AI & SOCIETY
https://doi.org/10.1007/s00146-025-02466-9

OPEN FORUM

When AI meets AI: analyzing AI bills using AI

The chamber and partisan effects in U.S. AI Governance

Heonuk Ha[1]

Received: 25 January 2025 / Accepted: 24 June 2025

Abstract
With the rapid advancement of Artificial Intelligence (AI) technology and its pervasive integration into society, governments worldwide have introduced a range of AI-related policies. In the United States, the use of AI technology has surged significantly since 2021, driven by the emergence of generative AI and its transformative potential. In response, the U.S. Congress has proposed numerous AI-related bills, reflecting growing legislative engagement with AI governance. This study examines 204 AI-related bills introduced during the 117th and 118th Congresses (2021–2024) through computational text analysis, employing topic modeling to identify recurring legislative themes and sentiment analysis to assess congressional attitudes toward AI policies. The findings reveal distinct variations in legislative focus and tone across chambers and political parties, offering a nuanced understanding of how AI-related issues are framed within U.S. policymaking. In addition, the results highlight how AI is connected to broader opportunities and concerns, including national security, technological innovation, and public service delivery. By applying machine learning techniques to legislative texts, this research provides a systematic and scalable approach to understanding AI policymaking. The study contributes to broader discussions on the partisan and institutional dynamics shaping AI legislation in the United States, offering insights into how emerging technologies are shaped by legislative priorities, regulatory attitudes, and broader political contexts.

Keywords AI governance · Congressional law-making · Legislative analysis · Machine learning · Topic modeling · Sentiment analysis

1 Introduction

The rapid pace of technological advancement presents both opportunities and challenges for governments worldwide. Emerging technologies, such as artificial intelligence (AI), blockchain, and biotechnology, have the potential to revolutionize economies, transform work environments, enhance public services, and address pressing societal issues. In particular, over the past few decades, AI technology has evolved significantly, demonstrating major breakthroughs in computational power and efficiency. From early innovations like Deep Blue (1997) and AlexNet (2012) to the emergence of generative AI in 2020, AI's capabilities have rapidly expanded, enabling new applications across various sectors of society.[1]

However, these innovations have also intensified governance challenges, including regulatory gaps, ethical dilemmas, and disparities in access to their benefits. To govern effectively in this dynamic landscape, governments have struck a balance between fostering innovation and ensuring robust oversight, creating an environment that promotes progress while mitigating risks. In this rapidly evolving landscape, governments worldwide have adopted diverse AI regulatory strategies, reflecting varying political, economic, and geopolitical priorities. Through strategic planning and adaptive governance, governments have guided the development and responsible use of AI technologies across society and the public sector, striving to maximize their effectiveness while promoting equitable and transformative outcomes. This effort necessitates addressing complex trade-offs, such

✉ Heonuk Ha
heonukha@umich.edu

1 Institute for Social Research, University of Michigan–Ann Arbor, Ann Arbor, USA

1 Source: World Economic Forum, https://www.weforum.org/stories/2024/10/history-of-ai-artificial-intelligence/.

as fostering competition while safeguarding data privacy and mitigating social inequalities exacerbated by technological change. By navigating these challenges, governments have assumed a pivotal role in cultivating an environment where technological innovation drives societal progress and serves the broader public good.

In the U.S. system of governance, Congress plays a pivotal role in shaping AI policy, as legislative efforts provide the foundation for technology regulation, effective use, funding, and oversight. The process of law-making in Congress is inherently complex, shaped by partisan competition, institutional dynamics, and evolving policy priorities. Members of Congress (MCs) propose bills based on factors, such as chamber-specific considerations, party platforms, majority control, committee affiliations, and constituency interests (Gailmard and Jenkins 2007; Ballard 2022; Lewallen 2024). Therefore, previous research has explored agenda-setting and position-taking strategies in legislative behavior, particularly in areas like foreign policy (Wood and Peake 1998), public health (Weissert and Weissert 2008; Lazarus 2013), and education (Manna 2006). Although information and technology have long been regarded as critical to the United States' present and future interests, research on technology governance policy and the differing legislative priorities across parties and chambers remains underexplored, partly because it is widely perceived as a relatively less controversial and politically divergent policy area, particularly in AI policy (Zhang and Dafoe 2019).

With AI gaining strategic importance in national security, economic competitiveness, and global governance, congressional engagement with AI policymaking has intensified in recent years in the U.S. The United States, which hosts the world's one of the largest number of AI companies and employees, has seen a growing legislative response to AI-related issues.[2] Since AI policymaking in the U.S. remains decentralized, shaped by chamber-specific legislative priorities and partisan debates, this study seeks to understand how these institutional and partisan differences influence AI governance in the U.S. Congress.

This study examines 204 AI-related bills introduced in U.S. Congress between 2021 and 2024, employing computational text analysis techniques, including topic modeling and sentiment analysis. By analyzing these legislative texts, the research explores how agenda-setting and position-taking strategies shape congressional engagement with AI policy. The research specifically investigates the differing priorities and attitudes toward AI policy development across legislative chambers (House and Senate) and political parties (Democratic and Republican). Through topic modeling, the study identifies the key issues emphasized in these bills, highlighting legislators' focal areas. Additionally, sentiment analysis is employed to assess legislators' evaluative stances toward AI policy proposals, offering insights into the tone and orientation of congressional discourse on AI.

The remainder of the paper is organized as follows: Sect. 2 provides an overview of the legislative process in the U.S. Congress. Section 3 reviews relevant literature on congressional law-making, technology governance, and methods for bill and text analysis. Section 4 outlines the text-format bill datasets used in this study, while Sect. 5 details the content analysis techniques, both topic modeling and sentiment analysis. Section 6 presents the findings, highlighting the focus and sentiment of AI bills and evaluating how chamber and partisan differences influence legislative approaches. Finally, Sect. 7 outlines the study's contributions, acknowledges limitations, and proposes directions for future research to advance understanding of AI policymaking and governance.

2 Background: U.S. Congress and law-making

The U.S. Constitution grants all legislative powers to Congress, encompassing both the House of Representatives and the Senate.[3] As a result, Congress has played a pivotal role in the U.S. governance system under the separation-of-powers framework, particularly through the exercise of its legislative authority.

While both the House and the Senate must approve a bill for it to become law, reflecting the principle of equal representation for all states, the two chambers have distinct roles and processes. For instance, the Constitution (Article I, Sect. 7) grants the House exclusive authority to initiate tax and revenue, related legislation. Conversely, the Senate holds the unique power to draft and approve measures related to presidential nominations and treaties based on Article II, Sect. 2 of the Constitution. These differences underscore the complementary functions of the two chambers within the legislative process. In addition, institutional rules, such as the Senate filibuster, the House Rules Committee, and committee jurisdiction, play a critical role in shaping which issues reach the floor for debate.

[2] Source: Statista, https://www.statista.com/statistics/1452378/ai-distribution-by-country-worldwide/, https://www.statista.com/statistics/1428259/apac-perceived-likelihood-of-ai-transforming-jobs-by-country/.

[3] U.S. Constitution Article I—Section 1: "All legislative Powers herein granted shall be vested in a Congress of the United States, which shall consist of a Senate and House of Representatives." Source: https://constitution.congress.gov/constitution/article-1/.

In particular, the drafting, introduction, and passage of bills in Congress lie at the core of the federal government's legislative function, with each bill's trajectory illustrating the intricate interplay of political, institutional, and procedural forces. The legislative process commences when a member of Congress, referred to as the sponsor, formally introduces a bill. It is then referred to one or more standing committees based on its subject matter. If the bill withstands committee scrutiny, it proceeds to the floor of the originating chamber for debate and voting. Once approved, it advances to the other chamber, where it undergoes a comparable procedure. Final passage requires the assent of both chambers, after which the bill is presented to the President for enactment or veto (Oleszek et al. 2015).

The duration required for a bill to pass varies considerably, contingent upon factors, such as the bill's complexity, the prevailing political environment, and shifting legislative priorities. Key actors in this process include committee chairs, ranking members, and party leaders who negotiate compromises and advocate for party objectives (Anderson et al. 2003; Krutz 2005; Sinclair 2016). In addition, external stakeholders, such as lobbyists, federal agencies, and advocacy groups, exert influence by providing expertise and shaping public opinion, thereby affecting legislative outcomes.

Between the 80th Congress (1947–48) and the 117th Congress (2021–22), the House of Representatives introduced an average of 10,299 bills per 2-year session and passed approximately 1166 bills (including both public and private), yielding an average passage rate of 12.6%. Over the same period, the Senate introduced an average of 3819 bills and passed 1086 bills, resulting in an average passage rate of 28.3%.[4]

As technology continues to evolve at a rapid pace, Congress faces ongoing challenges to ensure that legislation remains timely and effective. The balance of innovation with regulation, the treatment of international competition, and the mitigation of societal risks remain pressing concerns. In response, Congress, across both chambers, has introduced a wide range of technology-related legislation addressing issues, such as research and development funding, intellectual property rights, and regulatory frameworks. In recent years, legislators have introduced numerous AI-specific bills, with particular attention to data privacy, algorithmic transparency, national security, and the societal implications of AI, especially during the 117th and 118th Congresses.

[4] Source: Brooking's Vital Statistics on Congress https://www.brookings.edu/articles/vital-statistics-on-congress.

3 Theoretical framework

3.1 Law-making and agenda-setting, position-taking

The federal law-making in the United States provides a rich context for examining how legislative chambers, political parties, and the individual constituents of members of Congress (MCs) influence legislative outcomes. Therefore, previous research has examined the effects of chamber, party, and individual member characteristics on the bill process, particularly from the perspectives of agenda-setting and position-taking.

Members of Congress play a critical role in the U.S. governing system, engaging in a wide range of responsibilities, including crafting and passing legislation, overseeing the executive branch, allocating federal resources, and addressing constituents' needs through advocacy and direct services. Notably, members of Congress are primarily motivated by re-election, which drives many of their activities (Mayhew 2004; Carson and Jenkins 2011). In particular, their roles and strategies in sponsoring and voting on legislation are shaped by diverse motivations, such as achieving electoral success (Campbell 1982; Schiller 1995), promoting constituents' interests (Fenno 1978; Kessler and Krehbiel 1996; Canes-Wrone et al. 2002; Koger 2003), and reflecting their ideology and partisanship (Aldrich 1995; Cox 2005; Fowler 2006).

Previous research has examined the differences between the two chambers in law-making. For example, Grofman et al. (1991) show that the Senate is more liberal than the House based on Americans for Democratic Action (ADA) scores. Similarly, Bailey (2007) finds that, since the 1960s, the House median has been slightly more conservative than the Senate median in roll-call voting. Furthermore, Ballard (2022) reveals that the House exhibits a higher level of agenda control compared to the Senate, although both chambers demonstrate strong negative agenda control. However, there is limited research exploring the differences in policy preferences and voting behavior between the two chambers, both in terms of overall legislative priorities and specific policy agendas.

Scholars have also examined the dynamics between political parties in the congressional law-making process, noting that political parties play a central role in shaping the legislative agenda, often aligning it with their ideological objectives and electoral strategies. Therefore, previous research highlights significant differences in legislative priorities and strategies between political parties. For instance, Democrats tend to emphasize social welfare, education, and environmental issues, while Republicans prioritize tax cuts, national defense, and deregulation (Lee 2016). These partisan differences reflect broader ideological divides and are often intensified during periods of divided government (Binder 2004).

3.2 Technology governance and AI policy

Weill (2008) defines IT governance as "[s]pecifying the framework for decision rights and accountabilities to encourage desirable behavior in the use of IT" (p. 3). This concept, along with its associated governance strategies, has been increasingly adopted in both the private and public sectors (Weill and Ross 2004; Campbell et al. 2010). In parallel, technology governance has emerged as a critical field of study in response to the rapid advances and widespread integration of technology in societal and institutional domains (Taeihagh 2021; Ulnicane et al. 2021).

Early research on technology governance has emphasized the importance of fostering an innovative and collaborative environment to advance technology development and ensure its widespread adoption for social benefit (Ergas 1987; Metcalfe 1995). In addition, scholars have highlighted the critical role of effective governance mechanisms in promoting responsible development, deployment, and regulation of technology while addressing its ethical, social, and economic implications (Moor 2005; Pardo et al. 2012; Fishenden and Thompson 2013; Alreemy et al. 2016; Brey 2017; Manoharan and Ingrams 2018). With the rapid integration of AI into society, growing attention has been directed toward the governance of AI technologies, emphasizing their effective application in public administration while addressing concerns related to ethics, transparency, privacy, bias, and equity (Zeng 2020; Valle-Cruz et al. 2020; Taeihagh 2021; Schiff et al. 2022; Engler 2023; Khan et al. 2024).

Consequently, scholars have examined various technologies and AI policies at both the country-specific and comparative levels, utilizing various governance tools and documents. The focus of technology and AI-related legislation varies significantly across regions and countries, reflecting differences in priorities, capacities, and contextual needs. As a result, researchers have conducted in-depth analyses of these variations to better understand their implications for policy and governance.

