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A Comparative Study of U.S. and China's AI Policy Evolution (2017-2023) from the Perspective of Multiple Streams Framework

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Abstract: *This study examines the evolution of artificial intelligence (AI) policies between China and United States. The research focuses on the uniqueness of AI and how public policy tools can be adapted to support a closer link between innovation and national goals. As AI reaches deeper into the global community, it also brings new challenges. These challenges include data privacy concerns, algorithmic bias, and the urgent need to manage innovation fairly. Governments are now under increasing pressure to establish strong policy frameworks. These frameworks must strike a balance between rapid technological change and the protection of social stability. At the same time, AI has become an important part of national governance. It also plays a crucial role in global competition. Therefore, it is important for the state to use AI in a strategic and forward-looking manner.In the era of smart technologies, AI is a major driver of national competitiveness. This study compares the AI policy paths of China and the United States - two global leaders in this field - over the period 2017 to 2023. The study adopts a 'policy tools-policy subjects' approach, and uses the Multiple Streams Framework (MSF) as a theoretical framework to further explain how policies change over time. Therefore, this paper more comprehensively analyses the intrinsic mechanism of AI policy changes between China and the United States from 2017 to 2023, and compares the AI strategy designs of the two countries from a relatively perfect perspective. Comparing the advanced experiences of China and the United States, the two world leaders in AI, in AI policy planning will provide an effective reference for the future policy planning of the entire AI industry in the world.*

Keywords: *Artificial Intelligence, Multiple Streams Framework, United States, China, Public Policy*

1. Introduction

As Henry Ford famously noted, innovation requires transcending established norms rather than merely improving them. Since its formal inception at the 1956 Dartmouth Conference (McCarthy et al., 1956), artificial intelligence (AI) has become a transformative force, reshaping industries, economies, and governance (Wu, 2022). AI applications now span smart manufacturing, healthcare, public safety, and social governance, with generative AI technologies, such as ChatGPT, further embedding AI into daily life and accelerating digital transformation. This growing societal impact has prompted governments to develop policies balancing technological innovation with social governance, influencing problem identification, design, implementation, and evaluation, while regulating AI through investment, legal frameworks, ethical standards, and industrial guidance. China and the United States, as global AI leaders, have integrated AI into national strategies since 2017 via the New Generation Artificial Intelligence Development Plan and the U.S. National AI Strategy. In 2021, U.S. private AI investment reached $58 billion, compared to China's $17 billion (Stanford AI Index, 2022). The U.S. emphasizes market-driven, research-led innovation (He, 2021; Xiao, 2017), whereas China adopts a state-led industrial policy approach, linking AI to manufacturing, agriculture, and urban management (Zhang et al., 2022). These differences highlight the role of institutional logics and policy design in shaping AI development. Understanding AI's technological foundations, societal impact, and policy dynamics is therefore crucial for examining its co-evolution with public governance and the strategic rationale behind national AI policies.

Literature Review I: Theories of Policy Change

Research on policy change has developed a range of theoretical perspectives. Brewer (1983) conceptualized policymaking as a continuous cycle of revision and adjustment, while Anderson (1900)

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highlighted policy replacement and modification as central mechanisms. Hogwood (1993) classified change into innovation, succession, maintenance, and termination. Hall (1993) distinguished incremental versus paradigm-shifting change, and Heclo (1974) emphasized the role of policy learning. To explain these dynamics, scholars have advanced frameworks such as the Advocacy Coalition Framework, punctuated equilibrium theory, institutional rational choice, and especially the Multiple Streams Framework (MSF) (Kingdon, 1984). The strength of MSF lies in its explanatory logic: changes in the problem or political stream may open policy windows, which policy entrepreneurs can exploit, leading to convergence of streams and subsequent policy change. This framework has been widely applied to domains including environment, health, and education, yet its use in analyzing AI policy remains limited.

