatory-driven strategy also harmonizes the European market and enables the EU to exert the Brussels Effect, influencing global regulatory frameworks and solidifying its role as an ethical leader in international AI governance (Krarup and Horst, 2023; Bradford, 2020). In the US, while it is often considered a market-led governance model, significant emphasis is placed on the “government role” in AI governance. The government coordinates market dynamics and supports industries through national strategies, specialized agencies, and targeted investments (Dignam, 2020). To maintain global technological leadership in AI, it employs a dual strategy: expanding access to foreign markets to drive industrial growth and influence global standards, while implementing technological restrictions to block competitors and protect critical innovations. This approach ensures the safeguarding of technological dominance, bolsters economic competitiveness, and reinforces national security (Sampath, 2021; Roberts et al., 2021; Bareis and Katzenbach, 2022).

It should be noted that a common trend is observed across China, the EU, and the US, as all three increasingly emphasize scientific research, institutional systems and human rights to uphold the ethical considerations of AI governance while pursuing scientific advances. While the EU has consistently prioritized these aspects due to its human-centered values and regulatory tradition, the recent shifts in focus in China and the US reflect a governance mindset of "development first, management second." This shift has become particularly evident in response to the emergence of various negative social events involving AI, such as algorithmic bias, privacy breaches, and labor market disruptions. The growing calls from the scientific community, heightened public scrutiny of AI systems, the transnational nature of AI's societal impacts, and the mounting pressure to develop responsible AI have all played a significant role in driving this trend (Dignam, 2020; Sampath, 2021; Taeihagh, 2021; Zhang et al., 2021).

### 6.2. Theoretical implications

First, this study provides a comprehensive policy framework for AI governance by identifying three critical categories and their and elaborating on their intrinsic elements, mutual relationships. This framework not only encompasses the key topics widely discussed in existing academic literature but also addresses previously unexplored aspects, offering insights into governance priorities, action strategies, and future directions for AI (Yang and Huang, 2022). Moreover, it accounts for the interdependencies between policy drivers, technological developments, and societal impacts, proposing a balanced and dynamic approach for AI governance (Roberts et al., 2021; Wilson, 2022; Yu et al., 2022). Therefore, by capturing the complexity of governance dynamics, this framework bridges the gap between fragmented approaches to AI governance, presenting an integrated and holistic perspective that advances the theoretical understanding of AI governance (Birkstedt et al., 2023; Sigfrids et al., 2022a; Batool et al., 2023).

Second, the study highlights the strategic focus of China, the EU, and the US in AI governance, shaped by their distinct political and cultural contexts. As global leaders, these regions share overarching objectives but differ in emphasis: China prioritizes "research and application", the EU emphasizes "social impact", and the US focuses on "government role". Therefore, while their grand narratives on AI governance are isomorphic, their specific policy actions differ significantly (Guenduez and Mettler, 2023; Djeffal et al., 2022). Despite differing motivations, all three increasingly prioritize institutional systems to address technological risks and uphold human rights (Wu et al., 2020; Li et al., 2023). These findings underscore the influence of political and cultural systems on national AI strategies, provide nuanced insights into the evolving dynamics of global AI governance, and lay foundation for future international collaboration.

Third, this study introduces a novel method for policy text analysis, advancing the application of computational tools in social science research. STM proves particularly effective in handling large volumes of unstructured textual data, enabling the identification of latent topics, topic interrelationships, prevalence patterns and covariate effects (Hollibaugh, 2019). By fostering a synergy between human expertise and automated algorithms, STM diminishes human biases, enhances objectivity, and integrates interpretability into machine-driven insights. Therefore, STM significantly advances data-driven theory development and practical evaluation in policy research. Furthermore, STM demonstrates analytical versatility, with applications extending to news articles, academic research, social media content, and technology patents, offering broad utility to academic and practical research endeavors (Guenduez and Mettler, 2023; Choi and Woo, 2022; Bagozzi and Berliner, 2018).

