

A Diffusion-Centered View of U.S.-China Technological Competition

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I. Innovation vs. Diffusion Capacity

Discussions about national scientific and technological (S&T) capabilities tend to center on which state first generates new-to-the-world breakthroughs (*innovation capacity*). Evaluations of technological leadership in artificial intelligence (AI) instead should give greater weight to a state's *diffusion capacity*, or its ability to spread and adopt innovations, after their initial inception, across productive processes. When there is a substantial disparity between these two facets of a nation's S&T capabilities, innovation-centric assessments of its power to leverage S&T advances for sustained economic growth will prove misleading.¹

This insight is especially relevant for understanding the dynamics of global economic competition in AI, or the ability of states to exploit technological changes and maintain higher economic growth rates than its rivals. Historically, this mechanism has been central to the rise and fall of great powers.² The point has less bearing on other channels by which AI and emerging technologies could influence national security, which garner substantial attention from policymakers in both the U.S. and China. Innovation-centric assessments may be rightly prioritized in such contexts, such as the significance of S&T systems to prestige and reputation, control over global supply chains, and military power.³ Still, appropriate attention to diffusion capacity can better inform other S&T dimensions of state power. For instance, there can be a large disparity between a military's ability to first field advanced military systems and its ability to adopt such systems throughout its branches and subunits.⁴

In many cases, there is not much daylight between a state's diffusion capacity and its innovation capacity. These two parameters can be highly correlated. After all, the state that first pioneered a new method has a first-mover advantage in the widespread adoption of that technique. In addition, absorbing innovations from international sources is difficult without the tacit

¹ This paper draws from Jeffrey Ding, "The Diffusion Deficit in Scientific and Technological Power: Re-assessing China's Rise," *Review of International Political Economy* (2023).

² Kennedy, Paul M. *The Rise and Fall of the Great Powers: Economic Change and Military Conflict from 1500 to 2000*. New York: Random House, 1987.

³ Gilady, Lilach. *The Price of Prestige*. Chicago: Univ. of Chicago Press, 2017, 55-89; Malkin, Anton. "The Made in China Challenge to US Structural Power: Industrial Policy, Intellectual Property and Multinational Corporations." *Review of International Political Economy* 0, no. 0 (October 1, 2020): 1-33; Paarlberg, Robert L. "Knowledge as Power: Science, Military Dominance, and U.S. Security." *International Security* 29, no. 1 (2004): 122-51.

⁴ Ding, Jeffrey and Allan Dafoe. (2023). *Engines of Power: Electricity, AI, and General-purpose, Military Transformations*. *European Journal of International Security*, 1-18.

knowledge embedded in the original context of technological development.⁵ Diffusion and innovation are entangled, overlapping processes.⁶

However, in some circumstances, diffusion and innovation capacity can widely diverge. Aside from innovation capacity, many other factors can shape a country's adoption rate of new technologies, including institutions that incentivize technology transfer, trade openness, and human capital.⁷ The "advantages of backwardness" sometimes enable laggards to diffuse new technologies faster than the pioneering states.⁸ Confronting a world of globalized science and technology flows, even the most advanced economies must be able to intensively absorb and diffuse innovations first incubated in other countries. According to one estimate derived from data on Organisation for Economic Co-operation and Development countries, 93 percent of total factor productivity increases in these high-income countries derive from knowledge that originated abroad.⁹

As a result, diffusion capacity indicators can be better predictors of a state's long-term growth trajectory than innovation capacity indicators. The latter may be more unreliable given the uncertain, protracted pathway between a new technology's introduction and its ultimate impact on productivity growth. To this point, one study found that two standard innovation capacity indicators, R&D intensity and patenting rates, tracked less well with subsequent changes in productivity than indicators of activities related to broadly disseminating information about new products and processes.¹⁰

When there is a substantial gap between diffusion and innovation capacity, assessments based solely on innovation capacity indicators will be misleading because they undervalue the process by which new advances are embedded into productive processes. Specifically, a "diffusion deficit" characterizes situations when a state has a strong innovation capacity but weak diffusion capacity, which suggests that it is less likely to sustain its rise than innovation-centric assessments depict. For example, innovation-centric assessments overestimated the Soviet Union's scientific and technological capabilities in the postwar period. Taking diffusion capacity

⁵ Fadly, Dalia, and Francisco Fontes. "Geographical Proximity and Renewable Energy Diffusion: An Empirical Approach." *Energy Policy* 129 (June 1, 2019): 422–35; Keller, Wolfgang. "International Technology Diffusion." *Journal of Economic Literature* 42, no. 3 (September 2004): 752–82.