Literature Review II: AI Policy Studies

Existing research on AI policy in China and the United States falls into three major strands. The first is policy classification: scholars categorize AI policies by instruments or content, including supply, demand, and ethical principles (Zhou, 2022). The second is policy evaluation: researchers employ statistical metrics, text mining, or economic modeling to assess policy effects (Fei, 2021; Furman, 2022). For example, Furman (2022) finds that U.S. AI policy is distinctly market-driven, while Zhang (2019) reveals uneven implementation across local governments. The third is comparative research, which analyzes cross-national differences. Guan (2021) highlights shifting priorities from development to ethics in China and Europe, while Chen (2021) identifies divergent pathways but also mutual learning. Hine (2022) underscores persistent institutional barriers between China and the U.S. Despite this growing body of work, few studies systematically examine AI policy evolution through the lens of policy process theories. Against this backdrop, this study adopts MSF as its analytical framework to explain the dynamics of AI policy evolution in China and the United States from 2017 to 2023. Specifically, it addresses two core questions: (1) How have Chinese and U.S. AI policies differed in instruments and themes since 2017? (2) What political factors have shaped their formulation and implementation? By situating AI within the broader logic of public policy change, this study bridges the gap between technology-focused research and policy process theory, contributing to both comparative policy studies and the understanding of AI governance.

2. Basic Concepts and Theoretical Foundations

2.1 Basic Concepts

1) Artificial Intelligence

AI research has been shaped by two intellectual traditions: symbolic AI and connectionism. Symbolic AI uses logic and mathematics to model input–output processes but struggled with real-world complexity (Nilsson, 2009, 64). Connectionism simulates brain mechanisms with artificial neural networks, gaining prominence with deep learning and backpropagation (Rumelhart & Mcclelland, 1986, 3;). Cnns, rnns, and the transformer architecture (Vaswani et al., 2017, 5998) enabled breakthroughs in image, speech, and natural language processing, culminating in large-scale genai models like GPT (Radford et al., 2018, 1). Chatgpt exemplifies gen AI, using a two-stage pretraining–fine-tuning approach to generate human-like text (Brown et al., 2020, 1877).

2) Artificial intelligence policy

AI policy encompasses policies promoting AI development and AI applications in policymaking (Zeng et al., 2023, 167). Policies guide AI through fiscal investment, regulation, ethical frameworks, and talent programs (Yang & Huang, 2023, 238), while AI empowers policy science by integrating multi-source data, enhancing empirical analysis, and simulating complex policy environments (Galvez & Richards, 2021; Vaswani et al., 2017, 5999-6003; Sun & Li, 2024, 7;). Generative AI supports large-scale text mining, sentiment analysis, and virtual policy experiments, enabling policy researchers to extract insights from complex, unstructured data (Binns, 2020, 391-393; Morales et al., 2023, 10).

2.2 Theoretical Foundation

1) Quantitative Research Theory for Policy Literature

Policy documents reflect government actions and societal resource allocation (Wu Qiyuan, 1989, 42-50; Easton, 1953, 24;). Quantitative analysis of policy texts transforms unstructured data into structured knowledge, revealing policy evolution, instrument combinations, and co-evolution of technology and institutions (Laver, 2003).

2) Multiple Streams Framework

Kingdon's Multiple Streams Framework (MSF) conceptualizes policy emergence as the convergence of Problem, Policy, and Political Streams (Kingdon, 1984; Birkland, 2006). The Problem Stream identifies societal issues, the Policy Stream provides proposals and solutions, and the Political Stream reflects power structures and public opinion. MSF has been applied globally and in China to study diverse policy domains, highlighting the interdependence of problems, solutions, and political context (Bi, 2007; Zhou, 2005;).

2.3 Analytical Framework

This study compares AI policies in China and the U.S., focusing on policy tools (supply-side, environment-side, demand-side) and policy themes, integrating analysis of policy actors. Supply-side instruments include R&D funding, talent cultivation, and infrastructure development. Environment-side tools cover legal frameworks, ethical standards, and industry guidelines. Demand-side tools stimulate adoption via procurement, subsidies, and pilot projects (smart cities, defense programs).Keyword analysis extracts core policy themes. This approach systematically examines AI policy evolution, instrument distribution, and strategic adjustments, providing empirical insights into China and U.S. AI governance.

3. Research on Chinese and American AI Policy Literature Based on "Policy Tools-Policy Subjects"

3.1 Current Status of AI Strategies in China and the U.S.

China's AI strategy began with the 2017 New Generation Artificial Intelligence Development Plan, followed by the Politburo's collective study (2018) and the Guiding Opinions on AI–Real Economy Integration (2019). Subsequent policies, including the Digital Countryside Strategy and the 14th Five-Year Plan for Digital Economy Development, promoted applications in autonomous vehicles, education, governance, and legislation. The Ministry of Science and Technology created the AI Development and Research Center and pilot zones to advance implementation (Liu, 2022). These steps elevated AI to a national strategy, characterized by top-level design, industrial upgrading, and local demonstration projects. In recent years, generative AI has become a global benchmark, pushing China to stress ecosystem-building.