Engler (2023) compares AI policies in the United States and the European Union, highlighting significant differences in their approaches. He argues that U.S. policies are characterized by a decentralized structure that emphasizes non-regulatory support and fosters innovation through federal agencies. In contrast, the European Union adopts a stricter regulatory framework, particularly for high-risk AI applications, prioritizing transparency and accountability (Engler 2023; Outeda 2024). In the case of China, Roberts et al. (2021) argue that the country's AI development plan strategically integrates AI across a wide range of sectors, including defense and social welfare, while addressing ethical considerations to enhance international competitiveness, economic growth, and social governance. Wang et al. (2025) conduct a topic analysis of 139 AI policies from the United States, the European Union, and China, revealing distinct focuses in their AI policy approaches. Specifically, the analysis shows that the U.S. emphasizes the "government's role," the EU prioritizes "social impact," and China focuses on "research and application." Attard-Frost et al. (2024) analyze 84 AI governance initiatives in Canada, finding that they primarily focus on programs, policies, and strategies related to industry innovation, technology adoption, AI research, and public administration, while comparatively less attention is given to ethics, workforce development, AI education, and digital infrastructure. Liebig et al. (2024) examine subnational AI strategies in Germany, finding that these policy documents primarily emphasize knowledge transfer between research and industry, AI commercialization, the distinct economic identities of individual states, and the integration of ethical principles. Okolo (2023) highlights how countries in the Global South are leveraging AI to drive progress in agriculture, healthcare, and education, despite initial development being concentrated in the West. However, they emphasize the need for governance frameworks to address ethical concerns while balancing innovation and development priorities.

While prior research has advanced our understanding of national and comparative AI governance strategies, less attention has been given to how emerging AI issues are framed and prioritized during the legislative process, particularly within the U.S. Congress. This study contributes to the technology governance literature by analyzing how members of Congress engage with AI policymaking during the early stages of policy development in a decentralized legislative environment.

3.3 Bills analysis using text analysis techniques

With the advancement of machine learning techniques, there is a growing body of literature that uses text as a dataset for analysis in social science research. Computational and qualitative content analysis methods have enabled researchers to extract meaningful insights from large volumes of textual data efficiently and systematically.

Governmental documents have been extensively used to uncover detailed information on policy directions, strategies, and the priorities of the governing actors. Among these, bill analysis has become a critical tool for examining legislative priorities, identifying policy trends, and understanding the motivations driving lawmakers. In legislative studies, content analysis methods, such as qualitative text analysis, are widely used to explore the context and framework of legislative language using techniques such as coding and thematic analysis (Entman 1993; Krippendorff 2018). By analyzing the language, structure, and content of the bills, researchers uncover key topics, policy preferences, and ideological positions (Diermeier et al. 2012; Grimmer and Stewart 2013).

Furthermore, with advancements in technology, natural language processing (NLP) techniques have been increasingly applied to classify bills into policy domains, assess legislative sentiment, and track shifts in policy focus over time (Laver et al. 2003; Benoit et al. 2009; Lowe et al. 2011; Benoit et al. 2019). These methods provide a systematic and scalable approach for analyzing extensive legislative texts, offering valuable insights into the policymaking process and its evolution.

Among these NLP techniques, topic modeling has become particularly prominent in the study of political and governance texts, as it enables researchers to uncover latent themes and trends across large corpora. One of the most commonly applied methods is Latent Dirichlet Allocation (LDA), a three-level hierarchical Bayesian model used to identify clusters of related topics and to track their evolution over time (Blei et al. 2003). Scholars have employed LDA on a range of textual data sources, including government documents, newspapers, and social media, to extract insights into policy preferences, issue framing, and the dynamics of public discourse (Shirota et al. 2014; Bastani et al. 2019; Negara et al. 2019; Griciūtė et al. 2023; Zhou et al. 2023).

For example, Quinn et al. (2010) demonstrate the utility of topic modeling in analyzing legislative texts to identify policy priorities and partisan narratives. Similarly, Wilkerson and Casas (2017) find that the Democratic Party places greater emphasis on topics, such as human rights, healthcare, gender, race, education, and agriculture, whereas Republican members focus more on issues related to government, defense, business, and the budget based on their analysis of the topics in the speeches of the members.

In addition, sentiment analysis, a subset of natural language processing (NLP), has gained a significant traction in the analysis of textual data. Recent advances, including the application of deep learning models, such as recurrent neural networks and transformers, have enhanced the accuracy and scalability of sentiment analysis. In this context, sentiment analysis captures both broad sentiment polarity (positive, negative, and neutral) and more nuanced emotional dimensions, such as anger, fear, or optimism (Soroka et al. 2015; Nguyen et al. 2015; Rudkowsky et al. 2018; Chandrasekaran et al. 2021).

In legislative studies, sentiment analysis has been widely used to examine the language of bills, providing information on political alignment, policy framing, and the tone of discourse. For example, Rheault et al. (2016) analyze sentiment, defined as aggregate levels of emotional change over the past century, in parliamentary debates in the United Kingdom, focusing on issues, such as economic recessions, elections, and wars. Similarly, Proksch et al. (2019) study the sentiments expressed in the speeches of political actors in multiple countries over time. In another example, Rudkowsky et al. (2018) investigate the patterns of negativity in Austrian parliamentarian speeches using word embedding techniques.

While prior research on law-making, agenda-setting, and position-taking has deepened understanding of congressional behavior, it often relies on sponsorship patterns or roll-call votes, offering limited insight into the substantive content of legislation. This study addresses this gap using computational text analysis to examine how members of Congress frame AI-related issues. By analyzing the content of AI bills, this study contributes to the law-making literature by extending research on partisan and institutional dynamics into the emerging domain of technology governance. Also, it further highlights how institutional structures and partisan dynamics shape the framing of AI governance challenges, extending existing scholarship beyond executive-driven approaches to include the congressional law-making process.

4 Bill data and text pre-processing

Policy documents and tools in U.S. governance encompass a range of instruments, including executive orders, bills, resolutions, regulations, proclamations, and various agency documents. Congressional bills are particularly important as they represent the primary mechanism for enacting new laws, shaping federal policy, and allocating resources. They ensure representation and accountability, as they must undergo rigorous debate and approval by elected officials in both legislative chambers, reflecting the will of the people and the checks and balances central to the U.S. constitutional framework.

The U.S. Congress has made all legislative documents since the 1st Congress (1789), including legislation, committee reports and publications, treaty documents, and the Congressional Record, publicly accessible on its official website.[5] This platform provides comprehensive information on bills, including full texts, amendments, resolutions, and detailed updates on bill statuses. These legislative documents offer extensive details, such as bill names and titles, timelines for each legislative stage, summaries, full texts, actions, amendments, sponsors and co-sponsors, committees, and related bills. In addition to the official Congress website, supplemental data sources, such as GovInfo,[6]

[5] Congress: https://www.congress.gov/.

[6] GovInfo: https://www.govinfo.gov/.

ProQuest,[7] GovTrack,[8] CQ Almanac,[9] and LexisNexis,[10] provide additional information on bills, sponsors, and co-sponsors spanning long time periods.

Furthermore, various research institutes and organizations also curate and provide processed information on bills, often tailored to specific policy interests, and several of these institutions focus on technology and AI policy. For example, the Brennan Center for Justice[11] and the American Action Forum[12] publish policy reports on AI legislation and track AI-related bills introduced in Congress. These resources offer insight into the evolving legislative landscape on technology and AI bills.

This research primarily draws from three key sources, Congress.gov, the Brennan Center for Justice, and the American Action Forum, to compile a dataset of AI legislation from the 117th and 118th Congresses. The dataset includes detailed information, such as bill names and titles, introduction dates, sponsor details (name, branch, party affiliation, and constituency), committees, and concise bill summaries ranging from 10 to 50 words.

To prepare the data for text analysis, the bill summaries are pre-processed to enhance the effectiveness and accuracy of analytical models. Text pre-processing steps include tokenizing the text, converting it to lowercase, removing punctuation and stopwords, and eliminating extra whitespace, following established methodologies from prior research (Rheault et al. 2016; Hollibaugh 2019; Fraccaroli and Giovannini 2020; Park 2021). After pre-processing, the text data are vectorized using bag-of-words (BOW) methods, facilitating its use in subsequent topic analysis.

5 Methods: content analysis using machine learning

This study employs machine learning techniques to analyze the summary of 204 AI bills introduced in the U.S. Congress between 2021 and 2024. Specifically, topic modeling and sentiment analysis are used to uncover latent themes within the summary of bills and evaluate their overall emotional tone. These approaches enable a systematic and scalable analysis of large legislative datasets, providing a deeper understanding of the priorities and framing of AI policy across chambers and political parties. Machine learning-based content analysis can be particularly suitable for this research because it reduces subjective biases inherent in manual coding while allowing the discovery of patterns that might not be immediately apparent. By quantifying both the thematic structure (via topic modeling) and sentiment (via sentiment analysis) of legislative text, this study achieves a nuanced understanding of how AI is framed in policymaking.

5.1 Topic modeling

To identify underlying themes within the legislative text, this study applies Latent Dirichlet Allocation (LDA), a widely used unsupervised machine learning algorithm for topic modeling (Blei et al. 2003). LDA assumes that documents are mixtures of latent topics, where each topic is characterized by a distribution over words.[13]

$$P(w|d) = \sum_z P(w|z)P(z|d),$$

where

- $P(w|d)$: The probability of a word w occurring in a document d,
- $P(w|z)$: The probability of a word w given a topic z,
- $P(z|d)$: The probability of a topic z given a document d.

For this study, the corpus consists of summaries of AI-related bills introduced in the U.S. Congress between 2021 and 2024. Five topics are extracted using $k = 5$, determined based on coherence scores to balance interpretability and model performance. Pre-processing steps include tokenization, lowercasing, and the removal of stop words and punctuation. Sparse terms were removed using a sparsity threshold of 95%.[14]

7 ProQuest: https://congressional.proquest.com/.

8 GovTrack: https://www.govtrack.us/

9 CQ Almanac: https://library.cqpress.com/cqalmanac/.

10 LexisNexis: https://www.lexisnexis.com/.

11 Brennan Center for Justice: https://www.brennancenter.org/our-work/research-reports/artificial-intelligence-legislation-tracker.

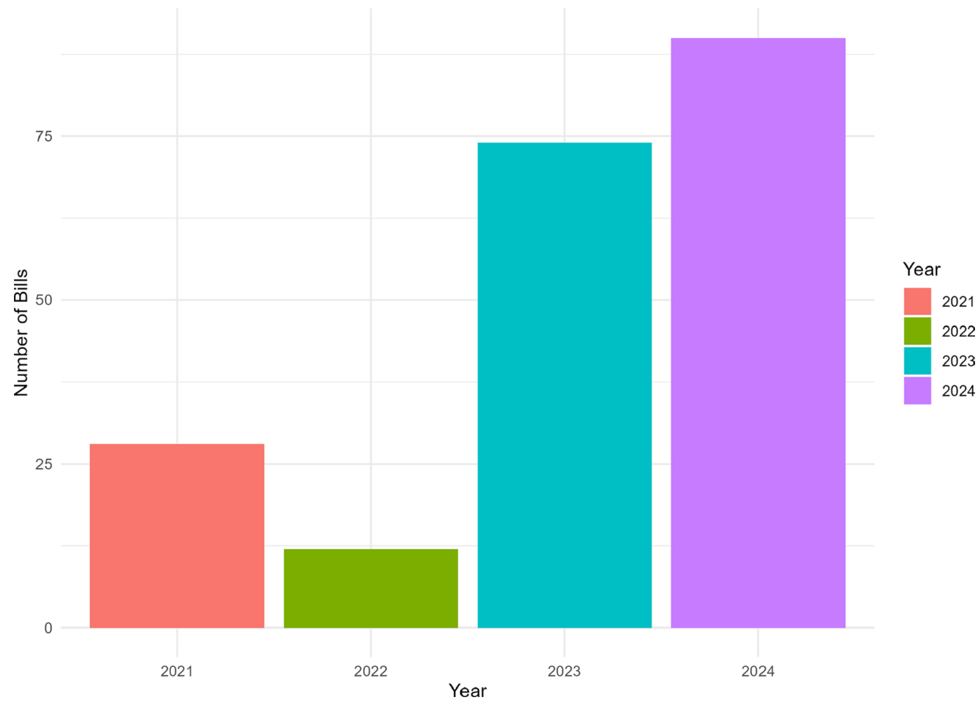
12 American Action Forum: https://www.americanactionforum.org/list-of-proposed-ai-bills-table.

13 The LDA model follows a generative process:

1. Each document d has a topic distribution $\theta_d \sim \text{Dirichlet}(\alpha)$, where α controls the sparsity.
2. Each topic z has a word distribution $\phi_z \sim \text{Dirichlet}(\beta)$, where β controls the sparsity of words in a topic.
3. For each word w_{dn} in document d:
   (a) Sample a topic $z_{dn} \sim \text{Multinomial}(\theta_d)$,
   (b) Sample a word $w_{dn} \sim \text{Multinomial}(\phi_{z_{dn}})$.

