Asia Pacific Perspectives

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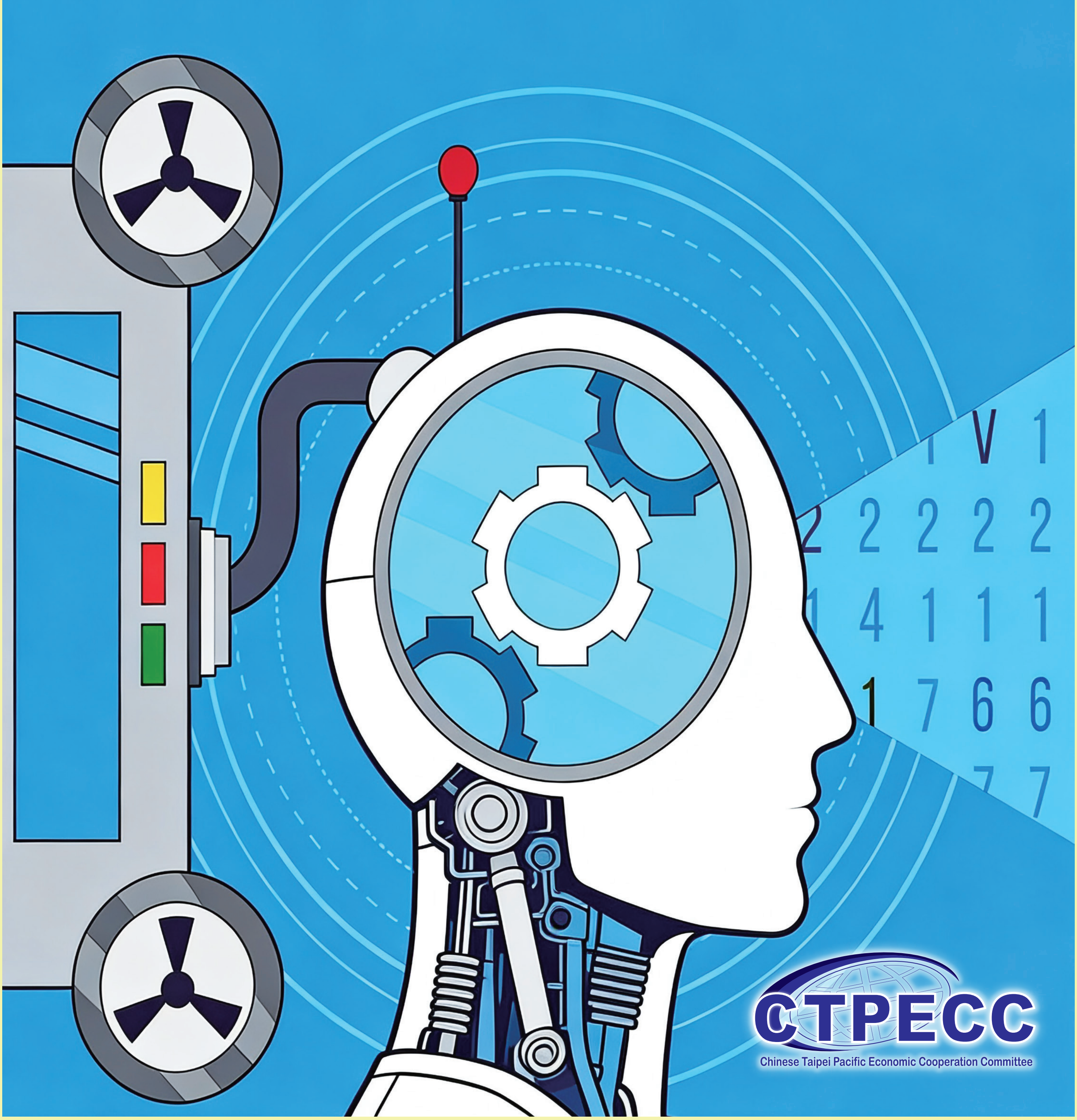
From Openness to Intelligence



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About the CTPECC

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The Benefits of Open-Source Models for the Development of China's AI Industry

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1.Introduction

AI technology has become a critical field internationally, with every nation investing substantial resources in sovereign AI, AI computing infrastructure, and industrial AI applications to ensure they do not fall behind in the AI race. As competition between the United States and China in technology intensifies, various forms of AI-related technological development and exchange have become increasingly restricted. For example, the United States has imposed controls on the export of advanced computing technologies, restricting the flow of cutting-edge computing chips to countries with potential national security threats; China has implemented controls on rare earth materials needed for chip manufacturing, while simultaneously encouraging domestic enterprises and research institutions to independently develop advanced technologies in response to the blockade of critical technology imports.