In the U.S., AI was formalized as a national strategy with the 2016 National Strategic Plan for AI R&D, reinforced by the 2017 National Security Strategy and the 2019 Executive Order on AI, which launched the National AI Initiative (Feldstein, 2019). U.S. implementation emphasizes government coordination and cross-sector collaboration, relying on research grants, NSF-led AI centers, and legislation such as the CHIPS and Science Act (National AI Initiative Office, 2021).Both countries position AI as a strategic response to technological change, but with different orientations. China adopts a government-led, industrial policy model, focusing on integration with manufacturing, smart cities, and data security through laws like the Data Security Law. The U.S., by contrast, follows an innovation-driven model, prioritizing frontier research, private–public partnerships, and national security applications, including the Joint AI Center (Allen, 2020). Tensions surfaced with U.S. export controls on Chinese AI chips in 2022, underscoring AI's geopolitical significance.

3.2 Data Sources and Analytical Framework

This study collected 2017–2023 national-level AI policy samples from China and the U.S. : 11 documents from China's State Council Policy Library and 9 from the U.S. OSTP database. Based on policy instruments theory (Rothwell & Zegveld, 1985), policy tools are categorized into supply-side, environment-side, and demand-side (Li, 2016). A Policy Tools–Policy Subjects analytical framework was constructed using manual text coding to systematically compare the two countries' AI policies, revealing differences in policy tools and themes. Sample selection followed three principles: official documents, explicit AI content, and high representativeness, ensuring openness, relevance, and authority as shown in Table 1.

Policy provisions are the basic unit elements for subsequent policy statistics and analyses. In this study, 20 policies were structured by removing macro-general content such as policy background and

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purpose, screening out clear and specific policy provisions, and coding them in the order of 'policy number - policy chapter - provision number'. For example, A1-4-1 indicates the first policy article in Chapter 4 of the policy document numbered A1. In the end, there were 278 policy articles in China and 207 in the United States, totaling 485 policy articles.

Table 1 List of Chinese and US AI policies

States	Policy No.	Policy name	Date of enactment	Agency
China	A1	The MOS and TOS for enterprises on the development of artificial intelligence	2017.3.10	DST
	A2	New Generation Artificial Intelligence Development Plan	2017.7.8	PRC
	A3	Action Plan for Artificial Intelligence Innovation in Higher Education	2018.4.2	MOE
	A4	Guidelines for Next Generation Artificial Intelligence Innovation	2019.8.29	DST
	A5	Letter on building a new generation of national artificial intelligence	2019.11.2	DST
	A6	Opinions on promoting the development of artificial intelligence	2019.11.8	SFDA
	A7	Guidelines for the Construction of National New Generation of Artificial Intelligence	2019.12.1	DST
	….			
	A10	Opinions on Accelerating the Promotion of Economic Development	2022.7.29	DST
	A11	Interim Measures for the Management of Generative Artificial Intelligence	2023.8.15	NDR
U.S	B1	THE NATIONAL ARTIFICIAL INTELLIGENCE RESEARCH PLAN	2016.10	NSTC
	B2	PREPARING FOR THE FUTURE OF ARTIFICIAL INTELLIGENCE	2016.10	NSTC
	B3	Artificial Intelligence and National Security	2020.10.11	CRS
	B4	THE NATIONAL ARTIFICIAL INTELLIGENCE RESEARCH	2019.6	NSTC
	……			
	B9	NATIONAL ARTIFICIAL INTELLIGENCE RESEARCH	2023.5.	NSTC

Source: Independently drawn by the author

3.3 Content Analysis of Chinese and US AI Policies Based on Policy Tools

This study intends to draw on the classification ideas of Rothwell and Zegveld to classify AI policy tools into supply-type, environment-type and demand-type, specifically including 16 types (see Table 2). Among them, supply-type policy tools refer to the government's expansion of supply through manpower, capital, technology, infrastructure and other factors of production to provide initial power support for the startup and extension of the AI industry chain, which is mainly manifested in the policy's impetus to the development of AI; environment-type policy tools refer to the creation of a favourable policy environment for the development of AI through political means such as top-level design, or the use of tax incentives, market control Economic means such as maintaining a fair and orderly market order, indirectly affecting the future development trend of AI technology and industry, mainly manifested as the influence of policy on AI development; demand-based policy tools refer to the stimulation of AI industry development through the adoption of outsourcing, procurement, projects and other ways to stimulate the consumer demand and implementation of AI products and technology applications, mainly manifested as the policy on AI development.