⁶ Taylor, Mark Zachary. *The Politics of Innovation: Why Some Countries Are Better Than Others at Science and Technology*. 1st edition. New York, NY: Oxford University Press, 2016.

⁷ Comin, Diego, and Bart Hobijn. "An Exploration of Technology Diffusion." *American Economic Review* 100, no. 5 (December 2010): 2031–59.

⁸ Gerschenkron, Alexander. "Economic Backwardness in Historical Perspective (1962)." *The Political Economy Reader: Markets as Institutions*, 1962, 211–28.

⁹ Madsen, Jakob B. "Technology Spillover through Trade and TFP Convergence: 135 Years of Evidence for the OECD Countries." *Journal of International Economics* 72, no. 2 (July 1, 2007): 464–80.

¹⁰ Alexopoulos, Michelle. "Read All about It!! What Happens Following a Technology Shock?" *American Economic Review* 101, no. 4 (June 2011): 1144–79.

seriously would have provided a more balanced assessment of the Soviet Union's scientific and technological capabilities.¹¹

II. China's Diffusion Deficit

Is China poised to become a science and technology superpower? Existing assessments of China's S&T capabilities tend to center on its aptitude in generating novel breakthroughs. To warn about challenges to U.S. technological leadership, analysts typically cite China's impressive performance in indicators of innovation capacity, such as R&D expenditures, scientific publications, and patents.¹² Less attention, if any, is paid to China's diffusion capacity. For example, the Senate Select Committee on Intelligence's 2022 report on protecting U.S. innovation, which included a lengthy section on China's technological rise, mentions "innovation" or "crown jewels" over ten times. The terms "diffusion" or "adoption" do not appear at all.¹³

Yet, China faces a diffusion deficit: its diffusion capacity trails significantly behind its innovation capacity. Similar to issues with evaluating the Soviet Union's S&T ecosystem in the 1970s, this means that conventional assessments overestimate China's S&T capabilities. It is necessary to reorient such assessments toward a diffusion-centric lens, which show that China is far less likely to sustain its rise than innovation-centric assessments suggest.

Innovation-centric views of China's AI capabilities paint an overly optimistic picture of China's challenge to U.S. technological leadership. Influential reports emphasize China's growing strength in AI-related innovation, backed by indicators on R&D expenditures, leading AI startups, and valuable internet companies. Likewise, to support its warning that China is poised to overtake the U.S. in the capacity to generate new-to-the-world advances in AI, the National Security Commission on AI's final report cites shares of breakthrough papers in AI and investments in startups. These evaluations align with viewpoints that are bullish on China's overall technological capabilities, which also point to similar indicators of innovation capacity, such as R&D expenditures, scientific publications, and patents.

A diffusion-centric perspective, based on a close examination of China's adoption of information and communications technologies (ICTs), paints a different picture. While China has been successful at large-scale deployment in a few key domains — consumer-facing applications like mobile payments and high-speed rail — these achievements do not characterize the overall trend in ICTs. Chinese businesses have been slow to embrace digitization, as measured by adoption

¹¹ For more on this historical case, see Jeffrey Ding. (2023). "The Diffusion Deficit in Scientific and Technological Power: Re-assessing China's Rise." *Review of International Political Economy*.

¹² Kennedy, Andrew B. "Powerhouses or Pretenders? Debating China's and India's Emergence as Technological Powers." *The Pacific Review* 28, no. 2 (March 15, 2015): 281–302.

