U.S. GOVERNMENT ACCOUNTABILITY OFFICE

ARTIFICIAL INTELLIGENCE

A Framework to Assess U.S. Competitiveness and Inform Policy Options

A report to congressional requesters

May 2026
GAO-26-107624

Highlights of GAO-26-107624, a report to congressional requesters

May 2026

Artificial Intelligence: A Framework to Assess U.S. Competitiveness and Inform Policy Options

Why GAO Developed This Framework

Artificial intelligence (AI) could spur economic growth, enhance societal well-being, and improve national security. These possibilities have led to a global AI competition, in which nations that fall behind risk losing economic advantages and global influence. To be competitive, the U.S. needs to consider risks of AI deployment, such as job dislocation and increased energy consumption.

Assessing U.S. competitiveness in AI presents challenges. The ability of the U.S. to successfully develop and deploy AI technologies depends on a broad mix of factors, including private and public investment, talent attraction, regulatory environments, and computing infrastructure. GAO was asked to develop a framework to assess U.S. AI capabilities, capacity, and competitiveness compared to other nations. GAO developed this framework to help analysts prioritize among the many factors that affect AI competitiveness. The framework is also designed to help analysts develop policy options to improve U.S. competitiveness.

To develop this framework, GAO conducted a literature search to find articles on frameworks and measurements to evaluate AI capabilities and capacity and reviewed key reports on AI competitiveness and assessment methods. GAO also interviewed, surveyed, and met with experts from government agencies, academia, industry, nonprofit organizations, and more.

How to Use the Framework

GAO's framework is a method for assessing AI capabilities and capacity in the U.S. and its competitiveness. A nation's competitiveness in AI is how well it develops or deploys AI technologies compared to other nations. Policymakers may be interested in knowing how the U.S. compares to other nations in the AI race. GAO developed this framework to help analysts from government, industry, academia, and elsewhere obtain and provide structured information to policymakers about AI competitiveness.

The complexity of factors affecting AI competitiveness makes it difficult to decide which factors are more important than others. The framework organizes relevant factors into four pillars: Science & Technology, Human Capital, Governance, and Economy. Each pillar is further divided into subpillars, such as R&D; laws, regulations and policies; workforce; and investment and financing. Analysts can use these pillars and subpillars to systematically consider the breadth of factors relevant to the needs of policymakers seeking information on our nation's AI capabilities and capacity versus those of other nations.

Factors Affecting AI Competitiveness

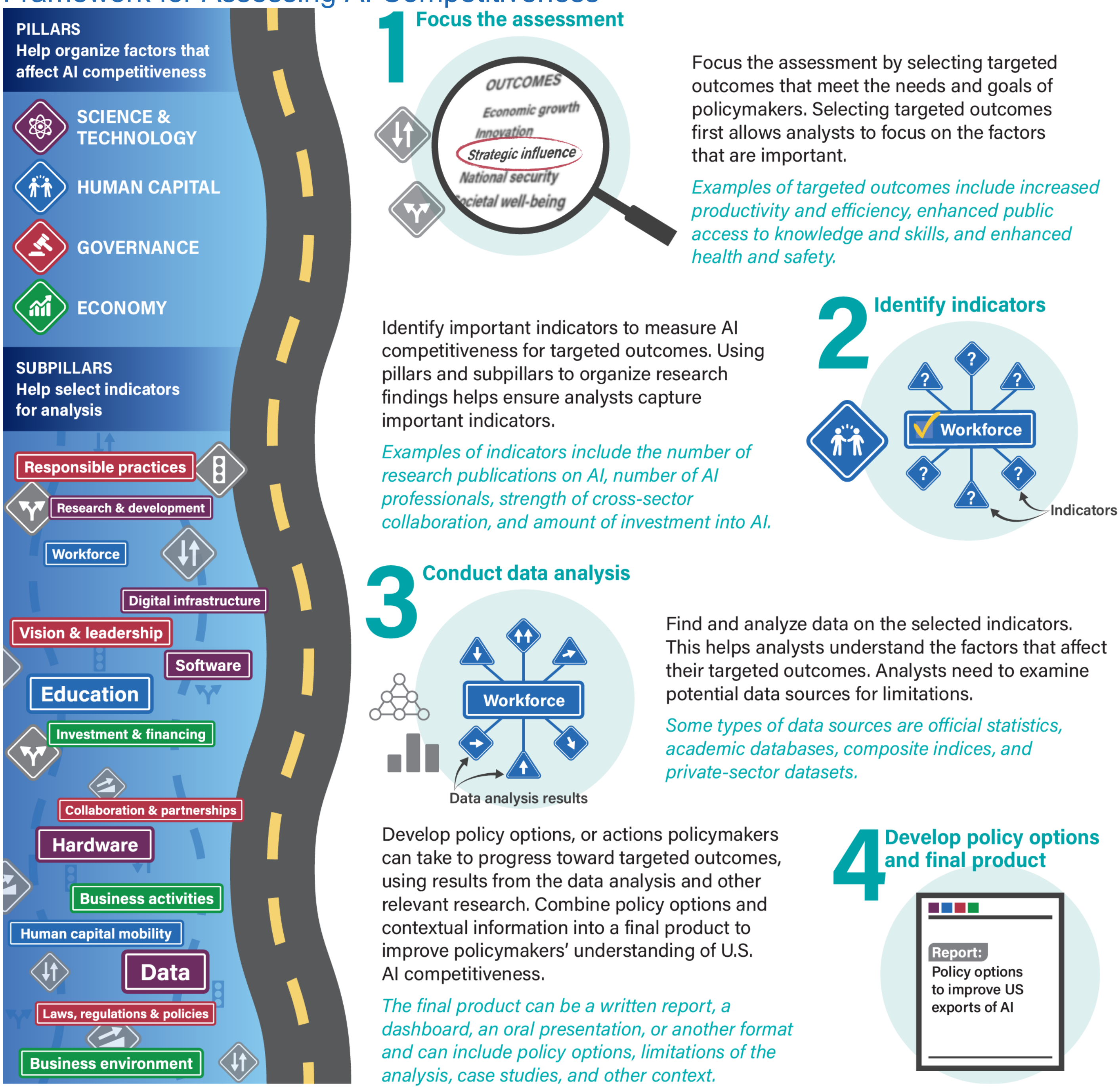
Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO-26-107624

Analysts can use the framework for different purposes and policymaker needs. For example, if U.S. policymakers express interest in helping U.S. companies export AI technologies, analysts can use the framework to rank the U.S. and its peers in their progress toward outcomes of AI competitiveness, such as the ability to influence global technology standards. These rankings can in turn inform policies to help the U.S. improve its AI capabilities, capacity, and competitiveness.

The framework involves four steps that allow analysts to tailor their assessment:

1. Focus the assessment by selecting targeted outcomes of AI competitiveness.
2. Identify indicators for measurement or evaluation.
3. Conduct data analysis.
4. Develop policy options and final product.

Framework for Assessing AI Competitiveness



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO−26−107624

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Abbreviations

AI	artificial intelligence
GDP	gross domestic product
ISO	International Organization for Standardization
NIST	National Institute of Standards and Technology
OECD	Organisation for Economic Co-operation and Development
R&D	research and development
STEM	science, technology, engineering, and mathematics
UNESCO	United Nations Educational, Scientific and Cultural Organization

Foreword

May 21, 2026

Congressional Requesters

Artificial intelligence (AI) is broadly recognized as the defining technology of the 21st century, and its potential effects are often compared to the way electricity redefined everyday life in the early 1900s. Although AI presents risks, nations are engaged in a global competition for superiority because they recognize AI's strategic importance. For example, a recent executive order provides that U.S. policy is to "sustain and enhance America's global AI dominance."[1] Additionally, China and the European Union asserted that they aim to become global leaders in AI.[2] Nations have developed strategies and policies encompassing a range of AI-related goals focusing on competitiveness. These national commitments reflect the implications of AI competitiveness for goals such as economic growth, societal well-being, and national security.

Assessing AI competitiveness, or whether the U.S. is performing as well as or better than other nations in AI development or deployment, presents challenges. One challenge is that successful development and deployment of AI at the national level depends on a complex mix of factors related to science and technology, human capital, governance, and the economy. Another challenge is the breadth of potential indicators to measure a nation's ability to develop or deploy AI. Assessing AI competitiveness is also a challenge because it depends not only on a nation's current capabilities and capacity but also on a nation's ability to sustain and improve them over time.

You asked us to develop a methodology to evaluate U.S. competitiveness in AI relative to other nations, and this report presents a framework for doing so and informing policy options. The framework addresses the challenges of assessing U.S. competitiveness in AI by organizing the range of factors and indicators to consider in assessing AI capabilities and capacity. The framework asks analysts to first identify policymakers'

[1]Exec. Order No. 14179, *Removing Barriers to American Leadership in Artificial Intelligence,* 90 Fed. Reg. 8741 (Jan. 23, 2025).

[2]State Council of the People's Republic of China, *New Generation Artificial Intelligence Development Plan*, trans. by Graham Webster, Rogier Creemers, Elsa Kania, and Paul Triolo, DigiChina (Stanford, CA: Aug. 1, 2017), https://digichina.stanford.edu/work/full-translation-chinas-new-generation-artificial-intelligence-development-plan-2017/; European Commission, *AI Continent Action Plan* (Brussels: 2025).

primary goals for competitiveness in AI. With a goal in mind, analysts can better prioritize the key factors affecting competitiveness, identify appropriate indicators for those factors, and assess policy options to drive improvements.

We used a deliberative process and consulted a wide range of experts to develop this framework. We extend special thanks to those who commented and suggested improvements to the framework. Thank you for sharing your insights, experience, and time.

Analysts from government, academia, and elsewhere can use our framework to assess strengths and weaknesses in U.S. AI development and deployment and to help policymakers by informing AI policy. This report focuses on a broad assessment of trends in the AI field rather than measuring changes in specific organizations' software or hardware.

If you or your staff have any questions about this report, please contact us at ThomasS2@gao.gov or WrightC@gao.gov. Contact points for our Offices of Congressional Relations and Media Relations may be found on the last page of this report. GAO staff who made key contributions to this report are listed in the last appendix.

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List of Requesters

The Honorable Martin Heinrich
United States Senate

The Honorable M. Michael Rounds
United States Senate

The Honorable Charles E. Schumer
Minority Leader
United States Senate

The Honorable Todd Young
United States Senate

Introduction

U.S. policymakers seek to understand which nations are competitive in AI. AI is used in everyday applications, such as severe storm forecasts, disease diagnosis, and facial recognition. Integrating AI into the economy offers benefits such as increased productivity or innovation as well as risks such as potential compromise of data privacy or job dislocation. This combination of AI's broad applicability and its benefits and risks makes AI an area of strategic importance for U.S. policymakers.

The objective of this report is to develop a framework for assessing U.S. AI competitiveness. For this report, the U.S. is competitive in AI if it performs as well as or better than other nations toward a specified outcome, which can be economic, societal, or strategic. AI competitiveness includes leadership in technological capabilities and innovation, as well as economic competitiveness such as development of AI in ways that improve U.S. productivity. Table 1 describes some of the terms used in this report.

Table 1: Definitions and Terms Used in This Report

Definitions
Competitive: performing as well as or better than other nations on a chosen indicator, which can include measures for technology or the economy
Development: the process of creating and refining AI tools or systems to meet various needs and challenges
Deployment: the process of adopting and integrating AI tools or systems into real-world environments for practical use
Terms used in GAO's AI Competitiveness Framework
Outcome: economic, societal, or strategic effect of AI development or deployment, with targeted outcomes as intended effects of AI competitiveness
Pillar: an organizational structure for the factors that are critical to AI development and deployment
Subpillar: a factor that could be important to achieving targeted outcomes of AI development and deployment
Indicator: a measure or observation of actions, conditions, or other factors relevant to AI competitiveness
Driver: an indicator of AI competitiveness that describes actions or conditions that cause or enable an outcome
Signal: an indicator of AI competitiveness that describes progress toward an outcome

Source: GAO analysis. | GAO-26-107624

Analysts from government, academia, and elsewhere can use our framework to assess a nation's strengths and weaknesses in AI development and deployment and to help policymakers by informing AI policy. This report focuses on a broad assessment of trends in the AI field rather than measuring changes in specific organizations' software or hardware.

For this report, we define AI as a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. This derives from a commonly cited definition in federal law and is also consistent with how the Organisation for Economic Co-operation and Development defines AI.[3]

We developed the framework using the following sources: (1) literature on AI, competitiveness, innovation, and assessment methodologies and frameworks for AI; (2) interviews and meetings with experts; (3) responses to a survey distributed to experts; and (4) internal review by GAO experts.

Experts who participated in our interviews, survey, and the 24 expert meeting participants were from academia, federal agencies, industry, non-profit organizations, and other institutions. Some experts had technical expertise (e.g., software and hardware development) pertaining to AI development and deployment, and some had nontechnical expertise (e.g., economics, governance, and human capital) pertaining to AI development and deployment. See appendix I for a detailed discussion of our objectives, scope, and methodology. See appendix II for a list of experts who participated in our expert meetings.

We conducted our work from June 2024 to May 2026 in accordance with all sections of GAO's Quality Assurance Framework that are relevant to our objectives. The framework requires that we plan and perform the engagement to obtain sufficient and appropriate evidence to meet our stated objectives and to discuss any limitations in our work. We believe that the information and data obtained, and the analysis conducted, provide a reasonable basis for any findings and conclusions in this product.

[3]National Artificial Intelligence Initiative Act of 2020 within the William M. (Mac) Thornberry National Defense Authorization Act for Fiscal Year 2021, Pub. L. No. 116-283, § 5002(3), 134 Stat. 3388, 4524 (2021) (codified at 15 U.S.C. § 9401(3)); "Explanatory memorandum on the updated OECD definition of an AI system," OECD Artificial Intelligence Papers, Organisation for Economic Co-operation and Development, March 5, 2024, https://doi.org/10.1787/623da898-en.

Why National AI Competitiveness Matters

AI competitiveness matters because AI capabilities and capacity affect nations' abilities to pursue strategic goals, such as economic growth or national security. One thing that could improve nations' overall competitiveness is strategic collaboration and partnerships with other nations. For example, in October 2025, the U.S. and Japan agreed to align their AI standards and development frameworks to promote the ability of their AI systems to work together. If nations shape their regulations using the same standards as foundations, firms may find it easier to operate across markets even when actual regulations differ between nations.

In some instances, gains for one nation can directly translate to losses for others. For example, nations that attract top researchers and engineers from other nations strengthen their own capabilities while simultaneously weakening other nations' talent pools. To stay competitive, nations that successfully build AI capabilities and capacity to develop or deploy AI would also need to build capacity to sustain AI deployment and improve AI systems over time. In contrast, nations with limited AI capabilities and capacity may be unable to develop the talent, infrastructure, or investment needed for AI development, AI deployment, or both.

How Nations May Achieve AI Competitiveness Through AI Development, Deployment, or Both

AI development and deployment offer different paths toward competitiveness. AI development is the process of creating and refining AI tools or systems to meet various needs and challenges. AI deployment is the process of adopting and integrating AI tools or systems into real-world environments for practical use.

Nations may develop AI, deploy AI, or both, depending on their available resources, existing capabilities, and targeted outcomes. Nations with more resources and better enabling conditions, such as financial resources, access to large markets, high-skilled workers, and a stable business environment, will likely find it feasible to engage in both development and deployment of AI technologies. For example, the U.S. and China currently develop and deploy AI technologies.

Nations do not have to both develop and deploy AI to be competitive, but a nation that leads in AI development could benefit from being first to introduce a new technology. For example, a nation's firm that pioneers a new AI product or service may capture a significant market share of an AI technology before competitors from other nations enter the market. Nations that mainly focus on development may not capture the long-term benefits, or outcomes, of AI deployment. Also, nations with limited AI capabilities and capacity risk losing economic advantages, relying on other nations' AI technologies, and potentially undermining their own global influence. Additionally, nations that deploy AI without a long-term focus risk building fragmented systems, remaining in extended pilot testing, or limiting their ability to allocate resources efficiently.

Nations may want to prioritize pursuing AI development and deployment in sectors that are strategically important to them. For example, the importance of agriculture varies across the economies of the European Union. Nations where agriculture plays a larger economic role are likely to prioritize AI integration in farming practices to boost productivity and efficiency.

A nation's existing infrastructure can affect its deployment of AI. More specifically, some nations could struggle to deploy AI because of outdated information technology infrastructure, known as legacy systems. In 2024, a U.S. congressional report identified legacy systems, such as those used to deliver public services in the U.S., as a barrier to adopting AI.[4] In contrast, nations with fewer legacy systems could deploy AI quickly. For example, one report suggests that lower-income nations with fewer legacy systems could deploy AI-enabled technologies in health care more quickly than higher-income nations could.[5] As an analogy, African nations bypassed fixed-line broadband infrastructure over recent decades and adopted mobile internet technology directly, enabling rapid expansion of communication systems.[6]

[4]Bipartisan House Task Force on Artificial Intelligence, *Bipartisan House Task Force Report on Artificial Intelligence* (Washington, D.C.: Dec. 2024).

[5]Broadband Commission for Sustainable Development, *Reimagining Global Health through Artificial Intelligence: The Roadmap to AI Maturity* (Sept. 2020).