### 6.3. Practical implications

First, AI governance emphasizes the discursive processes among multiple stakeholders to achieve consensus. Governments must consider the diverse interests and perspectives of these stakeholders and take responsibility for integrating their voices, balancing industry and research development with ethical and regulatory frameworks. While industry and research priorities often align with national goals for technological and economic advancement, ethical considerations require greater attention. These risks are exacerbated when ethical concerns are overlooked or reduced to superficial gestures, potentially undermining the objectives of responsible AI governance (Ulnicane et al., 2021; Fatima et al., 2022). To address this, governments should adopt a human-centered approach, rooted in principles of human rights and social well-being, to establish robust institutional frameworks that prioritize ethics in AI. Such frameworks ensure responsible innovation, reinforce public trust, and create a positive feedback loop that sustains both technological development and societal confidence. Bridging the gap between policy intentions and practical implementation is essential, as effective governance ultimately depends on the ability to translate ethical and regulatory standards into actionable outcomes. By anchoring AI governance in ethical imperatives and aligning it with societal needs, policymakers can foster a balanced environment where innovation and trust coexist.

Second, public participation plays a pivotal role in ensuring that AI governance aligns with ethical considerations and serves the public interest, as citizens—being the final users of AI products—can provide valuable insights into their societal implications. However, current mechanisms for public engagement are often limited to performative gestures rather than substantive commitments, lacking the structures needed for meaningful participation (Kerr et al., 2020; Wilson, 2022). To address this, governments must establish robust mechanisms to facilitate explicit and genuine public involvement in AI governance. Examples include engaging citizens in informed discussions on specific AI-related issues, creating diverse panels to propose recommendations on ethical standards or deployment strategies, establishing online platforms for feedback and reporting algorithmic harms, and conducting open forums for deliberation on regulatory proposals or standards. In addition to developing mechanisms, capacity-building initiatives are essential to empower citizens with the knowledge and skills needed for effective participation (Wang and Liang, 2024). Educational campaigns, workshops, and accessible resources can bridge the knowledge gap, particularly given the technical complexity of AI. These efforts ensure that participation is both inclusive and impactful, enabling citizens to contribute as informed and active stakeholders in the governance process.

Third, AI governance requires industry and academia to build a comprehensive technological ecosystem that engages stakeholders across the entire AI lifecycle, from design and development to deployment and monitoring (Minkkinen et al., 2022). Central to this effort is the need to foster technical consensus on critical issues such as interpretability, fairness, and robustness. Consensus-building facilitates cross-sector collaboration, aligning industry, academia and other stakeholders on shared priorities. Building on this foundation, the establishment of clear and enforceable industry-wide standards becomes essential to ensure both technical performance and ethical accountability. These standards tackle key challenges, including algorithmic bias, privacy concerns, and AI misuse, fostering public trust and mitigating risks that could erode confidence in AI technologies (Straub et al., 2023). By integrating collaborative consensus-building with enforceable standards, industry and academia can create a governance ecosystem that balances technological progress with ethical imperatives, laying the groundwork for value-driven innovation and sustainable development.

Fourth, international cooperation is crucial for AI governance due to the global nature of its challenges and opportunities. Effective collaboration requires recognizing and respecting the political systems, economic priorities, and cultural values that shape national governance frameworks. While divergent interests may create obstacles, dialogue rooted in mutual trust and shared goals—such as establishing global ethical standards, ensuring AI system interoperability, and addressing transnational issues like algorithmic bias, cybersecurity, and cross-border data governance—can help bridge differences (Roberts et al., 2021; Roberts et al., 2023; Tuzov and Lin, 2024). To achieve this, international frameworks should aim to harmonize governance standards while allowing flexibility for local contexts. Practical mechanisms include multilateral agreements, global AI governance summits, and cross-border research collaborations that foster consensus, knowledge-sharing, and regulatory alignment. Additionally, ensuring equitable participation by supporting capacity-building and technology transfer for developing nations is essential for a fair and inclusive AI governance model (Sampath, 2021). These efforts collectively lay the foundation for a global governance system that balances innovation with societal well-being, promoting ethical AI development on a sustainable scale.