¹³ Senate Select Committee on Intelligence. "Organizational Assessment: The National Counterintelligence and Security Center." September 2022.

rates of digital factories, industrial robots, smart sensors, and key industrial software.¹⁴ The International Telecommunication Union's ICT Development Index provides a composite measure of the level of access to and use of ICTs in countries around the world. On this metric, China ranks 83rd in the world, which trails the U.S. by 67 places.¹⁵ China also significantly trails the U.S. in an influential index for adoption of cloud computing, which is essential to implementing AI applications. In 2018, U.S. firms averaged a cloud adoption rate of over 85 percent, more than double the comparable rate for Chinese firms.

When it comes to disseminating AI advances across the entire economy, robust linkages between academic and industry settings are especially crucial. The U.S. has built a strong connective tissue in this respect. Per data on the years 2015 to 2019, the U.S. was the world leader in the number of academic-corporate hybrid AI publications — publications co-authored by at least one researcher from industry and one researcher from academia. This more than doubled China's number of hybrid AI publications.¹⁶ Indeed, China's official state news agency has highlighted the lack of technical exchanges between universities and industry as one of five key weaknesses in China's AI talent ecosystem.¹⁷

It is now becoming increasingly common for reports to claim that China has overtaken the U.S. in certain measures of elite research in AI.¹⁸ One important distinction to make is that these claims tend to draw on indicators based on AI publications in *journals*. In fast-moving fields like AI, a country's performance in conference publications may be a much better indicator of its high-end talent than journal publication-based indicators. As Stanford University's AI Index pointed out in 2021, "the United States has consistently (and significantly) more AI conference papers (which are also more heavily cited) than China over the last decade."¹⁹

¹⁴ Alibaba Research Institute. "From Connected to Empowered: Smart+ Assisting the High-Quality Development of China's Economy [从连接到赋能：'智能+'助力中国经济高质量发展]," March 11, 2019; Synced [机器之心]. "Market Research Report on Supply and Demand for Digital Intelligentization Solutions for China's Small and Medium Enterprises [中国中小企业数智化解决方案供应市场研究报告2020]," October 2020; Techxcope [战略前沿技术]. "Innovation Is More than Invention: Detailed Explanation of the German Industry-University-Research Systems' Big Four [创新不止于发明：德国产学研体系四大金刚详解]," November 18, 2020.

¹⁵ International Telecommunications Union. "Measuring the Information Society Report 2017," 2017. <https://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis2017.aspx>.

¹⁶ Zhang, Daniel, Saurabh Mishra, Erik Brynjolfsson, John Etchemendy, Deep Ganguli, Barbara Grosz, Terah Lyons, et al. "The AI Index 2021 Annual Report." Stanford Human-Centered Artificial Intelligence Institute, 2021.

¹⁷ Xinhua. "News Analysis: Examining the Five Shortcomings of China's AI Talent System [新闻分析：透视中国人工智能人才体系五大短板]." Xinhua News Agency, August 28, 2019. http://www.gov.cn/xinwen/2019-08/28/content_5425310.htm.

¹⁸ See, for example, Nikkei Asia. "China Trounces U.S. in AI Research Output and Quality." January 15, 2023. <https://asia.nikkei.com/Business/China-tech/China-trounces-U.S.-in-AI-research-output-and-quality>.

¹⁹ Zhang, Daniel, Saurabh Mishra, Erik Brynjolfsson, John Etchemendy, Deep Ganguli, Barbara Grosz, Terah Lyons, et al. "The AI Index 2021 Annual Report." Stanford Human-Centered Artificial Intelligence Institute, 2021.

Lastly, to analyze whether China’s overall diffusion capacity in science and technology varies significantly from its innovation capacity, I separated indicators included in the Global Innovation Index, a widely-used benchmark for national S&T capabilities published by the World Intellectual Property Organization, into these dimensions. For example, the GII ranks countries globally by the quality of their top three universities and their top three firms’ R&D expenditures. I categorize these as indicators of innovation capacity. The GII also ranks countries by indicators that correlate strongly with a country’s capacity to diffuse new advances, including the extent of linkages between businesses and universities.