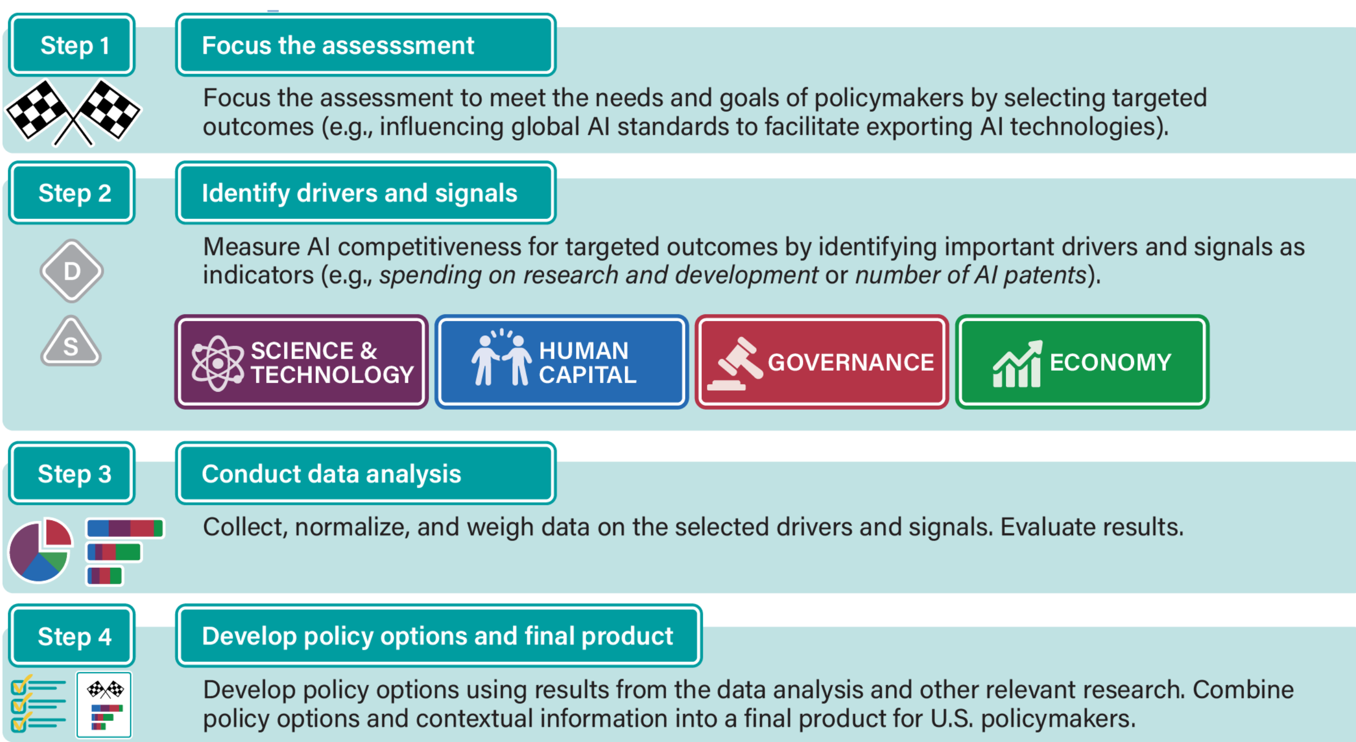
[6]Broadband, or high-speed internet, allows users to access the internet. Fixed-line broadband delivers internet service though a stationary connection to a specific location, and mobile broadband delivers internet service through wireless cellular networks.

Part I: Overview of the Framework

Assessing U.S. AI competitiveness can be challenging because successful AI development and deployment depend on a wide range of factors. We built a customizable framework that asks analysts to specify the goals for competitiveness in AI to meet policymakers' needs. The specified goals help analysts focus on factors that affect competitiveness and help identify policy options to drive improvements.

Our framework for assessing U.S. AI competitiveness involves four steps: (1) focus the assessment by selecting targeted outcomes of AI competitiveness, (2) identify drivers and signals for measurement or evaluation, (3) conduct data analysis, and (4) develop policy options and final product. Figure 1 depicts an overview of this framework.

Figure 1: Overview of Framework for Assessing U.S. AI Competitiveness



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO-26-107624

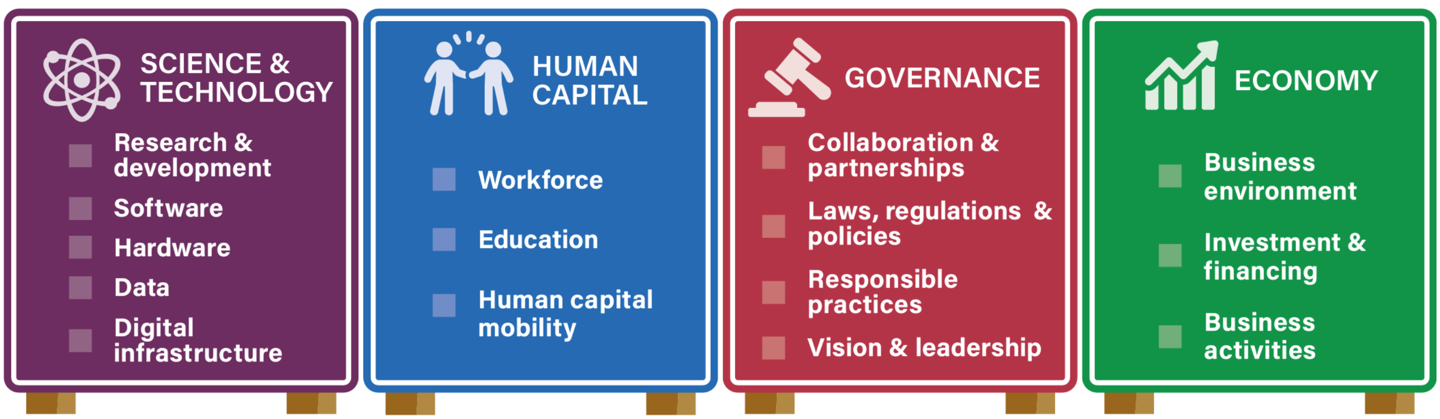
Some organizations have developed frameworks for assessing national AI capabilities and capacity (see app. III). Although some of those frameworks have different purposes, including assessing readiness and responsible development, they share similar indicators to measure AI competitiveness.

Pillars and Subpillars Organize Indicators of AI Competitiveness

We summarized key factors for assessing competitiveness from existing frameworks and consulted experts to validate their importance to AI competitiveness.[7] Similar to other frameworks, we use a pillar and subpillar structure to help analysts select and organize applicable indicators for their assessment.

The four pillars critical to AI development and deployment are science and technology, human capital, governance, and economy (see fig. 2). Each pillar is divided into subpillars, which are factors that could be important to achieving targeted outcomes. Indicators are measures of a subpillar.

Figure 2: Four Pillars Important to AI Development or Deployment and Their Subpillars



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO-26-107624

Selecting Targeted Outcomes Helps Analysts Focus Their Assessment

Analysts start by selecting targeted outcomes, which could include national goals set by U.S. policymakers. This step allows analysts to narrow the assessment to the most relevant factors. A complex mix of factors influences the ability of the U.S. to develop and deploy AI technologies in the short term and long term. These factors involve a range of sectors and institutions. For example, research institutions conduct fundamental AI research and train talent, while private companies translate research into commercial applications and scale AI solutions across industries. Government agencies provide funding, create

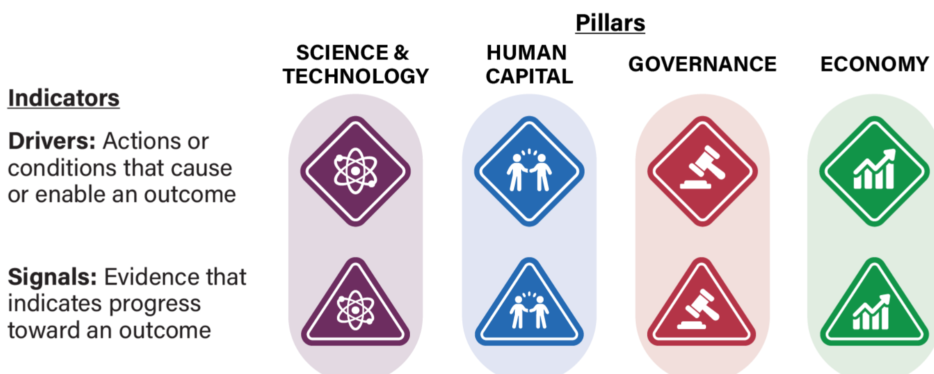
[7]See app. I for our methodology.

policy frameworks, and address national security considerations, while public acceptance shapes the extent to which AI technologies are deployed to achieve their intended effects. Working together, these factors translate AI research into deployed capabilities that lead to targeted outcomes, such as increased productivity and efficiency across sectors. By centering their assessment of AI competitiveness on specific outcomes, analysts can narrow down the factors that influence competitiveness, inform the selection of subpillars and indicators, and identify actions to improve those outcomes.

Drivers and Signals Can Inform Actions to Achieve Targeted Outcomes

To inform actions to achieve targeted outcomes, we separate indicators into drivers and signals of competitiveness (see fig. 3). Drivers describe actions or conditions that cause or enable an outcome. Signals describe progress toward an outcome. Separating drivers from signals can help analysts identify actions or conditions that could enhance competitiveness and develop policy options to address them.

Figure 3: Definitions of Drivers and Signals, as Used in the AI Competitiveness Framework



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO−26−107624

Table 2 provides examples of drivers and signals.

Table 2: Illustrative Examples of Drivers and Signals of Competitiveness in AI Development and Deployment

To assess AI competitiveness, analysts should use drivers and signals that are relevant to the targeted outcomes. The following examples are relevant to AI development or deployment.

AI development	AI deployment
• *R&D investment* can be a driver of competitiveness as such investment enables advancements in AI models and related technologies.	• *Education* and *training* can be drivers of competitiveness as both can enhance a nation's understanding of AI and prepare its workforce to use AI to optimize tasks and their roles.
• *Research publications* or *patents on AI and related fields* can be signals of progress.	• *Estimates of AI use by businesses* can be a signal of progress.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Part II: How to Use the Framework

Introduction: Why Use the Framework

The AI competitiveness framework is a tool analysts can use to respond to research questions, understand policy contexts, and address policymakers' needs. The framework supports intended uses such as the following:[8]

- **Ranking nations**. Analysts can use the framework to compare and rank nations by their AI competitiveness or performance in specific sectors. For example, analysts can rank nations by overall AI competitiveness, or analysts can rank nations by AI competitiveness in a specific sector, such as health care or the public sector.
- **Identifying emerging trends.** Analysts can use the framework to identify trends in AI competitiveness, including changes in nations' ranks or in the factors that drive AI competitiveness. For example, tracking progress on a specific aspect of AI competitiveness over time could show patterns of improving or declining national performance.
- **Assessing strengths and weaknesses.** Analysts can use the framework to understand the factors driving or hindering a nation's AI competitiveness. For example, a detailed analysis could show that a nation's strong R&D capabilities offset weaknesses in its workforce or digital infrastructure.
- **Guiding strategic decisions.** Analysts can use the framework to inform policy choices using the strengths and weaknesses revealed by an assessment. For example, a nation with strong infrastructure but weak R&D capabilities could maintain investment in infrastructure while also considering policy options to improve R&D capabilities, such as developing and attracting a skilled AI workforce.
- **Monitoring and evaluating progress**. Analysts can use the framework to monitor progress toward AI competitiveness goals and to support evaluation of the effectiveness of existing policies or investments. For example, tracking education indicators before and after implementing new funding programs may show the extent to which investment correlates with strengthening the AI talent pool.

Analysts' intended use of the framework informs what data the analysts need for their competitiveness assessment. For example, if analysts want to track changes in national AI capabilities and capacity over time, then they need historical data. However, unreliable or unavailable historical data could prevent a meaningful analysis. As analysts implement this

[8]This section draws on information from relevant literature and the seven frameworks described in app. III.

framework, they can adjust their intended uses depending on what data are available.

Excerpts of an Illustrative Scenario

In part II of the report, we include excerpts of a scenario to illustrate how to use the framework. Part III describes the full scenario that illustrates each step of the framework.

Source: GAO. | GAO-26-107624

Illustrative Example of Intended Use

Analysts in our scenario want to assess U.S. AI competitiveness. After considering policymakers' interests, the analysts decide to use the framework to rank nations. This will allow analysts to identify which nations are most and least competitive and understand performance compared to the U.S. across a set of indicators.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Step 1: Focus the Assessment

The first step to using this framework is to select the targeted outcomes of AI competitiveness to focus the assessment. Starting by selecting outcomes is important because it allows analysts to tailor the assessment to policymakers' needs from the beginning.

Select Economic, Societal, or Strategic Outcomes to Focus Assessment

Developing and deploying AI could result in many outcomes, so analysts should select some to focus the assessment as a key first step in this framework. Specifically, selecting targeted outcomes informs step 2, in which analysts narrow down the factors that influence competitiveness. In table 3, we list some potential outcomes of AI competitiveness that we gathered from experts.

Table 3: Examples of Targeted Outcomes from AI Competitiveness

Economic growth and innovation	Societal well-being	Strategic influence and national security
• Increased productivity and efficiency across sectors	• Enhanced health and safety	• Influence on global AI policy, standards, and value setting
• Creation of high-wage jobs	• Enhanced public sector performance	• Increased share of AI products and services in global market
• Increased rates of introduction of goods and services	• Improved quality of goods and services	• Enhanced national security
• AI-driven breakthroughs in non-AI R&D	• Enhanced access to knowledge and skills	• Geopolitical influence

Source: GAO analysis of information from survey and meetings of experts. | GAO-26-107624

Economic growth and innovation. AI could improve efficiency and productivity in the workplace and could create jobs in certain occupations or industries. Data from studies on the effects of AI on productivity and efficiency became available in 2023.[9] Studies have shown that workers with access to AI technology are able to complete certain tasks more

[9]Stanford University Institute for Human-Centered Artificial Intelligence, *Artificial Intelligence Index Report 2024* (Stanford, CA: Apr. 2024).

quickly and with better quality than their peers who did not use AI. For example, authors of a 2023 study found that workers with access to generative AI tools increased their productivity by 14 percent on average.[10] Experts we surveyed and studies have suggested that AI could create job opportunities for those with skills that support development or deployment of AI, as well as increase workforce productivity and efficiency. Additionally, AI could lead to the introduction of new products, which could lead to job creation in support of those products.[11] Analysts may also want to consider the extent to which policymakers have targeted outcomes for specific industries or sectors. As previously discussed, nations may want to prioritize pursuing AI development and deployment in sectors that are strategically important to them. For example, nations with significant manufacturing sectors may select as a target outcome increased goods and services related to AI robotics.

Societal well-being. Integrating AI into the private and public sectors could provide societal benefits such as enhanced health care and safety. For example, AI could be a helpful tool for health care professionals in providing better and more timely care for patients. More specifically, AI can help doctors identify bone fractures and detect early signs of diseases such as Alzheimer's.[12] Additionally, AI could be used to enhance public safety. For example, researchers are examining how to use AI to predict traffic conditions caused by nonrecurring incidents such as crashes, weather-related events, and disabled vehicles.[13]

AI also has the potential to improve public sector performance. AI could optimize tasks related to public services including modeling natural hazards, scheduling public transportation routes, and processing

[10]Erik Brynjolfsson, Danielle Li, and Lindsey R. Raymond, "Generative AI at Work," working paper 31161 (Cambridge, MA: National Bureau of Economic Research, Nov. 2023), http://www.nber.org/papers/w31161.

[11]Alexandre Georgieff and Raphaela Hyee, "Artificial Intelligence and Employment: New Cross-Country Evidence," *Frontiers in Artificial Intelligence,* vol. 5 (2022), https://doi.org/10.3389/frai.2022.832736.

[12]"7 Ways AI is Transforming Healthcare," Centre for Health and Healthcare, World Economic Forum, last modified August 13, 2025, https://www.weforum.org/stories/2025/08/ai-transforming-global-health/.

[13]U.S. Department of Transportation, Federal Highway Administration, *Exploratory Advanced Research Program: The Role of Artificial Intelligence and Machine Learning in Federally Supported Surface Transportation 2024 Updates*, FHWA-HRT-25-020 (Washington, D.C.: Dec. 2024).

information. For example, the Internal Revenue Service is piloting a new process for sampling tax returns for National Research Program audits. This process uses AI to improve the efficiency and selection of audit cases to help identify noncompliance.[14]

Additionally, AI can enhance public access to knowledge and skills. AI could help teachers provide more personalized education to students. More specifically, teachers have expressed that AI can be used to measure students' learning competencies and provide real-time feedback for each student.[15] Also, coders can use AI as a tool to enhance their skills in the field. For example, coders can use their knowledge of fundamental concepts and AI technology to learn new coding languages and optimize code.[16]

Strategic influence and national security. Leading in AI development and deployment may allow nations to gain soft power, which is the ability to influence others through attraction or persuasion. The ability to influence global AI policy, standards, and values represents one such form of soft power, enabled through a first-mover advantage. When a nation's firm is the first to develop or introduce a new technology, it has a first-mover advantage, which may allow it to capture a significant portion of the market or influence relevant standards before firms in other nations. National action plans often outline domestic efforts to influence global AI standards. For example, the U.S. issued an updated AI action plan in 2025 that emphasized the importance of developing American

[14]The three types of noncompliance discussed in the report include: 1) underreporting of tax liabilities on timely filed tax returns; (2) underpayment of taxes due from timely filed returns; and (3) nonfiling, when a taxpayer fails to file a required tax return altogether or on time. GAO, *Tax Gap: IRS Should Take Steps to Ensure Continued Improvement in Estimates*, GAO-24-106449 (Washington, D.C.: May 6, 2024).

[15]U.S. Department of Education, Office of Educational Technology, *Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations* (Washington, D.C.: May 2023).

[16]"Will AI Replace Programmers? Navigating the Future of Coding," Extended Studies Blog, University of California, San Diego, last modified March 22, 2024, https://extendedstudies.ucsd.edu/news-events/extended-studies-blog/will-ai-replace-programmers-navigating-the-future-of-coding.

open-source models that could influence global AI standards in some areas of business and research.[17]

Nations are heavily investing in AI technology to strengthen national security. For example, the Department of Defense is investing billions of dollars and making organizational changes to integrate AI into its warfighting plans. More specifically, the Air Force demonstrated an AI capability that piloted a U-2 aircraft and autonomously identified enemy launchers during a simulated strike mission.[18] Other potential uses for AI in national security include fully autonomous ships and facial recognition.[19]

Illustrative Example of Step 1: Focus the Assessment
Policymakers in our scenario expressed interest in understanding how their nation compares to other nations in facilitating export of AI technologies. To address this using the framework, analysts focus their assessment on nations' abilities to influence global AI standards.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Consider Undesired Outcomes of AI Development and Deployment

Analysts using this framework should also consider undesired outcomes of increased efforts to develop and deploy AI. Irrespective of whether a nation is competitive in AI, increased development and deployment could lead to undesired outcomes. This section provides examples of those undesired outcomes that we gathered from experts. Considering

[17]The White House, *Winning the Race: America's AI Action Plan* (Washington, D.C.: July 2025). The Open Source Initiative defines open source AI models as models "made available under terms and in a way that grant the freedoms to: use the system for any purpose and without having to ask for permission; study how the system works and inspect its components; modify the system for any purpose, including to change its output; [and] share the system for others to use with or without modifications, for any purpose. Open Source Initiative®, "What is Open Source AI," accessed April 22, 2026, https://opensource.org/ai/open-source-ai-definition.

