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The AI triad: divergent technological pathways and their global implications

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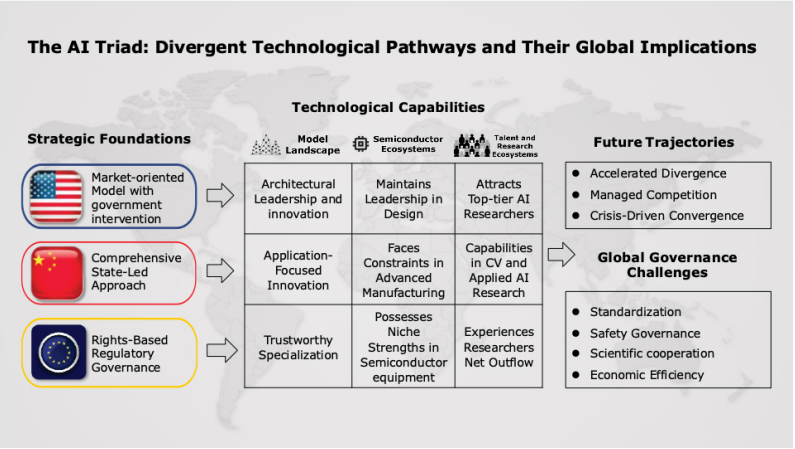
Abstract

Artificial intelligence (AI) is rapidly transforming the global landscape in science, technology, and governance. However, how the policy paradigms shape the respective AI ecosystems, technological capabilities, and the broader global governance landscape remains elusive. To answer this question, we conduct a mixed-methods approach combining qualitative policy analysis with quantitative technical assessment to connect high-level policy paradigms to the materials, technical capabilities, and innovation pathways of AI systems in China, the United States, and the European Union. By synthesizing policy documentation, technical performance data, and industrial analysis, we identify three fundamentally divergent development paradigms that are creating irreversible technological path dependencies. The United States maintains structural advantages in foundational model innovation and semiconductor design; China demonstrates exceptional capabilities in rapid commercialization and domain-specific applications; while the European Union adopts a distinctive path focused on trustworthy AI and regulatory standard-setting. Our findings reveal significant technological fragmentation across multiple dimensions: architectural approaches, computational infrastructures, talent distribution, and application ecosystems. This fragmentation poses substantial challenges to global standardization, international cooperation, and AI safety governance. The research concludes that current trajectories suggest increasing technological divergence rather than convergence, thereby necessitating new frameworks for managed coexistence.

Keywords: Artificial intelligence strategy, Foundation models, Technological sovereignty, AI governance, Policy comparison, Innovation ecosystems

Graphical abstract



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Introduction

Artificial intelligence (AI) has rapidly become a defining catalyst of global transformation, reshaping the foundations of economies, governance systems, and social structures across the world. The burgeoning landscape of AI development is differentiated by national approaches, particularly evident in the landmark initiatives introduced by China, the European Union, and the United States. These distinct policy architectures—China's integrationist model, Europe's regulatory model, and the U.S. competitive model—reflect deep-seated differences in political systems, economic philosophies, and societal values[1], moving beyond mere geographic distinctions to fundamentally different approaches to AI development. While previous research has documented policy differences among these actors, few studies have systematically connected these strategic paradigms to concrete technological pathways and their global implications.

Recent national initiatives including China's "AI Plus (AI+) Initiative" (August 26, 2025)[2], the European Union (EU) Commission's AI Continent Action Plan (April 9, 2025)[3], and the U.S.'s "Winning the AI Race: America's AI Action Plan" (July 23, 2025)[4] further institutionalize these divergent governance models and solidify their positions as the principal centers shaping global AI trajectories. These developments highlight the need for an integrated analytical framework capable of connecting high-level policy paradigms to the materials, technical capabilities, talent, and innovation pathways of AI system development.

This paper addresses this crucial gap by examining what we term the "AI Triad" —the crystallization of global AI leadership around these three dominant centers of technological development and governance[5]. Understanding these divergences is crucial for forecasting technological evolution, economic competitiveness, and geopolitical dynamics. Therefore, this paper is guided by the overarching question: How do the policy paradigms of China, the European Union, and the United States shape their respective AI ecosystems, technological capabilities, and the broader global governance landscape?