14 The trained LDA model is implemented in R using the `topicmodels` package. The number of topics ($k = 5$) is selected based on maximizing the coherence score. The `tidy()` function is used to extract probabilities of words topic for interpretation, ensuring that each topic is interpretable and relevant to the legislative context. Each bill is assigned to a single topic based on the highest probability from the LDA model. Specifically, document-topic probabilities (gamma values) are extracted, and each bill is classified under the topic with the highest gamma score. This ensures that every bill is counted

Fig. 1 AI bills introduction by year



5.2 Sentiment analysis

Sentiment analysis is conducted to assess the emotional tone of legislative texts, categorizing words as positive, negative, or neutral. A lexicon-based approach is employed, using the Bing sentiment lexicon to assign sentiment scores to individual words. For each bill, sentiment scores are determined by tokenizing the text and matching each word with its corresponding sentiment label from the Bing lexicon. The total count of positive and negative words is computed for each document, and the sentiment score for a bill d is defined as

$$\text{Sentiment Score} = \text{Positive Word Count} - \text{Negative Word Count}. \tag{1}$$

Based on this score, each bill is classified into one of three categories:

- **Positive**: If the sentiment score is greater than zero, indicating a prevalence of positive sentiment.
- **Negative**: If the sentiment score is less than zero, reflecting concerns or risks associated with AI legislation.
- **Neutral**: If the sentiment score is equal to zero, meaning that the document contains an equal number of positive and negative words or lacks sentiment-laden words entirely.

The sentiment scores are aggregated at the document level to determine the overall tone of each bill. Sentiment proportions for positive, negative, and neutral words are also analyzed by chamber and party to uncover differences in the framing. For instance, positive sentiment may reflect optimism regarding AI's potential, while negative sentiment highlights concerns or risks.[15]

6 Results

6.1 Overview: AI legislation in U.S. Congress

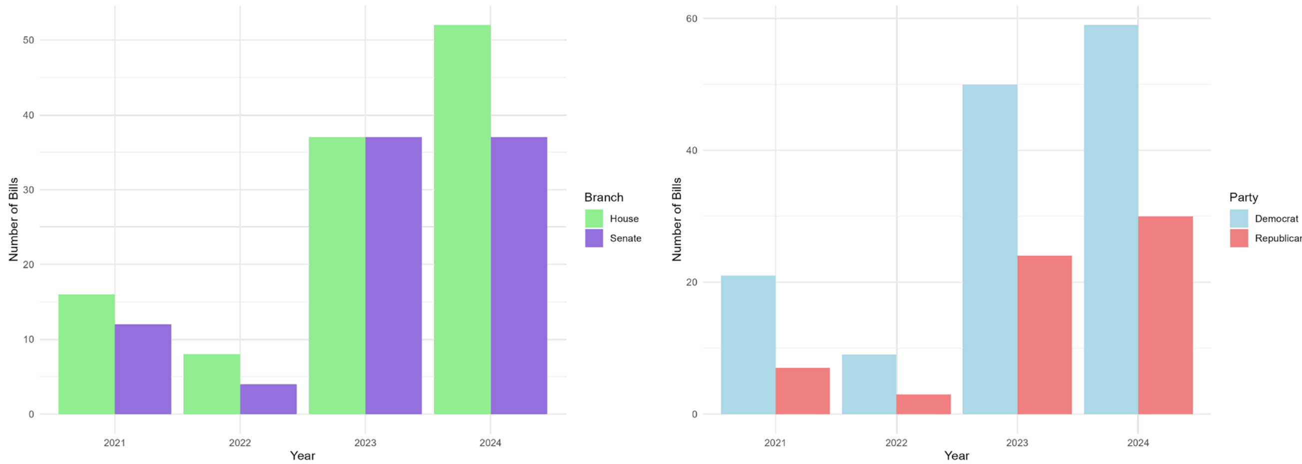
Between 2021 and 2024, during the 117th and 118th Congresses, a total of 204 AI-related bills were introduced. Of these, 113 bills originated in the House of Representatives, while 91 bills were introduced in the Senate, highlighting slightly higher legislative activity on AI in the House.

In terms of party affiliation, Democrats introduced the majority of the bills, accounting for 139 proposals. Republicans contributed 64 bills, while there was a single bill introduced by an independent legislator. This distribution demonstrates a significant partisan difference, with Democrats

Footnote 14 (continued)

once in the topic analysis, aligning with a best-match classification approach.

[15] Sentiment analysis was performed using the `tidytext` package in R. The process includes tokenizing the text into words, retrieving the Bing sentiment lexicon, and performing an inner join to match tokens with sentiment scores. The aggregated sentiment scores are used to evaluate the overall emotional tone of each bill.



(a) Chamber (b) Party

Fig. 2 AI bills by chamber and party

Table 1 Number of AI-related bills by party and chamber

Chamber and Party	Count
House Democrat	72
House Republican	41
Senate Democrat	67
Senate Republican	23
Senate Independent	1

leading the legislative push on AI-related issues during this period.

The number of AI-related bills introduced in Congress showed a clear upward trajectory between 2021 and 2024, as shown in Fig. 1. In 2021, fewer than 30 bills were introduced, with a slight decline in 2022 to fewer than 20 bills. However, legislative interest in AI accelerated significantly in 2023, with the number of bills more than tripling compared to 2022. By 2024, the number of bills reached its peak, exceeding 80 proposals, indicating a growing recognition of AI as a key policy area.

The chart in Fig. 2a displays the number of AI bills introduced in the House and the Senate. In 2021 and 2022, the House had a moderate lead in bill introductions, and this trend persisted in 2023 and 2024, with the House experiencing significant growth, surpassing 60 bills in 2024, compared to fewer than 40 bills introduced by the Senate. The marked increase in House activity indicates a stronger legislative focus and greater capacity to address AI-related issues compared to the Senate more recently.

Figure 2b highlights the party distribution of AI bills introduced in Congress. Democrats consistently introduced more than twice as many AI bills as Republicans across all years. In 2021, Democrats sponsored nearly 20 bills, while

Table 2 Number of AI-related bills by state

State	Count
California	30
Michigan	15
Massachusetts	13
New York	13
Florida	12
South Dakota	9
Virginia	8
Washington	8
Texas	7
Arizona	6
Colorado	6
Vermont	6

Republican contributions remained below 10. This disparity widened considerably in 2023 and 2024, with Democrats introducing over 50 bills annually, compared to fewer than 30 bills from Republicans. The upward trend for both parties, particularly among Democrats, reflects a growing bipartisan recognition of AI's legislative importance, although Democrats continue to play a more prominent role in advancing AI-related initiatives.[16]

Table 1 provides a breakdown of AI bills by congressional chamber and party affiliation for the period 2021–2024.

[16] Senator Joe Manchin left the Democratic Party in 2024 and sponsored one AI bill that year, with his party affiliation coded as Independent in the bill dataset. Accordingly, I follow this classification and consider his party affiliation as Independent in this analysis, ensuring consistency with the original dataset.

House Democrats introduced the most bills (72), followed by Senate Democrats with 67 bills. House Republicans contributed 41 bills, significantly more than Senate Republicans, who introduced only 23 bills. A single bill was sponsored by a Senate Independent. This distribution underscores the Democrats' proactive role in shaping AI legislation during this period.

Table 2 highlights the geographic distribution of AI-related bills introduced across states. California (CA) leads significantly with 30 bills, reflecting the state's prominent role as a hub for technological innovation and its position as a global leader in the tech industry. Michigan (MI) follows with 15 bills, with its interest in AI applications. Other states with significant legislative activity include Massachusetts (MA) and New York (NY), each introducing 13 bills, and Florida (FL) with 12 bills, indicating widespread regional engagement with AI policy. Smaller states, such as South Dakota (SD) (9 bills) and Vermont (VT) (6 bills), also appear active, suggesting that AI policy is a national priority that transcends state size and economic focus.

6.2 Analysis I: topic analysis

The prevalence of AI-related legislative topics reveals key agenda-setting dynamics within the U.S. Congress. Table 3 presents the results of a topic modeling analysis applied to 204 AI-related bills introduced between 2021 and 2024. The five identified topics represent the primary policy domains emphasized in congressional AI legislation, reflecting evolving concerns, competing priorities, and the strategic framing of AI issues by legislators. This analysis reveals that AI policymaking in Congress spans a wide range of domains, from national security and technological leadership to healthcare, data privacy, and public administration. Each topic illustrates a distinct facet of the legislative response to AI, underscoring the multidimensional nature of contemporary discussions on AI policy development.

Topic 1) Technology and innovation: This theme underscores AI's role in driving technological advancements and bolstering national security. Legislative attention in this domain emphasizes intelligence programs, national standards, and defense, highlighting AI's strategic significance in fostering innovation and safeguarding critical infrastructure. Key terms, such as "technology," "intelligence," "program," and "artificial", dominate this topic, indicating a strong focus on leveraging AI for technological advancements and defense-related applications. Terms like "standards" and "national" suggest a legislative interest in establishing AI guidelines and maintaining technological leadership, particularly in defense and security sectors.

Topic 2) Government operations and content regulation: This topic captures the intersection of AI with federal administrative functions and content oversight. Terms like "bill," "requires," "federal," and "agencies" emphasize regulatory frameworks, while "content," "civil," and "generative" point to AI's growing role in managing digital communication, misinformation, and generative technologies. This legislative theme also suggests concerns about the administrative implementation of AI tools and the normative challenges of overseeing AI-generated content in the public sphere.

Topic 3) Research, education, and security: This category represents legislative support for integrating AI into national research agendas, educational infrastructure, and security strategies. Terms, such as "research," "education," "security," and "science", indicate a combined interest in fostering innovation, preparing the future workforce, and mitigating security threats. Terms, such as "development," "authorizes," and "activities", further suggest congressional efforts to institutionalize AI development through federal support for academic and security-related initiatives.

Topic 4) Data and digital governance: This theme centers on data protection, digital platforms, and federal commissions aimed at regulating AI's interaction with personal data and digital ecosystems. It reflects a legislative emphasis on balancing innovation with privacy and security. This topic is characterized by terms like "data," "commission," "federal," and "platforms," pointing to the legislative focus on privacy, algorithmic accountability, and oversight. This area reflects the recognition of the importance of safeguarding data rights while promoting innovation, particularly through the creation of new commissions and governance frameworks to regulate AI's societal implications.

Topic 5) Healthcare and human services: This theme captures AI's applications in health services and human

Table 3 Topic analysis: AI-related legislative themes and terms

Topic	Theme	Terms
1	Technology and Innovation	Technology, bill, intelligence, program, artificial, standards, national, department, defense, develop
2	Government Operations and Content Regulation	Bill, use, requires, systems, federal, content, agencies, civil, generative, used
3	Research, Education, and Security	Research, national, education, security, science, development, authorizes, bill, including, activities
4	Data and Digital Governance	Data, bill, commission, federal, act, digital, individuals, platforms, establishes, creates
5	Healthcare and Human Services	Health, certain, bill, requires, related, services, including, human, department, congress

welfare. The focus includes healthcare advancements, human-centric AI solutions, and related services, showcasing legislative attention to improving public health and well-being through AI. Key terms, such as "health," "services," "human," and "department", signal legislative interest in integrating AI to improve service delivery and efficiency in healthcare and social services. The inclusion of terms like "requires," "related," and "including" indicates policy designs that mandate specific uses of AI while preserving ethical and human-centric standards.

Figure 7 in the Appendix illustrates the most significant terms associated with each of the five identified topics from the AI-related legislative text analysis. Each bar chart shows the relative importance or frequency of specific terms within a given topic, offering insights into the themes emphasized in the legislative discourse. The emphasis on terms like "technology," "data," "research," and "health" indicates that Congress is addressing both the opportunities and challenges of AI across innovation, governance, education, and public welfare. Additionally, Table 10 provides the top terms for each topic along with their corresponding coefficients, providing further insight into the lexical patterns and semantic structure underlying each thematic category.

Also, Fig. 8 in the Appendix illustrates the distribution of document-topic proportions for the five topics identified by the LDA model. Across all topics, the distributions are heavily skewed toward low proportions, indicating that most documents contain a small presence of each topic. This pattern suggests that the legislative texts are thematically diverse, with only a subset of bills showing strong alignment with a single dominant theme.

Figure 3 illustrates the prevalence of topics identified in the analyzed policy texts. The most prevalent topics, such as "Technology and Innovation" and "Government Operations and Content Regulation," highlight the primary areas of focus in AI policies. These topics reflect an emphasis on leveraging technology for innovation and the role of AI in improving governmental functions. Also, topics like "Healthcare and Human Services" and "Data Governance" demonstrate emerging areas of interest. This topic distribution reveals not only the multifaceted nature of AI policymaking but also the expanding focus of legislative attention as AI continues to permeate different sectors of governance and public life.