[18]The U-2 is a single jet-engine, high-altitude reconnaissance aircraft developed by Lockheed Martin for the U.S. Air Force. The aircraft first flew in 1955. It can be deployed anywhere in the world to gather surveillance and signals intelligence data in real time. GAO, *Artificial Intelligence: Status of Developing and Acquiring Capabilities for Weapon Systems.* GAO-22-104765 (Washington, D.C.: Feb. 17, 2022). See also Department of War, "Artificial Intelligence Strategy for the Department of War: Memorandum for Senior Pentagon Leadership, Commanders of the Combatant Commands, and Defense Agency and DOW Field Activity Directors" (Washington, D.C.: Jan. 9, 2026).

[19]GAO, *Artificial Intelligence: Status of Developing and Acquiring Capabilities for Weapon Systems*, GAO-22-104765 (Washington D.C.: Feb. 17, 2022).

undesired outcomes and potential mitigations can present a broader understanding of AI competitiveness to policymakers. Where appropriate, analysts can incorporate mitigation in their competitiveness assessment or develop policy options for consideration.

One example of an undesired outcome is the likely increase in energy demand as AI usage continues to expand. The amount of energy used to power data centers, which house the information technology infrastructure needed to deploy AI applications and services, will likely increase as the number of data centers increases. The Electric Power Research Institute estimates that data centers in the U.S. could consume up to 9 percent of the nation's electricity demand by 2030.[20] One potential mitigation is R&D to develop hardware that offers substantial energy savings. Fully addressing concerns associated with increasing energy demand will likely require additional mitigations.

Another example of an undesired outcome is worker dislocation, in which workers are laid off or terminated—perhaps due to permanent closure of a facility or enterprise—and are unlikely to return to that industry. As more companies adopt and invest in AI, workers who do not have the skills to develop or deploy AI could be dislocated. Workers in occupations vulnerable to displacement by AI, such as administrative support or sales, could also experience job dislocation. Job loss can lead to negative economic impacts and declines in the psychological and physical health of the affected worker. Investing in upskilling or reskilling workers to transition to jobs that use AI can partially address worker dislocation and job loss.[21] Some dislocated workers may need additional or other forms of support during transition. The extent to which workers can transition into new roles, such as through training and workforce development efforts, can influence how effectively the nation's economy adapts to these changes and long-term competitiveness.

A third example of an undesired outcome of widespread AI deployment is the potential for disruptions if cyberattacks compromise AI systems. While cyberattacks are not unique to AI, AI-assisted cyberattacks may increase

[20]U.S. Department of Energy, *Clean Energy Resources to Meet Data Center Electricity Demand*, Grid Deployment Office, accessed, November 25, 2025, https://www.energy.gov/gdo/clean-energy-resources-meet-data-center-electricity-demand.

[21]Upskilling is the practice of an employee acquiring advanced skills or expanding their existing skill set to adapt to changes in the job market through additional education and training. Reskilling is when individuals whose jobs could be displaced by AI learn new skillsets, which could minimize job dislocation.

the risks for AI systems. Protecting AI systems from such threats can improve public attitude towards AI.[22] Managing AI risks, including cybersecurity risks, is a key part of responsible AI development and deployment.

Step 2: Identify Drivers and Signals

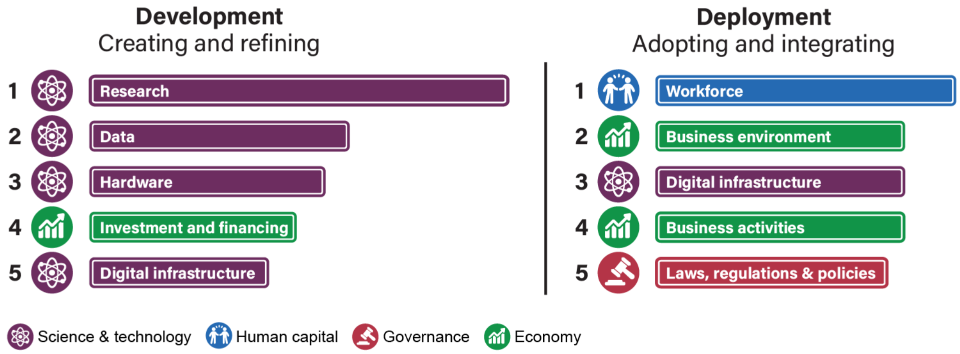
After selecting targeted outcomes of AI competitiveness, analysts should decide which subpillars among the four pillars are most important to those outcomes. For each subpillar, we provide examples of indicators that could drive competitiveness or signal progress toward an outcome. The indicators are from frameworks developed by other organizations, which offer suggestions for analysts choosing drivers and signals.

Analysts can conduct research, such as literature reviews or expert consultation, to determine which subpillars within the four pillars are most important to the targeted outcomes. Depending on the scope of assessment and selected outcomes, analysts could determine that some pillars have more relevant subpillars than other pillars do. It is up to analysts to determine which pillars and subpillars are important to the targeted outcome. Then, analysts identify drivers and signals for those subpillars.

Figure 4 lists five subpillars that experts we surveyed ranked as most important to AI competitiveness in development or deployment. For development, experts overwhelmingly ranked research as the most important subpillar, followed by data. For deployment, the rankings were more evenly spread across the five subpillars.

[22]Although AI can enable threat actors to increase the volume and impact of cyberattacks, AI tools for cybersecurity can be used to counter those attacks.

Figure 4: Five Subpillars that Experts Ranked as the Most Important to AI Competitiveness in Development or Deployment



Source: GAO analysis of survey responses from experts (data); GAO (graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO−26−107624

Notes: Development is the process of creating and refining AI tools or systems to meet various needs and challenges. Deployment is the process of adopting and integrating AI tools or systems in real-world environments for practical use. Subpillars that appeared more often in experts' rankings of subpillars important to AI development or deployment are listed on top.

The 57 experts who responded to our survey ranked their top three subpillars that are most important to development and their top three subpillars that are most important to deployment. This figure presents the five subpillars that appeared most often in experts' top three subpillars.

Some indicators can be drivers or signals in more than one pillar or subpillar. For example, investment in R&D can be a driver in either the Economy pillar or the Science and Technology pillar. As another example, AI researchers can be a driver of R&D in the Science and Technology pillar or a signal of workforce in the Human Capital pillar for AI development. Below, we provide more information about each pillar and subpillar, including examples of relevant drivers and signals.

Illustrative Example of Step 2: Identify Drivers and Signals

After deciding to focus on nations' abilities to influence global AI standards, analysts in our scenario conduct a literature review and identify the following topics as among those important to influencing global AI standards: technical expertise, collaboration, and market influence. Analysts use the research results to select relevant subpillars and identify the drivers and signals of nations' abilities to influence global AI standards.

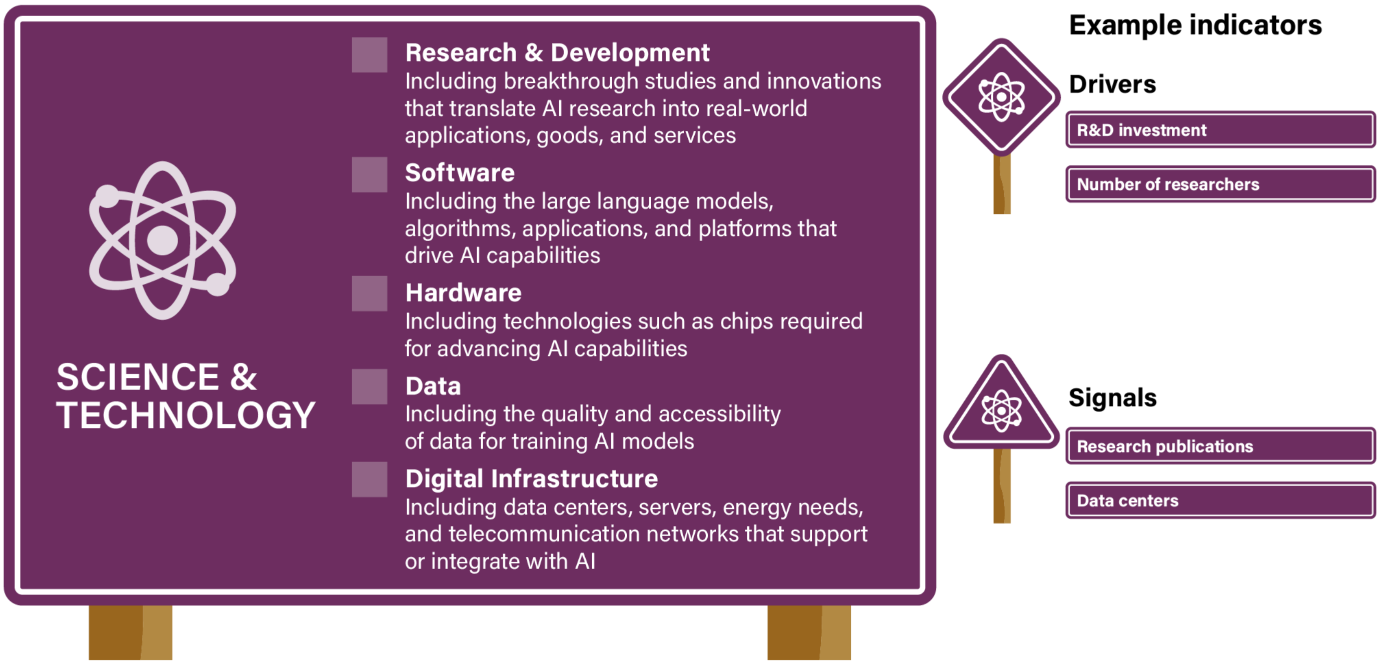
Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Science and Technology

The science and technology pillar includes the extent to which a nation pursues, generates, and applies knowledge to develop and deploy AI. This pillar consists of five subpillars: R&D, software, hardware, data, and digital infrastructure (see fig. 5).

Figure 5: The Science and Technology Pillar and Its Subpillars



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO−26−107624

Research & Development

R&D contributes to innovation and competitiveness. For example, research on computer science and engineering leads to breakthroughs in AI, including model development, improved performance of hardware that supports AI, and reduced energy use. In addition, research on governance and societal effects of AI supports innovations by helping to anticipate and mitigate risks, which can enhance AI trustworthiness. Drawing on knowledge gained from research, developers create real-world applications, goods, and services. Drivers or signals in the R&D subpillar include the following:

- ***Research outputs***, such as the number of abstract submissions to conferences, research publications, and patents, signal progress towards different stages of AI development. While final approval of papers submitted for journal publications or patent applications can take months, conferences allow researchers to present their work before publication. Hence, the number of abstract submissions to conferences signals a nation's early-stage R&D activities. These signals capture quantity of research outputs. The number of times a research publication or patent is cited is often used as a signal of quality.

- ***R&D investment (by public and private entities)*** and ***the number of researchers, data scientists, and software developers*** (i.e., workforce indicators) are financial and human resources that drive R&D. (See Economy and Human Capital pillars on pp. 39 and 26.)

Illustrative Example of Step 2: Research and Development (R&D) Subpillar

Analysts in our scenario research the pillars and subpillars and identify R&D as one of the subpillars that contributes to a nation's ability to influence global AI standards. Analysts' research shows that one way that R&D contributes to innovation and competitiveness is by producing AI standards grounded in the sciences and real-world experience, making them implementable, useful, and more likely to be adopted internationally.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews; Icons-Studio/stock.adobe.com (icon). | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Software

AI software is a product of R&D. Drivers or signals of the software subpillar include the following:

- ***Notable AI models*** are key building blocks of AI applications that signal progress toward developing AI systems. Model usage can signal deployment and can drive innovations in other sectors.
- **Investment and workforce indicators** are drivers of notable AI models, as these indicators demonstrate financial resources and human capital for R&D. (See Economy and Human Capital pillars on pp. 39 and 26.)

Hardware

Hardware, such as graphic processing units and other semiconductor chips, is necessary to perform the large number of mathematical operations needed to train AI models. Drivers or signals of the hardware subpillar include the following:

- ***Sales of semiconductor chips*** signal a nation's capacity to produce hardware necessary for AI development and deployment. (See also the Economy pillar for trade on p. 40 and trade policies on p. 38. Trade signals a nation's ability to produce an AI component, and trade policies could influence hardware production and sales.)
- ***Investment and firms' engagement in R&D*** could drive improvements in performance and efficiency of semiconductor chips

and help address concerns about energy use in large-scale AI deployment. (See also the Economy pillar for investment on p. 39.) Those improvements could also drive a decrease in the cost of semiconductor chips necessary to deploy AI, thereby enabling large-scale AI deployment.

Data

Data are key inputs into AI systems, and data availability, access, and quality affect the development of high-performance AI systems and the opportunities to deploy them widely. Drivers or signals of the data subpillar include the following:

- ***Data policies*** and a ***national data-sharing framework*** are two signals of data availability. Data availability and access provide opportunities to develop AI models. Open-data policies that give the public access to government data could enhance data availability and access for training AI models. A national data-sharing framework could also enhance data availability for AI training by ensuring data are findable by machine, accessible, and in a common data format. (See also the Governance pillar for responsible practices related to data privacy on pp. 32–33.)
- ***Existence of a government AI accountability framework*** could be a driver of data quality and representativeness, which could affect the performance of AI models.[23] Direct comparisons of data quality and representativeness between nations could be difficult even though data quality and representativeness are important factors to consider in assessing competitiveness. A government AI accountability framework could help organizations developing and deploying AI ensure that data used to train, test, and validate AI systems are of sufficient quality and appropriate for the intended purpose.
- ***Advancements in synthetic data research*** could be a driver of data representativeness and protection of data privacy. Generated to replace original data, synthetic data are artificially produced using computational methods to mirror the features of real data. Advancements in methods to create synthetic data provide opportunities to protect privacy while sharing data or to augment existing datasets to make them more representative of the population.

[23]Data representativeness refers to the extent to which a sample of data approximates the distribution of the characteristics being measured in the population from which it was drawn. In statistics, the term "population" refers to a collection of individuals, phenomena, or other observations for which inferences are to be made. Data representativeness affects the accuracy of AI models and the extent to which models are generalizable to a population.

Digital Infrastructure

The availability and performance of a nation's digital infrastructure, including supercomputers, data centers, and internet service, could signal AI competitiveness. Drivers or signals of the digital infrastructure subpillar include the following:

- ***Public-private partnerships*** could drive digital infrastructure, including supercomputing capacity, by leveraging resources to build such infrastructure.
- ***The number, performance, and capacity of supercomputers*** could signal a nation's capacity for cutting-edge research. Supercomputers use specialized hardware and software to achieve the high computing performance necessary for AI model development.
- ***Data centers*** signal the use of data for training AI models, and they enable nations to conduct large-scale AI experiments.
- ***Electric grid capacity*** could be another signal of the availability of complementary infrastructure to support AI development and at-scale deployment. As a nation's number of data centers increases to support AI development and deployment, the nation's energy demand is expected to increase. Efforts to ensure that electric-grid capacity meets increasing energy demand can drive competitiveness.
- ***Internet speed and access*** could also signal a nation's progress toward AI development and deployment in many ways. First, nations with faster internet connections can process real-time data more quickly. Plus, internet access enables a nation's population to use online AI tools, generating demand for their deployment. Also, internet users contribute data for AI training because some training datasets are developed by scraping the internet.

Table 4 shows examples of indicators to measure the subpillars in the Science and Technology pillar.

Table 4: Examples of Indicators to Measure the Subpillars in the Science and Technology Pillar

Science and Technology Indicators selected from other frameworks that analysts can use to measure science and technology capabilities and capacity related to AI competitiveness			
Research & Development			
• AI conference citations[d] • AI journal citations[d] • AI paper citations[e] • AI patent grants[d] • AI scientific publications (including papers, articles, and journal publications)[bcdeg] • Authors of significant machine learning systems by country[e] • Cited usage of top-performing graphics processing units (GPUs) and tensor processing units (TPUs) in AI papers[e]	• Contributions to foundational and applied research by citation count[e] • Contributions to foundational and applied research by publication count[e] • Ethical AI research[f] • Field-weighted citation impact[b] • Field-weighted download impact[b] • Filed AI patents by applicant[eg]	• Filed AI patents by inventor[eg] • Frontier technology readiness[a] • Granted AI patents by applicant[e] • Granted AI patents by inventor[e] • Innovation output[f] • Prominence of research institutions[g] • Number of developers contributing to AI projects on public code repositories[e] • R&D expenditure[acefg]	• R&D spending by software and computer services firms in top 2,500[b] • Research output[f] • Share of top 10 firms for semiconductor R&D spending by country[b] • Share of top 100 software and computer services firms for R&D spending by country[b] • Submissions to AI conferences[e] • Trademark applications[g]
Software			
• Academia-industry model production concentration[d] • AI projects on public code repositories[d] • Bookmarks of AI projects on public code repositories[d] • Commits on high-popularity open-source AI packages[e]	• Contributions to all top-performing models represented on public leaderboards[e] • Contributions to most downloaded models on public platforms[e]	• Contributions to top-performing pretrained models represented on public leaderboards[e] • Foundation model applications[d] • Foundation models[d]	• Notable machine learning models[d] • Open-access foundation models[d] • Policy for AI-driven cloud computing[f] • Significant machine learning systems[e]
Hardware			
• Aggregate system performance of supercomputers ranked in top 500[b] • Colocation of data centers[f]	• Computational capacity (petaflops) of large non-distributed super computers[e] • Exports of semiconductor manufacturing machines[e]	• Firms designing AI chips[b] • Imports of semiconductor manufacturing machines[e] • Share of Top 15 firms for semiconductor sales by country[b] • Supercomputers[cde]	• Supercomputers ranked in top 500[b] • Total integrated circuits imports[e] • Total integrated circuits exports[e]
Data			

• Availability of genetic data[b] • Availability of internet of things data[b] • Availability of mapping data[b] • Availability of procurement data[c] • Availability of productivity data[b]	• Available online content and data to train AI systems[f] • Contributions to most downloaded datasets on public platforms[e] • Data governance that supports safe and equitable generation and use of AI[c]	• Electronic health records systems[b] • Foundational model datasets[d] National data sharing framework[f] • Open data[c] • Open government data policies[f]	• Performance of national statistical systems[f] • Public availability of government datasets for AI training[e] Score on the Open Data Inventory[f] • Signatory of International Open Data Charter[f] • Statistical capacity[c]
Digital Infrastructure			
• 5G infrastructure[c] • Active mobile broadband subscriptions[f] • Average download speed[e] • Average fixed broadband download speed[f] • Average international bandwidth[f] • Broadband quality[c] • Compute capacity[d] • Cost of cheapest internet-enabled device[c] • Cost of internet access[a]	• Coverage by at least a 3G mobile network[f] • Distance to data center[f] • Fiber internet subscription[g] • Fixed broadband subscriptions[abg] • Fixed telephone lines[a] • Foundational IT infrastructure[c] • Gender gap in internet access[cf]	• Gender gap in mobile access[f] • Households with internet access[c] • Individuals using mobile payments[b] • Internet speed[d] • Internet users[aefg] • Mobile broadband subscriptions[fg] • Mobile cellular telephone subscriptions[acfg] • Mobile subscriptions per 100 persons[e]	• Number of data centers[f] • Population with access to electricity[ef] • Public sector's online services infrastructure[a] • Rural/urban gap in internet access[f] • Score on online services index[cf] • Secure internet servers[a] • Telecommunications infrastructure[c] • Wireless broadband subscriptions[a]

Source: GAO analysis of literature. | GAO-26-107624

Note: The indicators are from frameworks developed by other organizations and offer suggestions for analysts choosing drivers and signals. The superscripts for each indicator direct analysts to the relevant frameworks, which often include information about data sources. See app. III for further information and full citations.