This decomposition of the 2020 GII reveals that China’s diffusion capacity significantly lags behind its innovation capacity (Table 1). Using the GII’s figures, averaging China’s global ranking on indicators for innovation capacity gives an average of 13.8. However, if the same exercise is conducted using diffusion capacity indicators, China’s average ranking drops to 47.2. For reference, on the innovation capacity subindex, China’s score is very close to the U.S.’s average ranking (11.9). As for the diffusion capacity subindex, the gap widens significantly between China’s average ranking of 47.2 and the U.S.’s average ranking of 26.9. Table 1 displays the GII indicators used to calculate China’s diffusion capacity and innovation capacity.

Table 1: China's S&T Power: An Innovation-Diffusion Decomposition of the GII			
<i>Innovation Capacity Subindex</i>		<i>Diffusion Capacity Subindex</i>	
Indicator	China's global ranking	Indicator	China's global ranking
QS university rankings	3	ICT access	71
Gross expenditures on R&D	13	ICT use	53
Global R&D companies	3	University/industry research collaboration	29
Researchers, full-time equiv./mn pop.	48	State of cluster development	25
R&D performed by business	12	GERD financed by abroad	81
R&D financed by business	4	JV strategic alliance deals/bn	76
Patents by origin*	1	Patent families 2+ offices/bn PPP%GDP	27
Patent Cooperation Treaty patents by origin*	15	Intellectual property receipts, % total trade	44
Utility models by origin/bn PPP\$ GDP*	1	High-tech net exports, % total trade	5
Scientific & technical articles*	39	ICT services exports, % total trade	61
Citable documents H-index	13		
Average ranking	13.8	Average ranking	47.2

Source: Global Innovation Index 2020, World Intellectual Property Organization 2020. *per billion PPP\$ GDP.

III. China’s Diffusion Capacity in Large Language Models

One of the reasons this paper highlights China’s diffusion capacity in AI is because it is a general-purpose technology (GPT). Recognized by economists and economic historians as “engines of growth,” GPTs are defined by three characteristics.²⁰ First, they offer *great potential for continual improvement*. While all technologies offer some scope for improvement, a GPT

20 Bresnahan and Trajtenberg 1995. The following discussion is mostly drawn from Bresnahan and Trajtenberg 1995 and Lipsey, Carlaw, and Bekar 2005. Other accounts employ similar definitions, albeit with some modifications; see Bresnahan 2010; Jovanovic and Rousseau 2005. For a critical view of the GPT concept, see Field 2008.

“has implicit in it a major research program for improvements, adaptations, and modifications.”²¹ Second, GPTs acquire *pervasiveness*. As a GPT evolves, it finds a “wide variety of uses” and a “wide range of uses.”²² The former refers to the diversity of a GPT’s use cases, while the latter alludes to the breadth of industries and individuals using a GPT.²³ Third, GPTs have *strong technological complementarities*. In other words, the benefits from innovations in GPTs come from how other linked technologies are changed in response and cannot be modeled from a mere reduction in the costs of inputs to the existing production function. For example, the overall energy efficiency gains from merely replacing a steam engine with an electric motor were minimal; the major benefits from factory electrification came from electric “unit drive,” which enabled machines to be driven individually by electric motors, and a radical redesign of plants.²⁴

Among the possible GPTs that could significantly impact shifts in global economic leadership, AI stands out. Scholars of GPTs converge on ICTs as a continued driver of technological revolution. Kenneth Carlaw, Richard Lipsey, and Ryan Webb, three pioneers of GPT-based analysis, identify programmable computing networks as the basic GPT that is driving the modern ICT revolution.²⁵ Crucially, AI could open up a new trajectory for this ICT revolution. Recent breakthroughs in deep learning have improved the ability of machines to learn from data in fundamental ways that can apply across hundreds of domains, including medicine, transportation, and other candidate GPTs like biotechnology and robotics. This is why AI is often called the “new electricity”—a comparison to the prototypical GPT. Economists regard it as the “next GPT”²⁶ and “the most important general-purpose technology of our era.”²⁷

Several studies have found evidence for a GPT trajectory in AI. One study, using a novel dataset of preprint papers, finds that articles on deep learning conform with a GPT trajectory.²⁸ Using patent data from 2005 to 2010 to construct a three-dimensional indicator for the GPT-ness of a technology, Petralia ranks technological classes based on their GPT potential.²⁹ His analysis finds that image analysis, a field that is closely tied to recent advances in deep learning and AI,

21 Lipsey, Bekar, and Carlaw 1998, 39.

22 Cantner and Vannuccini 2012.

23 One does not imply the other. For instance, a screw has a “wide range of use” since it is used to fasten things together across a large swath of productivity activities in the economy, but it does not have a “wide variety of uses” (Lipsey, Bekar, and Carlaw 1998, 39).