Our theoretical lens posits that these three distinct models lead to irreversible technological path dependencies, profoundly influencing architectural approaches, computational infrastructures, and application ecosystems. To investigate this, the paper employs a mixed-methods approach combining qualitative policy analysis with quantitative technical assessment and aims to 1) provide an integrated analysis connecting policy frameworks to the materials, technical capabilities, and innovation pathways of AI systems; 2) offer an empirical assessment of current capability distributions; and 3) analyze the implications of technological fragmentation for global governance.

Methodology and materials

This research employs a mixed-methods approach combining qualitative policy analysis (i.e., policy document analysis) with quantitative technical assessment. Below we give a detailed description of the methods.

Policy document analysis

Primary sources included China's "AI+" initiative, the U.S. Winning the AI Race "America's AI Action Plan", and the EU's AI Continent Action Plan. Documents were selected through purposive sampling, focusing on official national strategies, identified via government websites and policy databases (e.g., China's State Council publications, U.S. White House archives, the European Commission). Full texts were downloaded in PDF format and converted to plain text using Adobe Acrobat and Python's PyMuPDF library to ensure completeness.

The analysis employed qualitative content analysis following Hsieh and Shannon's framework[6] which included strategic objectives (e.g., leadership, self-sufficiency), implementation mechanisms (e.g., regulatory sandboxes, public-private partnerships), and resource allocation patterns (e.g., funding scales). We also incorporate a focused discussion of policy outcomes and challenges within the policy implications.

Technical capability assessment

We analyzed 13 major representative foundation models, selected based on prominence in public leaderboards (e.g., Hugging Face Open LLM Leaderboard, LMSYS Arena) and releases by leading organizations (e.g., OpenAI's GPT series, Anthropic's Claude, Meta's Llama, Chinese models like Qwen and GLM). Selection criteria included models with >10 billion parameters, trained after 2022, and with available performance data.

Standardized benchmarks reflecting general reasoning, linguistic competence, mathematical reasoning, and coding ability were used to assess model performance. Scores were sourced from established evaluation repositories of EleutherAI's LM EvaluationHarness. Scores are linearly rescaled to a 0–100 range to represent relative capability tiers for comparative policy interpretation rather than formal performance evaluation. An overall composite score was calculated as the mean of the four categories. Multivariate analyses were performed in R, including principal component analysis (PCA) to identify underlying capability structures and independent-samples t-tests to compare regional model groups ($p < 0.05$).

The semiconductor supply chains data were sourced from industry reports (e.g., SEMI World Fab Forecast, TrendForce AI Chip reports, McKinsey Global semiconductor reports) and technical documentation (e.g., TSMC annual reports, ASML investor presentations), covering 2018–2024. Assessment of computational infrastructure utilized data from the Stanford AI Index report (2020–2024 editions) and industry analyses (e.g., Epoch AI compute trends, NVIDIA DGX reports). Datasets were downloaded as CSV/Excel from official sites (aiindex.stanford.edu).

Innovation ecosystem mapping

Talent distribution and research ecosystems were analyzed using publication data from Web of Science, applying keywords related to the topics of artificial intelligence, machine learning, or deep learning, ranging from 2015 to 2025, complemented with professional network analysis to trace disciplinary structure, thematic priorities, geographic contributions, and temporal trends in global scientific output. Co-authorship and citation networks were used to identify knowledge hubs, emerging research clusters, and patterns of talent concentration across China, the U.S., and the European Union. Innovation patterns were examined through patent analysis and venture capital funding data from 2020–2024 (Table 1).