Figure 9 in Appendix displays the correlations between topics identified in the analyzed policy texts. It provides insights into the interrelationships between thematic areas

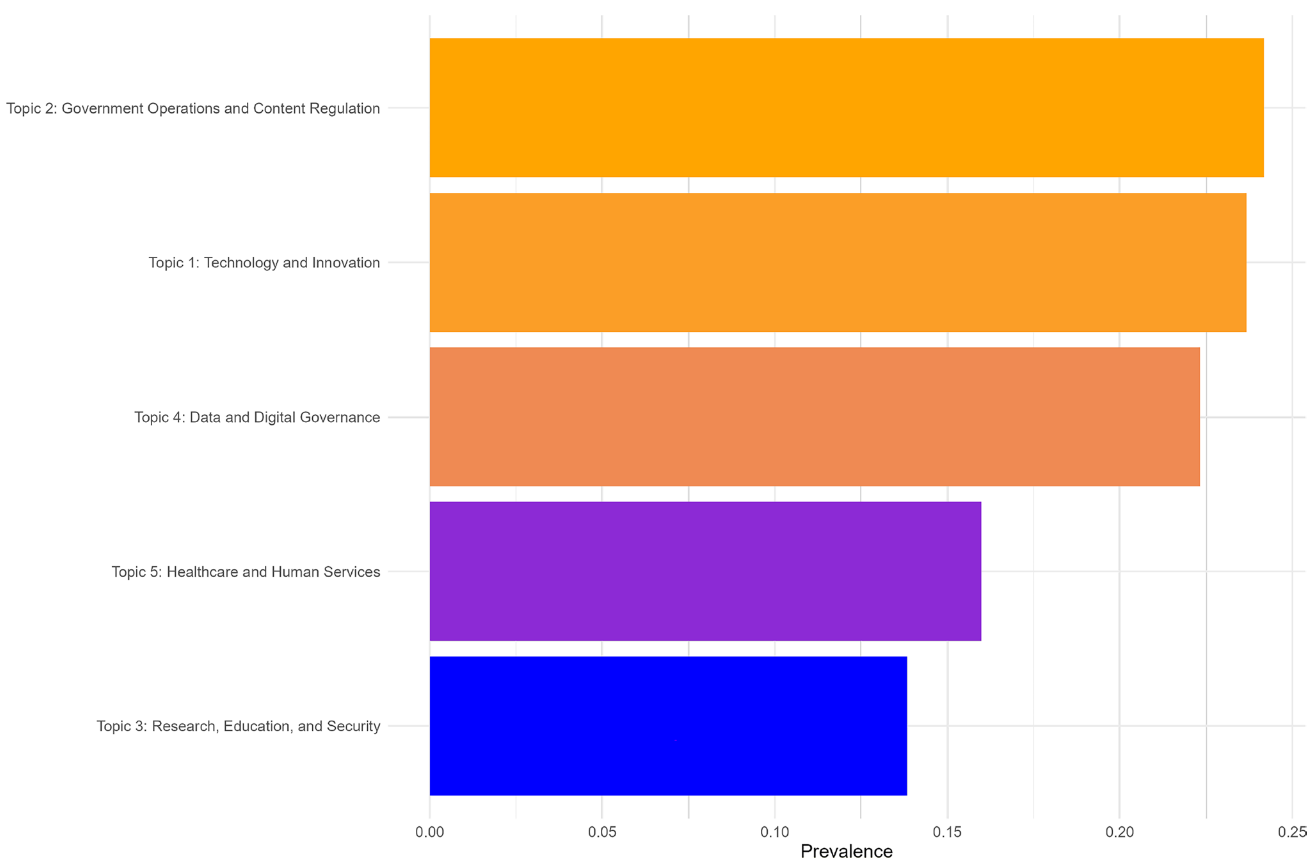


Fig. 3 Topic prevalence in policy texts

in the policy discourse, aiding in understanding how different policy priorities align or diverge.

Table 4 further elaborates on the topics distribution across the House and Senate. "Government Operations and Content Regulation" is the most prominent theme, with 36 House bills (31.86%) and 24 Senate bills (26.37%), highlighting its critical role in AI policymaking. "Technology and Innovation" and "Data and Digital Governance" are also key themes, with higher proportions in the Senate. "Healthcare and Human Services" remains the least emphasized topic in both chambers, reflecting its relatively lower priority in AI-related legislative efforts.

Table 5 provides an overview of topic engagement by party. Democrats exhibit the highest engagement with "Government Operations and Content Regulation" (39 bills, 28.06%), closely followed by "Data and Digital Governance" (33 bills, 23.74%) and "Technology and Innovation" (32 bills, 23.02%). Republicans, on the other hand, place their strongest emphasis on "Technology and Innovation" (22 bills, 34.38%) and "Government Operations and Content Regulation" (31 bills, 31.81%), a priority shared by both parties. However, Republicans show much less engagement with "Research, Education, and Security" (4 bills, 6.25%) compared to Democrats (19 bills, 13.67%). The differences in topic focus reflect varying legislative priorities, with Republicans emphasizing technology and innovation, while Democrats are more balanced across government operations, data governance, and healthcare. These findings align with prior research on congressional agenda-setting, where political actors strategically prioritize legislative issues that align with party goals and constituent interests.

Figure 4 illustrates the most frequently occurring terms in AI legislation, highlighting the thematic priorities of legislators. In this word cloud, which aggregates terms across all AI bills, central terms such as "bill," "requires," "technology," and "federal" dominate, reflecting a shared emphasis on regulatory and technological aspects of AI. Additional terms like "data," "health," "education," and "security" indicate a balanced legislative interest in AI's societal applications and associated risks. This figure encapsulates the collective concerns and priorities in AI policymaking across chambers and parties. Figure 10 in the Appendix highlights the most frequently used words in legislative texts related to AI.

Figure 11 in the Appendix illustrates word frequency by legislative chamber. Both House and Senate word clouds prominently feature terms like "bill," "AI," "requires," and "technology," reflecting a shared legislative focus. House bills emphasize "research," "data," and "national," indicating interest in AI development and data governance, whereas Senate bills highlight "federal," "health," "program," and "department," underscoring priorities in governance, public welfare, and institutional regulation. Additionally, Senate discussions feature terms such as "intelligence," "defense," and "security," signaling a focus on national security and defense applications.

Figure 12 in the Appendix displays word frequency by party. Both Democrats and Republicans frequently use terms like "bill," "AI," "requires," "data," "technology," and "federal," indicating shared legislative concerns. Democrats emphasize "health," "education," and "human," reflecting a focus on public services and ethical AI policies, alongside terms like "standards" and "programs," suggesting structured regulatory efforts. Republicans, however, prioritize "national security," "defense," "intelligence," and "risk," highlighting AI's role in security and military applications.

Table 4 Topic labels with distribution by chamber

Topic	Topic label	House (raw)	House (ratio)	Senate (raw)	Senate (ratio)
1	Technology and Innovation	29	25.66%	25	27.47%
2	Government Operations and Content Regulation	36	31.86%	24	26.37%
3	Research, Education, and Security	13	11.50%	11	12.09%
4	Data and Digital Governance	21	18.58%	23	25.27%
5	Healthcare and Human Services	14	12.39%	8	8.79%

Table 5 Topic engagement by party

Topic	Topic label	Dem (raw)	Dem (ratio)	Rep (raw)	Rep (ratio)
1	Technology and Innovation	32	23.02%	22	34.38%
2	Government Operations and Content Regulation	39	28.06%	21	32.81%
3	Research, Education, and Security	19	13.67%	4	6.25%
4	Data and Digital Governance	33	23.74%	11	17.19%
5	Healthcare and Human Services	16	11.51%	6	9.38%

Fig. 4 Word cloud: All AI bills

Additionally, terms like "China" and "cyber security" point to heightened geopolitical and security concerns.

Additionally, the lists in Tables 11, 12, and 13 in the Appendix highlight the most frequently used terms in AI-related bills, both overall and categorized by legislative chamber and party affiliation. These word clouds reveal both shared and distinct legislative priorities: Democrats focus on public welfare, education, and regulatory frameworks, while Republicans emphasize national security, defense, and geopolitical risks.

These topic modeling results reinforce key theoretical insights from the literature. The variation in topic prevalence across chambers and parties supports theories of agenda-setting and position-taking, where legislators advance issues aligned with institutional roles and partisan goals (Mayhew 2004; Ballard 2022). Republicans' focus on innovation and national security, contrasted with Democrats' broader emphasis on governance and public welfare, mirrors established partisan divides in technology policymaking. Moreover, the fragmented topic distributions and weak inter-topic correlations reflect a decentralized, issue-specific legislative approach—consistent with claims that U.S. AI governance is reactive and dispersed (Taeihagh 2021; Engler 2023). The emergence of five distinct themes illustrates the multifaceted nature of AI policymaking and highlights the value of computational methods for uncovering latent policy frames.

6.3 Analysis II: sentiment analysis

Sentiment analysis offers insights into the tone and framing of legislative discourse on AI-related bills. Therefore, the sentiment analysis results indicate key patterns of congressional position-taking on AI legislation. Specifically, it examines the chamber and partisan dynamics of legislators' sentiments, highlighting their attitudes toward the opportunities, challenges, and risks associated with AI.

Table 6 provides a summary of the overall sentiment distribution for 204 AI bills introduced between 2021 and 2024. The majority of bills exhibit positive sentiment, accounting for 90 bills or 44.1% of the total, which indicates that the legislative discourse on AI topics is predominantly framed in

Table 6 Overall sentiment analysis of AI bills

Sentiment	Count	Ratio
Negative	54	0.265
Neutral	60	0.294
Positive	90	0.441

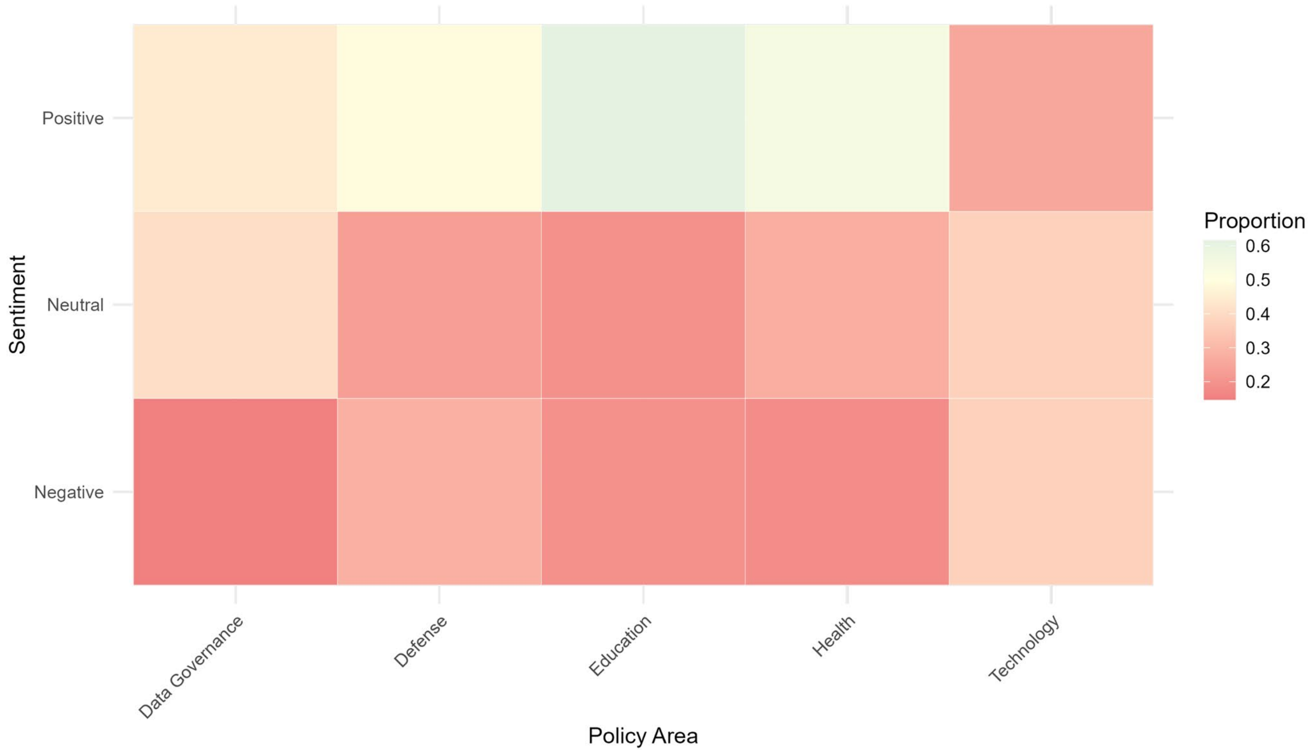


Fig. 5 Sentiment distribution by policy focus in AI bills

Table 7 Sentiment analysis ratios by category and branch

Chamber	Neg	Neu	Pos	Total	Neg ratio	Neu ratio	Pos ratio
House	26	31	56	113	0.230	0.274	0.496
Senate	28	29	34	91	0.308	0.319	0.374

an optimistic light, highlighting potential opportunities and benefits. The neutral sentiment category, comprising 60 bills (29.4%), reflects a balanced perspective where legislators may acknowledge the complexities and uncertainties associated with AI, opting for a more measured stance. Finally, the negative sentiment category includes 54 bills (26.5%), representing a significant minority that raises concerns about the risks, ethical dilemmas, or potential harms of AI. Figure 13 in the Appendix illustrates the yearly proportions of sentiments in AI bills. Positive sentiment consistently represents the largest proportion, reflecting an overarching optimistic framing of AI's potential. Neutral sentiment exhibits a steady increase throughout the years, while negative sentiment, though the least prominent, experiences a modest rise in 2024.