24 Devine 1982.

25 Carlaw, Lipsey, and Webb 2007.

26 Trajtenberg 2018.

27 Brynjolfsson and McAfee 2017; see also Teece 2018, 1370.

28 Klinger, Mateos-Garcia, and Stathoulopoulos 2021.

29 The three dimensions correspond to the three characteristics of GPTs: scope for improvement, the variety of applications to products and processes, and complementarity with existing and new technologies. These are measured by patenting growth rates, a text-mining algorithm that looks for patterns in technology-specific vocabulary, and co-occurrence of claims in patents (Petralia 2020, 9–10).

ranks among the top technological classes in terms of GPT-ness.³⁰ Another effort employs online job posting data to differentiate among the GPT-ness of various technological domains, finding that machine learning technologies are more likely to be GPTs than other technologies such as blockchain, nanotechnology, and 3D printing.³¹

Over the past few years, Chinese labs have quickly followed in the footsteps of U.S. labs to build large language models (LLMs), text generation systems such as ChatGPT. In a recent *Foreign Affairs* piece, Helen Toner, Jenny Xiao, and I argued that “When it comes to LLMs, China trails years, not months, behind its international competitors.” This gap is a product of many factors, including a reliance on Western counterparts to open up new paradigms of AI development, political constraints on free speech, and relative lack of high-quality Chinese-language data for training.

China’s pace of LLM development is also impeded by bottlenecks in the supply of semiconductors. In *Foreign Affairs* article, we laid out this case in detail:

*Due to the outsized computational demands of LLMs, the international competition over semiconductors inevitably affects AI research and development. The Chinese semiconductor industry can only produce chips several generations behind the latest cutting-edge ones, forcing many Chinese labs to rely on high-end chips developed by U.S. firms. In recent research analyzing Chinese LLMs, we found 17 models that used chips produced by the California-based firm NVIDIA; by contrast, we identified only three models built with Chinese-made chips.*³²

*Huawei’s PanGu- α , released in 2021, was one of the three exceptions. Trained using Huawei’s in-house Ascend processors, the model appears to have been developed with significantly less computational power than best practices would recommend. Although it is currently perfectly legal for Chinese research groups to access cutting-edge U.S. chips by renting hardware from cloud providers such as Amazon or Microsoft, Beijing must be worried that the intensifying rhetoric and restrictions around semiconductors will hobble its AI companies and researchers.*³³

It is worth noting that the innovation-diffusion distinction is also relevant for discussions about the national security implications of LLMs. Almost all the attention has gone toward which country can develop the next breakthrough in foundation models; much less attention goes

30 Ibid., 2020, 7. Image analysis ranks sixth. The technological classes that rank higher, from highest to lowest, are television, telecommunications, radiant energy, illumination, and electrical communications.

31 Goldfarb, Taska, and Teodoridis 2021.

32 Jeffrey Ding and Jenny Xiao. “Recent Trends in China’s Large Language Model Landscape.” *Centre for the Governance of AI*. April 2023.

33 “Chinese AI Groups use cloud services to evade US chip export controls.” *Financial Times*. March 8, 2023.

toward what happens after large models are trained and their adoption rate across different types of industries. From my preliminary research in this area, it seems that China still faces a large “implementation gap” in terms of making LLMs cost-effective to be used by small and medium-sized businesses.³⁴ General-purpose technologies like AI take time to diffuse, and if AI does truly transform the global economy, we are still in the early stages.