Policy paradigms: strategic foundations

The U.S. approach exemplifies a market-oriented model enhanced by strategic government intervention. The "Winning the Race: America's AI Action Plan" establishes three strategic pillars with distinctive characteristics. The plan emphasizes "removing regulatory barriers" and fostering private investment, continuing the tradition of industry-led technological development. This approach has catalyzed massive

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Table 1 Data sources

Source category	Specific sources	Access method	File format
Policy Documents	China's "AI+", U.S. "America's AI Action Plan", EU AI Act	Official websites	PDF → TXT
Benchmarks	Massive Multitask Language Understanding, A Graduate-level Google-Proof Q&A, etc	LMSYS, Hugging Face Open LLM Leaderboard	CSV
Industry Reports	SEMI, TrendForce, AI Index 2020-24	Direct download	PDF/Excel
Talent distribution	Web of Science	Professional network analysis	TXT
Publications	Web of Science	API query	BibTeX/TSV

private R&D investment exceeding $50 billion annually in AI development[7], demonstrating strong effectiveness in mobilizing capital toward frontier innovation and maintaining global leadership, though equity concerns arise as benefits concentrate in a few tech hubs and firms. This momentum has recently been amplified by the Trump administration's "AI Genesis Mission," which deepens federal involvement in frontier AI to secure long-term strategic advantage[8].

A defining feature is the explicit use of export controls and investment restrictions to maintain technological advantage. The October 2022 semiconductor export controls represented a watershed moment in technological decoupling[9], effectively curbing advanced chip access for competitors while raising efficiency challenges through disrupted global supply chains and higher domestic costs. The CHIPS and Science Act directs $52.7 billion toward domestic semiconductor manufacturing, addressing critical vulnerabilities in advanced chip production; early outcomes show attracted investments from firms like TSMC and Intel, yet sustainability is tested by prolonged fab construction timelines (3–5 years), talent shortages, and ballooning energy demands of AI compute infrastructure.

China's "AI+" initiative[2] represents the culmination of a comprehensive state-led approach initiated with the 2017 Next Generation Artificial Intelligence Development Plan (Table 2). The strategy exhibits several distinctive features. The policy leverages China's "whole-nation system" to direct resources toward strategic priorities, with local governments establishing over 30 AI industrial parks and special zones. Unlike the U.S. focus on foundational research, China's strategy emphasizes practical integration, setting specific targets for AI adoption across manufacturing (70 percent by 2027), healthcare, and governance. In response to technological containment, the strategy prioritizes development of domestic alternatives in semiconductors (SMIC), AI frameworks (PaddlePaddle), and foundation models.

China's state-led AI strategy has proven effective in advancing national goals, reflected in rapid growth in patents, publications, and practical AI applications[10]. Initiatives have expanded education and research capacity, reinforcing China's competitive position and its objectives for 2030 and 2045[5]. However, geopolitical tensions may weaken long-term efficiency, and equity concerns arise from labor substitution and mental-health impacts. Despite commitments to privacy, security, and ethical governance, balancing rapid AI deployment with robust social and ethical safeguards remains difficult, and scholars argue for stronger regulatory frameworks.

The EU's approach presents a rights-based regulatory governance that combines comprehensive regulation with initiatives to enhance technological competitiveness (Table 2). Key characteristics include precautionary regulation, strategic autonomy, and standard-setting power. The AI Act establishes a four-tiered risk classification system with strict requirements for high-risk applications, reflecting the EU's precautionary principle[3]. This proactive stance aims to ensure ethical and safe AI development and deployment across the EU and potentially set a global benchmark for AI regulation, influencing practices beyond its borders through the "Brussels Effect".

The "Apply AI" strategy explicitly aims to reduce external dependencies, allocating $10 billion to develop European capabilities in strategic sectors. However, harmonizing diverse national regulatory environments and ensuring consistent rule application remain difficult[10], while the risk-based framework has been criticized for ambiguous categories and a larger-than-expected proportion of systems falling under "high-risk". Monitoring and enforcement are further complicated by regulatory complexity and cross-border applications[11]. Additional issues include the lack of a universally accepted definition of AI, the exclusion of military and security uses, and mounting sustainability concerns as AI deployment increases energy consumption and emissions.

Beyond formal state-led strategies, public opinion, labor-market transitions, social acceptance, and AI-ethics debates play increasingly important roles in shaping how AI policies are formulated and implemented across the United States, China, and the European Union. In the U.S., public trust concerns and ongoing debates over labor displacement influence regulatory restraint and industry-led governance models. In China, high social acceptance of digital technologies and state narratives emphasizing national development help facilitate large-scale AI deployment, though concerns over workplace stress and algorithmic management are gaining visibility. In the EU, strong civil-society engagement and rights-based public discourse have directly shaped the precautionary orientation of the AI Act and its emphasis on transparency, accountability, and risk mitigation. Incorporating these societal dynamics provides a more complete foundation for cross-national comparison, revealing how social forces interact with institutional structures to produce divergent AI governance trajectories.