[a]Gen-AI: Artificial Intelligence and the Future of Work

[b]Who is Winning the AI Race: China, the EU, or the United States?

[c]The Government AI Readiness Index 2024

[d]The Global AI Vibrancy Tool 2024

[e]The Global Artificial Intelligence Index 2024

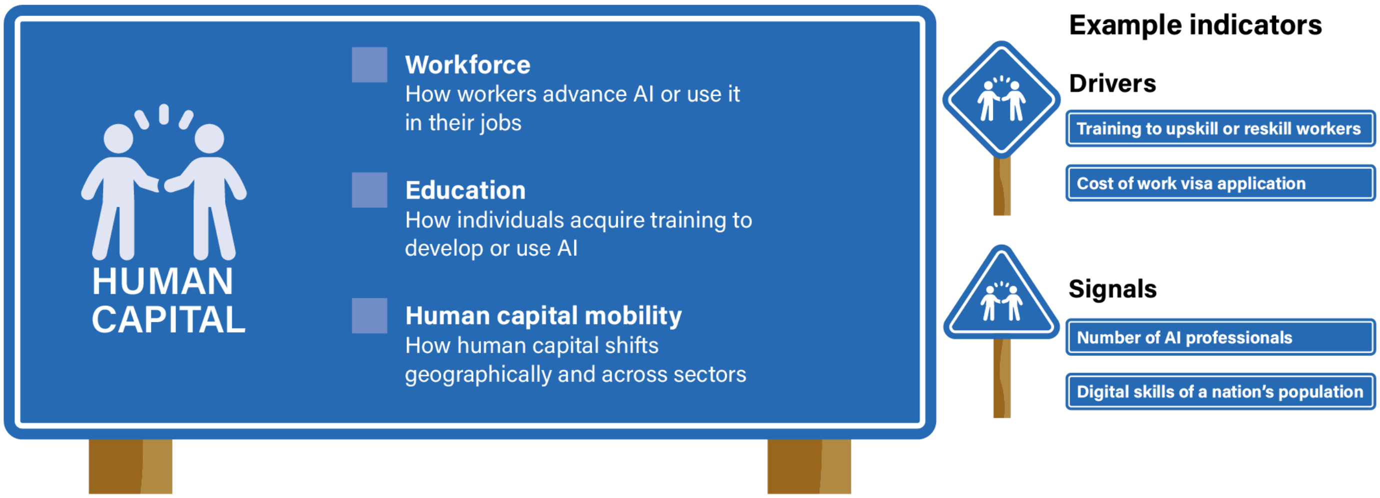
[f]Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence

[g]The Global Competitiveness Report 2019

Human Capital

The human capital pillar includes the skills, knowledge, and experiences a nation needs for a workforce to develop and deploy AI technology. This also includes workforce readiness, defined by the ability of workers to acquire in-demand skills, transition into new roles, and support the deployment of AI technologies across sectors. The human capital pillar consists of three subpillars: workforce, education, and human capital mobility (see fig. 6).

Figure 6: The Human Capital Pillar and Its Subpillars



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO-26-107624

Workforce

Competitiveness in AI development depends in part on the size and quality of a nation's workforce. Workforce readiness, which includes the ability of workers to develop skills to use AI tools or transition into emerging occupations, can affect how quickly organizations integrate AI technologies into their operations. A skilled workforce is critical to advancing AI technologies and integrating them into the economy. Signals of the workforce subpillar include the following:

- ***Number of AI and related professionals*** signals the size of current workforce. The workforce needed to develop or deploy AI includes researchers in computer science, hardware, AI ethics, and other relevant areas; software and hardware developers; data scientists; and testers and evaluators. Signals for education (e.g., number of Ph.D. graduates in AI related fields) are also indicative of future workforce size.
- ***Job vacancies in AI or related professions*** could signal workforce demand and any skill gaps in the workforce.
- ***Prominence of research institutions*** and ***researchers' h-index*** are signals of workforce quality. Research institutions that are ranked favorably or renowned for their computer science programs could be more likely to attract and train high-quality researchers and AI-related professionals. The h-index is a metric commonly used in academia to

measure the significance of an individual's cumulative research contributions.

- ***Digital skills of a nation's population*** could be a signal for a nation's readiness to use AI when it is deployed. Digital skills are necessary to use and understand AI. Studies have shown positive relationships between people's understanding of AI and their willingness to use AI tools. The workforce needed to deploy AI includes individuals who are willing and know how to use AI applications to optimize tasks.

Education

Education can equip individuals with the knowledge and skills to develop AI or to use AI in their work. Education and training programs, including those in partnerships with industry, also play a role in building a talent pipeline prepared to support AI development and deployment. Education at different levels prepares a nation's workforce in different ways. Drivers and signals of the education subpillar include the following:

- ***Number of graduates in science, technology, engineering, and mathematics (STEM)*** is a signal of the future workforce for AI development and deployment. K-12 education in STEM ensures a talent pipeline as it prepares students who aim to pursue higher education in computer science and other AI-related fields. College graduates in computer science and other related fields may pursue R&D in AI and related fields necessary for AI development. College graduates in STEM could signal workforce capacity for AI deployment, as STEM education increases students' digital skills and exposure to AI tools.[24]
- ***Prominence of research institutions*** could signal the quality of higher education.
- ***Availability of training to upskill or reskill workers*** is a driver of an AI-ready workforce and a potential strategy to address worker dislocation. This could include informal training, on-the-job training, and online education that is not part of a formal degree program. These opportunities could enhance AI competitiveness by preparing a nation's workforce for AI deployment through upskilling and reskilling.[25] In addition, effective reskilling could help organizations fill

[24]Digital skills refer to an individual's ability to use digital devices or technologies effectively.

[25]Upskilling enhances individuals' skills on how to use AI in their existing roles and be more productive. It could also help individuals advance along their career paths. Reskilling teaches new skillsets to individuals whose jobs could be displaced by AI, which could minimize job dislocation.

gaps in skills that are critical to achieving their strategic objectives. However, reskilling may not be a driver of competitiveness for nations that are using AI to address gaps caused by an aging or shrinking workforce.

- ***Availability of AI-related apprenticeship programs*** is a driver of AI-ready workforce. Such programs could contribute to a pipeline of AI professionals and offer another way to fill skill gaps.

Illustrative Example of Step 2: Education Subpillar

Analysts in our scenario review the framework structure and identify education as one of the subpillars that is important to a nation's ability to influence global AI standards. Nations could build a workforce capable of leading and influencing global AI standards processes if they integrate advanced technological skills into their educational systems and maintain partnerships between academia and industry.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews; Icons-Studio/stock.adobe.com (icon). | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Human Capital Mobility

Human capital mobility—the ability and willingness of individuals with specific skills, knowledge, and experience to move across geographic locations, industries, or organizations—could affect a nation's access to top talent and hence competitiveness. Drivers of the human capital mobility subpillar include the following:

- ***A nation's investment in AI*** and ***the prominence of its research institutions*** are two drivers of human capital mobility. Top AI talent could be more willing to move across geographic locations, industries, or organizations to pursue opportunities in a nation that invests more in AI or has a larger number of prominent research institutions than others.
- ***Cost of visa application for high-skilled tech workers*** could either drive or hinder the human capital mobility of AI experts and workers from other nations. Top talent may be less likely to move to a nation with high work visa application fees.

Table 5 shows examples of indicators to measure the subpillars in the Human Capital pillar.

Table 5: Examples of Indicators to Measure the Subpillars in the Human Capital Pillar

Human Capital

Indicators selected from other frameworks that analysts can use to measure human capital capabilities and capacity related to AI competitiveness

Workforce

- Active labor market policies[ag]
- AI hiring rate[d]
- AI researchers[be]
- AI study programs in English[d]
- AI talent concentration[df]
- AI-related PhDs[f]
- AI-related post-doctoral students[f]
- Answers related to AI questions on public websites[e]
- Cooperation in labor-employer relations[g]
- Cost to terminate redundant workers[g]
- Data scientists and engineers[e]
- Digital skills among active population[a]
- Diversity of workforce in AI[g]
- Education of AI researchers[b]
- Existing AI professionals[e]
- Female STEM graduates[ac]
- Flexibility of wage determination[ag]
- Gender diversity of IT graduates[e]
- Gender diversity of science graduates[e]
- Gender equality in AI talent concentration[de]
- Healthy life expectancy[g]
- H-Index rating[e]
- Hiring and firing practices[g]
- Information and communications technology graduates in tertiary education[f]
- Information and communications technology skills[c]
- IT graduates[e]
- Job postings requiring AI-related skills[df]
- Law or policy to enhance diversity in AI workforce[f]
- National retention rate of AI scientists[e]
- Number of data scientists, AI researchers, and engineers on employment platforms[e]
- Pay and productivity[ag]
- Population covered by social protection schemes[a]
- Public reliance on professional management[g]
- Questions related to AI on public websites[e]
- Ratio of wage and salaried female workers to male workers[g]
- Relative AI skill penetration (i.e., self-reported prevalence and intensity of AI skills in the workforce)[df]
- Share of current employees working as data scientists[f]
- Skillset of graduates[ag]
- STEM graduates[ace]
- STEM graduates in tertiary education[f]
- Top AI researchers[b]
- Workers in firms adopting AI[b]
- Workers in firms piloting AI[b]
- Workers' rights, by international labor standards[g]

Education

- Activity on public code repositories[c]
- AI courses in ethics for the general population[f]
- Coursera data science score[ef]
- Education programs including technical and ethical aspects of AI[f]
- Extent of staff training in AI[g]
- Gender breakdown of STEM graduates[f]
- Gender breakdown of STEM graduates expected to work as STEM professionals when they are 30[f]
- Government strategy to improve digital skills in public sector[f]
- Mean years of schooling[g]
- Primary, lower secondary, and secondary students with access to computer[f]
- Primary, lower secondary, and secondary students with access to internet[f]
- Public education expenditure[a]
- Public perception of critical thinking in teaching[g]
- Pupil-to-teacher ratio in primary education[g]
- Quality of engineering and technology higher education[c]
- Quality of vocational training[g]
- School life expectancy[g]
- Science literacy of 15-year-olds by gender[f]
- Score on Human Capital Index[a]
- Share of top 100 computer science universities by country[e]
- Skillset of graduates[a]
- Technical AI courses for general population[f]
- Tertiary education programs with 1+ module on ethics in AI[f]
- Tertiary education programs dedicated to AI (or related field)[f]
- Tertiary education programs with 1+ module in AI (or related field)[f]

Human Capital Mobility

• Cost of visas for high-skilled tech workers[e]	• Ease of hiring foreign labor[g]	• Internal labor market mobility[ag]	• Net migration flow of AI skills[d]

Source: GAO analysis of literature. | GAO-26-107624

Note: The indicators are from frameworks developed by other organizations and offer suggestions for analysts choosing drivers and signals. The superscripts for each indicator direct analysts to the relevant frameworks, which often include information about data sources. See app. III for further information and full citations.

[a]Gen-AI: Artificial Intelligence and the Future of Work

[b]Who is Winning the AI Race: China, the EU, or the United States?

[c]The Government AI Readiness Index 2024

[d]The Global AI Vibrancy Tool 2024

[e]The Global Artificial Intelligence Index 2024

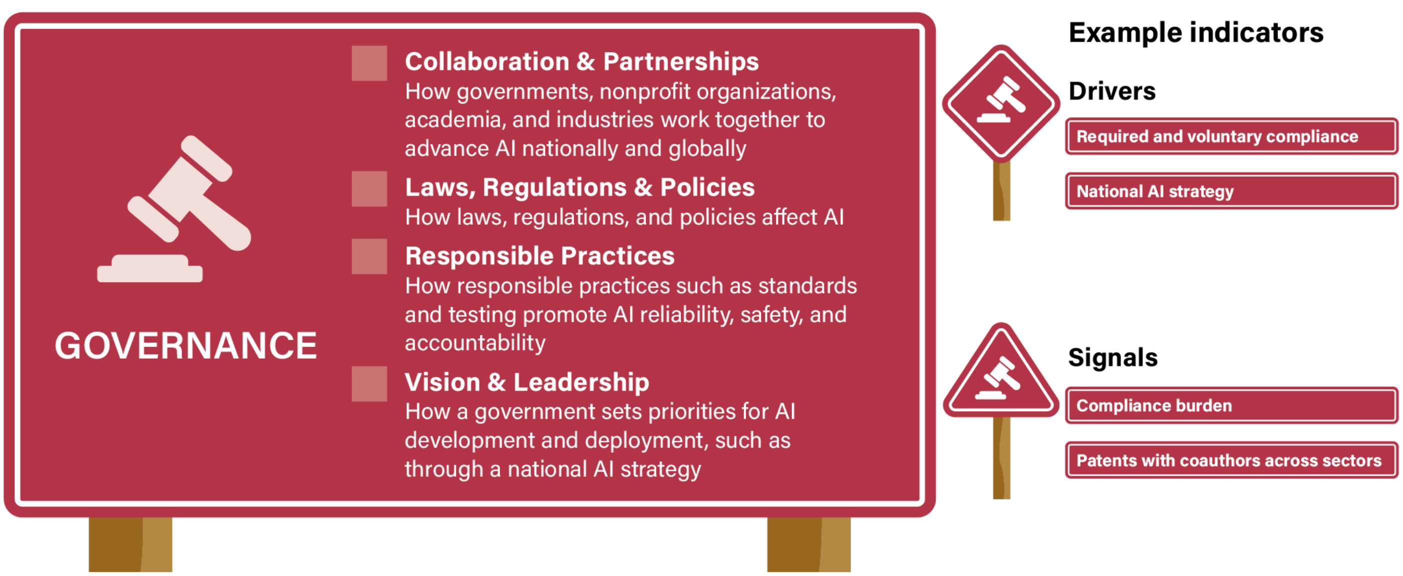
[f]Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence

[g]The Global Competitiveness Report 2019

Governance

The governance pillar includes how a nation's systems of rules, practices, and processes affect AI competitiveness. The governance pillar consists of four subpillars: collaboration and partnerships; laws, regulations, and policies; responsible practices; and vision and leadership (see fig. 7).

Figure 7: The Governance Pillar and Its Subpillars



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO−26−107624

Collaboration and Partnerships

Collaboration and partnerships can facilitate knowledge- and resource-sharing between stakeholders, and they can help ensure AI development leads to deployment. Scholars have argued that public-private partnerships enhance innovation in various industries.[26] AI competitiveness requires access to tangible resources (such as supercomputers) and intangible resources (such as intellectual property) that can be distributed across organizations, sectors, or nations. Drivers or signals of the collaboration and partnerships subpillar include the following.

- ***Research publications and patents with coauthors from more than one sector*** signal cross-sector collaboration. Collaboration between researchers from different sectors could facilitate or accelerate translation of knowledge gained from research into practical applications ready for use in public or private sectors.
- ***A nation's participation in international bodies that set AI policies or standards*** drives collaboration that could enhance competitiveness. Collaboration that fosters shared standards could increase firms' access to markets for AI products and services in collaborating nations. Similarly, collaboration on global AI policies could help firms by reducing the need to adapt AI products and services to different national policies, lowering compliance costs for exports to nations with compatible policies. Therefore, firms that implement those policies and standards may find it easier to operate across markets.