### 6.4. Limitations and future directions

This study has some limitations that can be improved by future research. First, the analysis focuses on the AI policy texts of three leading actors—China, the EU, and the US—which do not encompass the full diversity of global AI governance perspectives. Future research should expand to include not only other key players, such as India, Japan, and South Korea, but also less-developed nations. This would enhance the comprehensiveness and inclusivity of global AI governance analysis, reflecting the needs and challenges of a broader spectrum of stakeholders. Second, while the STM approach effectively integrates subjective judgment with data-driven insights, it also inherits limitations from both. Its reliance on pre-processing techniques and the subjectivity in interpreting topic models may impact the consistency of findings. Combined with the broad scope of policies analyzed, this could limit the depth of insights into individual documents and unique contexts. Future research could address these challenges by incorporating qualitative analyses and triangulating STM results with other methods to better capture the subtleties and implications of specific policies.Third, this study examines primarily legally binding policy texts, which represent formal policy frameworks in AI governance. However, multilateral organizations and global conferences also contribute significantly to AI governance through policy initiatives and governance principles,[8] warranting further investigation into their narratives and frameworks. Fourth, it is acknowledged that "what the text says" and "what is actually done" in public policy can sometimes diverge significantly. Future research can take qualitative methods to carefully trace the dynamics and complexities in the policy chain from formulation to implementation. In this respect, our analysis can serve as a baseline for subsequent detailed research. Lastly, policy frameworks represent only one lens through which to observe global AI governance. Expanding the analysis to include think-tank reports, news articles, and conference proceedings could offer additional dimensions for understanding AI governance in practice.

## 7. Conclusion

In the context of the fast-paced evolution of AI governance, this study provides a comprehensive analysis of policy frameworks from leading entities—China, the EU, and the US—using the STM technique. The findings identify 13 topics grouped into 3 categories, uncovering distinct governance priorities and consistent development trends across these regions. These results culminate in a policy framework for AI governance that integrates a structured approach with dynamic interrelationships. Theoretically, this study offers nuanced insights into global AI governance, explores divergent priorities and shared trends among key actors, and advances methodology for policy analysis. Practically, it highlights the need to balance industry development with ethical imperatives, foster public participation, build robust technological ecosystems, and promote international cooperation. Future research could build upon these efforts by expanding the analysis to include other developed and less-developed nations, triangulating STM results with complementary analytical methods, incorporating multilateral efforts and non-legally binding governance frameworks, addressing the gap between policy design and implementation, and exploring alternative materials such as think-tank reports and news articles. These directions aim to enhance the comprehensiveness and depth of AI governance research while addressing emerging challenges in this evolving field.

## CRediT authorship contribution statement

**Shangrui Wang:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yuanmeng Zhang:** Data curation, Formal analysis, Investigation, Validation, Writing – review & editing. **Yiming Xiao:** Writing – review & editing, Validation, Methodology, Funding acquisition, Data curation. **Zheng Liang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

## Fundings

This work was supported by National Science and Technology Major Project (2023ZD0121700); Tsinghua University Independent Research Program (20223080026); Beijing Innovation Center of Humanities and Social Sciences; and the 2024 Philosophy and Social Science Planning Project of Guangdong Province (GD24YGL20);

## Declaration of competing interest

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

## Appendix A

[8] Global framework proposed by relevant multilateral organizations include The G20 AI Principles, 2019 OECD Principles on Artificial Intelligence, 2021 UNESCO Recommendation on the Ethics of AI; and relevant global conferences include AI for Good Global Summit, IEEE's Global Initiative on Ethics of Autonomous and Intelligent Systems, International AI Cooperation and Governance Forum.