Table 2 Classification and meaning of AI policy tools

Tool Type	Tool Name	Specific Meaning
Supply-oriented	Talent Development	Cultivate and introduce professional talents through AI discipline development
	Capital Investment	Government financial assistance (e.g., subsidies, grants) for AI stakeholders
	Technology Support	Provide foundational research and core technology development (e.g., NLP, AI chips) for AI applications and industrial growth
	Information Services	Establish data-sharing platforms or databases of AI-related information and provide consulting services
	Infrastructure Construction	Build AI R&D labs, interdisciplinary resource centers, and other hardware facilities
	Organizational Development	Establish government agencies to oversee and promote the healthy development of AI technologies and industries
Environment-oriented	Regulatory Control	Create fair market conditions by formulating laws and regulations
	Risk Management	Prevent and manage potential risks of AI to ensure societal safety
	Tax Incentives	Provide tax reductions for enterprises and individuals engaged in AI R&D, investment, production, and consumption
	Intellectual Property Law	Legally safeguard AI-related innovations and protect national technological security
	Policy Strategies	Develop AI-related policies, including goal planning, social

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		governance, and implementation safeguards
Demand-oriented	Public Procurement	Use government funds to procure AI-related products and applications from third parties
	Outsourcing	Delegate AI R&D projects to enterprises or private research institutions to accelerate progress
	Scientific Projects	Fund AI research projects for universities and institutions
	Public-Private Partnership	Collaborate with private entities, universities, and research institutes to cultivate the AI market
	International Collaboration	Engage in technical exchanges, standards development, and partnerships with overseas governments, enterprises, and institutions

Source: Rothwell & Zegveld. Industrial Innovation and Public Policy: Preparing for the 1980s and the 1990s, Chapter 4, 82-85 pages

This study examines the use of policy instruments in Chinese and U.S. AI policies through systematic content analysis of national-level documents issued between 2017 and 2023. The sample comprises 11 Chinese documents (278 provisions) and 9 U.S. documents (207 provisions). Following Rothwell and Zegveld's (1985) framework, instruments were classified into supply-side (e.g., financial support, talent development, infrastructure), environment-side (e.g., legal frameworks, standards, regulatory measures), and demand-side (e.g., government procurement, public–private partnerships) categories. A keyword dictionary was employed to identify and count occurrences, with multiple instruments potentially coded per provision.

Analysis shows that Chinese provisions contained 456 mentions of policy instruments (173 supply-side, 228 environment-side, 55 demand-side), while U.S. provisions contained 327 mentions (134, 164, 30, respectively). On average, each provision referenced 1.64 instruments in China and 1.58 in the U.S., indicating frequent simultaneous application of multiple tools. The detailed frequency distribution of instrument usage is presented in Table 3.As shown in Table 3, both countries deploy a broadly balanced combination of supply, environment, and demand instruments, reflecting comprehensive policy frameworks supporting AI development. Supply- and environment-oriented instruments dominate, indicating governmental emphasis on resource allocation and formal institutional conditions. In contrast, the relatively limited use of demand-side instruments suggests insufficient attention to market-pull mechanisms, which may constrain industry growth and disrupt value chains.

Table 3 Results of AI policy analysis between China and the US based on policy instruments

Tools Type	Name of Tools	China	U.S
Supply-orient	Talent Development	29 (17%)	18 (13%)
	Capital Investment	26 (15%)	38 (28%)
	Technology Support	28 (16%)	28 (21%)
	Information Serviecs	50 (29%)	23 (17%)
	Infrastructure Construction	40 (23%)	28 (21%)
	Overall	**173 (38%)**	**134 (41%)**
Environment-orient	Organization Development	28 (12%)	12 (7%)
	Regular Control	48 (21%)	51 (31%)
	Risk Management	32 (14%)	31 (19%)
	Tax Incentives	12 (5%)	3 (2%)
	Intellectual Property Protection	14 (6%)	0(0%)
	Policy Strategies	96 (42%)	67 (41%)
	Overall	**228 (50%)**	**164 (50%)**
Demond-orient	Public Procurement	0 (0%)	0 (0%)
	Outsourcing	4 (7%)	0 (0%)
	Scientific Projects	15 (27%)	5.1 (17%)
	Public-Private Partnerships	24 (43%)	20 (63%)
	Overall	**55 (12%)**	**30 (9%)**