In recent years, there has been more scrutiny of China’s investments in the human capital necessary to adapt to emerging technologies such as AI. As technology races forward, skills must keep pace. Some studies inflate China’s capacity to diffuse AI advances at scale because of its sheer quantity of computer science graduates.³⁵ General counts of graduates, without accounting for the quality of education, overstate China’s capacity to cultivate a broad base of AI engineers. Comparisons of computer science education, in particular, can mislead, if the quality of such training is not considered.³⁶ Consider one quality baseline for AI education: a university meets this standard if it employs at least one researcher that has published at least one paper in a leading AI conference. According to data from the years 2020-2021, China was home to only 29 universities that met this standard; the U.S. accounted for 159 such universities.³⁷

To be sure, China has made important investments in enhancing AI education. In 2018, the Chinese Ministry of Education approved the creation of an AI major, which was quickly adopted by universities around the country.³⁸ For instance, a February 2021 survey report on China’s computer vision talent found that 7 percent of respondents (which included students in the computer vision field) had studied the new AI major. These initiatives followed from the designation of “AI 2.0”, an initiative to significantly boost AI education and development, as one of 16 Megaprojects in 2017.³⁹ Since many of these efforts will take a long time to bear fruit, it is too early to make definitive conclusions about China’s efforts to align its human capital investments with its techno-industrial policy aims in AI.

Indeed, China’s investments in human capital will be a significant factor in shaping its capacity to adopt AI at scale. There is some evidence that the Chinese government prioritizes R&D

³⁴ Jeffrey Ding. 2022. “ChinAI #199: China’s Hugging Face?” <https://chinai.substack.com/p/chinai-199-chinas-hugging-face>; Jeffrey Ding. 2023. “ChinAI #236: The LLM Implementation Gap” <https://chinai.substack.com/p/chinai-236-the-llm-implementation>.

³⁵ Allison, Graham, and Eric Schmidt. “Is China Beating the U.S. to AI Supremacy?” Belfer Center for Science and International Affairs, August 2020.

³⁶ Loyalka, Prashant, Ou Lydia Liu, Guirong Li, Igor Chirikov, Elena Kardanov, Lin Gu, Guangming Ling, et al. “Computer Science Skills across China, India, Russia, and the United States.” *Proceedings of the National Academy of Sciences* 116, no. 14 (April 2, 2019): 6732–36.

³⁷ Analysis based on the CSRankings website. For details on the original methodology, see Tencent Research Institute and Boss Zhipin 2017, 12.

³⁸ Ding, Jeffrey. “China’s current capabilities, policies, and industrial ecosystem in AI.” Testimony before the US-China Economic and Security Review Commission Hearing on Technology, Trade, and Military-Civil Fusion: China’s Pursuit of Artificial Intelligence, New Materials, and New Energy (2019).

³⁹ Ding, Jeffrey. “Deciphering China’s AI dream.” *Future of Humanity Institute Technical Report* (2018).

investments, which sometimes trades off other pathways to productivity growth based around technology adoption and broad-based education.⁴⁰ The consistency of China's fulfillment of R&D spending targets does not extend to the fulfillment of education funding benchmarks.

A comparison of China with other newly industrialized economies illustrates this point. Based on 2018 data, China's public expenditures on education as a ratio of GDP was lower than the corresponding figure for Brazil, Malaysia, Mexico, and South Africa.⁴¹ By contrast, China's R&D spending as a percentage of GDP far exceeded that of these countries. One possible explanation for this disparity, according to a group of experts on China's science and technology system, is the longer time required for efforts in education policy to yield tangible progress in technological development.⁴² Related research has shown that the Chinese government has neglected low levels of upper secondary education attainment, possibly due to the over-reporting of such rates by the Ministry of Education.⁴³

IV. Conclusion and Policy Recommendations

Given the above analysis of China's diffusion and innovation capacity, the following policy recommendations could help safeguard U.S. interests:

First, keep calm and avoid overhyping China's AI capabilities. My research suggests that the U.S.'s lead in AI capabilities over China should endure. Policies on AI competition with China should be made from a position of strength, not fear and weaknesses. More specifically, claims that U.S. regulatory action on AI will allow China to race ahead in this domain do not hold water, and they should not confound deliberations over sensible guardrails on rapidly-advancing AI systems.⁴⁴

Second, invest in technology diffusion. In the context of general-purpose technologies such as AI, policies directed at broadening the AI talent base, such as by further supporting community colleges in developing the AI workforce, may be just as, if not more, important as producing the best and brightest AI experts.⁴⁵ The U.S. should also invest in "technology diffusion

⁴⁰ Brandt, Loren, John Litwack, Elitza Mileva, Luhang Wang, Yifan Zhang, and Luan Zhao. "China's Productivity Slowdown and Future Growth Potential." Policy Research Working Paper. World Bank Group, June 2020.