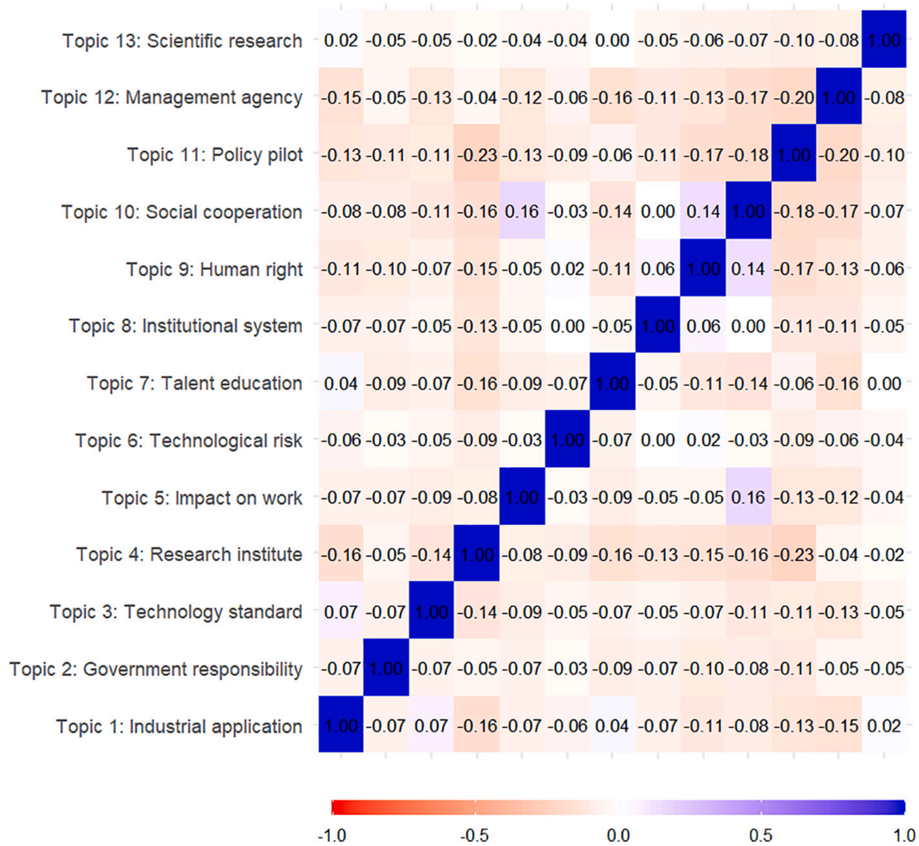


**Fig. A1.** Topic correlation matrix.

## Data availability

Data will be made available on request.

## References


Af Malmborg, F., Trondal, J., 2021. Discursive framing and organizational venues: mechanisms of artificial intelligence policy adoption. Int. Rev. Adm. Sci. 89, 39–58. https://doi.org/10.1177/00208523211007533.

Bagozzi, B.E., Berliner, D., 2018. The politics of scrutiny in human rights monitoring: evidence from structural topic models of US state department human rights reports. Polit. Sci. Res. Methods 6, 661–677. https://doi.org/10.1017/psrm.2016.44.

Bai, X., Zhang, X., Li, K.X., Zhou, Y., Yuen, K.F., 2021. Research topics and trends in the maritime transport: a structural topic model. Transp Policy (Oxf) 102, 11–24. https://doi.org/10.1016/j.tranpol.2020.12.013.

Bareis, J., Katzenbach, C., 2022. Talking AI into being: the narratives and imaginaries of national AI strategies and their performative politics. Sci. Technol. Hum. Values 47, 855–881. https://doi.org/10.1177/01622439211030007.

Batool, A., Zowghi, D., Bano, M., 2023. Responsible AI governance: a systematic literature review. Arxiv Preprint Arxiv:2401.10896.

Birkstedt, T., Minkkinen, M., Tandon, A., Mäntymäki, M., 2023. AI governance: themes, knowledge gaps and future agendas. Internet Res. 33, 133–167. https://doi.org/10.1108/INTR-01-2022-0042.

Blei, D.M., 2012. Probabilistic topic models. Commun. ACM 55, 77–84. https://doi.org/10.1145/2133806.2133826.

Bradford, A., 2020. The Brussels Effect: How the European Union Rules the World. Oxford University Press.

Castro, D., Mclaughlin, M., 2021. Who Is Winning the AI Race: China, the EU, or the United States? — 2021 Update.

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., Floridi, L., 2018. Artificial intelligence and the 'good society': the US, EU, and UK approach. Sci. Eng. Ethics 24, 505–528. https://doi.org/10.1007/s11948-017-9901-7.

Charmaz, K., 2015. Grounded theory. Qualitative Psychology: A Practical Guide to Research Methods 3, 53–84.

Choi, H., Woo, J., 2022. Investigating emerging hydrogen technology topics and comparing national level technological focus: patent analysis using a structural topic model. Appl. Energy 313, 118898. https://doi.org/10.1016/j.apenergy.2022.118898.

de Almeida, P.G.R., Dos Santos, C.D., Farias, J.S., 2021. Artificial intelligence regulation: a framework for governance. Ethics Inf. Technol. 23, 505–525. https://doi.org/10.1007/s10676-021-09593-z.

Desiere, S., Struyven, L., 2021. Using artificial intelligence to classify jobseekers: the accuracy-equity trade-off. J. Soc. Policy 50, 367–385. https://doi.org/10.1017/S0047279420000203.