Source: Independently drawn by the author
Note: The data in this table is derived from a textual analysis of 11 Chinese and 9 U.S. national-level AI policy documents, containing 278 and 207 policy provisions, respectively. The classification of policy tools is based on the policy tool theory proposed by Rothwell & Zegveld *Frequency: The number of times a specific policy tool appears in the policy documents.

*Percentage: The proportion of a tool within its respective policy tool category. For example, China's "Talent Development" accounts for 17% (calculated as 29 ÷ 173).*Overall Percentage: The proportion of a tool category within the total policy tools. For example, supply-side tools in China account for 38% (calculated as 173 ÷ 456).

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*Talent Development: China (29 times, 17%) places greater emphasis on AI talent cultivation compared to the U.S. (18 times, 13%).

*Financial Investment: The U.S. (38 times, 28%) invests more heavily in financial support, reflecting its resource allocation toward AI innovation.

*Regulatory Control: The U.S. (51 times, 31%) places a stronger emphasis on regulating AI development through laws and standards.

*Public Procurement: Neither country uses this tool (0 times, 0%), indicating a deficiency in demand-side tools.

Firstly, supply-based policy instruments are more frequently used. Among them, the application of ‘talent training’ in China and the United States is slightly weaker, possibly because AI policy is mainly driven by industry, science and technology, and network-related departments, which may overlook discipline construction, talent cultivation, and labour upgrading. In terms of financial input, China mentions it only 15%, while the U.S. emphasises ‘scientific and technological support’ to underpin AI innovation. China focuses more on information construction and data resources, frequently mentioning ‘information service’ (29%) and ‘infrastructure construction’ (23%) to build a robust data ecosystem.

Second, environmental policy tools are most frequently used. Both countries rely on ‘policy strategies,’ which provide flexible support such as target planning and social governance. For instance, the U.S. policy Preparing for the Future of Artificial Intelligence requires regular reporting of AI milestones to higher authorities and society. ‘Tax incentives’ and ‘intellectual property protection’ are briefly mentioned, with limited guidance. ‘Organisational construction’ in the U.S. is only 7%, which may cause ambiguity in agency roles. ‘Regulatory control’ is widely used but may expose implementation weaknesses. Regarding ‘risk management,’ the U.S. places more emphasis on technological security than China.

Third, demand-based policy tools are least used. Tools like ‘public procurement’ are virtually absent, limiting diversified implementation. Both countries emphasise ‘public-private cooperation’ (China 43%, U.S. 63%), fostering an active AI ecosystem. In short, China and the United States show different focuses. The U.S. promotes AI innovation via direct financial support, such as the National AI Initiative Act (2020), federal R&D grants, and large appropriations through the NSF and the Chip and Science Act (National AI Initiative Office, 2021, 10–15; U.S. Congress, 2021, 2–5; 2022, 1–3). China prefers government-led industrial policies and infrastructure investment, exemplified by the National Science and Technology Major Project ‘New Generation of AI’ and local initiatives like the Shenzhen AI Industrial Park (Wu, 2021, 62–68).

4. Analysis of the Dynamic Mechanisms in the Evolution of AI Policies in China and the United States: A Multiple Streams Framework Perspective

Amid rapid AI advancements and intensifying technological competition, public policy plays a pivotal role in guiding national strategies and allocating resources. AI policy evolution reflects not only governmental responses to technological change but also differences in governance philosophies, policy pathways, and institutional logic. Comparing China and the United States offers significant insights. This study examines AI policies in both countries between 2017 and 2023 using Kingdon’s (1984) Multiple Streams Framework (MSF), which analyzes policy evolution through the convergence of problem, policy, and politics streams at critical policy windows, highlighting intrinsic drivers and institutional constraints (Kingdon, 1984).