Although U.S. companies hold a leading advantage in large language model (LLM) technology development, Chinese companies have leveraged vast domestic datasets combined with open-source model architectures to develop their own domestic AI industry applications. As a result, the two countries' development trajectories in the AI technology domain are expected to present distinctly different structural patterns going forward. In terms of current trends, the United States benefits from past investments in cutting-edge key technologies and its command over advanced chip R&D and supply chains, placing the U.S. AI industry in a leading position in original large language models and advanced computing chips. Mainland China, meanwhile, benefits from internal regulatory mechanisms and a whole-of-nation development approach, and is also showing globally leading performance in various AI applications—for instance, China currently holds a leading position in the real-world deployment of physical AI such as humanoid robots and autonomous vehicles, forming an industrial ecosystem capable of exporting globally.

Between 2024 and 2025, China achieved globally recognized accomplishments in the open-source model development of the artificial intelligence (AI) industry. From the open-source large models of companies such as DeepSeek, Alibaba's Qwen series, Tencent's Hunyuan, Zhipu GLM, and Moonshot's Kimi, to the government's active promotion of open-source ecosystems and international cooperation, China's AI industry has transformed from a "follower" to a "leader." Throughout this competitive process, open-source models in both hardware and software have provided considerable assistance to mainland China's AI industry development. Through the open-source model, local companies have not only gained the opportunity to synchronize with the world in chip design, but have also strengthened Chinese enterprises' capabilities in AI algorithm applications through various open-source initiatives, thereby shaping the current distinctive features of China's AI industry development.

2.Mainland China's AI and Semiconductor Industries

Chip computing power is an important foundation for developing the AI industry. After China faced the U.S.'s strategic high-tech export controls, obtaining advanced computing chips became a critical issue for China's AI industry development. The development of the chip industry involves advanced semiconductor technology R&D and scalability. With the assistance of indigenous equipment and technology, China has gradually achieved 5–7 nanometer manufacturing capabilities; however, constrained by inherent limitations of production equipment, yield rate issues have persistently troubled Chinese enterprises, and overseas advanced manufacturing processes have also been subject to U.S. policy restrictions, unable to meet the enormous AI industry demand in the Chinese market.

The AI computing market presents a different developmental picture. Currently, mainland China holds a 15% share of the AI language model market. In addition to domestic Chinese enterprises continuously leveraging local data to develop Chinese large language models, the open-source model has also enabled Chinese companies to develop application-focused AI technology through methods such as algorithmic distillation from existing large language models. This has created, outside of the United States, another significant international source of AI services.

3.Open-Source Models Help China Enter the International Stage

Due to the U.S.-China technology war, the open-source model has become an important pathway for mainland China to develop its AI industry. Through the open-source model in the technology industry, Chinese enterprises can modify and extract various large language models to enhance their own AI technology application capabilities. They can also obtain important information technology development intelligence through the open-source model, allowing China's AI industry to continue accessing the latest developments even in the face of U.S. containment policies.

Taking DeepSeek as an example, the company rose rapidly starting in 2024. The DeepSeek-V3 and DeepSeek-R1 models released in early 2025 achieved performance comparable to or even surpassing closed-source models such as GPT-4o and Claude-3.5-Sonnet at a training cost dozens of times lower than comparable American models. DeepSeek models have been widely applied in areas such as government services, education, automotive, healthcare, and smart cities. For instance, Shenzhen's government service systems, Hong Kong government departments, BMW, and BYD have all integrated DeepSeek into their local AI systems, driving intelligent upgrading of industries.

Other Chinese companies have also been competing to invest in large language model development. Taking Alibaba as an example, the company has continuously upgraded its Qwen series models since 2023, officially open-sourcing the Qwen3 series in April 2025. The series encompasses two MoE models (Qwen3-235B-A22B and Qwen3-30B-A3B) and six Dense models, supporting multiple scales from 0.6B to 235B parameters to meet needs ranging from individual research to enterprise-level deployment. In February 2025, the Qwen series accounted for over 30% of global downloads on Hugging Face, with derivative models exceeding 100,000, making it one of the world's largest open-source model families. Qwen3's multi-version design and low-cost deployment characteristics have led to its widespread application in scenarios such as financial risk control, medical diagnosis, intelligent driving, and humanoid robots, driving the intelligent transformation of industries. Its native support for the MCP protocol and the Qwen-Agent framework lowers the threshold for intelligent agent development and facilitates AI application deployment.