Dignam, A., 2020. Artificial intelligence, tech corporate governance and the public interest regulatory response. Camb. J. Reg. Econ. Soc. 13, 37–54. https://doi.org/10.1093/cjres/rsaa002.

Djeffal, C., Siewert, M.B., Wurster, S., 2022. Role of the state and responsibility in governing artificial intelligence: a comparative analysis of AI strategies. J Eur Public Policy. https://doi.org/10.1080/13501763.2022.2094987.

Dwivedi, Y.K., Sharma, A., Rana, N.P., Giannakis, M., Goel, P., Dutot, V., 2023. Evolution of artificial intelligence research in technological forecasting and social change: research topics, trends, and future directions. Technol Forecast Soc Change 192, 122579. https://doi.org/10.1016/j.techfore.2023.122579.

Fatima, S., Desouza, K.C., Buck, C., Fielt, E., 2022. Public AI canvas for ai-enabled public value: a design science approach. Gov. Inf. Q. 39, 1–16. https://doi.org/10.1016/j.giq.2022.101722.

Fatima, S., Desouza, K.C., Dawson, G.S., 2020. National strategic artificial intelligence plans: a multi-dimensional analysis. Econ Anal Policy 178–194.

Fatima, S., Desouza, K.C., Denford, J.S., Dawson, G.S., 2021. What explains governments interest in artificial intelligence? A signaling theory approach. Economic Analysis and Policy 71, 238–254. https://doi.org/10.1016/j.eap.2021.05.001.

Filgueiras, F., 2022. The politics of AI: democracy and authoritarianism in developing countries. J Inf Technol Politics 19, 449–464. https://doi.org/10.1080/19331681.2021.2016543.

Glaser, B., Strauss, A., 2017. Discovery of Grounded Theory: Strategies for Qualitative Research. Routledge.

Guenduez, A.A., Mettler, T., 2023. Strategically constructed narratives on artificial intelligence: what stories are told in governmental artificial intelligence policies? Gov. Inf. Q. 40, 101719. https://doi.org/10.1016/j.giq.2022.101719.

Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. Calif. Manag. Rev. 61, 5–14. https://doi.org/10.1177/0008125619864925.

Hannigan, T.R., Haans, R.F.J., Vakili, K., Tchalian, H., Glaser, V.L., Wang, M.S., Kaplan, S., Jennings, P.D., 2019. Topic modeling in management research: rendering new theory from textual data. Acad. Manag. Ann. 13, 586–632. https://doi.org/10.5465/annals.2017.0099.