China’s AI policy, initiated with the 2017 New Generation Artificial Intelligence Development Plan and reinforced by subsequent central-level documents and the 14th Five-Year Plan for Digital Economy Development, emphasizes AI as a national strategy, state-led industrial policy, and integration with local governance, with recent attention to generative AI and ecosystem building (Liu, 2022). In the United States, AI became a national strategy with the 2016 National AI R&D Strategic Plan, furthered by national security strategies and the 2019 Executive Order establishing the National AI Initiative. While both countries prioritize AI strategically, China relies on top-down industrial coordination, whereas the U.S. emphasizes research-driven, cross-sector collaboration (Liu, 2022, 45).

4.1 Theoretical Framework: The Explanatory Logic of MSF

AI’s broad scope across fields results in policies with rapid change, wide impact, and high technical

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complexity. Policy formulation is thus dynamic and multi-factorial. MSF, originally applied to U.S. federal agenda-setting, posits three independent "source streams"—problem, policy, and political—which converge under certain conditions to open policy windows (Kingdon, 1984, 164). Scholars have applied MSF to Chinese policy contexts, e.g., Zhu (2020, 35), Huang (2022, 125), Chen (2020, 3).

The problem stream concerns how issues of social concern enter government agendas via indicators, focusing events, and feedback mechanisms (Kingdon, 1995, 90-109). The policy stream involves a "primordial policy soup" of competing options requiring technical feasibility, value compatibility, and implementability (Kingdon, 1995, 116-120). The political stream encompasses government changes, national ideology, media influence, and civic sentiment, varying by regime type (Kingdon, 1995, 145-165). Policy windows, triggered by crises or political opportunities, enable change, mediated by policy entrepreneurs with institutional access and resource mobilization capabilities (Zahariadis, 2003, 30; 2014, 50).

Compared to other frameworks, MSF's strengths include explaining policy episodes under structural uncertainty, integrating problem identification, policy screening, and political opportunities, and capturing agenda-setting dynamics in different regimes (Cairney, 2012, 80; Sabatier, 2007, 65). AI policy's complexity, ethical concerns, and multi-source influences make MSF particularly suitable (Cairney & Jones, 2016, 37). Institutional differences further shape the streams' relative influence, e.g., centralized regimes exhibit top-down political dominance, while decentralized regimes rely on expert-driven policy streams. MSF limitations include blurred stream boundaries in centralized contexts and varying roles of policy entrepreneurs across political systems.In summary, MSF provides a dynamic, structural, and three-dimensional framework for analyzing AI policy, focusing on issue construction, policy mobilization, and political opportunity. This framework will guide the subsequent analysis of problem identification, policy supply, and political fit mechanisms in China and the U.S.

4.2 The Evolution of AI Policies in China and the United States

Policy formation occurs within political institutions, ideologies, and social structures. AI challenges governance logic and societal value distribution (Heidegger, 1977, 12). MSF allows examination of both how and why policies are formed.

1) Chinese AI Policy

First Stage (2017–2018): Strategic Initiation and Planning

The 2017 designated AI as a core technology with three-stage goals to 2030 (State Council, 2017, 2-3). Emphasis was on foundational research, algorithm breakthroughs, and computing resources. The specified a three-tier standard system (National Standardization Administration, 2018, 3). This stage reflects a centralized, state-led strategic mobilization (Wang, 2021, 327).

Second Stage (2019–2021): Integrated Development and Institutional Construction

In 2019, policy emphasized "AI+" integration with manufacturing and agriculture. Institutional mechanisms addressed practical barriers and supported high-quality economic growth (Hu, 2020, 29). Cities introduced local AI plans, e.g., Guangzhou's "AI and Digital Economy Pilot Zone." Policies transitioned from top-level strategy to operational tools, constructing cognitive frameworks (Schmidt, 2010, 3).

Third Stage (2021–2023): Ethical Governance and Ecosystem Innovation

Post-2021 policies emphasized high-quality development, ethics, and national security. The 2022 outlined research institution-centered governance (Ministry of Science and Technology, 2022, 2-10). Ethical principles—human-centricity, fairness, transparency—were institutionalized (Ministry of Science and Technology, 2022, 2-6). AI expanded to education, justice, healthcare, and strategic resources were prioritized (14th Five-Year Plan). Local innovation ecosystems emerged in Beijing and Shanghai. The stage reflects a shift from development-first to regulation-first, with public policy as a discursive tool shaping social order (Dryzek, 2006, 193-195).