American company OpenAI accused Chinese AI startup DeepSeek of "free-riding," alleging it attempted to replicate models from multiple U.S. AI companies including OpenAI as the training basis for its own systems, and warned that this could constitute technology theft. This incident raised concerns in the international community about China's open-source AI security strategy and intellectual property protection, becoming a contentious focal point in the U.S.-China AI competition. Meanwhile, countries such as South Korea, Italy, Australia, and the United States have raised questions about DeepSeek's data security, restricting its use in government agencies and implementing risk management measures. These restrictions indicate that the global influence of open-source AI has put multiple national governments on alert and may even trigger a new wave of technology control measures.

The rise of Chinese open-source AI models is driving a reorganization of global AI industry chains. The global AI market is projected to reach 1.8 trillion USD by 2026, with Chinese open-source AI contributing over 30%, driving Asia-Pacific regional industry chain value to exceed 500 billion USD. Some Japanese companies have begun relying on Chinese models, with Japan's AI industry dependence on Chinese models expected to reach 40% by 2026, driving upgrades in the electronics and automotive industries. If U.S. enterprises do not shift toward open-source, their market share could fall below 50%, with supply chain disruption risks in 2026. The CEO of European AI startup Mistral AI has directly stated that the rapid pace of China's open-source technology upgrades is putting real pressure on U.S. companies. China's AI market scale is projected to reach 600 billion USD by 2026, accounting for one-third of the global AI industry—demonstrating that although countries have adopted containment policies, in terms of industrial applications, the influence of Chinese AI enterprises' open-source model is gradually expanding.

4.The Battle of Models: Open-Source vs. Closed-Source

During 2024–2025, Chinese open-source AI models performed impressively on international platforms such as Hugging Face and GitHub. In July 2025, nine of the top ten trending entries on Hugging Face were occupied by Chinese models. Alibaba's Qwen series surpassed 300 million global downloads with over 100,000 derivative models, surpassing Meta's Llama to become the world's number one open-source model family. Models such as DeepSeek, Qwen, and Kimi competed with closed-source models like GPT-4o and Claude 3.5 Sonnet on multiple international benchmark tests including the Hugging Face Open LLM Leaderboard, WebDev, AIME, and LiveCodeBench, with some metrics even surpassing American counterparts.

Chinese enterprises are actively participating in the international open-source community, promoting technical exchange and collaboration. The Hugging Face community launched the Open-R1 project in early 2025, systematically promoting DeepSeek-R1's training process and datasets, emphasizing transparency and community participation, attracting global developers to contribute code and data. Alibaba's Qwen3 series has been uploaded to open-source platforms such as GitHub, Hugging Face, and ModelScope, promoting model adaptation and optimization across various hardware through a free download model and cooperation with multiple chip manufacturers.

Compared to U.S. enterprises that use closed-source models to build ecosystems, mainland Chinese enterprises leverage open-source ecosystems to strengthen the application capabilities of domestic AI technology across various fields, while also developing high-performance AI large models and using the open-source model to expand the influence of Chinese AI technology on global industries. This differs from the industrial development model of U.S. enterprises, which continuously expand their ecosystems through financial system financing and inter-enterprise cooperation under a closed-source model. China's open-source AI model global market share reached 15% in 2025 and is projected to rise to 25% in 2026, driving the global AI industry's transition toward open-source.

According to statistics, 40% of Chinese AI models are used for high-density professional work such as programming and design, indicating that China's AI applications have begun moving toward substantively improving enterprise productivity, rather than solely being developed with general consumer use in mind. Chinese open-source AI models compete on the core strengths of low cost, high performance, and flexible deployment. DeepSeek-V3's training cost is far lower than Meta's Llama 3.1-405B and GPT-4, significantly lowering the capital threshold for enterprise developers. Streamlined models can also effectively reduce the demand for expensive computing power—for Alibaba's Qwen3 model, for example, only 4 H20 graphics cards are needed to run in a typical deployment environment, with an overall deployment cost of 25% to 35% of DeepSeek-R1, making it more attractive to the large number of small and medium-sized enterprises.