Figure 5 illustrates the distribution of sentiments across five key policy areas in AI-related bills: Data Governance, Defense, Education, Health, and Technology.[17]

Positive sentiment is most prominent in Health and Education, reflecting optimism about AI's potential to enhance public welfare, healthcare services, and educational systems. In contrast, neutral sentiment is substantial in Data Governance and Technology, indicating a cautious or balanced stance, where legislators acknowledge both opportunities and risks associated with AI's applications in data

[17] Policy domains are categorized based on the presence of specific keywords in the cleaned text summaries of bills. For instance, the "Defense" domain includes keywords, such as "defense," "military," "security," "intelligence," "cybersecurity," "threat," and "risk." The "Education" domain covers terms like "education," "learning," "school," "university," "teaching," "students," "research," "training," and "academic." Similarly, the "Health" domain encompasses keywords, such as "health," "medicine," "care," "covid," "pandemic," "public health," "disease," "hospitals," "wellness," and "mental health." The "Data Governance" domain includes terms like "data," "privacy," "platform," "governance," "digital," "big data," "database," "analytics," and "information." Finally, the "Technology" domain is categorized using keywords, such as "technology," "innovation," "artificial intelligence," "AI," "robotics," "automation," "machine learning," and "standards." All categorizations are conducted using case-insensitive pattern matching.

management and technological advancements. Negative sentiment is pronounced in Defense, likely driven by concerns about AI's implications for security, military applications, and ethical dilemmas, reflecting heightened apprehension in areas with potentially severe consequences. This variation underscores how sentiment framing in AI policymaking is shaped not only by partisan and institutional factors, but also by issue-specific contexts and perceived risks.

Table 7 presents the breakdown of sentiment between the House and Senate, indicating a more cautious or critical approach in the Senate compared to the House. The House displays a higher proportion of positive sentiment (49.6%), whereas the Senate demonstrates a more balanced distribution, with positive sentiment accounting for 37.4%, alongside relatively higher proportions of neutral (31.9%) and negative sentiment (30.8%). The differences in sentiment between the House and Senate suggest that senators, given their longer terms and broader constituencies, may adopt more cautious and balanced positions on AI legislation compared to House members.

Table 8 highlights the sentiment distribution by party affiliation, revealing that Democrats generally frame AI legislation more optimistically, whereas Republicans adopt a more reserved or cautious approach. Democrats introduced a large number of AI-related bills (139), with 46% of their bills exhibiting positive sentiment, compared to 26% negative and 28% neutral. In contrast, Republicans, who introduced 64 bills, displayed a slightly more balanced sentiment distribution, with 39% positive, 28% negative, and 33% neutral. This aligns with established research on position-taking, where legislators strategically frame policy issues to reflect party ideologies and appeal to key constituencies.

Table 9 highlights remarkable differences in sentiment framing of AI bills across chambers and party affiliation. House Democrats show a predominantly positive sentiment, with 48.6% of their bills classified as positive. While this optimistic framing aligns with their broader support for AI-related opportunities, a significant share of negative (26.4%) and neutral (25.0%) bills indicates a nuanced approach that acknowledges regulatory and ethical challenges. House Republicans exhibite the highest proportion of positive sentiment among all groups, with 51.2% of their bills framed positively. Their relatively lower shares of neutral (31.7%) and negative (17.1%) sentiment suggest a pragmatic yet forward-leaning stance on AI policy.

Senate Democrats, in contrast, demonstrate a more balanced distribution of sentiment. Positive bills comprised 43.3%, followed by 31.3% neutral and 25.4% negative. This balance reflects a deliberative approach, weighing AI's benefits against its potential risks. Senate Republicans are the most critical group, with nearly half of their bills (47.8%) classified as negative. Neutral sentiment accounted for 34.8%, while only 17.4% of their bills exhibited a positive framing. This distribution underscores a cautious or skeptical view of AI, focusing more on potential risks and regulatory concerns.

Figure 6a presents a bar chart displaying the raw distribution of sentiment categories across party–chamber groups, while Fig. 6b offers a proportional breakdown within each group. These visualizations highlight the divergent approaches to AI-related legislation across institutional and partisan lines. They underscore how party affiliation and chamber membership shape the tone of legislative discourse—ranging from optimism and support to caution and critique—reflecting distinct priorities and framing strategies in the evolving landscape of AI policymaking.

6.4 Implications

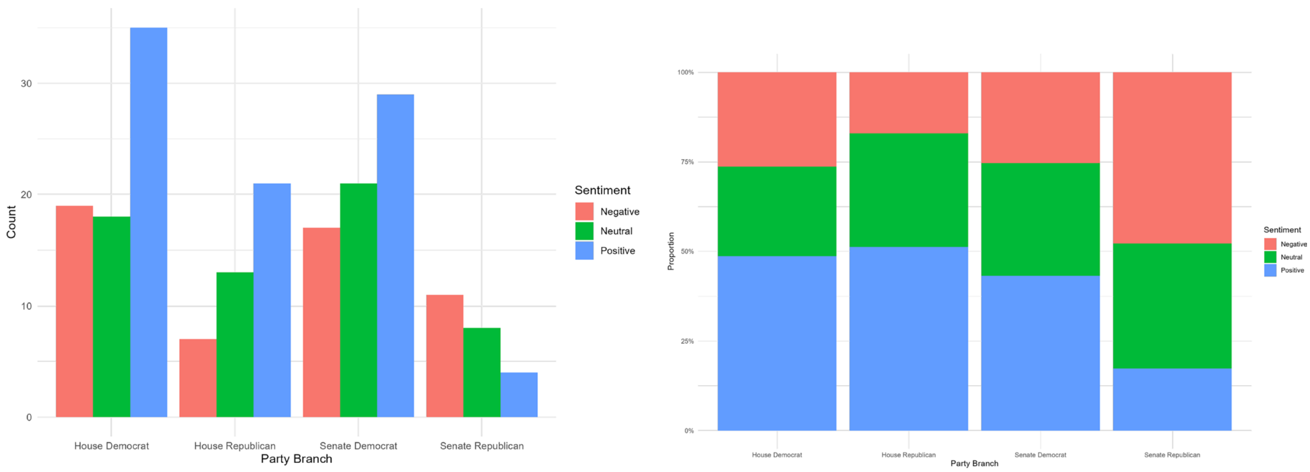
Legislative priorities across chambers: The analysis reveals distinct legislative priorities between the House and the Senate. The House focuses on topics, such as Government Operations and Content Regulation and Technology and Innovation, highlighting its emphasis on regulating AI in

Table 8 Sentiment ratios by party

Party	Neg	Neu	Pos	Total	Neg ratio	Neu ratio	Pos ratio
Dem	36	39	64	139	0.259	0.281	0.460
Rep	18	21	25	64	0.281	0.328	0.391
Ind	0	0	1	1	0	0	1

Table 9 Sentiment ratios by chamber and party

Chamber	Party	Neg	Neu	Pos	Total	Neg ratio	Neu ratio	Pos ratio
House	Dem	19	18	35	72	0.264	0.250	0.486
House	Rep	7	13	21	41	0.171	0.317	0.512
Senate	Dem	17	21	29	67	0.254	0.313	0.433
Senate	Rep	11	8	4	23	0.478	0.348	0.174
Senate	Ind	0	0	1	1	0	0	1



(a) Bar Chart

(b) Proportional Stacked Chart

Fig. 6 Sentiment analysis by party and branch

federal systems and advancing technological standards. The Senate prioritizes Technology and Innovation and Data and Digital Governance, reflecting its commitment to fostering innovation while addressing long-term concerns like privacy, accountability, and data governance. Sentiment analysis underscores these differences, with the House exhibiting greater optimism, while the Senate adopts a more cautious and balanced stance, emphasizing strategic considerations in AI policymaking.

Partisan differences in AI policymaking: Democrats and Republicans exhibit divergent priorities in framing AI-related legislation. Democrats emphasize public welfare, with a focus on health, education, and human-centric AI policies, reflecting optimism about AI's societal potential. Republicans, on the other hand, prioritize national security, defense, and risk mitigation, with a stronger emphasis on safeguarding against external threats and addressing geopolitical concerns. Sentiment analysis reveals that while Democrats are generally more optimistic, Republicans, particularly in the Senate, maintain a more reserved or critical approach, demonstrating how broader ideological divides influence AI legislative agendas.

Bipartisan themes and shared focus areas: Despite partisan differences, there is significant bipartisan alignment on key themes such as regulating AI systems and addressing data governance. Both parties recognize the importance of creating standards for data protection, accountability, and innovation. This shared focus highlights the collective acknowledgment of AI's transformative potential and its role in reshaping governance. Sentiment analysis further supports this consensus, with optimism dominating the discourse but tempered by recognition of AI's complexities and risks, emphasizing the need for balanced and collaborative policymaking between the two parties.

Implications for AI governance frameworks and policymaking collaboration: The interplay of chamber-specific and partisan priorities highlights the need for a cohesive AI governance framework. The House's focus on content regulation, agency oversight, and AI applications across various policy areas underscores the importance of robust administrative mechanisms, while the Senate's emphasis on innovation and data governance highlights the need for strategic planning. Despite differences, shared priorities like data governance and regulatory standards provide opportunities for bipartisan collaboration. By framing AI policy as a nonpartisan issue that addresses societal and security concerns, policymakers can create balanced frameworks that foster innovation while ensuring ethical and effective AI adoption.

Geopolitical and global governance implications: The legislative focus remains fragmented and domestically oriented, lacking a coherent strategy for shaping international AI norms. The analysis suggests that while Congress is beginning to engage with the global dimensions of AI, there is still a need for legislative efforts that explicitly address international collaboration, norm-setting, and the U.S. role in global AI policymaking. Recognizing AI as both a domestic governance issue and a geopolitical imperative is essential for ensuring that U.S. policymaking remains responsive, competitive, and globally relevant.

7 Discussion and conclusion

This study offers a comprehensive analysis of AI-related legislation in the U.S. Congress from 2021 to 2024, uncovering key thematic and emotional dimensions across chambers and political parties. By employing machine learning techniques, it quantifies patterns in legislative texts, providing a scalable framework for analyzing policy discourse. The integration of topic modeling and sentiment analysis further reveals the interplay between thematic focus and emotional framing, deepening our understanding of how narratives surrounding AI governance are constructed and debated. The research highlights how legislative chambers and political parties prioritize distinct aspects of AI policymaking, offering empirical insights into the dynamics of governing emerging technologies.

The findings underscore the fragmented yet complementary roles played by the House and Senate, and by Democrats and Republicans, in shaping the U.S. AI policy landscape. While the House emphasizes administrative oversight and AI applications in public-facing domains, the Senate tends to prioritize strategic planning, innovation, and long-term governance frameworks. Similarly, partisan differences emerge in the tone and thematic framing of legislation, with Democrats generally adopting a more optimistic, human-centric approach and Republicans—particularly in the Senate—focusing on risks, national defense, and geopolitical competition.

These results contribute to broader theories of agenda-setting, institutional incentives, and partisan framing in the policymaking process. The study extends existing models of congressional behavior by demonstrating how emerging technologies like AI are integrated into traditional partisan and institutional structures, rather than radically transforming them. It shows that technology governance, while novel in content, is deeply embedded in familiar legislative dynamics of issue prioritization, ideological signaling, and strategic framing. By systematically mapping how chambers and parties frame AI policy, the research contributes to ongoing debates about how legislatures respond to complex, rapidly evolving technological domains.

These results point to the need for a more cohesive and collaborative approach to AI policy development. Bridging ideological and institutional divides will be essential for developing comprehensive policies that balance innovation with ethical standards, and economic competitiveness with democratic accountability. While the U.S. has made significant strides in promoting data regulation and ethical AI across policy sectors, it does so within a global landscape where other jurisdictions—such as the European Union and China—are actively shaping regulatory norms. Therefore, domestic policymaking needs to be informed by international coordination. Effective governance of AI will require not only internal consensus but also external alignment, particularly on issues, such as cross-border data flows, algorithmic accountability, and global standards.

While the research provides valuable insights, certain limitations exist. Legislative texts, while rich in content, may not capture the full spectrum of debates surrounding AI. Machine learning methods, though robust, are influenced by data quality and pre-processing decisions, which could affect the findings. Given that this analysis relies on bill summaries rather than full legislative texts, the study has limitations in capturing the full scope of legal language, regulatory provisions, and amendments. Future research could complement this approach by incorporating doctrinal analysis of complete bill texts and committee reports to enhance the depth of legal interpretation and policy evaluation. Additionally, the study's U.S.-centric focus may limit the applicability of its conclusions to nations with different political and legislative frameworks. As AI policy remains in the developmental stage, follow-up research should continuously examine newly introduced AI-related bills alongside a broader array of policy documents, including executive orders, agency policy guidelines, regulatory frameworks, white papers, international agreements, and industry standards, to provide deeper insights into the foundation of AI policymaking and regulation.

As AI continues to transform various sectors, the U.S. government plays a critical role in shaping policies that regulate its development, deployment, and impact. This research also highlights the differing roles and strategies of legislative chambers and political parties in policymaking within a polarized political landscape. By offering insights into the dynamics of AI policy in the U.S. Congress, this study provides a foundation for understanding the evolving AI policy environment and informing future approaches to its development and regulation.

Appendix: Figures

See Figs. 7, 8, 9, 10, 11, 12 and 13.