2) U.S. AI Policy

First Stage (2016–2018): Strategic Proposal and National Security

The 2016 <National AI R&D Strategic Plan> framed AI as foundational for economic and national security (NSTC, 2016, 2). Governance integrated technology, ethics, and policy. Policies were incremental, shaped by technical research institutions (NSF, DARPA, Ivy League centers) and

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instrumental rationality (Weber, 1922, 26).

Second Stage (2019–2021): Strengthening Research Systems and Institutional Coordination

The 2019 Executive Order launched the National AI Initiative, coordinating agencies via OSTP. The 2020 National AI Initiative Act institutionalized policy execution. Research networks like the National AI Research Institutes Program were established. Ethical norm-building gained prominence with the 2021 Draft AI Risk Management Framework and Blueprint for an AI Bill of Rights. Policies shifted from strategic framing to operationalized, collaborative governance (Howlett, 2019, 27-45).

Third Stage (2022–2023): Policy Deepening and Global Diffusion

Domestic governance emphasized accountability and ethical boundaries. The 2022 Blueprint outlined safety, non-discrimination, privacy, explainability, and human control. Policies embedded procedural justice and value-based institutional arrangements (Rawls, 1971, 12-24, 136). The 2023 CHIPS and Science Act integrated AI governance into global strategy via G7 and EU consultations, advancing normative and institutional leadership.

4.3 Multiple Streams Framework Perspective Analysis

While the previous sections traced the general evolution of AI policies in China and the United States, observing policies in terms of stages alone cannot fully explain how policies emerge, why they are promoted at particular times, and how they are institutionalized. To capture these dynamics, this section applies the Multiple Streams Framework (MSF), which provides a systematic lens to analyze the mechanisms underlying AI policy evolution in both countries. Central to the MSF is the problem stream, which emphasizes issue recognition and framing. In China, the formation of policy issues is driven primarily by national goal rationality, with AI emerging as a strategic tool to achieve technological sovereignty and industrial autonomy, particularly in response to U.S. technology decoupling in high-performance computing and chip exports (Feldstein, 2019). The New Generation Artificial Intelligence Development Plan (2017) exemplifies this logic, asserting that “guided by the major needs of national security and economic and social development, efforts will be made to break through the key core technologies restricting the development of the industry.” In this context, problem identification is rarely independent but closely intertwined with the politics stream (Zhao, 2022), reflecting concerns for national security, industrial upgrading, and independent controllability (Li, 2021). Chinese policy entrepreneurs, including regime insiders, technical experts, and researchers, translate potential issues into institutional discourse through research reports, strategic blueprints, and authoritative documents, such as the Chinese Academy of Engineering’s AI Development Roadmap (Wang, 2022). This process can be described as normative construction, in which issues are embedded within national visions and value systems before being extended to concrete policies. By contrast, in the United States, the emergence of policy issues follows a pluralistic and contested logic, shaped by public opinion, social movements, and technological crises. Policy entrepreneurs—including scholars, industry leaders, and NGOs—actively shape debates through congressional hearings, media publications, and policy briefings (Fjeld, 2020). Here, issue recognition is dynamic and socially constructed, reflecting interpretive politics where public problems emerge through continuous contestation rather than being predefined by a central authority.The policy stream further illuminates the distinction in how solutions are generated and institutionalized. In China, AI policy is constructed through a system-driven, top-down approach coordinated by the state, with the Ministry of Science and Technology spearheading documents such as the AI Innovation Action Plan, Smart Manufacturing Development Plan, and the White Paper on Artificial Intelligence Standardization (MOST, 2017). Policy tools are structured in a three-tier hierarchy, aligning national strategic goals with sector-specific tasks and supporting mechanisms such as funding guidance or talent incentives. National research institutions, including the Chinese Academy of Engineering and the Chinese Academy of Sciences, provide technical and cognitive support, creating a pathway of knowledge governance from research to decision-making (Jasanoff, 2005). The United States, however, relies on a network-autonomous, actor-driven model, where policy solutions are generated through open collaboration among federal agencies, universities, think tanks, and technology companies. Programs like the National Institute for Artificial Intelligence, launched by the NSF in 2020, exemplify cross-disciplinary and multi-sector coordination, covering areas such as trusted AI and agricultural intelligence. Ethical frameworks are particularly emphasized, with instruments like the NSCAI report and the AI Bill of Rights integrating fairness, privacy protection, accountability, and human-centric principles into policy design, reflecting a public-good orientation (Rawls, 1971; Sandel, 2010). While both countries emphasize instrumental rationality in policy tools, China prioritizes policy guidance with values supplemented later, whereas the U.S. demonstrates preemptive ethical awareness but often faces

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fragmented implementation.