5.Conclusion

The open-source model has promoted the rise of Chinese AI startups and the flourishing of innovation ecosystems. Startups such as DeepSeek, Moonshot AI, and Zhipu have attracted developer and capital support through open-source strategies, becoming important players in global AI innovation. The activity level of Chinese enterprises in the global AI open-source community has significantly increased. Alibaba's "ModelScope" community has gathered over 2,300 open-source models, attracting 2 million developers worldwide, with the Qwen series achieving over 300 million global downloads and more than 100,000 derivative models.

The open-source model has also promoted the flow of talent between enterprises and academia between China and the world, accelerating technological innovation. China has the world's largest developer community, with tens of millions of programmers actively participating in open-source projects, forming a powerful reserve of engineers and community momentum. Through the open-source model and the continuous participation of international talent, China has been able to continue developing a globally competitive AI industry and related technology applications under the structural conditions of American blockades on key technologies.

The development of the open-source model not only allows mainland China to continue engaging with the world's most cutting-edge AI technologies, but also encourages other countries to broadly adopt the AI technologies and algorithms developed by China, forming a mutually reinforcing structure. On one hand, it strengthens applications of the latest Western models and training content as a foundation for low-cost AI system deployment; on the other hand, it enhances the market share of Chinese AI products through the international user community of the open-source model. Whether this developmental pattern will lead to the convergence of institutions through AI algorithms embedding Chinese values, thereby strengthening the competitive capabilities and voice of Chinese enterprises in the future digital economy, is something that deserves particular attention in the process of future AI technology application.

From Openness to Intelligence: Inclusive Platforms Turning Citizen Participation into Measurable and Verifiable Sustainability Outcomes in the Asia-Pacific

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I.Challenges and Opportunities of the Smart Economy

The Asia-Pacific region is undergoing profound transformation as global economic and technological structures are rapidly reconfigured. Two forces are particularly salient: the accelerated diffusion of artificial intelligence (AI) and digital technologies, and the normalization of extreme climate and social risks. These dynamics are not isolated but deeply intertwined, shaping both the vulnerabilities and opportunities of societies in the region.

The World Meteorological Organization (WMO) projects a 70% probability that the five-year average temperature for 2025–2029 will exceed the 1.5°C threshold. This exceedance is short-term and does not equate to the long-term Paris Agreement target, yet it signals the urgency of adaptation and mitigation. Meanwhile, the United Nations Environment Programme (UNEP) warns in its Emissions Gap Report that global emissions must decline substantially by 2035 compared to 2019 levels. Current commitments remain insufficient, underscoring the gap between ambition and implementation.

Against this backdrop, the concept of the "smart economy" must be redefined. It should not be understood merely as faster computation or higher automation. Rather, it must sustain social functioning under uncertainty, enhance resilience, and expand equitable benefits. If smart transformation is confined to corporate AI adoption or government digitalization, it risks bottlenecks: outcomes that are difficult to understand, trust, or scale. Without inclusiveness, intelligence becomes a technological upgrade benefiting only a minority while leaving the majority as passive observers.

II.Reinterpreting the Path from Openness to Intelligence

The phrase "from openness to intelligence" requires careful reinterpretation.

- Openness is not a rhetorical slogan but the institutionalization of social participation, data interoperability, and governance collaboration as public infrastructure.
- Intelligence is not technological showmanship but the transformation of dispersed participatory actions into Measurable, Reportable, and Verifiable (MRV) sustainability outcomes. This enables policy, finance, and trust to expand together.

III. New Perspectives for Open Platform Governance

1.Inclusiveness as a Prerequisite

Climate and sustainability actions are inherently cross-sectoral and long-term. Mitigation and adaptation are dispersed across transport, buildings, energy, health, education, and land governance, with benefits often requiring years to materialize. If only a few corporations or government agencies act, even advanced systems cannot cover everyday life. Conversely, when citizens, schools, and communities become co-producers, the smart economy gains adoption and legitimacy. Inclusiveness lowers barriers, enabling resource-constrained regions and vulnerable groups to participate rather than be excluded from technological discourse.

2. Participation Architecture

Scaling participation requires sustainable entry points. Campuses combine education, facility management, volunteer mobilization, and monitoring. Community health systems, through social prescribing, integrate nature-based and community activities into health services. Sports associations and mobility networks convert individual motivations into collective actions. Connected through open platforms and common standards, these venues form cross-sectoral "participation supply chains."