Illustrative Example of Step 2: Collaboration and Partnerships Subpillar

Analysts in our scenario review the framework structure and identify collaboration and partnerships as one of the subpillars that contributes to a nation's ability to influence global AI standards. Through collaborations and partnerships, nations can exchange information and champion their priorities for global AI standards with nations and organizations that share similar values.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews; Icons-Studio/stock.adobe.com (icon). | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Laws, Regulations, and Policies

Laws, regulations, and policies can hinder, encourage, or direct AI development and deployment. Uncertainties related to current or future policies could stifle innovation. These may include policies affecting workforce training, labor force participation, and the ability of workers and businesses to adapt to technological change. Clear regulations around AI,

[26]See Lucia Xiaoyan Liu, Stewart Clegg, and Julien Pollack, "The Effect of Public–Private Partnerships on Innovation in Infrastructure Delivery," *Project Management Journal*, vol. 55, no. 1 (2024): 31–49; and references cited therein.

data issues, intellectual property, and labor standards could enhance investors' confidence and drive an increase in investment. Signals of the laws, regulations, and policies subpillar include the following:

- ***Compliance burden***, which can be measured as costs or in surveys, is a signal of regulatory ease or barriers. While laws, regulations, or policies can protect privacy and address ethical concerns, excessive application of or overly prescriptive regulations could discourage innovation because of the potential compliance burden on firms.[27]
- ***Data protection regulations*** that make data easier or harder to collect or use are signals of regulatory barriers. Although data protection regulations can enhance responsible development and deployment of AI, some data protection regulations or policies could affect a nation's data availability for AI development and deployment. (See next section for data privacy laws that drive responsible practices.) Data protection regulations or policies that balance innovation and accountability could encourage development of AI tools that the public trust and use.
- ***Number of AI laws passed*** can be a signal of development and deployment and how a nation's government responds to those activities. Nations can pass AI laws to accelerate innovation, support deployment, or provide oversight.[28]

Responsible Practices

Those who use responsible practices when developing or deploying AI could enhance AI trustworthiness.[29] AI trustworthiness can influence deployment rates and hence national AI competitiveness. Responsible practices that promote AI reliability, safety, accountability, and transparency protect human rights such as the right to fair and equal

[27]For ways to measure compliance costs, see Richard Fullenbaum and Tyler Richards, "The Impact of Regulatory Growth on Operating Costs," *Mercatus Working Paper* (Arlington, VA: Mercatus Center at George Mason University, Aug. 2020), https://www.mercatus.org/research/working-papers/impact-regulatory-growth-operating-costs.

[28]Number of AI laws passed reflects a nation's legislative activities on AI, but it does not reflect whether laws passed achieve their intended purposes.

[29]According to NIST, trustworthy AI systems have the following characteristics: valid and reliable; safe, secure and resilient; accountable and transparent; explainable and interpretable; privacy-enhanced; and fair with harmful bias managed. See "3. AI Risks and Trustworthiness" in *Artificial Intelligence Risk Management Framework (AI RMF 1.0)*, NIST AI-100.1 (January, 2023).

treatment and the right to privacy. Drivers and signals of the responsible practices subpillar include the following:

- ***Required and voluntary compliance*** with laws, regulations, policies, and standards are signals of responsible practices. For example, standards for testing, evaluating, verifying, and validating AI models and systems can increase the trustworthiness of AI systems. These standards could also be the basis for developing further practices and standards that facilitate responsible use. This signal could be assessed using an AI accountability framework.[30]
- ***Data privacy laws*** that govern the collection and use of personal information could drive responsible practices. As more AI systems are developed and deployed, more people and organizations access large quantities of data, which could contribute to privacy risks. Another concern is the lack of understanding of how AI systems collect and use data to make decisions. Nations' privacy laws and an AI accountability framework could address some of those concerns.
- ***Public attitude toward AI*** could be a signal of responsible practices. AI development and deployment that incorporate responsible practices to ensure products and services align with a nation's values could improve public attitude toward AI. Public concern over AI trustworthiness could hinder use or sales of AI products and their deployment.

Vision and Leadership

Strong vision and leadership in setting national priorities and policies and aligning efforts to drive targeted outcomes could enhance a nation's AI competitiveness. A national AI strategy could present a vision for AI development and deployment and help coordinate resources, incentivize relevant industries to build complementary infrastructure, and include initiatives to prepare the workforce for changing demands. (For more on preparing a workforce to develop and use AI, see the Education subpillar in the Human Capital pillar on pp. 27–28.) An effective national strategy could accelerate AI development and deployment to maximize benefits while mitigating potential harms.

One signal of vision and leadership is ***the presence of a national AI strategy***. Such a strategy could drive other pillars if it describes actions that involve public investment in AI (Economy pillar), policies and standards (Governance pillar), or workforce training (Human Capital

[30]GAO, *Artificial Intelligence: An Accountability Framework for Federal Agencies and Other Entities*, GAO-21-519SP (Washington, D.C.: June 30, 2021).

pillar). However, the presence of a strategy does not provide any information about its effectiveness.[31]

Table 6 shows examples of indicators to measure the subpillars in the Governance pillar.

Table 6: Examples of Indicators to Measure the Subpillars in the Governance Pillar

Governance Indicators selected from other frameworks that analysts can use to measure governance related to AI competitiveness			
Collaboration & Partnerships			
• International co-inventions[g]	• Multistakeholder collaboration[g]	• Participation in International Organizational Standards (ISO) AI Committee[e]	• State of cluster development[g]
Laws, Regulations & Policies			
• Binding AI regulation or soft law[f] • Burden of government regulation[g] • Comprehensive framework for data management and publication[f] • Conflict of interest regulation[g] • Data protection and privacy laws[cf]	• Efficiency of legal framework in challenging regulations[g] • Efficiency of legal framework in settling disputes[g] • Freedom of Information Act[f] • Freedom of the press[g] • Government effectiveness (i.e., the quality of public services, civil service, and independence)[ac]	• Intellectual property protection laws[g] • Judicial independence[g] • Laws or policies on procurement of AI systems[f] • Laws or policies to integrate AI tools into the education system[f] • Laws to protect due process rights[f] • Legal framework's adaptability to digital business models[a] • Level of data protection regulation[e]	• Perception of incidences of corruption[g] • Protection of property rights[g] • Quality of land administration[g] • Regulatory barriers for available data to train and use AI systems[b] • Regulatory quality[c]
Responsible Practices			
• AI social media posts[d] • AI-related social media conversations net sentiment[d] • Commitment to sustainability[g] • Conference submissions on responsible AI topics[d] • Digital health policy[f] • Ethical principles in AI[c] • Framework on notice or takedown for violating AI policies[f]	• Law or policy for educators to teach AI ethics[f] • Law or policy on impact of AI on social media[f] • Law or policy on remedying harm caused by AI[f] • Law or policy to reduce digital gender gap[f] • Law or policy to reduce digital socioeconomic or geographical gap[f]	• Policy for addressing impact of AI on the environment[f] • Policy on use of AI for preservation of cultural heritage[f] • Policy on use of AI for preservation of Indigenous languages[f] • Population that thinks AI is harmful[e] • Presence of right to explanation[e] • Prioritization of sectors that would benefit from AI[f] • Public trust in AI[f]	• Score on the E-Participation Index (i.e., government use of online tools to engage citizens in policymaking)[fg] • Social capital (e.g., cohesion and engagement, family networks, and political participation)[g] • Social media share of voice on AI[d]

[31]GAO previously reported on the desirable characteristics of a national strategy. See GAO, *Cybersecurity: A Better Defined and Implemented National Strategy Is Needed to Address Persistent Challenges,* GAO-13-462T (Washington, D.C.: Mar. 7, 2013).

• Government accountability (i.e., the extent to which a country's citizens participate in selecting their government)[c]	• Participation in standardization of AI and digital technologies[f]	• Public trust in government websites and applications[f] • Score on cybersecurity index (Kaspersky or Global Cybersecurity Index)[cef]	• Strength of auditing and accounting standards[g] • Transparency in use of AI systems[f]
Vision & Leadership			
• Adoption of emerging technologies[c] • AI legislation passed[de] • AI mentions in legislative proceedings[de] • Dedicated AI strategy considers AI ethics[e] • Dedicated AI strategy on training or upskilling[e]	• Dedicated AI strategy received external consultation[e] • Dedicated AI Strategy signed by senior member of government[e] • Government adaptability (i.e., public perception of government stability, vision, and responsiveness to change)[g]	• Government has dedicated AI governmental body[e] • Government has dedicated AI minister[e] • Government has measurable AI targets[e] • Government responsiveness to change[c] • Government/ministries responsible for AI governance[f]	• National AI strategy[cdef] • Public Sector AI Skills Development[e] • Time scale of dedicated strategy[e] • Tracking of previous years' efforts on AI[e]

Source: GAO analysis of literature. | GAO-26-107624

Note: The indicators are from frameworks developed by other organizations and offer suggestions for analysts choosing drivers and signals. The superscripts for each indicator direct analysts to the relevant frameworks, which often include information about data sources. See app. III for further information and full citations.

[a]Gen-AI: Artificial Intelligence and the Future of Work

[b]Who is Winning the AI Race: China, the EU, or the United States?

[c]The Government AI Readiness Index 2024

[d]The Global AI Vibrancy Tool 2024

[e]The Global Artificial Intelligence Index 2024

[f]Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence

[g]The Global Competitiveness Report 2019

Economy

The economy pillar includes a nation's economic activities and policies that could influence or be affected by competitiveness in AI development and deployment. The economy pillar consists of three subpillars: business environment, investment and financing, and business activities (see fig. 8).

Figure 8: The Economy Pillar and Its Subpillars

Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO−26−107624

Business environment

The business environment—including market size, competition, taxes, and market regulations—refers to the conditions that influence the way firms operate and grow. This subpillar shapes the costs, risks, and incentives that encourage or discourage certain business decisions, such as investing in R&D, pursuing revenue opportunities, entering or exiting the market, and projecting returns on investment. A stable, predictable business environment could encourage firms to invest in growing their businesses (referred to as firm-level investment) and engage in long-term planning for AI. Drivers or signals of the business environment subpillar include the following:

- ***Revenue from AI-related goods and services*** signals a nation's market size, which could shape firms' decisions to innovate or invest to improve their goods and services.[32] A larger market size for AI goods and services provides more revenue opportunities for firms and could encourage innovation and investment. In contrast, smaller market size could discourage firms from developing or deploying AI goods or services because of limited revenue opportunities and reduced expectations for returns on investment. High revenue from sales of AI-related goods and services in domestic and foreign

[32]Market size refers to both total number of potential customers and demand for goods or services. AI goods and services include automated systems, data analysis tools, or smart technologies.

markets signals large market size and potential for innovation and investment.

- ***Geographic clustering of industries***, also known as agglomeration, is another determinant of innovation and, therefore, a driver of underlying competitiveness.[33] Agglomeration creates an environment that fosters innovation through sharing of common inputs (e.g., patent attorneys, commercial labs for product testing, and trade organizations), matching skills with local labor markets (which enables specialized workers to readily find new positions without having to relocate), and knowledge exchange.
- ***Tax policies*** that affect the cost of business activities and the returns on investment that firms expect can drive or hinder AI development and deployment. For example, R&D credits, reduced corporate tax rates for tech companies, or tax deductions for AI-related expenses can incentivize firm-level investment in AI by allowing the firm to keep or reinvest a large share of its profits. However, tax incentives with uncertain durations may not have the intended effect because the uncertain duration can affect firms' cash flow. Moreover, tax incentives are a form of tax expenditures that have low visibility. Hence, having good information on whether U.S. national goals related to AI are achieved via the tax expenditures is difficult but important.[34]
- ***Trade policies***, including trade agreements, could drive AI competitiveness by affecting how easily firms can access raw materials for various AI components.[35] Trade policies could enhance competitiveness by allowing firms access to lower-cost raw materials, partially assembled components, or testing. For example, designing, fabricating, and testing semiconductor chips involve many complex steps, and firms in some nations could specialize in a particular step. Therefore, as a semiconductor chip is produced, it can move across

[33]Agglomeration can arise organically as firms locate but can also be encouraged by regulations and incentives. Some studies showed that AI deployment tends to be higher in AI agglomeration than other areas. See Mark Muro and Shriya Methkupally. *Mapping the AI Economy: Which Regions are Ready for the Next Technological Leap?* (Washington, D.C.: Brookings Metro, 2025).

[34]We previously observed that policymakers should assess tax expenditures based on whether the expenditure achieves its purpose, whether it is equitable, its consequences for the federal budget, and how it can be evaluated, among other things. See GAO, *Tax Expenditures: Background and Evaluation Criteria and Questions*, GAO-13-167SP (Washington, D.C.: November 29, 2012).

[35]Raw materials for AI components include cobalt, nickel, tungsten, and rare earth elements that are mined and processed mostly by a small number of nations.

borders multiple times before it gets incorporated into an AI system. Trade policies that ease firms’ access to partially assembled components or to testing services of semiconductor chips that are mostly provided by certain nations could enhance competitiveness. Trade agreements that increase access to foreign markets for AI-enabled or AI-related goods and services could also enhance competitiveness.

Illustrative Example of Step 2: Business Environment Subpillar

Analysts in our scenario review the framework structure and identify business environment as one of the subpillars that contributes to a nation’s ability to influence global AI standards. Market size and competition can encourage or discourage certain business decisions such as making R&D investments and pursuing revenue opportunities. Nations with large domestic markets or whose companies dominate certain AI sectors may see their standards become global standards.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews; Icons-Studio/stock.adobe.com (icon). | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Investment and financing

Investment and financing affect the availability and accessibility of funding and influence the scale and pace of AI activities. Drivers or signals of the investment and financing subpillar include the following:

- ***Public and private R&D investment*** is a driver because it funds research to advance knowledge in AI-related fields including software, hardware, and ethics. This investment could also be a driver and a signal in other pillars and subpillars. For example, public R&D investment could be a driver that enables the training of students in relevant fields, developing a pipeline of AI-related professionals. (See Science and Technology and Human Capital pillars on pp. 21 and 27–28.) Market size and tax policies could influence private R&D investment, which signals the effect of those two drivers on innovation.
- ***Capital markets***, and other highly developed financial markets, are drivers as they play a key role in efficiently channeling funds from savers to promising investment opportunities, including investments in infrastructure to support emerging technologies like AI. For example, venture capital and private equity provide financial resources to transform ideas from research to commercialization. More specifically, venture capital tends to provide investment to support many early-stage AI startups. On the other hand, private equity tends to provide investments to companies with technologies ready for commercialization.

Business activities

Business activities—including entrepreneurship, firm entry and exit from the market, and trade—provide indicators of competitiveness in AI development.[36] The scale and focus of business activities demonstrate the extent to which AI is developed in a nation and deployed in its economy. Drivers or signals of the business activities subpillar include the following.

- ***Entrepreneurship*** signals the pool of promising AI technologies for commercialization. One indicator of entrepreneurship is the number of early-stage AI startups. Startups can either create their own AI models or build on existing models to develop practical AI products and services that can be marketed and integrated into business or government operations. Once commercialized, startups' products contribute to a nation's domestic and international market share of AI products. Customers who use startups' AI products could provide feedback to inform product improvements and create a positive feedback loop in a nation's competitiveness.
- ***AI incubators and accelerators*** are business structures that could drive a nation's competitiveness through their support of entrepreneurs.[37] Evidence suggests that incubators and accelerators increase survival rates of AI startups by geographically clustering startups and providing business advice, mentorship and financing. The prevalence of AI incubators and accelerators exemplifies a few aspects of all the subpillars within the economy pillar. For example, incubators and accelerators facilitate geographic clustering by locating entrepreneurs near to one another, sometimes even in the same workplace.[38] (See geographic clustering in the Business Environment subpillar on p. 37.) Additionally, the financing that incubators and accelerators provide signal the extent to which venture capitalists and private equity firms are willing to support startups. (See capital markets in the Investment and Financing subpillar on p. 39.)

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[36]As an example of how the pillars of this framework intersect with one another, workforce availability (in the Human Capital pillar)—specifically labor shortages in AI—could increase international competition for entrepreneurs.

[37]Incubators support startups with business creation and development. Compared to incubators, accelerators select startups that are more developed for participation than incubators.

[38]Alejandro Amezcua, Tiago Ratinho, Lawrence A. Plummer, and Parvathi Jayamohan, "Organizational sponsorship and the economics of place: How regional urbanization and localization shape incubator outcomes," *Journal of Business Venturing*, vol. 35, no. 4 (2020), https://doi.org/10.1016/j.jbusvent.2019.105967.

- ***Firm entry and exit***, or business dynamism, signal innovation and efficient resource allocation. Firm entry refers to new businesses starting up, and firm exit refers to existing businesses closing or leaving markets. High firm-entry rates bring fresh ideas and technologies that push existing firms to improve, while high firm-exit rates allow resources to flow from less successful AI approaches to the more successful ones. Nations with a business environment that eases firm entry and exit could build strong AI sectors that can compete globally because high firm entry and exit rates signal the sectors' ability to adapt faster to technological changes.
- ***Trade***, or industry-level import and export patterns, could be a signal of a nation's most competitive products and sectors in AI-related goods and services. For example, if a nation exports a lot of AI goods and services, this signals that their domestic firms have achieved the scale, innovation capacity, and operational efficiency necessary to compete internationally. Conversely, if a nation imports a specific AI good or service, this can signal an aspect of AI in which a nation is least competitive.

Table 7 shows examples of indicators to measure the subpillars in the Economy pillar.