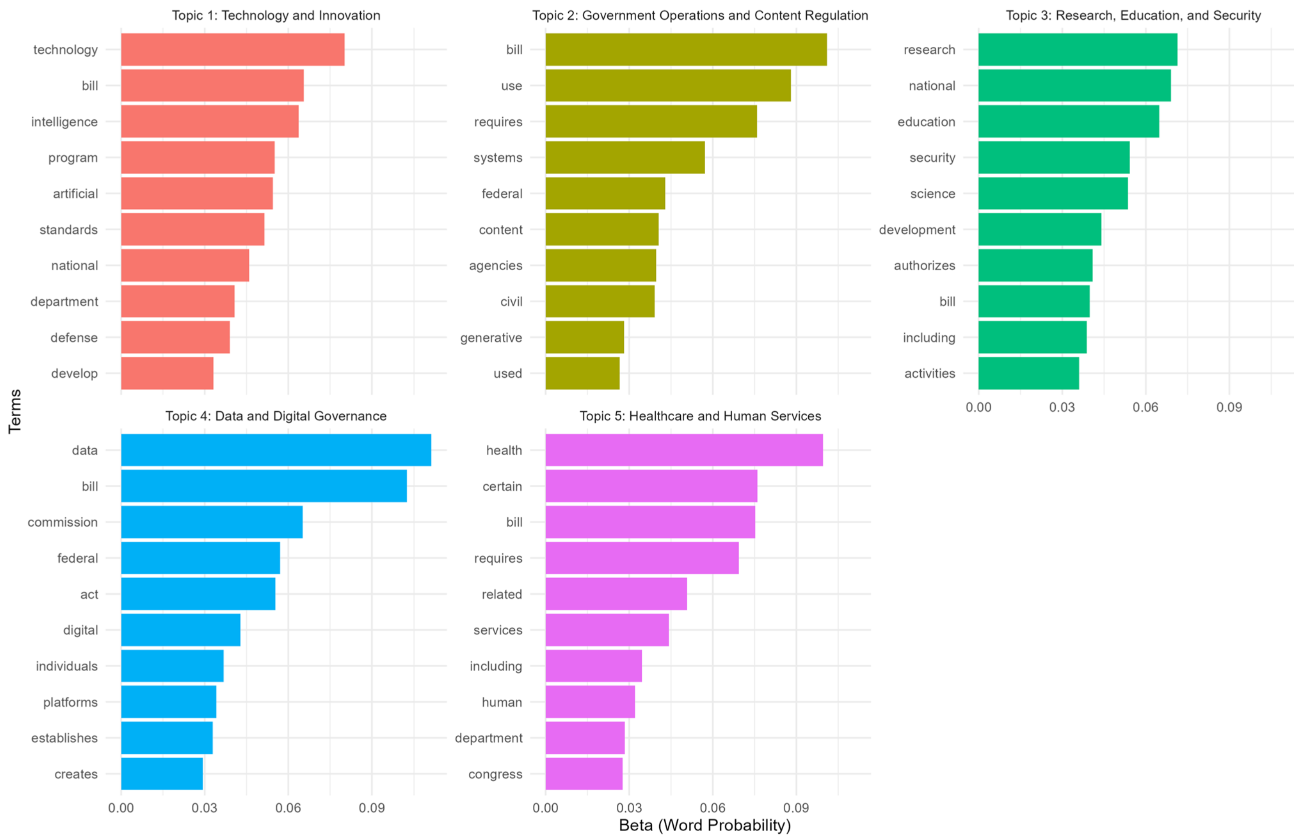


Fig. 7 Top terms by topic

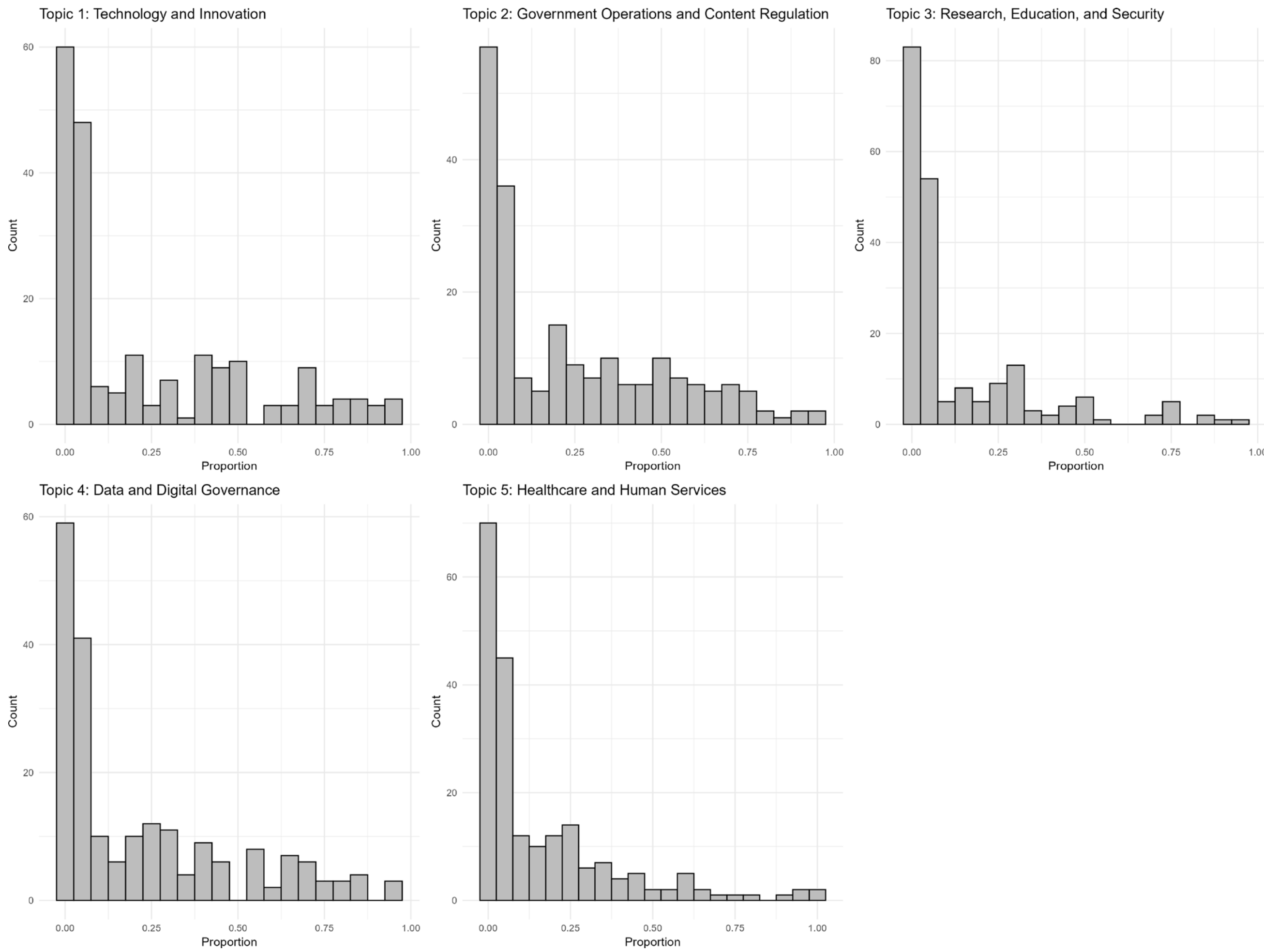


Fig. 8 Distribution of document-topic proportions across topics. Note: The x-axis indicates the proportion of the topic within each document, ranging from 0 (minimal presence) to 1 (complete dominance), while the y-axis shows the number of documents corresponding to each proportion range. Topic 1 displays the widest spread of proportions, suggesting that this topic is relatively more prominent across the corpus compared to other topics. In contrast, Topics 2 through 5 exhibit a more concentrated presence at lower proportions, with fewer documents where these topics dominate

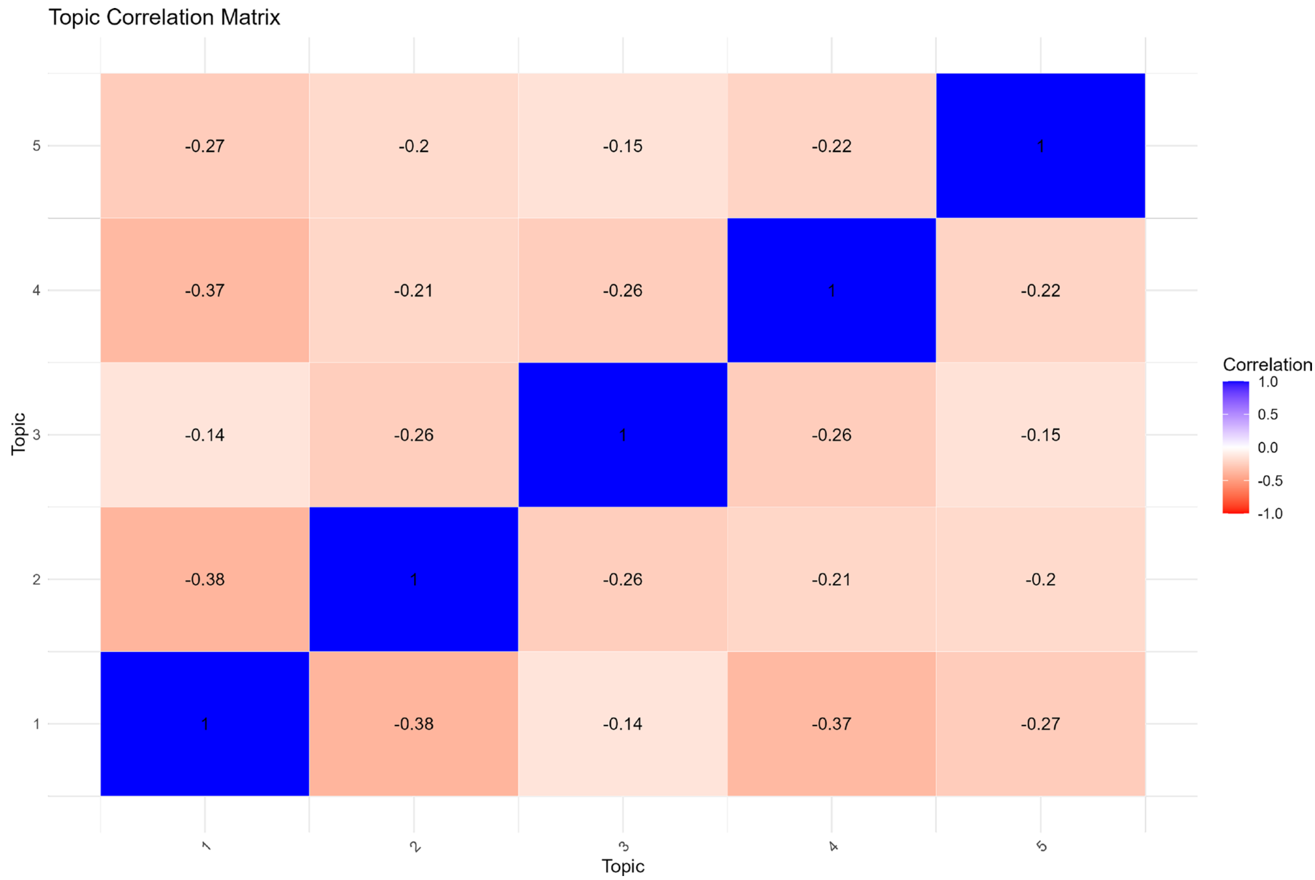


Fig. 9 Topic correlation matrix. Note: Each box represents the correlation between two topics, with darker blue indicating strong positive correlations and darker red indicating strong negative correlations. The numerical values in the boxes quantify these correlations, ranging from – 1 (perfect negative correlation) to 1 (perfect positive correlation). In this figure, most correlations appear weak, with values clustered around 0, suggesting limited overlap or independence between topics. Therefore, the correlation matrix indicates that the topics are well separated and capture distinct themes. The moderate negative correlations and the overall weak correlations (near 0) demonstrate that the LDA model has successfully divided the corpus into meaningful and non-redundant topics