3. AI for Verification and Feedback

Many sustainability actions fail to scale not due to lack of enthusiasm but lack of credible evidence. Platformization transforms each act into verifiable data footprints: time, location, type, evidence (photos, sensors, records), maintenance status, and third-party audits. AI contributes in three ways:

- Reducing verification costs through image recognition, anomaly detection, and risk-based sampling.
- Providing feedback to individuals and communities via dashboards that translate

abstract goals into tangible outcomes.

- Supporting policy and resource allocation by identifying vulnerable areas, predicting risks, and optimizing investments.

4. Blockchain as the Trust Layer

AI enables scalable verification, while blockchain provides the immutable, traceable trust layer. The World Economic Forum notes that combining blockchain with digital MRV tools enhances transparency and integrity, strengthening real-time visibility of mitigation and carbon sequestration outcomes. A practical design is "on-chain trace, off-chain storage": hashes of IDs, timestamps, and audit records are stored on-chain, while raw evidence and personal data remain off-chain under authorization. This ensures privacy while reducing reliance on single databases in cross-border or cross-sector collaboration.

Blockchain is not a panacea. AI is more likely to attack pre-chain inputs—fabricating photos, locations, or sensor data—than altering the chain itself. Thus, trust layers must integrate multi-source verification and audit systems: AI anomaly detection, risk-based sampling, third-party audits, and multi-evidence checks, reinforced by immutable records. The World Bank's pilot in climate markets similarly concluded that blockchain enhances transparency but requires institutional and governance support. To align with sustainability, platforms should adopt low-energy consensus or permissioned architectures, avoiding the paradox of "trust at the cost of high energy consumption."

5. MRV and Governance

Open platforms risk greenwashing and trust erosion, as well as data misuse and privacy concerns. Governance must balance transparency and protection. Transparency requires common data fields, evidence formats, sampling rules, completeness metrics, and disclosure methods. Protection requires minimal data collection, clear authorization, cybersecurity standards, audits, and exit mechanisms. Roles must be delineated: governments provide regulation and credibility; civil society and enterprises expand mobilization and innovation; third parties conduct audits and evaluations. These principles echo IPCC guidelines and ISO 14064-1 standards.

6. Institutionalization and Efficiency

Far from reducing efficiency, inclusiveness enhances it when institutionalized and verifiable. Community and school participation in monitoring reduces failure rates in afforestation and restoration, lowering public expenditure. Circular bioeconomy initiatives—recycling agricultural residues into biochar, compost, or bioenergy—create local jobs and strengthen land resilience. Verified outcomes reduce investment uncertainty, encouraging enterprises and financial institutions to commit to long-term natural capital and resilience projects. Inclusiveness provides scale, intelligence provides credibility, and blockchain provides traceability; together they generate sustainable growth momentum.

7. Pragmatic Policy Pathways: Minimum Viable Stack (MVS)

Given diverse institutional capacities, Asia-Pacific economies should adopt a pragmatic pathway: establish a minimum viable stack, then expand. At minimum, this includes common MRV fields and formats, audit and quality control mechanisms, a visualization dashboard, and a cross-sectoral coordination office. To strengthen credibility, add a trust layer by hashing key events and version records on-chain. Initial pilots can focus on two to three visible venues (e.g., campuses, community health, demonstration zones), producing operational versions within 90 days, then expanding to more sectors and local governments within 12 months. Interoperable standards and comparable outcomes reduce transaction costs in cross-border collaboration and financing, making replication across diverse contexts easier.

IV. Practical Cases in the Asia-Pacific

Asia-Pacific economies are already combining openness and intelligence in diverse ways:

- Taiwan: The Ministry of Education's "Net-Zero Campus Demonstration Program" integrates energy management with student participation, producing traceable mitigation outcomes. ICT industries collaborate with research institutions to develop AI-based disaster prediction platforms, enhancing community resilience.
- Japan: The Financial Services Agency introduced "Adaptation Finance Guidelines," requiring financial institutions to set measurable adaptation goals in agriculture, water, health, and ecosystems, supported by MRV mechanisms.
- Singapore: Under the Smart Nation initiative, the "Smart City Platform" integrates transport, energy, and environmental data, with open APIs enabling enterprises and communities to co-develop applications.
- Korea: The Ministry of Environment launched a "Digital Carbon Accounting" project, using blockchain and AI to verify corporate emissions and reductions, while establishing cross-sectoral data-sharing platforms.