Taken together, these policy paradigms (Table 2) illustrate how institutional structures and political incentives generate distinct forms of technological path dependence across the AI Triad[12]. In

Table 2 Policy paradigm comparison

Dimension	United States	China	European Union
Primary driver	Market innovation	State direction	Regulatory governance
Key policy instrument	R&D funding, Export controls	Planning targets, Resource allocation	Risk-based regulation
International approach	Strategic containment	Selective engagement	Standard exporting
View of data	Economic asset	National resource	Personal privacy

the United States, the deep entrenchment of market-based innovation ecosystems and venture-capital financing reinforces a technology stack optimized for private-sector scalability[13]. China's centralized coordination mechanisms institutionalize long-term commitments to state-led AI diffusion, making large-scale application integration the dominant developmental trajectory[10]. The European Union's rights-based regulatory architecture, rooted in the precautionary principle, creates a governance path that privileges safety, transparency, and compliance[10]. These institutional and political configurations do not merely shape short-term policy choices—they lock each ecosystem into divergent developmental paths that later manifest as structural fragmentation at the global level.

Technological capabilities: comparative assessment

Foundation model landscape

The foundation model ecosystem reveals significant divergence in architectural approaches and capabilities (Fig. 1). The comparative assessment relies primarily on bibliometric indicators and publicly available model-performance datasets, which provide systematic and cross-nationally comparable evidence. However, bibliometric data exhibit inherent time lags and cannot fully capture rapidly evolving frontier innovations, including military AI development, proprietary industry R&D, and specialized domain-specific applications that remain outside public documentation. The selection of foundation indicators therefore reflects data availability rather than an exhaustive mapping of technological capabilities.

United States: Architectural leadership

U.S. organizations demonstrate continued leadership in scaling laws and architectural innovation. GPT-4 Turbo's mixture-of-experts architecture enables unprecedented scale while maintaining inference efficiency (Table 3). Gemini Ultra's native multimodal capabilities represent significant architectural advancement, processing visual, audio, and textual information through integrated encoding[14]. Claude 3 (Anthropic) advances AI safety through constitutional AI techniques. Performance comparisons (Table 3) show that GPT-4 and Claude 3 achieve the highest composite scores globally, reflecting the maturity of U.S. research pipelines and large-scale compute infrastructure.

China: Application-focused innovation

Chinese models demonstrate remarkable efficiency in adapting transformer architectures to specific domains. Ernie 4.0's knowledge-enhanced training achieves superior performance on Chinese-language tasks despite using approximately 50 percent fewer parameters than comparable U.S. models. This efficiency reflects both computational constraints and strategic focus on practical applications. Qwen-VL (Alibaba) demonstrates strong capabilities in e-commerce and manufacturing domains. DeepSeek shows remarkable training efficiency despite computational constraints. As shown in Table 3, Qwen2.5 narrows the performance gap with frontier systems

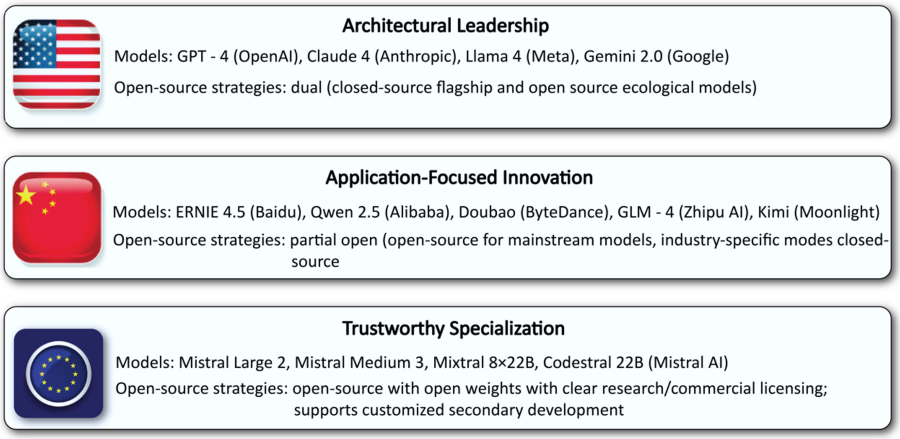

Fig. 1 Foundation model landscape for different countries or regions.