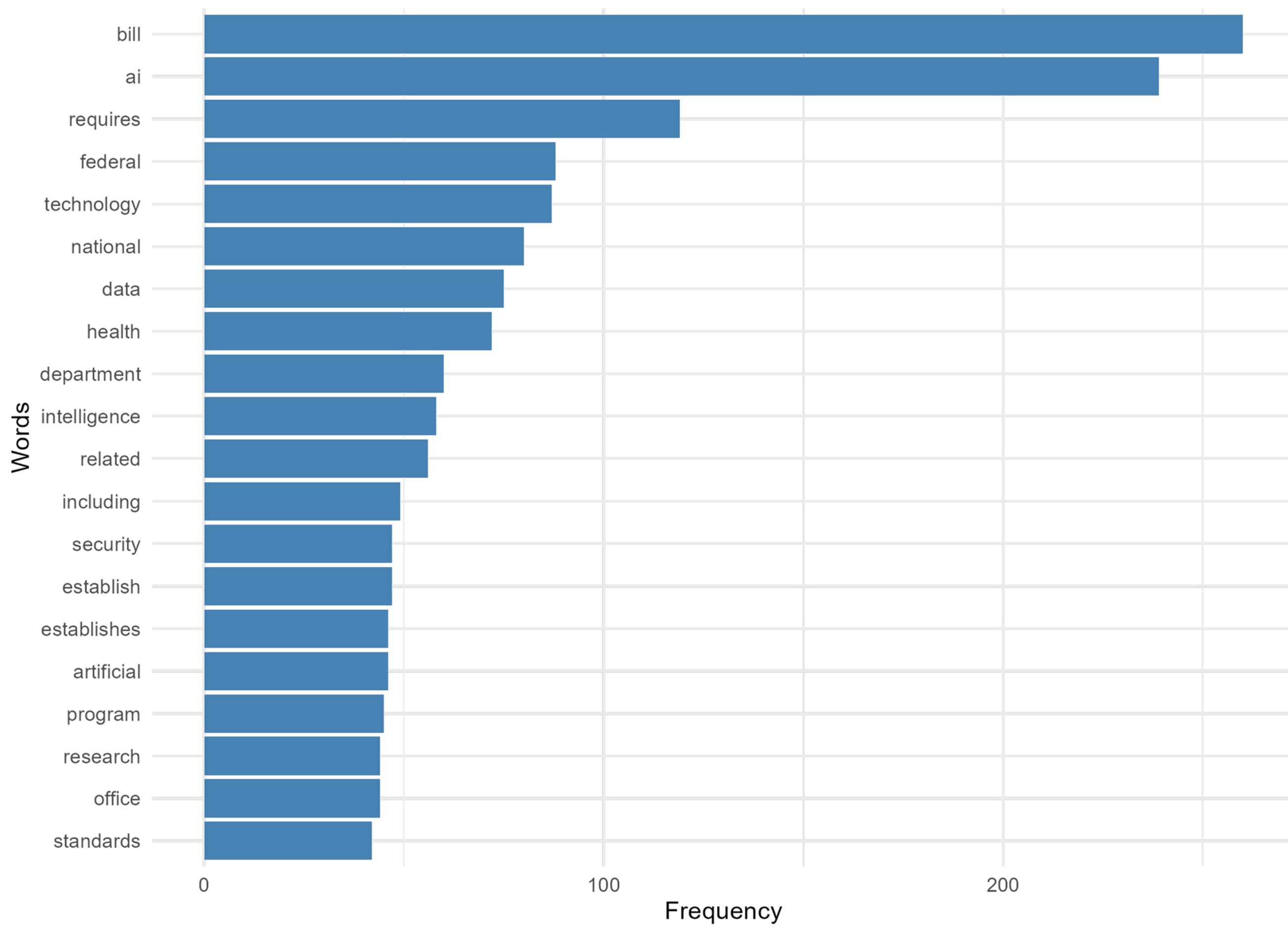
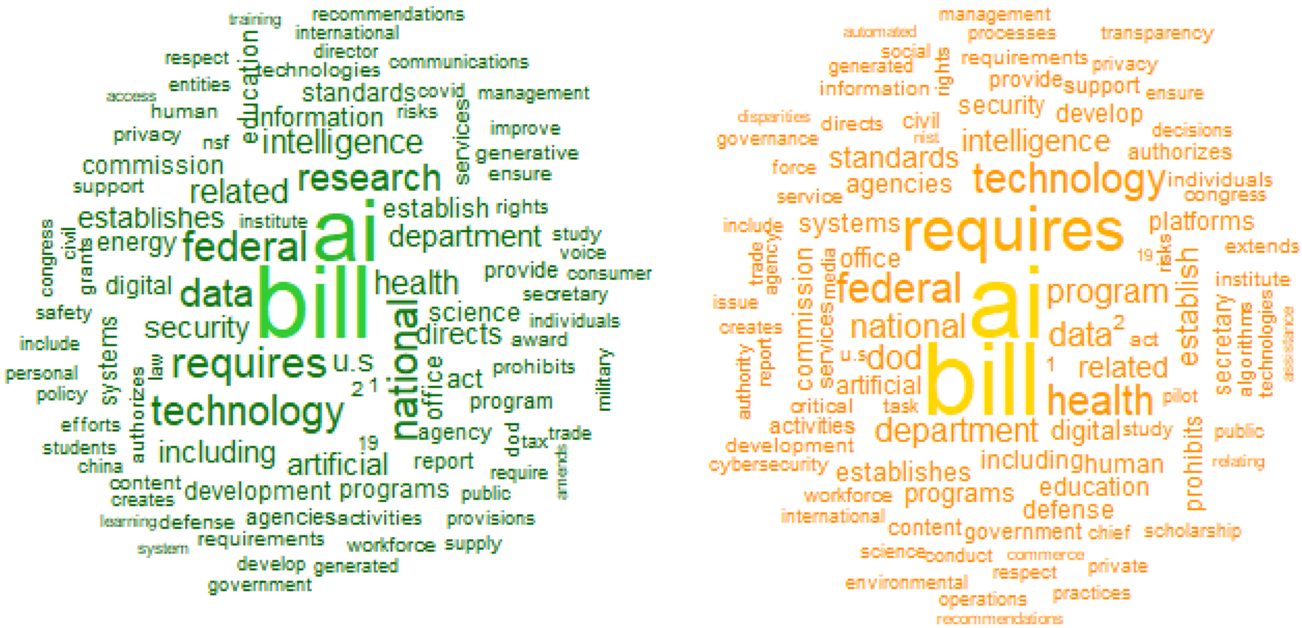
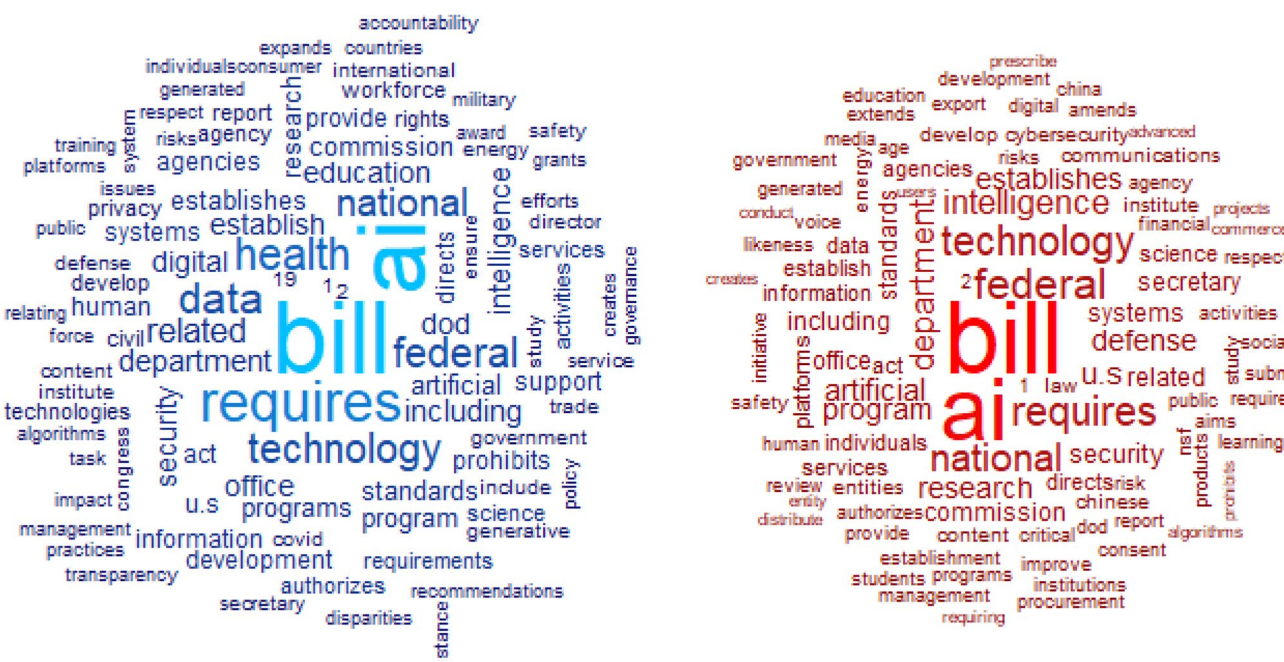


Fig. 10 Top 20 words used in Word Cloud



(a) House (b) Senate

Fig. 11 Word cloud: AI bills by chamber



(a) Democrat (b) Republican

Fig. 12 Word cloud: AI bills by party

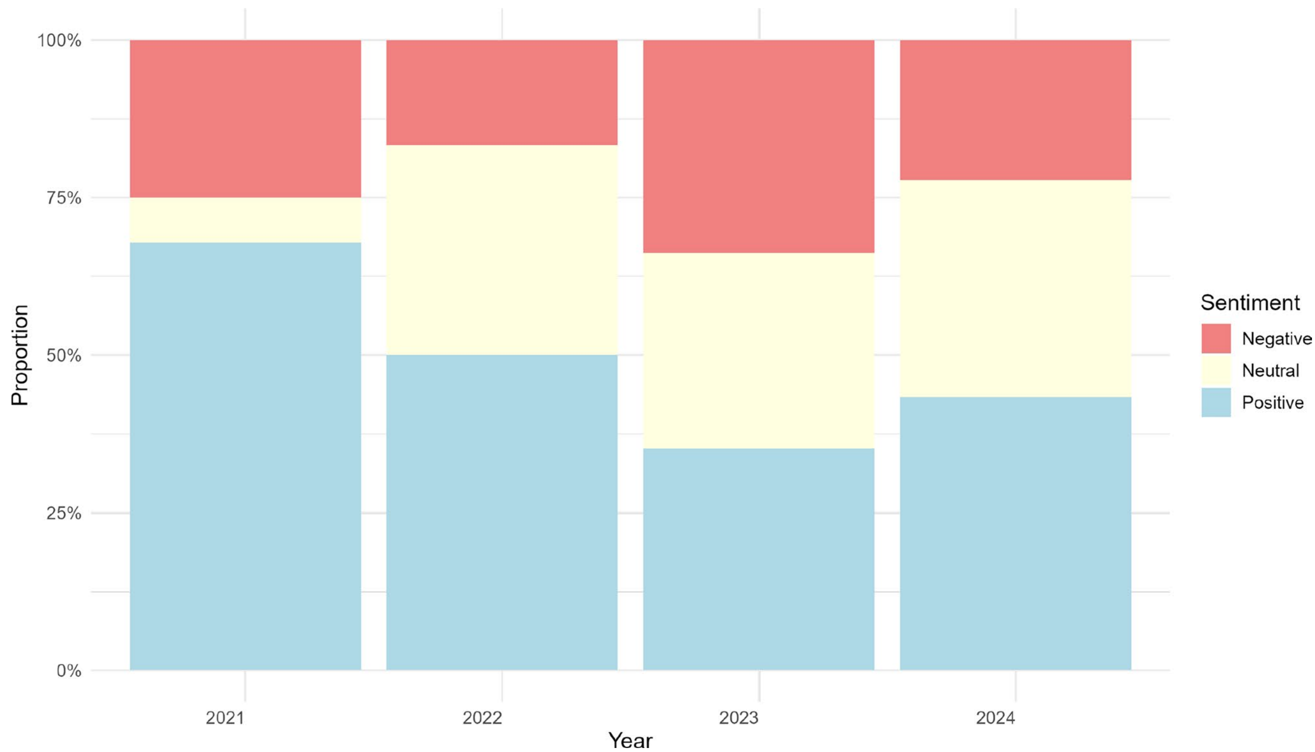


Fig. 13 Sentiment proportions in AI-related bills by year

Appendix: Tables

See Tables 10, 11, 12 and 13.