These cases illustrate varied pathways: some emphasize financial regulation, others urban governance, education, or community mobilization. Together, they demonstrate how openness and intelligence can converge into regionally adaptable smart economy models.

Conclusion: Making the Smart Economy a Collective Sustainability Outcome

The transition from openness to intelligence should not mean moving from "expert decisions" to "black-box automation," but from "dispersed goodwill" to "verifiable collective outcomes." When openness is institutionalized as interoperable platforms and transparent governance, when intelligence is realized as verification, feedback, and resource allocation, and when blockchain provides a traceable trust layer, the Asia-Pacific can transform AI and emerging technologies into inclusive and sustainable growth momentum.

The true competitiveness of the smart economy lies not only in technological leadership, but in enabling broad participation, generating trusted sustainability outcomes, and aligning policy and markets under a common credible mechanism that accelerates collective progress.

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What Past Industrial Revolutions Teach Us About AI Adoption

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Framing the Question

Artificial intelligence has become one of the defining topics of contemporary discourse, shaping debates on economic growth and productivity as much as on social impact and ethics. It has evolved into a catch-all concept, attracting intense interest from policymakers, firms, and investors eager to claim a stake in its promise. Often described as a fourth industrial revolution—following steam, electricity, and computation—the current wave of AI innovation has been marked by rapid breakthroughs and relentless momentum. Yet beneath this excitement lies a more consequential transition: the shift from an era of frontier innovation to one of widespread diffusion.

As new applications emerge at accelerating speed and development cycles compress, early structural strains are becoming visible. Constraints in energy infrastructure, widening social inequalities, environmental pressures, and the inefficiencies of large-scale experimentation suggest that the next phase of AI development will require a recalibration of priorities—one that moves beyond speed and novelty toward building the institutional and economic foundations necessary for sustainable adoption.

Ding's Framework: Diffusion versus Innovation

Much of today's debate around artificial intelligence implicitly equates global technological leadership with innovation at the frontier: larger models, higher benchmark scores, and escalating research expenditure. Jeffrey Ding's distinction between innovation and diffusion, however, offers a more useful framework for understanding how general-purpose technologies translate into economic impact.[1] Innovation captures the creation of new

1.Jeffrey Ding,"China's Challenges and Capabilities in Human Capital for General-Purpose Technologies" Testimony before the U.S.-China Economic and Security Review Commission Hearing on China's Challenges and Capabilities in Educating and Training the Next Generation Workforce, February 24, 2023. https://www.uscc.gov/sites/default/files/2023-02/Jeffrey_Ding_Testimony.pdf.

capabilities at the technological frontier; diffusion describes the extent to which those capabilities are adopted, adapted, and embedded across firms, sectors, and societies.[2]

While innovation metrics are highly visible and relatively easy to quantify, they provide only a partial picture. Frontier breakthroughs demonstrate technical possibility, but they do not guarantee widespread productivity gains. Diffusion, by contrast, is slower, less measurable, and often institutionally constrained. It depends on organizational capacity, complementary infrastructure, human capital, and regulatory coherence—factors that determine whether a technology becomes transformative or remains confined to narrow applications.

Ding's framework challenges the assumption that technological races are won solely through speed or scale. Historically, centralized systems under planned governance have often excelled at directed innovation while struggling with decentralized adoption. If diffusion rather than invention ultimately determines the economic payoff of general-purpose technologies, then the Industrial Revolution itself must be reconsidered not as a sequence of heroic breakthroughs, but as a prolonged process of learning, imitation, and institutional adaptation.

Innovation Before Modern Growth, a culture of adaptation

Innovation is frequently treated as a hallmark of modern economic systems, emerging only with formal R&D, patenting, and scientific research. Yet pre-industrial Europe experienced persistent technological change even in the absence of these institutions. The challenge lies not in the absence of innovation, but in how difficult it is to measure. Many productivity-enhancing improvements were incremental, anonymous, and embedded in everyday practice rather than formal invention.

Traditional Malthusian models emphasize stagnation, while neoclassical frameworks privilege discrete technological shocks. Neither fully captures the cumulative nature of pre-modern technological change. Small improvements in tools, processes, and organization—though individually modest—collectively raised productivity over time. These changes were often invisible to contemporaries and remain difficult for historians to quantify, yet they formed the substrate upon which later industrialization rested.