Table 7: Examples of Indicators to Measure the Subpillars in the Economy Pillar

Economy Indicators selected from other frameworks that analysts can use to measure economic capabilities and capacity related to AI competitiveness			
Business Environment			
• Attitudes towards entrepreneurial risk[g] • Average days taken for patent office to provide approval[e] • Banks' regulatory capital ratio[g] • Border clearance efficiency[g] • Budget transparency[g] • Buyer sophistication[g] • Competition in services[g] • Complexity of tariffs[g] • Cost of starting a business[g] • Credit gap[g]	• Debt dynamics (i.e., debt-to-gross domestic product ratio)[g] • Distortive effect of taxes and subsidies on competition[g] • Domestic credit to private sector[ag] • Extent of market dominance[g] • Employer willingness to delegate authority[g] • Free movement of people and capital[a] • Government promotion of investment in emerging technologies[c]	• Gross domestic product (GDP)[g] • Gross domestic product for computer programming and related activities[f] • High tech exports as a share of trade[f] • Inflation[g] • Insolvency recovery rate[g] • Insolvency regulatory framework[g] • Insurance premium[g] • Labor tax rate (i.e., taxes and mandatory contributions on labor paid by businesses)[g] • Mean tariff rate[a]	• Non-AI unicorns (i.e., private non-AI companies valued at over $1 billion)[c] • Non-performing loans[g] • Non-tariff barriers[ag] • Number of AI companies acquired[e] • Postal reliability index[a] • Soundness of banks[g] • Time spent dealing with government regulations[c] • Time to start a business[g] • Trade tariffs[g] • Use of mobile phone for online transactions[a] • Value of AI companies acquired[e]

Investment & Financing			
• AI firms with $1M+ in funding[b] • AI merger and acquisition investment[d] • AI minority stake investment[d] • AI private investment[d] • AI public offering investment[d] • Average funding of AI company[e] • Average startup funding[e]	• Company expenditure on AI R&D[f] • Company expenditure on AI services as share of intermediate consumption[f] • Company investment in emerging technologies[c] • Computer software spending[c] • Dedicated spending on AI[e] • Dedicated spending on public AI compute infrastructure[e]	• Financing of small- and medium-sized enterprises[g] • Funding of AI startups[e] • Government has publicly dedicated money to AI[e] • Government investments in public AI compute infrastructure[e] • Government investments in the training of national AI foundation model[e]	• Newly funded AI companies[d] • Spend period of dedicated governmental AI budgets[e] • Total funding of AI companies[e] • Venture capital availability[cg] • Venture capital and private equity deals[b] • Venture capital and private equity funding[b]
Business Activities			
• Acquisitions of AI firms[b] • AI companies[e] • AI companies on country's stock exchange[e] • AI market capitalization[g] • AI startups[be]	• AI unicorns (companies valued at over $1 billion)[ce] • Businesses using AI[e] • Employee perceptions of companies embracing disruptive ideas[g]	• Exports of semiconductor devices and parts[d] • Growth of innovative companies[g] • Imports of AI goods and services[g] • Listed AI companies (in public stock exchanges)[e]	• Shareholder governance[g] • Value of trade in information and communication technology services[c] • Value of trade in information and communication technology goods[c]

Source: GAO analysis of literature. | GAO-26-107624

Note: The indicators are from frameworks developed by other organizations and offer suggestions for analysts choosing drivers and signals. The superscripts for each indicator direct analysts to the relevant frameworks, which often include information about data sources. See app. III for further information and full citations.

[a]Gen-AI: Artificial Intelligence and the Future of Work

[b]Who is Winning the AI Race: China, the EU, or the United States?

[c]The Government AI Readiness Index 2024

[d]The Global AI Vibrancy Tool 2024

[e]The Global Artificial Intelligence Index 2024

[f]Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence

[g]The Global Competitiveness Report 2019

Step 3: Conduct Data Analysis

After selecting targeted outcomes and identifying relevant drivers and signals, analysts should conduct a data analysis to understand the factors that affect the targeted outcomes of AI competitiveness. We lay out the sequence of decisions and actions in conducting a data analysis. An iterative data analysis helps ensure decisions are appropriate and fit together. Conducting a data analysis requires analysts to select data sources and data measures that capture drivers and signals, analyze the data, and evaluate the results.

Select Data Sources and Data Measures

Analysts should select appropriate data sources and data measures.[39] This requires identifying available data sources, examining them for data limitations, and determining which data measures enable comparison across nations, scale, and time frames.

Data Sources

Data sources provide data on drivers and signals. To select data sources, analysts should determine which data sources are available and appropriate for analysts' intended uses and for each selected driver and signal. Data sources can include official statistics, academic databases, composite indices, and private-sector datasets. Analysts can use sources with quantitative data, qualitative data, or both. Quantitative data can be measured, counted, and statistically analyzed, while qualitative data captures qualities, characteristics, or experiences that cannot be easily measured with numbers.

Analysts should examine individual data sources to identify data limitations that can affect the analysis. Data limitations include the following:

- **Data availability.** Data availability concerns arise when data are incomplete or absent. One expert shared that finding complete data for government spending on AI can be difficult, noting that the data for a single nation can be spread across several documents or that data sources may not separate spending on AI into its own category. Data imputation allows analysts to fill in missing or incomplete data with calculated approximations using proven methods.
- **Data reliability.** Data reliability concerns arise when data are of poor quality, lack accuracy, or are not representative of the underlying phenomenon. Some experts expressed concerns about data representativeness, noting that some data sources related to AI competitiveness overrepresent the U.S. and it could be difficult to remove U.S. bias when evaluating AI competitiveness across nations. For example, data from professional networking sites or online training platforms could overrepresent U.S. or English-speaking populations, biasing cross-national comparisons. Data reliability

[39]This section draws on information from the seven frameworks described in app. III, the GAO guide for assessing data reliability, and the Organisation for Economic Co-operation and Development (OECD) handbook on constructing composite indicators. GAO, *Assessing Data Reliability* (Supersedes GAO-09-680G), GAO-20-283G (Washington, D.C.: Dec. 16, 2019). OECD, *Handbook on Constructing Composite Indicators: Methodology and User Guide* (Paris, France: OECD Publishing, 2008).

assessment allows analysts to address data reliability concerns, such as accuracy, relevance, and consistency.

- **Data comparability.** Data comparability concerns arise when combining data from different sources, time periods, sectors, or nations that use different measurement scales, definitions, or methods. For example, data sources could define key terms such as “AI talent” or “responsible AI” differently or use different methods to measure the same concept. Data transformation allows analysts to address data comparability concerns, such as skewness, extreme values, and scale adjustments.

Data availability challenges can require analysts to use proxy indicators. A proxy indicator uses available data to estimate a concept when direct measurement is limited, unavailable, or lacks comparability across nations. For example, analysts could use patent counts as a proxy for innovation activity or AI job postings as a proxy for the demand for AI skills. While proxies provide useful approximations, they capture related but not identical concepts. For example, job postings can be an unreliable indicator for actual demand because some companies list job postings with no immediate intention to hire someone. Whenever possible, analysts should check the accuracy of proxy indicators using methods such as correlation and sensitivity analyses.

Data reliability challenges can require analysts to assess data quality, such as whether data reflect and measure the underlying phenomenon or contain significant errors. Data with errors may be unreliable if the errors are substantial enough to cause a reasonable person who is aware of the errors to doubt a finding, conclusion, or recommendation supported by the data. For example, survey data aggregated from multiple entities may be unreliable because the entities use different data collection practices or sampling methods, creating data errors that may result in unreliable information.

Data comparability challenges can arise when combining data from multiple sources. Combining datasets can include merging data that supported different research questions, used different methods, or covered different time periods. For example, nations can use different methods and definitions to collect workforce data, which requires analysts to reconcile differences across nations. However, nations that consistently use the same methods and definitions allow analysts to compare data across time within that nation.

Illustrative Example of Step 3: Select Data Sources

Within the collaboration and partnerships subpillar, analysts in our scenario identify *participation in standards-developing organizations* as a potential driver of nations' abilities to influence standards. To find potential data sources, analysts review and evaluate membership data from standards-developing organizations, checking for concerns related to data availability, reliability, or comparability. For example, analysts evaluate membership data from the International Organization for Standards (ISO). They learn that membership status does not reliably indicate the ability to influence standards because the ISO has three membership levels and only full members vote on and influence proposed ISO standards. Therefore, analysts modify their driver to *be level of participation in standards-developing organizations* and continue to review other data sources.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Data Measures

Data measures allow analysts to make comparisons across nations, scale, and time frames. To select data measures, analysts should determine which of them are available and appropriate for each selected driver and signal. Different data measures reveal different aspects of AI competitiveness and serve different analytical purposes. Analysts should choose data measures that align with their intended uses of the framework. Table 4 presents three types of data measures.

Table 8: Types of Data Measures

Data Measure	Description and Use	Examples	Limitations
Absolute	Expresses the raw count, totals, or amounts in direct units. Conveys the magnitude of activity or resource without context of change or comparison.	Total AI investment, total number of AI companies, total computing power	Does not account for differences in entity size
Proportional (Relative)	Adjusts raw values by a relevant denominator, such as population or a whole, to express ratios, percentages, or rates. Enables fair comparisons across entities by accounting for differences in size.	AI researchers per capita, R&D spending as percentage of gross domestic product (GDP), patents per inventor	Can obscure total capacity or magnitude
Comparative (Relative)	Compares performance against benchmarks, peers, or baselines. Shows how entities perform compared to others or to a reference point.	AI research quality compared to global average citation rates, national performance compared to global average, year-over-year changes in the number of data centers	Depends on the choice of benchmark or comparison group

Source: GAO analysis of literature. | GAO-26-107624

Different types of data measures provide distinct insights into AI competitiveness. For example, an absolute measure of venture capital and private equity funding provides insight into the total available capital, while a proportional measure, such as funding per worker, provides insight into available capital per person. Using multiple data measures together can provide complementary information and a more complete picture of AI competitiveness. However, combining measures requires careful consideration because different measures capture similar information and can overrepresent some aspects of AI competitiveness or underrepresent others, perhaps failing to fully address the selected outcomes or intended uses.

Illustrative Example of Step 3: Select Data Measures

Analysts in our scenario identify *research and development (R&D) spending* as a potential driver of nations' abilities to influence global AI standards because it supports the work that leads to breakthroughs and innovations. In considering which data measure to use for R&D spending, analysts recognize the importance of proportional R&D spending but also consider including a total measure of R&D spending. Including both measures allows analysts to compare nations regardless of economic size. When combined with other indicators, such as AI patents or research publications on AI, analysts may be able to identify nations that achieve disproportionate innovation performance despite lower absolute R&D spending.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Analysts can also consider how data measures capture time. Data can capture information at a single point in time, providing a current snapshot, or across multiple time periods, revealing trends and patterns of change. For example, current AI deployment rates offer insight into current adoption levels, while deployment trends over 5 years could reveal growth trajectories and help distinguish meaningful patterns from temporary fluctuations. The choice between data from a specific point in time and data from across time periods depends on whether the aim is to assess the current state or understand dynamics over time.

Analyze Data and Evaluate Results

After selecting data sources and measures, analysts should analyze the data and evaluate the results to ensure findings are robust and meaningful.[40] Analyzing data can be technically demanding. Data analysis without care or clear intentions can lead to data manipulation, misinterpretation, or misleading messages.

Analysts may not need every step in this analysis approach, as a step may be appropriate for some intended uses and not for others. Analysts should document their analytical decisions and the limitations of their conclusions. Analyzing data can require addressing data limitations, using analytical techniques to examine and combine indicators, and using

[40]The analysis approach described in this report is an overview and draws on practices and technical guidelines discussed in the OECD handbook on constructing composite indicators. Analysts should consult specialized resources on composite indices for more detailed technical guidance.

uncertainty and sensitivity analyses to assess how decisions affect conclusions.

Analyze Data

Analysts should analyze the data to understand the factors that affect the targeted outcomes of AI competitiveness. This involves addressing data limitations, examining relationships among indicators, and using analytical techniques to enable meaningful insights.

Data limitations can cause analysts to adjust their decisions, including their intended uses for the framework, the selection of drivers or signals, or the methodology for the data analysis. For example, analysts ranking nations may have to exclude nations that lack consistent usable data, or analysts tracking trends over time may need to adjust time frames to periods with available data. Analysts should review data to identify data limitations that could distort their analysis, such as extreme values or inconsistencies.

Data imputation and transformation. Analysts could overcome data limitations using analytical techniques, such as data imputation and transformation. Data imputation allows analysts to address missing data by calculating values using a range of statistical methods. Analysts can exclude incomplete cases, replace missing values according to averages or relationships with other indicators, or use methods that generate multiple plausible values to reflect uncertainty. Data transformation allows analysts to address data limitations, such as uneven distribution and extreme values. Analysts may also need to transform data after analysis as part of data normalization (discussed below). Analysts should choose imputation and transformation methods according to the extent and pattern of missing data as well as analysts' intended uses of the framework.

Illustrative Example of Step 3: Missing Data

Analysts in our scenario find that several organizations offer certifications in AI standards, resulting in scattered and incomplete data sources. However, analysts identify a potential data source that could be a proxy indicator for *number of professionals certified in AI standards*. The source measures national effort to train public-sector employees in responsible AI. Analysts evaluate the data for availability, reliability, and comparability. They notice the source is missing data for most nations in one continent. Analysts may need to impute the missing data or consider another indicator if they decide to rank nations in that continent.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Multivariate analysis. Analysts should use multivariate analysis to examine relationships among indicators and to understand whether they capture distinct or overlapping aspects of AI competitiveness. Multivariate analysis allows analysts to assess how multiple indicators are related and how they affect the results and conclusions of a data analysis. Multivariate analysis also allows analysts to assess whether the assessment includes all relevant aspects of AI competitiveness without overrepresenting some or omitting others. Analysts can use insights from multivariate analysis to inform other analytical decisions, to understand which indicators vary together, and to better capture independent aspects of AI competitiveness.

Data normalization. Analysts can use data normalization to make data with different units and scales comparable by converting the data to a common scale. Common normalization methods include rescaling values to show how far they are from the average, rescaling values to a range between zero and one, and measuring how far values are from a reference number. Different normalization methods can produce different results, and some methods are more affected by extreme values than others. Analysts can choose normalization methods according to several considerations, such as whether to assess nations' performance in absolute terms or relative to each other or whether to limit the influence of extreme values.

Weighting and aggregation methods. Analysts should select weighting and aggregation methods that enable meaningful insights. Weighting assigns levels of importance to drivers and signals using equal weights or according to their relevance to AI competitiveness outcomes, data reliability, or other analytical considerations. Aggregation methods combine the weighted drivers and signals into a single composite score or set of scores, commonly referred to as an index. Some aggregation methods allow high performance on one indicator to balance out low performance on another, while other methods require meeting minimum levels across all indicators. For example, one method could produce a high overall score for a nation with strong R&D investment but few AI researchers, while another method would require strong performance on both indicators to receive a high overall score.

Illustrative Example of Step 3: Determine Weights

Analysts in our scenario test different weights to reflect the importance of selected drivers and signals, including equal weightings. For example, when analysts examine drivers and signals of nations' abilities to influence global AI standards, such as *policies for open-source models* and *number of AI patents*, analysts could weight all indicators equally or assign different weights according to individual indicator's relevance to AI competitiveness. After testing different weighting methods and analyzing the results, analysts implement the approach that allows for meaningful insights.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26-107624

Note: See part III for the full scenario that illustrates each step of the framework.

Evaluate Results

After analyzing data, analysts should evaluate the results, such as composite scores or rankings, to ensure they are robust and meaningful.

Analysts can use uncertainty and sensitivity analyses to assess how different analytical decisions affect the results and to identify which decisions have the greatest effect on results.

- **Uncertainty analysis.** Uncertainty analysis measures how much variation in the final results is due to different decisions, such as which indicators to include, how to normalize data, which weights to use, and which aggregation method to use. By testing multiple approaches, analysts can identify whether conclusions depend on specific decisions or remain stable across reasonable alternatives.
- **Sensitivity analysis.** Sensitivity analysis identifies which methodology decisions contribute most to variation in results by changing and analyzing decisions, revealing where small changes could substantially alter conclusions. Using sensitivity analysis, analysts can determine which decisions have the greatest effect on results, such as including or excluding specific indicators, changing the normalization method, adjusting weights, or using a different aggregation method.

Analysts should ensure results are transparent and traceable to underlying data. This involves disaggregating, or breaking down, composite scores or rankings to show which indicators drive performance. Breaking down results allows analysts to examine individual indicators and enables them to reveal what underlies the findings. For example, if two nations receive similar overall scores, breaking down those scores could reveal that one nation's performance is driven primarily by R&D investment and digital infrastructure while the other's is driven by education and governance. When possible, analysts should focus on broad trends and significant performance gaps rather than small numerical differences that can reflect data limitations or the margin of error.

Analysts should assess whether results align with other evidence and expectations. This includes comparing results to other published assessments, checking whether patterns make sense, and verifying that rankings reflect expert understanding. If results differ from expected patterns, analysts should investigate whether this reflects new insights or problems with the analysis.

Analysts should document their analytical decisions and the limitations of their conclusions. Documenting decisions increases transparency about how professional judgment may have influenced results and helps identify whether analytical decisions introduced bias or uncertainty that could lead to data manipulation, misinterpretation, or misleading messages.

Step 4: Develop Policy Options and Final Product

After selecting targeted outcomes, identifying relevant drivers and signals, and conducting a data analysis, analysts should develop policy options and a final product. Analysts should use the results from the data analysis and other relevant research to develop policy options.[41] Analysts should then combine these results and policy options with contextual information into a final product to improve policymakers' understanding of U.S. AI competitiveness. Analysts should communicate results clearly and document analytical decisions and their limitations to support informed decision-making. Analysts should also consider policymakers' needs and tailor the final product's format and level of detail accordingly.

Develop Policy Options

Analysts should use results from the data analysis and other relevant research to develop policy options that could address areas of low performance, enhance areas of high performance, or highlight other areas for action to progress toward the targeted outcomes.[42] Policy options are alternatives or different approaches that policymakers could implement to make progress toward targeted outcomes or mitigate undesired outcomes of AI competitiveness. Developing policy options involves creating a list of potential options, analyzing their trade-offs, and presenting options.

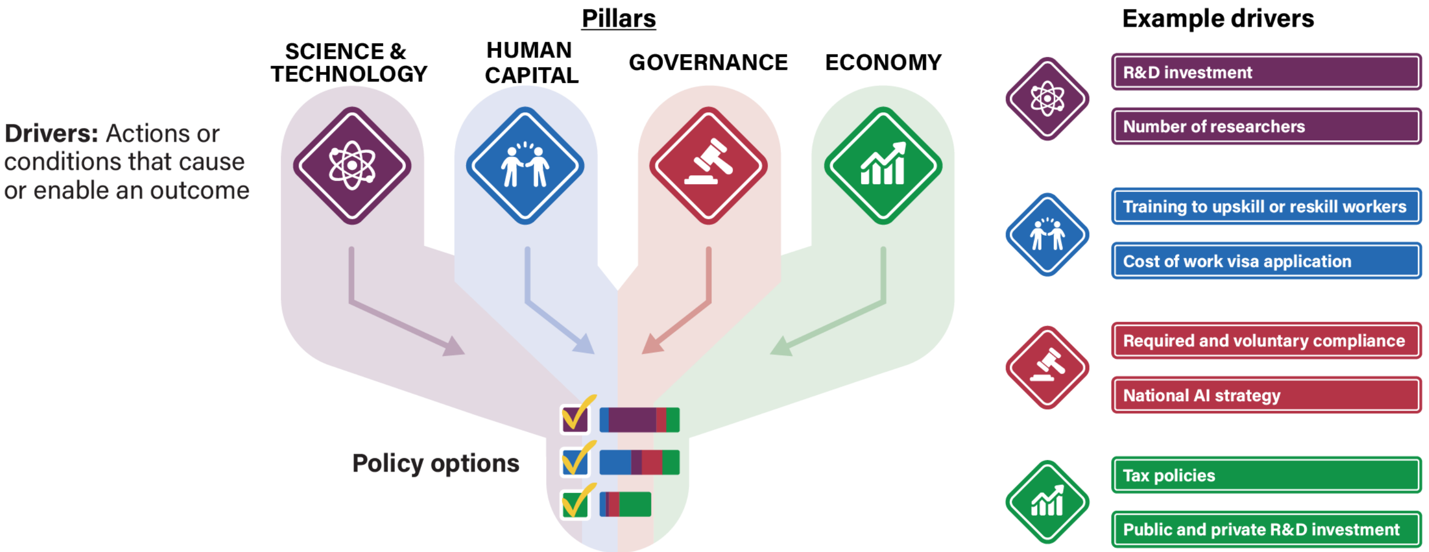
Analysts should create a list of policy options using results from the data analysis and other relevant research. To help develop policy options, the framework separates indicators into drivers and signals to help identify actions or conditions that enhance competitiveness. In step 2, analysts identified specific drivers that could enable progress toward the targeted outcomes selected in step 1. In this step, analysts should use results of the data analysis about those drivers to develop policy options (see fig. 9). The list of options should be relevant to the analysts' targeted AI

[41] Policy options are for policymakers to consider and take action on at their discretion. Analysts should strive to list policy options supported by analysis. However, the list may not be exhaustive, and policymakers may choose to consider other policy options not listed by analysts.