Table 10 Top terms and beta coefficients by topic

Topic	Term	Beta	Topic	Term	Beta
1	Technology	0.0802	3	Development	0.0440
1	Bill	0.0656	3	Authorizes	0.0409
1	Intelligence	0.0637	3	Bill	0.0398
1	Program	0.0551	3	Including	0.0387
1	Artificial	0.0544	3	Activities	0.0361
1	Standards	0.0515	4	Data	0.1110
1	National	0.0459	4	Bill	0.1020
1	Department	0.0407	4	Commission	0.0651
1	Defense	0.0391	4	Federal	0.0570
1	Develop	0.0331	4	Act	0.0553
2	Bill	0.1010	4	Digital	0.0428
2	Use	0.0880	4	Individuals	0.0368
2	Requires	0.0758	4	Platforms	0.0342
2	Systems	0.0572	4	Establishes	0.0329
2	Federal	0.0429	4	Creates	0.0293
2	Content	0.0406	5	Health	0.0996
2	Agencies	0.0397	5	Certain	0.0760
2	Civil	0.0391	5	Bill	0.0752
2	Generative	0.0281	5	Requires	0.0693
2	Used	0.0266	5	Related	0.0508
3	Research	0.0714	5	Services	0.0442
3	National	0.0690	5	Including	0.0346
3	Education	0.0649	5	Human	0.0321
3	Security	0.0542	5	Department	0.0284
3	Science	0.0535	5	Congress	0.0277

(Topic 1) Technology and Innovation; (Topic 2) Government Operations and Content Regulation; (Topic 3) Research, Education, and Security; (Topic 4) Data and Digital Governance; and (Topic 5) Healthcare and Human Services

Table 11 Top 30 words across all AI bills

Word	Frequency
Bill	260
AI	239
Requires	119
Federal	88
Technology	87
Health	78
Data	75
Act	73
System	72
Standards	66
National	63
Develop	60
Defense	57
Program	56
Intelligence	52
Requirements	49
Control	47
Platforms	46
Education	44
Content	42
Services	40
Digital	39
Department	38
Manage	36
Authorizes	32
Human	31
Including	30
Research	28
Systems	26
Establish	24

Table 12 Top 30 words by chamber: house and senate

Word (House)	Freq (House)	Word (Senate)	Freq (Senate)
Bill	142	AI	118
AI	121	Bill	118
Requires	51	Requires	68
Technology	49	Federal	40
Federal	48	Health	38
Data	45	Program	35
Health	43	National	33
National	40	Technology	33
Program	38	Department	32
Including	37	Data	30
Department	35	Security	28
Security	33	Related	27
Related	32	Defense	25
Establish	30	Artificial	24
Standards	29	Intelligence	23
Artificial	28	Establish	22
Research	27	Programs	21
Intelligence	25	Including	20
Office	24	Office	19
Develop	22	Establish	19
Platforms	21	Services	18
Services	20	Research	17
Digital	19	Systems	16
Developments	18	Develop	15
Management	17	Frameworks	14
Science	16	Digital	13
Tasks	15	Standards	13
Framework	14	Frameworks	13
Establishes	14	Establish	12

Table 13 Top 30 words by party: democrat and republican

Word (Democrat)	Freq (Democrat)	Word (Republican)	Freq (Republican)
Bill	180	Bill	79
AI	170	AI	68
Requires	91	Federal	29
Health	68	Requires	27
Data	65	Technology	26
Federal	60	System	23
System	48	National	21
Act	45	Standards	19
Technology	44	Defense	18
Standards	41	Data	17
National	40	Program	17
Develop	36	Act	16
Defense	34	Health	14
Program	32	Develop	12
Intelligence	29	Intelligence	12
Requirements	27	Requirements	10
Platforms	23	Department	10
Education	22	Platforms	9
Content	18	Education	8
Services	19	Authorizes	8
Digital	15	Certain	7
Manage	24	Manage	7
Authorizes	17	Research	6
Human	17	Human	6
Research	14	Systems	5
Including	12	Including	5
Systems	11	Establish	5
Establish	10	Congress	5

Author Contributions Heonuk Ha conducted the research, performed the analysis, and wrote the manuscript. All work presented in this study was solely completed by the author.

Data Availability The data sets used for this research will be shared in a suitable public repository.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

Aldrich H (1995) Why parties? The origin and transformation of political parties in America. University of Chicago Press

Alreemy Z, Chang V, Walters R, Wills G (2016) Critical success factors (CSFs) for information technology governance (ITG). Int J Inf Manage 36(6):907–916

Anderson WD, Box-Steffensmeier JM, Sinclair-Chapman V (2003) The keys to legislative success in the US house of representatives. Legis Stud Q 28(3):357–386

Attard-Frost B, Brandusescu A, Lyons K (2024) The governance of artificial intelligence in Canada: findings and opportunities from a review of 84 AI governance initiatives. Gov Inf Q 41(2):101929

Bailey MA (2007) Comparable preference estimates across time and institutions for the court, congress, and presidency. Am J Polit Sci 51(3):433–448

Ballard AO (2022) Bill text and agenda control in the house and senate. J Polit 84

Bastani K, Namavari H, Shaffer J (2019) Latent Dirichlet allocation (LDA) for topic modeling of the CFPB consumer complaints. Expert Syst Appl 127:256–271

Benoit K, Laver M, Mikhaylov S (2009) Treating words as data with error: uncertainty in text statements of policy positions. Am J Polit Sci 53(2):495–513

Benoit K, Munger K, Spirling A (2019) Measuring and explaining political sophistication through textual complexity. Am J Polit Sci 63(2):491–508

Binder SA (2004) Stalemate: causes and consequences of legislative gridlock. Rowman & Littlefield

Blei DM, Ng AY, Jordan MI (2003) Latent dirichlet allocation. J Mach Learn Res 3(Jan):993–1022

Brey P (2017) Ethics of emerging technology. The ethics of technology: Methods and approaches, pp 175–191

Campbell JE (1982) Cosponsoring legislation in the US Congress. Legislative Studies Quarterly, pp 415–422

Campbell J, McDonald C, Sethibe T et al (2010) Public and private sector IT governance: identifying contextual differences. Aust J Inf Syst 16(2)

Canes-Wrone B, Brady DW, Cogan JF (2002) Out of step, out of office: electoral accountability and house members' voting. Am Polit Sci Rev 96(1):127–140

Carson JL, Jenkins JA (2011) Examining the electoral connection across time. Annu Rev Polit Sci 14(1):25–46

Chandrasekaran G, Nguyen TN, Hemanth DJ (2021) Multimodal sentimental analysis for social media applications: a comprehensive review. Wiley Interdisciplinary Rev Data Min Knowl Discovery 11(5):e1415

Cox GW (2005) Setting the agenda: responsible party government in the US house of representatives. Cambridge UP

Diermeier D, Godbout J-F, Yu B, Kaufmann S (2012) Language and ideology in congress. Br J Polit Sci 42(1):31–55

Engler A (2023) The EU and US diverge on AI regulation: a transatlantic comparison and steps to alignment

Entman RM (1993) Framing: Toward clarification of a fractured paradigm. J Commun 43(4):51–58

Ergas H (1987) Does technology policy matter. Technology and global industry Companies and nations in the world economy 191:245

Fenno RF (1978) Home style: house members in their districts. Little & Brown

Fishenden J, Thompson M (2013) Digital government, open architecture, and innovation: why public sector IT will never be the same again. J Public Admin Res Theory 23(4):977–1004

Fowler JH (2006) Connecting the congress: a study of cosponsorship networks. Polit Anal 14(4):456–487

Fraccaroli N, Giovannini A (2020) Central banks in parliaments: a text analysis of the parliamentary hearings of the bank of England, the European central bank and the federal reserve

Gailmard S, Jenkins JA (2007) Negative agenda control in the Senate and house: fingerprints of majority party power. J Polit 69(3):689–700

Griciūtė B, Han L, Nenadic G (2023) Topic modelling of swedish newspaper articles about coronavirus: a case study using latent dirichlet allocation method. In: 2023 IEEE 11th International Conference on Healthcare Informatics (ICHI), pp 627–636. IEEE

Grimmer J, Stewart BM (2013) Text as data: the promise and pitfalls of automatic content analysis methods for political texts. Polit Anal 21(3):267–297

Grofman B, Griffin R, Glazer A (1991) Is the Senate more liberal than the House? Another look. Legislative Studies Quarterly, 281–295

Hollibaugh GE (2019) The use of text as data methods in public administration: a review and an application to agency priorities. J Public Admin Res Theory 29(3):474–490

Kessler D, Krehbiel K (1996) Dynamics of cosponsorship. Am Polit Sci Rev 90(3):555–566

Khan MS, Shoaib A, Arledge E (2024) How to promote AI in the US federal government: insights from policy process frameworks. Gov Inf Q 41(1):101908

Koger G (2003) Position taking and cosponsorship in the US House. Legis Stud Q 28(2):225–246

Krippendorff K (2018) Content analysis: an introduction to its methodology. Sage publications

Krutz GS (2005) Issues and institutions: "Winnowing" in the US congress. Am J Polit Sci 49(2):313–326

Laver M, Benoit K, Garry J (2003) Extracting policy positions from political texts using words as data. Am Polit Sci Rev 97(2):311–331

Lazarus J (2013) Issue salience and bill introduction in the House and Senate. In: Congress & the Presidency, vol. 40, pp 215–229. Taylor & Francis

Lee FE (2016) Insecure majorities: congress and the perpetual campaign. University of Chicago Press
Lewallen J (2024) Views on the hill: disagreement and effectiveness in US Senate agenda setting. Polit Policy 52(2):306–330
Liebig L, Güttel L, Jobin A, Katzenbach C (2024) Subnational AI policy: shaping AI in a multi-level governance system. AI Soc 39(3):1477–1490
Lowe W, Benoit K, Mikhaylov S, Laver M (2011) Scaling policy preferences from coded political texts. Legis Stud Q 36(1):123–155
Manna P (2006) School's in: Federalism and the national education agenda. Georgetown University Press
Manoharan AP, Ingrams A (2018) Conceptualizing e-government from local government perspectives. State Local Government Rev 50(1):56–66
Mayhew DR (2004) Congress: the electoral connection. Yale University Press
Metcalfe JS (1995) Technology systems and technology policy in an evolutionary framework. Camb J Econ 19(1):25–46
Moor JH (2005) Why we need better ethics for emerging technologies. Ethics Inf Technol 7(3):111–119
Negara ES, Triadi D, Andryani R (2019) Topic modelling twitter data with latent Dirichlet allocation method. In: 2019 International Conference on Electrical Engineering and Computer Science (ICECOS), pp 386–390. IEEE
Nguyen TH, Shirai K, Velcin J (2015) Sentiment analysis on social media for stock movement prediction. Expert Syst Appl 42(24):9603–9611
Okolo CT (2023) AI in the Global South: opportunities and challenges towards more inclusive governance. The Brookings Institution
Oleszek WJ, Oleszek MJ, Rybicki E, Heniff B Jr (2015) Congressional procedures and the policy process. CQ press
Outeda CC (2024) The EU's AI act: a framework for collaborative governance. Internet of Things, p. 101291
Pardo TA, Nam T, Burke GB (2012) E-government interoperability: interaction of policy, management, and technology dimensions. Soc Sci Comput Rev 30(1):7–23
Park JY (2021) When do politicians grandstand? Measuring message politics in committee hearings. J Polit 83(1):214–228
Proksch S-O, Lowe W, Wäckerle J, Soroka S (2019) Multilingual sentiment analysis: a new approach to measuring conflict in legislative speeches. Legis Stud Q 44(1):97–131
Quinn KM, Monroe BL, Colaresi M, Crespin MH, Radev DR (2010) How to analyze political attention with minimal assumptions and costs. Am J Polit Sci 54(1):209–228
Rheault L, Beelen K, Cochrane C, Hirst G (2016) Measuring emotion in parliamentary debates with automated textual analysis. PLoS ONE 11(12):e0168843
Roberts H, Cowls J, Morley J, Taddeo M, Wang V, Floridi L (2021) The Chinese approach to artificial intelligence: an analysis of policy, ethics, and regulation. Springer
Rudkowsky E, Haselmayer M, Wastian M, Jenny M, Emrich Š, Sedlmair M (2018) More than bags of words: sentiment analysis with word embeddings. Commun Methods Meas 12(2–3):140–157
Schiff DS, Schiff KJ, Pierson P (2022) Assessing public value failure in government adoption of artificial intelligence. Public Admin 100(3):653–673
Schiller WJ (1995) Senators as political entrepreneurs: using bill sponsorship to shape legislative agendas. Am J Polit Sci 186–203
Shirota Y, Hashimoto T, Sakura T (2014) Extraction of the financial policy topics by latent dirichlet allocation. In: TENCON 2014–2014 IEEE Region 10 Conference, pp 1–5. IEEE
Sinclair B (2016) Unorthodox lawmaking: new legislative processes in the US congress. CQ Press
Soroka S, Young L, Balmas M (2015) Bad news or mad news? Sentiment scoring of negativity, fear, and anger in news content. Ann Am Acad Pol Soc Sci 659(1):108–121
Taeihagh A (2021) Governance of artificial intelligence. Policy Soc 40(2):137–157
Ulnicane I, Knight W, Leach T, Stahl BC, Wanjiku W-G (2021) Framing governance for a contested emerging technology: insights from AI policy. Policy Soc 40(2):158–177
Valle-Cruz D, Criado JI, Sandoval-Almazán R, Ruvalcaba-Gomez EA (2020) Assessing the public policy-cycle framework in the age of artificial intelligence: from agenda-setting to policy evaluation. Gov Inf Q 37(4):101509
Wang S, Zhang Y, Xiao Y, Liang Z (2025) Artificial intelligence policy frameworks in China, the European Union and the United States: an analysis based on structure topic model. Technol Forecast Soc Chang 212:123971
Weill P (2008) Don't just lead, govern: How top-performing firms govern IT. MIS Q Exec 3(1):3
Weill P, Ross JW (2004) IT governance: How top performers manage IT decision rights for superior results. Harvard Business Press
Weissert CS, Weissert WG (2008) Governing health: the politics of health policy. JHU Press
Wilkerson J, Casas A (2017) Large-scale computerized text analysis in political science: opportunities and challenges. Annu Rev Polit Sci 20(1):529–544
Wood BD, Peake JS (1998) The dynamics of foreign policy agenda setting. Am Polit Sci Rev 92(1):173–184
Zeng J (2020) Artificial intelligence and China's authoritarian governance. Int Aff 96(6):1441–1459
Zhang B, Dafoe A (2019) Artificial intelligence: American attitudes and trends. Available at SSRN 3312874
Zhou S, Kan P, Huang Q, Silbernagel J (2023) A guided latent Dirichlet allocation approach to investigate real-time latent topics of Twitter data during Hurricane Laura. J Inf Sci 49(2):465–479