Hollibaugh, G.E., 2019. The use of text as data methods in public administration: a review and an application to agency priorities. J. Public Adm. Res. Theory 29, 474–490. https://doi.org/10.1093/jopart/muy045.
James, A., Whelan, A., 2022. 'ethical' artificial intelligence in the welfare state: discourse and discrepancy in australian social services. Crit. Soc. Policy 42, 22–42. https://doi.org/10.1177/0261018320985463.
Justo-Hanani, R., 2022. The politics of artificial intelligence regulation and governance reform in the european union. Policy. Sci. 55, 137–159. https://doi.org/10.1007/s11077-022-09452-8.
Kerr, A., Barry, M., Kelleher, J.D., 2020. Expectations of artificial intelligence and the performativity of ethics: implications for communication governance. Big Data Soc. 7. https://doi.org/10.1177/2053951a720915939.
Krarup, T., Horst, M., 2023. European artificial intelligence policy as digital single market making. Big Data Soc. 10, 74171027. https://doi.org/10.1177/20539517231153811.
Larsen BC. The geopolitics of AI and the rise of digital sovereignty; 2022. Available from: https://www.brookings.edu/articles/the-geopolitics-of-ai-and-the-rise-of-digital-sovereignty/ [Accessed.
Lee, S.E., Ju, N., Lee, K., 2023. Service chatbot: co-citation and big data analysis toward a review and research agenda. Technol Forecast Soc Change 194, 122722. https://doi.org/10.1016/j.techfore.2023.122722.
Li, B., Qi, P., Liu, B., Di, S., Liu, J., Pei, J., Yi, J., Zhou, B., 2023. Trustworthy AI: from principles to practices. ACM Comput. Surv. 55, 1–46. https://doi.org/10.1145/3555803.
Margetts, H.Z., Dorobantu, C.L., 2019. Rethink government with AI. Nature 568, 163–165. https://doi.org/10.1038/d41586-019-01099-5.
Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Ngo, H., Niebles, J.C., Parli, V., Shoham, Y., Wald, R., Clark, J., Perrault, R., 2023. Artificial intelligence index report 2023.
Mertha, A., 2009. "Fragmented authoritarianism 2.0": political pluralization in the chinese policy process. China Q. 200, 995–1012. https://doi.org/10.1017/S0305741009990592.
Minkkinen, M., Zimmer, M.P., Mantymaki, M., 2022. Co-shaping an ecosystem for responsible AI: five types of expectation work in response to a technological frame. Inf. Syst. Front. https://doi.org/10.1007/s10796-022-10269-2.
Nowlin, M.C., 2016. Modeling issue definitions using quantitative text analysis. Policy Stud. J. 44, 309–331. https://doi.org/10.1111/psj.12110.
Polyviou, A., Zamani, E.D., 2022. Are we Nearly There Yet? A desires & realities framework for europe's AI strategy, Inf Syst Front. https://doi.org/10.1007/s10796-022-10285-2.
Provan, K.G., Milward, H.B., 1995. A preliminary theory of interorganizational network effectiveness: a comparative study of four community mental health systems. Adm. Sci. Q. 40, 1–33. https://doi.org/10.2307/2393698.
Radu, R., 2021. Steering the governance of artificial intelligence: national strategies in perspective. Polic. Soc. 40, 178–193. https://doi.org/10.1080/14494035.2021.1929728.
Rhodes, R.A.W., 2007. Understanding governance: ten years on. Organ. Stud. 28, 1243–1264. https://doi.org/10.1177/0170840607076586.
Roberts, H., Cowls, J., Hine, E., Mazzi, F., Tsamados, A., Taddeo, M., Floridi, L., 2021. Achieving a 'good AI society': comparing the aims and progress of the EU and the US. Sci. Eng. Ethics 27. https://doi.org/10.1007/s11948-021-00340-7.
Roberts, H., Cowls, J., Hine, E., Morley, J., Wang, V., Taddeo, M., Floridi, L., 2023. Governing artificial intelligence in China and the european union: comparing aims and promoting ethical outcomes. Inf. Soc. 39, 79–97. https://doi.org/10.1080/01972243.2022.2124565.
Roberts, M.E., Stewart, B.M., Tingley, D., 2019. Stm: an r package for structural topic models. J. Stat. Softw. 91, 1–40. https://doi.org/10.18637/jss.v091.i02.
Roberts, M.E., Stewart, B.M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S.K., Albertson, B., Rand, D.G., 2014. Structural topic models for open-ended survey responses. Am. J. Polit. Sci. 58, 1064–1082. https://doi.org/10.1111/ajps.12103.
Robinson, S.C., 2020. Trust, transparency, and openness: how inclusion of cultural values shapes nordic national public policy strategies for artificial intelligence (AI). Technol. Soc. 63. https://doi.org/10.1016/j.techsoc.2020.101421.
Sampath, P.G., 2021. Governing artificial intelligence in an age of inequality. Glob Policy 12, 21–31. https://doi.org/10.1111/1758-5899.12940.
Saveliev, A., Zhurenkov, D., 2021. Artificial intelligence and social responsibility: the case of the artificial intelligence strategies in the United States, Russia, and China. Kybernetes 50, 656–675. https://doi.org/10.1108/K-01-2020-0060.
Sharma, A., Rana, N.P., Nunkoo, R., 2021. Fifty years of information management research: a conceptual structure analysis using structural topic modeling. Int. J. Inf. Manag. 58, 102316. https://doi.org/10.1016/j.ijinfomgt.2021.102316.