Table 3 Scores from different dimensions of different models

ID	Model	Parameters	Trained years	Reasoning	Linguistic	Math	Coding	Composite
USA	GPT-4	> 100 billion	2023	95	94	97	95	95
	Claude 3	> 100 billion	2024	94	95	96	91	94
	Llama	70 billion	2024	87	86	93	78	88
	Gemini	> 100 billion	2023–2024	93	94	95	89	93
China	ERNIE4.5	> 10 billion	2024	80	82	88	73	83
	Qwen2.5	72 billion	2024	89	91	92	85	90
	Doubao	> 10 billion*	2024	70	74	68	55	72
	GLM-4	> 100 billion	2024	82	83	90	79	86
	Kimi	> 100 billion*	2024	76	78	73	65	79
EU	Mistral Large 2	> 10 billion	2024	87	88	92	84	89
	Mistral Medium3	> 10B tier	2024	81	82	87	75	84
	Mixtral 8*22B	> 100 billion	2023–2024	84	85	89	81	84
	Codestral 22B	22 billion	2024	70	72	60	**90**	78

* Estimated parameter counts; exact values have not been independently verified.

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(composite score 90), indicating rapid capability growth from parameter-efficient designs.

European Union: Trustworthy specialization

EU model development emphasizes efficiency and compliance. Mistral AI's models demonstrate state-of-the-art performance per parameter, optimized for European languages and regulatory requirements. Aleph Alpha focuses on sovereign infrastructure with strong data governance features. Research institutions prioritize explainable AI and ethical alignment. Table 3 highlights that Mistral Large 2 delivers competitive reasoning and coding abilities despite smaller parameter budgets, underscoring the EU's strength in compact, efficient architectures.

These divergent architectural strategies reflect deeper forms of technological path dependence shaped by each region's resource endowments including compute availability (Fig. 1), data regimes, and industrial-policy priorities, further entrenching structural differences in model design and performance that make cross-ecosystem convergence increasingly difficult.

Semiconductor ecosystems

Semiconductor capabilities reveal critical strategic dependencies (Table 4). The United States maintains leadership in design (NVIDIA, AMD), a position reinforced by policies such as export controls that restrict China's access to advanced technology and critical components for high-end semiconductor manufacturing[15]. This strategic advantage is coupled with a dependence on Taiwan's manufacturing (TSMC) for advanced chips, creating both an advantage and vulnerability due to the concentration of AI accelerator design.

Conversely, China faces significant constraints in advanced manufacturing, primarily because of these U.S.-led export controls and multilateral agreements with allies like Japan and the Netherlands, which limit its access to state-of-the-art chip manufacturing equipment and technical know-how[16]. These restrictions directly contribute to its manufacturing gap, exemplified by SMIC being limited to 7-nm processes compared to TSMC's 3-nm capability[17]. This manufacturing gap creates a 2–3 year lag in cutting-edge AI hardware, even as these external pressures simultaneously spur China's efforts toward domestic innovation and self-sufficiency[15]. While European Union possesses niche strengths in semiconductor equipment (ASML's EUV lithography monopoly), it lacks scale in chip design or manufacturing.

Talent and research ecosystems

Analysis reveals significant concentration patterns. The United States attracts 68 percent of top-tier AI researchers[7], with strength in foundation model architecture and scaling laws. China retains 22 percent of top talent, with strong capabilities in computer vision and applied AI research. The European Union experiences net outflow, particularly to U.S. organizations, though it maintains strength in AI ethics and specialized applications.