Innovation in this period is best understood as an evolutionary process. As scholars such as Giovanni Dosi argue, technological progress emerges through experimentation, selection, and learning rather than sudden discovery. Firms and artisans tested techniques; markets and production constraints selected among them.[3] Much of this knowledge was tacit—acquired through practice rather than codified instruction—and accumulated through learning curves. Innovation, in this sense, was inseparable from diffusion: knowledge advanced only when it spread and was refined through use, it was a bottom-up approach.

Industrial Revolution and the Mechanics of Diffusion

Popular narratives often portray the Industrial Revolution as a triumph of scientific discovery. In

2.Jeffrey Ding, Technology and the Rise of Great Powers: How Diffusion Shapes Economic Competition (Princeton, NJ: Princeton University Press, 2024).

3.Giovanni Dosi, “Technological Paradigms and Technological Trajectories,” Research Policy 11, no. 3 (1982): 147–162, https://doi.org/10.1016/0048-7333(82)90016-6.

reality, formal science played a more limited role than is commonly assumed. Many of the most influential inventor-entrepreneurs of the eighteenth and early nineteenth centuries lacked advanced scientific training. Human capital mattered, but it was practical rather than theoretical. Basic literacy and numeracy, combined with apprenticeship-based training, proved sufficient for most early industrial innovation and was the backbone of the success of the industrial revolution.[4]

Apprenticeship systems functioned as a critical mechanism for technological diffusion. Through close master–apprentice relationships, skills were transmitted by modelling and imitation rather than codification. Apprentices learned not only techniques, but also values such as precision, discipline, and quality control. Knowledge was vertically structured: no single artisan possessed the entire body of expertise, yet collectively it formed a coherent system. Learning by doing allowed tacit knowledge to spread across generations and regions.

Innovation also emerged through collective invention rather than proprietary secrecy. In several early industrial sectors—most notably nineteenth-century iron production—firms openly shared information about furnace design and operating techniques. There were few patents, little university involvement, and no government-funded research.[5] Experimentation occurred through capital investment, and successful practices spread through labor mobility and informal communication. This openness lowered diffusion costs and accelerated convergence across firms. Cooperation emerged not from altruism, but from mutual benefit: expanding the collective knowledge base improved industry-wide productivity.

The second industrial revolution did not fundamentally alter the nature of innovation; it transformed the scale of diffusion. Electrification, standardization, and advances in transportation and communication enabled technologies to penetrate the broader economy. Organizational and managerial innovations allowed firms to coordinate complex production processes, while public infrastructure—power grids, education systems, and transport networks—supported widespread adoption. The economic impact of electricity and mass production was realized not at the point of discovery, but through decades of institutional adjustment and complementary investment.

Innovation versus Diffusion in the AI Era

Contemporary discussions of AI often frame development as a geopolitical competition, particularly between China and the United States seemingly locked in an AI arms race. This framing mirrors historical misunderstandings of technological progress. Frontier model performance and research investment offer limited insight into whether AI will generate broad-based productivity gains.

As with past industrial revolutions, AI faces diffusion constraints: energy supply, computing infrastructure, organizational readiness, workforce skills, and regulatory coherence. Centralized systems may excel at targeted innovation, but decentralized adoption requires institutional flexibility and learning capacity. Without these,

4.Stephan R. Epstein, “Craft Guilds, Apprenticeship, and Technological Change in Preindustrial Europe,” The Journal of Economic History 58, no. 3 (1998): 684–713. DOI:10.1017/S0022050700021109.

5.Robert C. Allen, “Collective Invention,” Journal of Economic Behavior & Organization 4, no. 1 (1983): 1–24. DOI: 10.1016/0167-2681(83)90023-9.

advances risk remaining confined to experimental or elite applications.

Historical experience suggests three lessons. First, diffusion depends more on institutional readiness than technical capability. Second, tacit knowledge—how humans interact with systems—matters as much as algorithms. Third, cooperation accelerates learning and reduces duplication, whereas excessive secrecy may slow adoption. These lessons caution against viewing AI solely through the lens of speed or rivalry.

The Great Divergence Revisited

Economic history raises a fundamental question: is long-run development a story of persistent advantage or repeated reversals of fortune? Between 1000 and 1900, Europe and China repeatedly traded places across dimensions such as income levels, technological sophistication, and state capacity. Nowhere is this more evident than in the contrast between China's early technological leadership and Europe's eventual industrial takeoff—the reversal commonly described as the Great Divergence.