[42] This section draws on information from the GAO guide for designing technology assessments. GAO, *Technology Assessment Design Handbook*, GAO-21-347G (Washington D.C.: Feb. 18, 2021).

competitiveness outcomes and intended uses of the framework. The results of the data analysis can provide insights into areas of high and low performance using individual drivers and signals or composite scores. Analysts can supplement these insights with relevant information on effective policy approaches and expert perspectives on feasibility and implementation.

Figure 9: Using Information About Drivers to Develop Policy Options



Source: GAO (analysis and graphic elements); Icons-Studio/stock.adobe.com (icons). | GAO-26-107624

After listing policy options, analysts should evaluate them using considerations such as magnitude of impact, resource requirements, ease of implementation, and degree of uncertainty to help policymakers understand trade-offs of the policy options. By examining these considerations, analysts can demonstrate that different options may be more effective for addressing specific drivers or signals, helping policymakers select approaches aligned with their goals.

Develop a Final Product

Analysts should develop a final product to improve policymakers' understanding of U.S. AI competitiveness. The final product combines results from the data analysis, other relevant research, policy options, and contextual information in a format tailored to policymakers' needs.[43] The final product should communicate findings clearly and transparently, including stating assumptions and limitations, to support informed decision-making about AI competitiveness. Compiling a final product involves combining analysis with contextual information, selecting an appropriate format, and documenting analytical decisions and their limitations.

Analysts should combine results from the data analysis and other relevant information with policy options and contextual information to provide a broader understanding of U.S. AI competitiveness. Analysts can enhance the value of their assessments by including narrative explanations of observations or unique national circumstances, such as differences in regulatory approaches and talent availability. Additional contextual information that analysts can provide includes relevant literature, expert perspectives, and other analyses. The additional information can help avoid oversimplifying the results of the analysis and help policymakers interpret results appropriately.

Analysts should present policy options and describe both opportunities and considerations to help policymakers understand how each option could enhance targeted outcomes or mitigate undesired outcomes. Analysts should clearly state assumptions made, limitations and challenges for each option, and the level of uncertainty about the possible effects of a policy option.

Analysts should present the results in a final product, which could be a written report, a dashboard, an oral presentation, or another format. Analysts should write simply and clearly about technical subjects, obtaining feedback from colleagues without technical expertise to improve readability for policymakers with nontechnical expertise. Analysts can use tables to present detailed numerical results and charts to highlight trends or comparisons. These visual elements can help policymakers quickly identify patterns and compare performance across results from the data analysis.

[43]This section draws on information from the seven frameworks described in app. III, the GAO guide for designing technology assessments, and the OECD handbook on constructing composite indicators.

Illustrative Example of Step 4: Develop a Final Product

Analysts decide to format their final product as a report. In addition to presenting total scores and rankings, analysts include how the drivers can inform policy options to expand advantages in areas of strength or to improve performance in areas of weakness. For example, analysts include a policy option to improve public-private partnerships and a comparative case study of the nations that lead in the ability to influence global AI standards.

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews. | GAO-26107624

Note: See part III for the full scenario that illustrates each step of the framework.

Analysts should document their analytical decisions and the limitations of their data analysis and conclusions to ensure transparency and to support the credibility of their final product. Documentation should describe decisions, such as indicator selection, normalization, weights, and aggregation, as well as explain how the decisions may affect the conclusions that analysts can draw from the results. Documentation should also describe how analysts addressed data limitations such as missing values, reliability concerns, or lack of comparability. Analysts should prepare this documentation throughout the process to ensure coherence and to support readers who want to understand or verify the analytical decisions.

Part III: A Scenario to Illustrate How to Use the Framework

The framework supports several intended uses and asks analysts to specify goals for competitiveness in AI to meet policymakers' needs. We provide a scenario to illustrate one way analysts can use the AI competitiveness framework. The scenario focuses on ranking nations' abilities to influence global AI standards. The scenario follows the steps of the framework as outlined in the report: (1) focus the assessment on targeted outcomes of AI competitiveness, (2) identify drivers and signals to measure or evaluate, (3) conduct data analysis, and (4) develop policy options and final product.[44]

Step 1: Focus the Assessment

Policymakers in our scenario expressed interest in understanding how their nation compares to other nations in facilitating export of AI technologies. To address this using the framework, analysts choose to focus their assessment on nations' abilities to **influence global AI standards** and use the assessment results to **rank nations**. Global AI standards include technical standards, such as privacy protocols and interoperability requirements, and governance considerations, such as ethical guidelines and risk management guidance. Nations that lead AI development and deployment may gain the ability to influence global AI standards. These standards could facilitate exports of AI technologies by promoting the ability of AI systems from different nations to work together.

Step 2: Identify Drivers and Signals

Analysts can conduct research, such as literature reviews or expert consultations, to determine which subpillars within the four pillars are most important to the targeted outcomes. Then analysts can identify drivers and signals for the selected subpillars.

In our scenario, analysts conduct a literature review and expert meetings. This research leads analysts to identify the following topics as important to influencing global AI standards: technical expertise, collaboration, market influence, workforce familiar with standards, and technical barriers to trade. Analysts use the research results to select relevant subpillars and identify drivers and signals (see table 9).

[44]We present this hypothetical scenario to illustrate the assessment process with plausible situations and decisions. This scenario is intended to provide guidance and may not reflect actual data limitations for available data sources.

Table 9: Drivers and Signals Chosen to Rank Nations' Abilities to Influence Global AI Standards

Research and development (R&D). R&D—including breakthrough studies and innovations that translate AI research into real-world applications, goods, and services—contributes to innovation and competitiveness.

Relevance to scenario: AI standards are more likely to be adopted internationally if they are implementable and useful, which means they are grounded in the sciences that support AI as well as in the real-world experiences of those who develop or deploy AI.

Drivers	Signals
• R&D spending[a]	• Number of publications about AI research[a] • Number of AI patents[a]

Explanation of sample indicators: *R&D spending* is a financial resource that could be a driver of technology breakthroughs that inform standards. *Number of publications about AI research* and *number of AI patents* could be signals of the volume of technical insights and real-world experience that can ground standards in science and practice. Additional indicators could include *number of submissions to AI conferences* or *number of top AI researchers*.

Software. Software—including the large language models, algorithms, applications, and platforms that drive AI capabilities—is a product of research and development.

Relevance to scenario: Nations with leading AI software, like foundation models and machine learning systems, could influence global AI standards as other nations use their platforms and tools and adopt their technical approaches and development practices.

Drivers	Signals
• Policies for open-source models[a]	• Number of notable machine learning models • Ratio of notable open-source models to notable proprietary models

Explanation of sample indicators: *Policies for open-source models* could be a driver of the visibility into system characteristics and technical approaches that can inform standards. *Number of notable machine learning models* and *ratio of notable open-source models to notable proprietary models* could be signals of leadership in AI that enables a nation's models to gain international adoption and their technical approaches to become standard practice. Additional indicators could include *open data policies* or *contributions on high-popularity open-source AI projects*.

Education. Education can equip individuals with the knowledge and skills to develop AI or to use AI in their work.

Relevance to scenario: Nations that integrate standards development into their educational systems and maintain partnerships between academia and industry could develop the expertise and relationships needed to lead and influence global AI standards processes.

Drivers	Signals
• Number of universities offering courses on AI standards or governance	• Academic publications on AI standards or governance • Number of professionals certified in AI standards[a]

Explanation of sample indicators: *Number of universities offering courses on AI standards or governance* could be a driver of offering education programs that build standards awareness and technical expertise. *Academic publications on AI standards or governance* and *number of professionals with certification in AI standards* could be signals of a workforce with expertise to contribute to standards development and implementation. Additional indicators could include *skillset of graduates* or *number of science, technology, engineering, and mathematics (STEM) graduates*.

Collaboration and partnerships. Collaboration and partnerships—including how governments, nonprofit organizations, academia, and industries work together to advance AI nationally and globally—facilitate knowledge- and resource-sharing between stakeholders, and they could help ensure AI development leads to deployment.

Relevance to scenario: Nations could exchange information and champion their priorities for global AI standards with nations and organizations that share similar values.

Drivers	Signals
• Participation in standards-developing organizations[a] • Collaborations between universities, governments, and industry participants	• Number of AI inventions with participants across nations or sectors

Explanation of sample indicators: *Participation in standards-developing organizations* and *collaborations between universities, governments, and industry participants* could be drivers of building the network of technical expertise needed to develop and promote standards. *Number of inventions with participants across nations or sectors* could be a signal of the ease of operating across multiple markets with different regulatory environments. Additional indicators could include *AI innovation clusters* or *private-public partnerships*.	
Laws, regulations, and policies. Laws, regulations, and policies—including how laws, regulations, and policies affect AI—can hinder, encourage, or direct AI development and deployment. **Relevance to scenario:** Firms may find it easier to operate across global markets if nations develop regulations based on shared standards, even when actual regulations differ among nations.	
Drivers	**Signals**
• Intellectual property protection laws[a]	• Number of AI-related laws or regulations enacted
Explanation of sample indicators: *Intellectual property protection laws* could be a driver of sustained AI innovations that inform standards development by incentivizing firms to invest in R&D through ownership rights. *Number of AI-related laws or regulations enacted* could be a signal of a nation's adoption of AI governance, which may influence other nations' AI governance decisions. Additional indicators could include *adaptability to digital business models*, *regulatory quality*, or *level of data protection regulation*.	

Business environment. The business environment—including market size, competition, taxes, and market regulations—can encourage or discourage certain business decisions such as making R&D investments, pursuing revenue opportunities, entering or exiting the market, and projecting returns on investment. **Relevance to scenario:** Nations with large domestic markets or whose companies dominate certain AI sectors could see their standards become global standards.	
Drivers	**Signals**
• Market dominance	• Share of top 100 software and computer services firms by revenue
Explanation of sample indicators: *Market dominance* could be a driver based on the ability of leading AI companies to influence industry standards. *Share of top 100 software and computer services firms by revenue* could be a signal of the number of firms in a nation that likely have the expertise and resources to influence global AI standards. Additional indicators could include *average days taken for patent office to provide approval or high-tech exports as a share of trade*.	

Source: GAO analysis of information from literature, survey and meetings of experts, and interviews; GAO (graphic elements); Icons-Studio/ stock.adobe.com (icons). | GAO-26-107624

Note: Drivers and signals in this table are not a complete list but a sample to illustrate how analysts can use the framework's pillar and subpillar structure to organize drivers and signals.

[a]Indicates drivers and signals used in our scenario discussion to illustrate the range of decisions analysts may need to make when using the framework.

Step 3: Conduct Data Analysis

Analysts will need to select data and data measures to analyze and evaluate for their intended uses of the framework. However, analysts may encounter data limitations that require them to adjust their decisions, including their intended uses for the framework, the selection of drivers or signals, or the methodology for the data analysis.

Select Data Sources and Data Measures

Analysts should examine and select appropriate data and data measures for each driver and signal. In our scenario, analysts use the framework to rank nations by their ability to influence global AI standards. The analysts evaluate and select data sources and data measures for each driver and signal chosen in step 2. We use a sample of drivers and signals from table 9 to illustrate some data limitations analysts can encounter and how analysts may address them.

Example driver: Participation in standards-developing organizations. Analysts in our scenario find that multiple standards-developing organizations publish membership information. Analysts review and evaluate membership data from these organizations, checking for concerns related to data availability, reliability, or comparability. For example, analysts evaluate membership data from the International Organization for Standards (ISO) and learn that membership status does not reliably indicate the ability to influence standards. To be represented in the ISO, a nation must be recognized by the United Nations and have a national standards organization, which can become a member of the ISO. However, the ISO has three levels of membership, and only full members can vote on and influence proposed ISO standards. Correspondent members can attend ISO meetings as observers, and subscriber members can stay informed about ISO's activities but cannot participate in them. Therefore, analysts modify their driver to be *level of participation in standards-developing organizations* and continue to review other data sources. Analysts examine how nations' participation has shifted in the last 10 years and whether the shifts in participation in standards-developing organizations over time provide useful information.

Example driver: R&D spending. Analysts in our scenario find that data sources for *R&D spending* vary in scope. Analysts are unable to find a data source showing AI-specific R&D spending and select a reliable source measuring broad R&D spending as a percentage of gross domestic product (GDP). The data are complete but skewed with extreme values, leaving most values clustered at the low end. Analysts select a data transformation method to resolve the issue. In considering which data measure to use for R&D spending, analysts recognize the importance of proportional R&D spending but also consider including a total measure of R&D spending. Including both measures allows analysts to compare nations regardless of their economic size. When combined with other indicators, such as *number of AI patents* or *number of research publications about AI*, analysts may be able to identify nations that achieve disproportionate innovation performance despite lower absolute R&D spending.

Example signal: number of professionals certified in AI standards. Analysts in our scenario find that several organizations offer certifications in AI standards, resulting in scattered and incomplete data sources for this signal. However, analysts identify a potential data source that could be a proxy indicator for this signal. The source measures national effort to train public-sector employees in responsible AI. Analysts evaluate data availability, reliability, and comparability and find that the source is missing data for most nations in one continent. Analysts may need to impute the missing data or consider another signal if they decide to rank nations in that continent.

Analyze Data and Evaluate Results

Analysts should analyze the selected data and data measures and evaluate the results. We use analytical techniques to organize and illustrate the decisions analysts can make during this step.

Data imputation and transformation. Analysts in our scenario review all selected data to address data limitations, examine relationships among indicators, and use analytical techniques to enable meaningful insights. Analysts identify some drivers and signals that have missing data. Analysts consider whether to exclude incomplete cases, replace missing values with averages, or use methods that generate multiple plausible values to reflect uncertainty. Further, analysts check the data for values that vary widely between nations or are difficult to compare. For example, some nations may be granted thousands of patents in a given year while others are granted hundreds, or some nations may spend billions on R&D while others spend millions. Analysts consider how to transform the different scales so they can compare nations and retain insight about high and low performers.

Multivariate analysis. Analysts evaluate the relationships between the drivers and signals and consider how to address data that are highly correlated or seem to capture the same underlying phenomenon. For example, the *number of publications about AI research* and *R&D spending* may measure overlapping aspects of research capacity and could distort nations’ rankings if both are included without adjustment.

Data normalization. Analysts normalize the drivers and signals, converting them to a common scale. They review a range of data normalization methods, including rescaling values to show how far they are from the average, rescaling values to a range between zero and one, and measuring how far values are from a reference number. The different methods can produce different results, and some methods are more affected by extreme values than others. They select the normalization method that fits their data and their intended use of ranking nations.

Weighting methods. Analysts in our scenario continue reviewing the data for the drivers and signals, this time checking for those that provide greater insight into the ability to influence global AI standards than others. Analysts consider methods for determining weights to reflect the relative importance of selected drivers and signals, including equal weightings. For example, when analysts examine drivers and signals of nations' abilities to influence global AI standards, such as *policies for open-source models* and *number of AI patents*, analysts could weight all indicators equally or assign different weights according to individual indicator's relevance to AI competitiveness. Analysts then test different weighting methodologies and analyze the results, implementing the approach that allows for meaningful insights.

Aggregation methods. In addition to considering how to weight drivers and signals, analysts consider how to aggregate the drivers and signals because different aggregation methods produce different results. For example, analysts examine one aggregation method that allows high performance in one driver, such as *intellectual property protection laws*, to compensate for low performance in another driver, such as *policies for open-source models*. Analysts also examine a method that produces a lower score for that same nation when analysts treat *both intellectual property protection laws* and *policies for open-source models* as essential for influencing global standards. Analysts test the different aggregation methods to understand their effects on results and select the method that best aligns with their intended use of the assessment, resulting in composite scores for each nation.

Uncertainty and sensitivity analyses. Analysts then evaluate the results from their data analysis using analytical techniques, such as an uncertainty analysis and a sensitivity analysis. Using uncertainty analysis, analysts measure variations due to different decisions, such as whether rankings remain stable when analysts include or exclude specific drivers or signals, when analysts use different normalization methods, or when analysts apply different weights to drivers and signals. Analysts also conduct a sensitivity analysis to identify which decisions have the greatest effect on their conclusions. For example, the analysts could find that changing the aggregation method substantially affects rankings. The information from these analyses helps analysts support their conclusions.

Finally, analysts in our scenario use the composite scores of the drivers and signals to rank nations. For the top-ranking nations, analysts break down composite scores to understand what drives performance. For example, analysts examine nations with similar overall scores to determine how each nation's performance in individual drivers and signals affects scores. By examining the ranking results, analysts can verify whether results align with experts' understanding of nations' abilities to influence global AI standards.

Step 4: Develop Policy Options and Final Product

Analysts should use results from the data analysis and other relevant research to develop policy options. Analysts should then develop a final product that combines results from the data analysis, other relevant research, policy options, and contextual information in a format tailored to policymakers' needs.