Across multiple dimensions, the visualizations reveal pronounced structural patterns in global AI-related scientific output. Publication shares across Web of Science categories show a strong concentration in engineering and computer science fields, particularly electrical and electronic engineering and artificial intelligence. Research linked to the UN Sustainable Development Goals indicates that scientific activity is most heavily aligned with Good Health and Well-Being (SDG 3), followed by Sustainable Cities (SDG 11), Climate Action (SDG 13), and Affordable and Clean Energy (SDG 7), reflecting global AI priorities and applications in health, urban sustainability, and climate-related challenges (Fig. 2). At the country level,

Table 4 Semiconductor ecosystems comparison

Capability	United States	China	European Union
AI chip design	Leading (NVIDIA, AMD)	Advancing (HiSilicon)	Limited
Advanced manufacturing	Dependent (TSMC)	Constrained (SMIC, 7 nm)	Limited
Equipment supply	Strong (applied materials)	Limited	Leading (ASML)
Computing capacity	Highest	Rapidly growing	Moderate

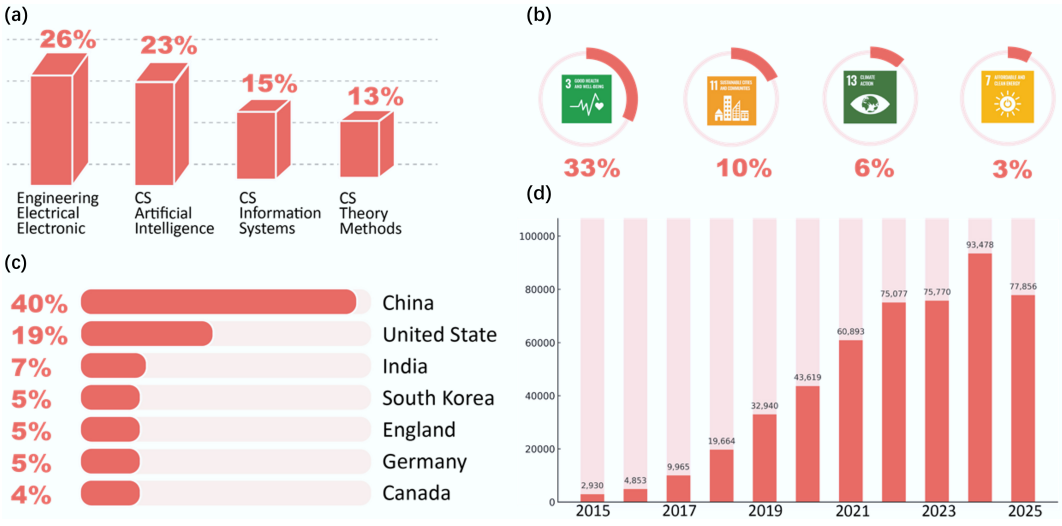

Fig. 2 Key dimensions of global research activities illustrated with 497,045 publications. The panels show (**a**) publication shares across major Web of Science categories, (**b**) contributions aligned with selected UN Sustainable Development Goals (SDGs), (**c**) publication distribution by country/region, and (**d**) annual publication counts from 2015 to 2025.

China emerges as the dominant contributor, producing approximately 40 percent of all publications, with the United States and India following as the next largest sources of scientific output. Temporal trends show a sharp and consistent rise in annual publication volume from 2020 onward, with 2024 reaching the highest level in the decade.

Application ecosystems and sectoral specialization

United States: Platform dominance

The U.S. exhibits strengths in platform-based applications:

- Consumer internet services leveraging network effects
- Enterprise software-as-a-service and cloud AI services
- Biotechnology and drug discovery applications
- Financial technology and algorithmic trading

The market-driven approach enables rapid scaling but often prioritizes engagement metrics over societal benefit.

China: Vertical integration

China's applications demonstrate a high degree of vertical integration:

- Industrial Internet of Things and smart manufacturing systems
- Integrated public security and social governance platforms
- Mobile ecosystems combining payments, social, and commerce
- Smart city infrastructure management

The state-guided model enables coordinated deployment at an unprecedented scale.

European Union: Niche excellence

EU applications excel in regulated domains:

- Industrial robotics and manufacturing automation
- Sustainable technology and environmental AI
- Medical devices and healthcare diagnostics
- General Data Protection Regulation compliant enterprise systems

The regulatory environment creates advantages in trust-sensitive applications, demonstrating how policy regimes shape long-term technological path dependence. For instance, the development of autonomous driving diverges across regions: U.S. firms prioritize software-centric systems and private-market deployment due to liability rules and decentralized state-level regulation; China's regulatory sandboxes and smart-city integration foster vertically integrated autonomous-mobility platforms; and the EU's strict data-protection rules constrain large-scale testing, reinforcing their specialization in component technologies and safety-critical systems. Similarly, the evolution of facial recognition differs: U.S. firms adopt privacy-preserving techniques under regulatory and litigation pressure, whereas in China, governance priorities promote data-intensive model development and deployment. These cases concretely link policy divergence to distinct technological trajectories.