Sigfrids, A., Nieminen, M., Leikas, J., Pikkuaho, P., 2022a. How should public administrations foster the ethical development and use of artificial intelligence? A review of proposals for developing governance of AI. Frontiers in human. Dynamics 4.
Sigfrids, A., Nieminen, M., Leikas, J., Pikkuaho, P., 2022b. How should public administrations foster the ethical development and use of artificial intelligence? A review of proposals for developing governance of AI. Frontiers in human. Dynamics 4.
Straub, V.J., Morgan, D., Bright, J., Margetts, H., 2023. Artificial intelligence in government: concepts, standards, and a unified framework. Gov. Inf. Q. 40, 101881. https://doi.org/10.1016/j.giq.2023.101881.
Sullivan M. Global AI regulation: a closer look at the US, EU, and china; 2023. Available from: https://transcend.io/blog/ai-regulation [Accessed.
Taeihagh, A., 2021. Governance of artificial intelligence. Policy Soc 40, 137–157. https://doi.org/10.1080/14494035.2021.1928377.
Tamakloe, R., Park, D., 2023. Discovering latent topics and trends in autonomous vehicle-related research: a structural topic modelling approach. Transp Policy (Oxf) 139, 1–20. https://doi.org/10.1016/j.tranpol.2023.06.001.
Tonidandel, S., Summerville, K.M., Gentry, W.A., Young, S.F., 2022. Using structural topic modeling to gain insight into challenges faced by leaders. Leadersh. Q. 33, 101576. https://doi.org/10.1016/j.leaqua.2021.101576.
Tuzov, V., Lin, F., 2024. Two paths of balancing technology and ethics: a comparative study on AI governance in China and Germany. Telecomm. Policy, 102850. https://doi.org/10.1016/j.telpol.2024.102850.
Ulnicane, I., Knight, W., Leach, T., Stahl, B.C., Wanjiku, W.G., 2021. Framing governance for a contested emerging technology:insights from AI policy. Polic. Soc. 40, 158–177. https://doi.org/10.1080/14494035.2020.1855800.
Valle-Cruz, D., Criado, J.I., Sandoval-Almazán, R., Ruvalcaba-Gomez, E.A., 2020. Assessing the public policy-cycle framework in the age of artificial intelligence: from agenda-setting to policy evaluation. Gov. Inf. Q. 37, 101509. https://doi.org/10.1016/j.giq.2020.101509.
von Essen, L., Ossewaarde, M., 2024. Artificial intelligence and european identity: the european commission's struggle for reconciliation. Eur. Politics Soc. 25, 375–402. https://doi.org/10.1080/23745118.2023.2244385.
Wang, S., Liang, Z., 2024. What does the public think about artificial intelligence? An investigation of technological frames in different technological context. Gov. Inf. Q. 41, 101939. https://doi.org/10.1016/j.giq.2024.101939.
Wilson, C., 2022. Public engagement and AI: a values analysis of national strategies. Gov. Inf. Q. 39, 101652. https://doi.org/10.1016/j.giq.2021.101652.
Wu, W., Huang, T., Gong, K., 2020. Ethical principles and governance technology development of AI in China. Engineering 6, 302–309. https://doi.org/10.1016/j.eng.2019.12.015.
Yang, C., Huang, C., 2022. Quantitative mapping of the evolution of AI policy distribution, targets and focuses over three decades in China. Technol forecast. Soc Change 174. https://doi.org/10.1016/j.techfore.2021.121188.
Yu, Z., Liang, Z., Xue, L., 2022. A data-driven global innovation system approach and the rise of china's artificial intelligence industry. Reg. Stud. 56, 619–629. https://doi.org/10.1080/00343404.2021.1954610.
Zhang, Y., Wu, M., Tian, G.Y., Zhang, G., Lu, J., 2021. Ethics and privacy of artificial intelligence: understandings from bibliometrics. Knowl.-Based Syst. 222, 106994. https://doi.org/10.1016/j.knosys.2021.106994.
Zhu, X., Zhao, H., 2021. Experimentalist governance with interactive central–local relations: making new pension policies in China. Policy Stud. J. 49, 13–36. https://doi.org/10.1111/psj.12254.

**Shangrui Wang** is a PhD candidate at School of Public Policy & Management, Tsinghua University. His research focuses on public policy and AI governance. He has published in Government Information Quarterly, Technology in Society, and so on.

**Yuanmeng Zhang** is a PhD candidate at School of Public Policy & Management, Tsinghua University. Her research focuses on digital governance. She has published in Cities, Computer in Human Behavior and so on.

**Yiming Xiao** is an associate professor at School of Public Administration, South China Agricultural University. His research focuses on energy poverty and digital governance. He has published in Resources Conservation and Recycling, Journal of Clean Production and so on.

**Zheng Liang** is a professor at School of Public Policy & Management, Tsinghua University. His research focuses on science and technology policy, technological innovation and management. He has published in Regional Studies, International Journal of Technology Management and so on.