⁴¹ Statistics based on the UNESCO Institute of Statistics Database.

⁴² Liu, Xielin, Sylvia Schwaag Serger, Ulrike Tagscherer, and Amber Y. Chang. "Beyond Catch-up—Can a New Innovation Policy Help China Overcome the Middle Income Trap?" *Science and Public Policy* 44, no. 5 (October 1, 2017): 656–69.

⁴³ Khor, Niny, Lihua Pang, Chengfang Liu, Fang Chang, Di Mo, Prashant Loyalka, and Scott Rozelle. "China's Looming Human Capital Crisis: Upper Secondary Educational Attainment Rates and the Middle-Income Trap." *The China Quarterly* 228 (December 2016): 905–26.

⁴⁴ Helen Toner, Jenny Xiao, and Jeffrey Ding. 2023. The Illusion of China's AI Prowess. *Foreign Affairs*. <https://www.foreignaffairs.com/china/illusion-chinas-ai-prowess-regulation>.

⁴⁵ West, Darrell M. *The Future of Work: Robots, AI, and Automation*. Brookings Institution Press, 2018, p. 112-113; National Security Commission on Artificial Intelligence. "Final Report." Washington, D.C.: NSCAI, March 2021. <https://www.nsc.ai.gov/2021-final-report/>, p. 175.

institutions,” including applied technology centers and dedicated field services, that encourage the adoption of AI techniques by small businesses.⁴⁶

Yet, instead of sustaining its advantages in adopting GPTs at scale, the United States is fixated on dominating innovation cycles in leading sectors. When it comes to a grand AI strategy, US policymakers are engrossed in ensuring that leading-edge innovations do not leak to China, whether by restricting the immigration of Chinese graduate students in advanced technical fields or by imposing export controls on high-end chips for training large models like ChatGPT. Previous industrial revolutions have demonstrated that no one country can monopolize foundational innovations in GPTs, so it will be infeasible for the U.S. to cut China off from AI.

A diffusion-centric approach would, instead, prioritize improving and sustaining the rate at which AI becomes embedded in a wide range of productive processes. Policies directed at broadening the talent pool, such as fully implementing the CHIPS and Science Act’s STEM workforce initiatives, deserve more attention. A recent publication by Minerva Technology Policy Advisors outlined a range of policies to encourage small and medium-sized businesses accelerate their adoption of AI innovations, including through initiatives to expand access to cloud computing and data infrastructure.⁴⁷ Run faster, since it is impossible to stop others from running the race at all in GPTs.

To be clear, a diffusion-oriented strategy does not necessarily exclude support for the exciting research progress in a country’s leading labs and universities. Undoubtedly, more R&D spending and better training grounds for elite scientists will also indirectly contribute to more widespread adoption of AI. All too often, however, these policies seem to be the boilerplate recommendation for any strategic technology. GPTs like AI are not like other technologies, and they demand a different toolkit of strategies.

When some of the leading thinkers of our era declare that the AI revolution will be more significant than the industrial revolution, it is difficult to not get caught up in their excitement. In these discussions about how to secure the future, scholars and policymakers gravitate toward which country will be first to generate new, foundational breakthroughs, largely neglecting what happens after their initial introduction. But the most effective strategy for attaining technological leadership may be one grounded in the humble undertaking of diffusion. For the U.S. to effectively compete with China in emerging technologies like AI, it must first rebalance its technology policy toward a diffusion-centered approach.

⁴⁶ Shapira, Philip, and Jan Youtie. “The next Production Revolution and Institutions for Technology Diffusion.” *The Next Production Revolution: Implications for Governments and Business*, 2017.

⁴⁷ <https://www.minervapolicy.com/ai-everywhere>.