Future trajectories and global implications

Technological fragmentation scenarios

Based on current trajectories, we identify three plausible scenarios for 2025–2030:

Scenario 1: Accelerated divergence

Technological stacks become increasingly incompatible, with separate standards for model deployment, data governance, and safety certification. This scenario is driven by intensifying geopolitical competition and regulatory divergence.

Scenario 2: Managed competition

Limited technical standards emerge for specific domains (AI safety, scientific collaboration) while competition continues in strategic applications. This requires sustained diplomatic engagement and technical working groups.

Scenario 3: Crisis-driven convergence

A major AI safety incident or geopolitical crisis forces rapid coordination on safety standards and governance frameworks.

Importantly, these scenarios emerge not only from geopolitical rivalry but also from accumulated economic and institutional lock-in effects. High sunk costs in semiconductor fabrication, proprietary data infrastructures, incompatible safety-certification regimes, and politically motivated digital-sovereignty policies collectively reinforce a self-perpetuating fragmentation dynamic, reducing the feasibility of later systemic convergence.

Critical uncertainties

Several factors could significantly alter current trajectories:

- Breakthroughs in AI safety or interpretability research
- Major supply chain disruptions affecting semiconductor access
- Unexpected political shifts altering strategic priorities
- Radical innovations reducing computational dependencies

Global governance challenges

The evolving fragmentation presents fundamental challenges:

Standardization: Incompatible technical standards increase costs and reduce interoperability for multinational enterprises and research collaborations.

Safety governance: Divergent safety standards and certification regimes create regulatory gaps and coordination challenges.

Scientific cooperation: Restrictions on talent mobility and technology transfer hinder global research progress.

Economic efficiency: Duplicative investments and market fragmentation reduce overall innovation efficiency.

Conclusion: Pathways to managed coexistence

The evidence examined in this study demonstrates that the AI Triad is evolving toward three distinct technological ecosystems with limited interoperability. This fragmentation poses significant challenges for global economic efficiency, scientific progress, and international security.

While complete technological convergence appears increasingly unlikely given current political and strategic realities, managed coexistence through coordinated frameworks offers a pragmatic path forward. Essential elements include:

Minimum interoperability standards: Technical standards enabling basic data exchange and model compatibility across ecosystems, particularly for scientific research and global emergency response.

Shared safety research: Coordinated research agendas addressing existential AI risks, potentially modeled on CERN-style international collaborations.

Controlled exchange mechanisms: Carefully designed channels for scientific exchange and talent mobility in non-sensitive research domains.

Sector-specific coordination: Regulatory coordination in domains with clear global benefits, such as climate change and pandemic response.

These dynamics underscore that fragmentation is not simply a contingent political outcome, but the result of deeply embedded forms of technological path dependence shaped by long-standing economic structures and institutional commitments.

The window for establishing such coordination mechanisms is rapidly closing as dependencies harden and geopolitical tensions intensify. The choices made by Triad members in the coming 24–36 months will likely determine whether the global AI ecosystem evolves toward destructive fragmentation or managed pluralism. Future research should focus on developing concrete technical standards for interoperability and governance models that can accommodate strategic competition while preserving essential cooperation.

Author contributions

The authors confirm their contributions to the paper as follows: Jingyu Lin: Writing-review & editing, Visualization, Methodology, Investigation, Data curation; Pei Hua: Writing-review & editing, Visualization; Guang-Guo Ying: Writing-original draft, Conceptualization, Methodology, Investigation, Data curation, Supervision, Funding acquisition, Project administration. All authors reviewed the results and approved the final version of the manuscript.

Data availability

This study did not generate new data. All data analysed in this study were obtained from publicly available databases, as described in the Methods section.

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Declarations

Competing interests

The authors declare that there is no conflict of interest.

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