For much of the pre-modern period, China was technologically advanced and economically sophisticated. Many inventions associated with later industrialization—paper, printing, the compass, gunpowder—emerged well before 1200 CE, particularly during the Song dynasty. Yet innovation slowed in subsequent centuries, even as Europe accelerated. By the nineteenth century, Europe had industrialized while China had not.

Traditional explanations emphasize geography, factor endowments, or political fragmentation. Europe's proximity to coal and its competitive state system mattered, but these factors alone are insufficient. China possessed high fiscal extraction capacity, advanced bureaucracy, and large markets—features often assumed to be prerequisites for development. Joel Mokyr offers a deeper explanation rooted not in resources or inventions, but in institutions of cooperation and knowledge transmission.[6]

In late imperial China, local public goods—such as education, water control, and dispute resolution—were increasingly supplied by extended kinship organizations, notably clans. These organizations sustained cooperation within tightly bounded groups through repeated interaction and moral norms, but they limited the circulation of knowledge beyond kinship boundaries. Skills and resources were often pooled to support a single (often male) promising individual, reinforcing hierarchy and inward-looking incentives.

By contrast, medieval and early modern Europe developed a different model of cooperation. The European marriage pattern produced nuclear family structures, weakening kin-based coordination and forcing cooperation to emerge through formal organizations rather than blood ties. Monasteries, guilds, universities, towns, and later corporations brought together unrelated individuals under shared rules, legal personality, and exit options. These institutions enabled trust among strangers, facilitated labor mobility, and allowed individuals to participate in multiple overlapping networks. Knowledge circulated across institutions rather than remaining trapped within families.

Political institutions reinforced these patterns. European governance evolved through territorially

6.Joel Mokyr, Avner Greif, and Guido Tabellini, Two Paths to Prosperity: Culture and Institutions in Europe and China, 1000–2000 (Princeton, NJ: Princeton University Press, 2025).

rooted authority, representative assemblies, and persistent challenges to centralized power. In China, the absence of formal constraints on imperial authority meant that political change occurred primarily through moral suasion or revolt. Cultural values reflected these institutional differences: European societies increasingly embraced universalist norms and openness to new ideas, while Chinese intellectual life became more backward-looking with the rise of Neo-Confucianism.

The Great Divergence, in this view, was not the result of superior European genius or Chinese stagnation. It emerged from differences in how societies organized cooperation, trust, and knowledge diffusion.

Culture, Cooperation, and AI Today

Mokyr's insights offer a powerful lens for interpreting today's AI landscape, particularly the rivalry between the United States and China. Contemporary debates focus on frontier performance—model size, compute capacity, and state investment—yet history suggests these measures capture innovation, not diffusion.

China's AI development reflects the strengths of a centralized, high-capacity state. Large-scale investment and coordinated industrial policy have produced impressive results in targeted domains. However, diffusion presents a more complex challenge. AI adoption across heterogeneous firms and sectors requires decentralized experimentation, organizational learning, and trust-based cooperation. Much of AI's economic value lies not in algorithmic performance, but in how systems are integrated into workflows and decision-making—domains dominated by tacit knowledge.

The United States, for all its fragmentation, retains structural advantages in diffusion. Its innovation ecosystem is embedded in dense networks of universities, startups, corporations, and professional communities. Labor mobility, venture capital, and relatively open information flows allow ideas to circulate rapidly across institutional boundaries. While coordination is imperfect, diffusion is facilitated by organizational diversity and competition.

Cultural differences echo those identified by Mokyr. American innovation culture places a premium on openness, risk-taking, and the legitimacy of overturning established practices. Trust among strangers enables cooperation beyond hierarchy. China's system, while effective within bureaucratic structures, faces greater difficulty fostering bottom-up experimentation across unrelated actors. The contemporary AI competition thus mirrors the dynamics of the Great Divergence: the decisive factor is not who innovates first, but who builds the cooperative foundations necessary for sustained diffusion.

Conclusion: From Openness to Intelligence

Past industrial revolutions teach us that technological leadership is neither inevitable nor permanent. Societies rise and fall not because of isolated inventions, but because of how they organize cooperation, transmit knowledge, and legitimize experimentation. The Great Divergence illustrates how early technological advantage can dissipate when diffusion mechanisms weaken. All this isn't to say that we are set on a predetermined path where the East is once again trumped by the West, the diffusion of technologies such as mobile payments in China suggests that there are some unaccounted-for intangible factors in its culture and system that may allow for widespread adaptation of new technologies. AI's future impact will depend on whether societies can once again do the unglamorous work of turning innovation into shared capability.

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