The politics stream, encompassing institutional power structures, public opinion, and legitimacy mechanisms, further differentiates the two contexts. In China, the centralized one-party system allows rapid integration of AI into national agendas through top-down directives, collective study sessions, and ministerial coordination, cascading policies from the central government to provincial and local levels. Bureaucratic mechanisms, guiding documents, and performance evaluations ensure efficient policy transmission and local adaptation (Mertha, 2009), while key leaders explicitly frame AI as central to technological revolution and industrial transformation. The U.S., in contrast, exhibits a polycentric, pluralistic politics stream rooted in federalism and separation of powers. Agenda-setting is shaped by executives, Congress, regulatory agencies, state governments, think tanks, and ngos, producing competitive yet adaptive policy discourse. Policy entrepreneurs operate across multiple layers, leveraging issue framing, window-of-opportunity identification, and coalition-building to integrate diverse perspectives into agenda priorities. Partisan differences further shape policy focus, with Democrats emphasizing ethics and regulation and Republicans prioritizing innovation and industrial freedom. This results in a “decentralized negotiated competition” logic, emphasizing procedural legitimacy and pluralistic feedback, in contrast to China’s centralized strategic push

Applying the MSF highlights how China and the United States construct, implement, and legitimize AI policies through fundamentally different mechanisms. China relies on regime-driven normative construction and centralized implementation, enabling rapid agenda integration and coordinated policy streams, whereas the U.S. employs socially contestable issue framing and network-based solution development, balancing pluralism, ethical considerations, and procedural legitimacy. These contrasts underscore the decisive role of institutional design in shaping policy formation, adoption timing, and governance logic, providing a nuanced understanding of AI policy evolution that transcends simple stage-based analysis.

5. Conclusion

This study employs the Multiple Streams Framework (MSF) and policy tools analysis to compare AI policy evolution in China and the U.S. between 2017 and 2023, focusing on divergences in instruments, institutional pathways, and the interplay of the three streams. It addresses how AI governance tools and priorities differ and what institutional and political factors shape them. China adopts a supply-side approach emphasizing state-led R&D, infrastructure, and talent development, complemented by environmental tools for data governance and ethics, and demand-side applications in manufacturing and urban management. Its trajectory shifted from strategic design (2017–2018), to institutional provision (2019–2020), and ethical/ecosystem innovation (2021–2023). The U.S., in contrast, emphasizes federal R&D grants, transparency and civil rights frameworks, and demand-side measures in defense, evolving from agenda-setting (2016–2018), to institutional coordination (2019–2021), and global regulatory influence (2022–2023). Overall, China pursues a centralized, state-led model embedding AI into the real economy, while the U.S. relies on a decentralized, market-driven approach prioritizing innovation and standards.

MSF clarifies these dynamics. In the problem stream, China frames AI around national sovereignty and security, embedding issues into national strategies via policy entrepreneurs; the U.S. derives problems from public debate, social movements, and crises. In the policy stream, China relies on vertically integrated mechanisms led by ministries and research institutes, while the U.S. uses decentralized networks across government, academia, and industry, emphasizing ethics and consultation. In the politics stream, China’s centralized system consolidates AI agendas swiftly, whereas U.S. federalism and pluralism produce negotiated, competitive agenda-setting. These contrasts highlight structural differences: China’s “state-centric” model prioritizes planning and top-down initiation, while the U.S. “deliberative-democratic” model relies on social-incident activation and advocacy.

Limitations include focus on central documents, qualitative analysis, and exclusion of other actors such as the EU or Japan. Future research should expand comparative scope and examine how AI itself reshapes governance through generative applications in decision-making and smart bureaucracies. In sum, AI functions as both policy object and governance resource, with Chinese and U.S. approaches reflecting distinct institutional rationalities, normative frameworks, and mobilization strategies. MSF tracing reveals the interaction of institutional cognition, normative embedding, and technological mobilization in policy evolution.

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