Analysts in our scenario review the composite scores and rankings, noting patterns and key observations. Analysts use this information to develop policy options. For example, analysts develop a policy option that focuses on a new public-private partnership. The policy option includes initiatives to provide resources to small- and medium-sized firms and nonprofit organizations to address the nation's poor performance in drivers of the collaboration and partnerships subpillar. When the analysts present the policy options, they describe both opportunities and challenges for each option to help policymakers understand different approaches for improving their nation's ability to influence global AI standards.

The analysts in our scenario develop a final product: a written report that combines results from the data analysis and other relevant research with policy options and contextual information to provide a comprehensive understanding of nations' abilities to influence global AI standards. For example, analysts include narrative explanations that highlight drivers and signals where nations outperform or underperform their peers. Analysts also include a comparative case study of the leading nations. Analysts also use tables to show detailed scores across drivers and signals and charts to compare overall performance across nations. Analysts document their methodology, describing decisions about indicator selection, normalization, weights, and aggregation. Analysts also document how they addressed the data limitations they found.

Appendix I: Objectives, Scope, and Methodology

Objectives

This report addresses the three objectives outlined below:

What outcomes reflect a country's competitiveness in artificial intelligence, and what factors drive these outcomes?

What are the key components of a framework for assessing international competitiveness in artificial intelligence?

What measurements and methodologies are effective for supporting such a framework?

Scope

We developed a framework to provide a broad assessment of competitiveness in the AI field rather than measuring changes in specific organizations' software or hardware. For this report, the U.S. is competitive in AI if it is performing as well as or better than other nations on a chosen indicator, which can include measures for technology or the economy.

The framework is appropriate for evaluating U.S. capabilities and capacity and assessing U.S. competitiveness in AI development and deployment. By capabilities, we refer to the range of tasks performed by AI, which can span many different sectors and industrial applications, and the quality of performance within a nation (e.g., quality of AI output, how well AI performs tasks, or how well AI performs compared to benchmarks). By capacity, we refer to a nation's resources and environment (e.g., human capital, infrastructure, economic environment, and governance) to develop and deploy AI capabilities. Although we developed this competitiveness framework specifically for AI, certain aspects of the framework can be adapted to other emerging technologies.

Methodology

To address the three objectives of this report, we conducted a literature search; used a modified Delphi methodology that included a survey that yielded 57 responses and four meetings that included a total of 24 experts; and interviewed a variety of subject matter experts, including federal officials, academic researchers, and representatives of industry organizations, private companies, and nongovernmental organizations.

We conducted our work from June 2024 to May 2026 in accordance with all sections of GAO's Quality Assurance Framework that are relevant to our objectives. The framework requires that we plan and perform the engagement to obtain sufficient and appropriate evidence to meet our stated objectives and to discuss any limitations to our work. We believe that the information and data obtained, and the analysis conducted, provide a reasonable basis for any findings and conclusions in this product.

Literature Search

For all objectives, we reviewed relevant literature identified by agency officials, experts, GAO staff, and our literature search. A GAO librarian conducted a literature search to find articles regarding AI definitions, appropriate development and deployment frameworks, and data and measurements to evaluate AI capabilities and capacity to assess AI competitiveness. The librarian searched multiple databases, including EBSCO, Gartner, ProQuest Dialog, and PolicyFile. We narrowed our search to articles published from 2014 through 2024.

Results from these searches included scholarly or peer-reviewed material; government reports; and publications from associations, nonprofit organizations, or think tanks. Using our professional judgment, we selected articles relevant to our objectives for further review.

Interviews

We conducted interviews with entities and individuals with knowledge and experience relevant to assessing AI competitiveness. We identified experts and organizations to interview based on criteria including subject matter expertise, literature references, and interview referrals. We interviewed officials from the Department of Commerce, Department of Defense, Department of Energy, Department of Labor, National Science Foundation, the Office of Science and Technology Policy, and one international governmental entity, as well as experts from the academic, private, and nonprofit sectors. Because the sample of subject matter experts is small, the results of our interviews are illustrative and represent important perspectives but are not generalizable to the broader population of subject matter experts.

Modified Delphi Method

We used a modified Delphi method, a multi-phased methodology, to identify areas of broad agreement among a group of experts. Specifically, we used the methodology to complement information gathered from the literature and interviews to help us create and validate the AI competitiveness framework. Our modified Delphi methodology was designed to fill information gaps from interviews and the literature review.

Phase 1: Survey

The first phase of the Delphi methodology was a survey that included open-ended and closed-ended questions to solicit experts' views on competitiveness in AI development and deployment. The open-ended questions asked experts about potential outcomes of AI competitiveness and deployment. The closed-ended questions asked experts to rate the importance of factors that can influence competitiveness in AI development and deployment. We identified the factors from literature.

We identified over 200 experts from relevant publications, AI conferences, GAO staff and interviewees, and web searches to fill identified gaps. Of those, 57 responded to the survey, and we analyzed their responses.

Phase 2: Expert Meetings

The results of the survey informed the second phase of the modified Delphi method. We convened a series of virtual expert meetings to inform our development of a framework for assessing AI competitiveness and the factors that influence it. A total of 24 experts participated. We identified these individuals by sector (federal, academia, industry, and nonprofits) and by their subject matter expertise, which covered areas significant to an AI competitiveness framework. (See app. II for a list of experts and their affiliations.)

We vetted the experts for potential conflicts of interest—any current financial or other interest that might impair objectivity. We determined all 24 experts to be free of reported conflicts of interest with no inappropriate biases. The comments of these experts generally represented their individual views and not the organizations with which they were affiliated. Their comments are not generalizable to the views of others in the field.

We held four moderated sessions about the framework’s pillars: (1) science and technology, (2) human capital, (3) governance, and (4) economy. We shared the results of our analysis of the Delphi survey with the experts and asked them to validate our findings about the key factors that influence AI development and deployment competitiveness and the outcomes of such competitiveness. The meetings were transcribed to ensure that we accurately captured the experts’ statements. We reviewed the transcripts to characterize the experts’ responses and to inform our understanding of the second and third objectives. Consistent with our quality assurance framework, we provided the 24 experts an opportunity to review a draft of the report and incorporated comments as appropriate.

Appendix II: Expert Participation

We convened four expert meetings to inform our work on the AI competitiveness framework; the meetings were held virtually on June 11, 16, and 18, 2025. The 24 experts who participated in these meetings are listed below. Many of these experts gave us additional assistance throughout our work, including eight, who reviewed our draft report for accuracy and provided technical comments.

Experts

Katie Antypas, Director of Advanced Cyberinfrastructure, National Science Foundation

Cynthia Breazeal, Dean for Digital Learning, Massachusetts Institute of Technology

Eric Breckenfield, Director of Technology Policy, NVIDIA

Flavio Calvino, Senior Economist, Organisation for Economic Co-operation and Development

Daniel Castro, President, Information Technology and Innovation Foundation

Christophe Combemale, Assistant Professor, Carnegie Mellon University

Benjamin Della Rocca, Analyst, Anthropic

Emin Dinlersoz, Principal Economist, U.S. Census Bureau

Pablo Fuentes Nettel, Principal Consultant, Oxford Insights

Avi Goldfarb, Professor, University of Toronto

Claudia Goldin, Professor, Harvard University

Lynne Graves, Technical Advisor – Defense Information Systems Agency, U.S. Department of Defense

Mary Gray, Senior Principal Researcher, Microsoft

Hannaneh Hajishirzi, Senior Director of AI, AI2; and Professor, University of Washington

Mike “Rabbi” Harasimowicz, Director for Artificial Intelligence Innovations, Lockheed Martin
Merve Hickok, President and Policy Director, Center for AI & Digital Policy
Stephanie Ifayemi, Senior Managing Director, Partnership on AI
Florence Jaumotte, Research Department Division Chief, International Monetary Fund
Brett Jefferson, Data Scientist, Pacific Northwest Laboratory
Cameron Kerry, Distinguished Visiting Fellow, Brookings Institution
Tifani O’Brien, Vice President and Director of Artificial Intelligence and Machine Learning Accelerator, Leidos
Matthias Oschinski, Senior Fellow, Georgetown University – Center for Security and Emerging Technology
Shaolei Ren, Associate Professor, University of California –Riverside
Elham Tabassi, Director of Artificial Intelligence and Emerging Technology, Brookings Institution

Appendix III: Examples of Frameworks and Indicators for Assessing National AI Capabilities and Capacity

Multiple organizations have developed frameworks (also known as indices) for assessing national AI capabilities and capacity or global competitiveness, each focusing on different aspects (Table 10). These frameworks provide insights into different dimensions of AI capabilities and capacity and vary in their methodological approaches, data sources, and assessment criteria. Some emphasize research metrics and human capital activity, while others focus on commercial applications or government AI strategies. In addition to these frameworks, some other organizations developed frameworks to assess specific attributes of AI.[1]

Table 10: Examples of Frameworks for Assessing National AI Capabilities and Capacity or Global Competitiveness

Creator	Name of index or report	Primary purpose
International Monetary Fund	Gen-AI: Artificial Intelligence and the Future of Work[a]	Assesses AI preparedness of 174 nations using a set of indicators that describes the nations' digital infrastructure, human capital and labor market policies, innovation and economic integration, and regulation and ethics.
Information Technology and Innovation Foundation	Who Is Winning the AI Race: China, the E.U. or the United States?[b]	Compares the relative standing of China, the European Union, and the U.S. in AI development. Examines the progress they have made in AI relative to each other in recent years.
Oxford Insights	The Government AI Readiness Index 2024[c]	Addresses how a given government can assess how ready it is to implement AI in the delivery of public services to its citizens.
Stanford Institute for Human-Centered AI	The Global AI Vibrancy Tool 2024[d]	Provides an annual comprehensive global ranking of 36 nations, along with detailed metric-specific comparisons.
Tortoise Media	The Global Artificial Intelligence Index 2024[e]	Measures nations' capacity to generate and sustain AI solutions, now and in the future.
United Nations Educational, Scientific and Cultural Organization (UNESCO)	Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence[f]	Helps nations understand where they stand on readiness to implement AI ethically and responsibly for all their citizens, highlighting what institutional and regulatory changes are needed.
World Economic Forum	The Global Competitiveness Report 2019[g]	Provides a yardstick for policymakers to assess their progress against the full set of factors that determine productivity.

Source: GAO analysis of literature. | GAO-26-107624

[a]Mauro Cazzaniga, Florence Jaumotte, Longji Li, Giovanni Melina, August J. Panton, Carlo Pizzinello, Emma Rockall, and Marina M. Tavares, *Gen-AI: Artificial Intelligence and the Future of Work* (Washington, D.C: International Monetary Fund, 2024), https://doi.org/10.5089/9798400262548.006.

[b]Daniel Castro and Michael McLaughlin, *Who is Winning The AI Race: China, the EU, or the United States? 2021 Update* (Washington, D.C.: Information Technology and Innovation Foundation, 2021), https://www2.datainnovation.org/2021-china-eu-us-ai.pdf.

[1]Examples of indices that assess specific attributes of AI include Rachel Adams, Fola Adeleke, Ana Florido, Larissa Galdino de Magalhães Santos, Nicolás Grossman, Leah Junck, and Kelly Stone. *Global Index on Responsible AI 2024 (1st Edition)*. (South Africa: Global Center on AI Governance, 2024), and Center for AI and Digital Policy. *Artificial Intelligence and Democratic Values 2025: A Comprehensive Review of AI Policies and Practices Worldwide* (Washington, DC: 2025).

[c]Pablo Fuentes Nettel, Emma Hankins, Richard Stirling, Giulia Cirri, Gonzalo Grau, Sulamaan Rahim, and Eddie Crampton, The *Government AI Readiness Index 2024* (United Kingdom: Oxford Insights, 2024), https://oxfordinsights.com/wp-content/uploads/2024/12/2024-Government-AI-Readiness-Index-2.pdf.

[d]Loredana Fattorini, Nestor,Maslej, Ray Perrault, Vanessa Parli, John Etchemendydy, Yoav Shooham, and Katrina Ligett, *The Global AI Vibrancy Tool 2024* (Stanford, CA: Stanford University, 2024), https://hai.stanford.edu/assets/files/global_ai_vibrancy_tool_paper_november2024.pdf.

[e] Serena Cesaro and Joe White, *The Global Artificial Intelligence Index 2024* (London, England: Tortoise Media, 2024), https://www.tortoisemedia.com/2024/09/18/the-global-artificial-intelligence-index-2024.

[f]United Nations Educational, Scientific and Cultural Organization (UNESCO), *Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence* (Paris, France: UNESCO, 2023), https://unesdoc.unesco.org/ark:/48223/pf0000385198.

[g]Klaus Schwab, *The Global Competitiveness Report 2019* (Geneva, Switzerland: World Economic Forum, 2019), https://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf.

Each framework listed in Table 10 includes indicators by which to measure AI development and deployment, often grouped by associative themes. Although these frameworks have different purposes, such as comparing nations' readiness to implement AI or nations' competitiveness, the indicators are often similar and occasionally overlap.

Table 11 is a list of the indicators from these frameworks, grouped by the subpillars of GAO's competitiveness framework. This is not an exhaustive list of all indicators of AI competitiveness; however, it offers suggestions for analysts choosing drivers and signals. We attribute each indicator to relevant frameworks via the superscripts. We consolidated indicators if they were the same or similar in multiple frameworks, as noted with multiple superscripts. In addition, we occasionally revised wording to use plain language. Therefore, indicator language in this table may not match language in existing frameworks exactly. Also, for simplicity, we removed references to specific units of measurement, such as when a framework included per-capita indicators. For example, if a framework included both "citations on AI related papers" and "citations on AI related papers per capita" we included only the former. After analysts have selected drivers and signals, they can reference table 8 in Part II for types of data measures and their potential uses. Analysts should consider which data measures serve their analytical purposes and align with their intended uses of framework.

Table 11: Example of Indicators to Measure Artificial Intelligence Capabilities and Capacity Used in Selected Frameworks

Science and Technology Indicators selected from other frameworks that analysts can use to measure science and technology capabilities and capacity related to AI competitiveness			
Research & Development			
• AI conference citations[d] • AI journal citations[d] • AI paper citations[e] • AI patent grants[d] • AI scientific publications (including papers, articles, and journal publications)[bcdeg] • Authors of significant machine learning systems by country[e] • Cited usage of top-performing graphics processing units (GPUs) and tensor processing units (TPUs) in AI papers[e]	• Contributions to foundational and applied research by citation count[e] • Contributions to foundational and applied research by publication count[e] • Ethical AI research[f] • Field-weighted citation impact[b] • Field-weighted download impact[b] • Filed AI patents by applicant[eg]	• Filed AI patents by inventor[eg] • Frontier technology readiness[a] • Granted AI patents by applicant[e] • Granted AI patents by inventor[e] • Innovation output[f] • Prominence of research institutions[g] • Number of developers contributing to AI projects on public code repositories[e] • R&D expenditure[acefg]	• R&D spending by software and computer services firms in top 2,500[b] • Research output[f] • Share of top 10 firms for semiconductor R&D spending by country[b] • Share of top 100 software and computer services firms for R&D spending by country[b] • Submissions to AI conferences[e] • Trademark applications[g]
Software			
• Academia-industry model production concentration[d] • AI projects on public code repositories[d] • Bookmarks of AI projects on public code repositories[d] • Commits on high-popularity open-source AI packages[e]	• Contributions to all top-performing models represented on public leaderboards[e] • Contributions to most downloaded models on public platforms[e] • Contributions to top-performing pretrained models represented on public leaderboards[e]	• Estimated total training compute of notable AI models[e] • Foundation model applications[d] • Foundation models[d] • Notable machine learning models[d] • Open-access foundation models[d]	• Policy for AI-driven cloud computing[f] • Significant machine learning systems[e]
Hardware			
• Aggregate system performance of supercomputers ranked in top 500[b] • Colocation of data centers[f]	• Computational capacity (petaflops) of large non-distributed super computers[e] • Exports of semiconductor manufacturing machines[e] • Firms designing AI chips[b]	• Imports of semiconductor manufacturing machines[e] • Share of Top 15 firms for semiconductor sales by country[b] • Supercomputers[cde]	• Supercomputers ranked in top 500[b] • Total integrated circuits imports[e] • Total integrated circuits exports[e]
Data			
• Availability of genetic data[b] • Availability of internet of things data[b]	• Available online content and data to train AI systems[f]	• Electronic health records systems[b] • Foundational model datasets[d]	• Performance of national statistical systems[f]

• Availability of mapping data[b] • Availability of procurement data[c] • Availability of productivity data[b]	• Contributions to most downloaded datasets on public platforms[e] • Data governance that supports safe and equitable generation and use of AI[c]	• National data sharing framework[f] • Open data[c] • Open government data policies[f]	• Public availability of government datasets for AI training[e] • Score on the Open Data Inventory[f] • Signatory of International Open Data Charter[f] • Statistical capacity[c]
Digital Infrastructure			
• 5G infrastructure[c] • Active mobile broadband subscriptions[f] • Average download speed[e] • Average fixed broadband download speed[f] • Average international bandwidth[f] • Broadband quality[c] • Compute capacity[d] • Cost of cheapest internet-enabled device[c]	• Cost of internet access[a] • Coverage by at least a 3G mobile network[f] • Distance to data center[f] • Fiber internet subscription[g] • Fixed broadband subscriptions[abg] • Fixed telephone lines[a] • Foundational IT infrastructure[c] • Gender gap in internet access[cf]	• Gender gap in mobile access[f] • Households with internet access[c] • Individuals using mobile payments[b] • Internet speed[d] • Internet users[aefg] • Mobile broadband subscriptions[fg] • Mobile cellular telephone subscriptions[acfg] • Mobile subscriptions per 100 persons[e]	• Number of data centers[f] • Population with access to electricity[ef] • Public sector's online services infrastructure[a] • Rural/urban gap in internet access[f] • Score on Online Services Index[cf] • Secure internet servers[a] • Telecommunications infrastructure[c] • Wireless broadband subscriptions[a]
Human Capital Indicators selected from other frameworks that analysts can use to measure human capital capabilities and capacity related to AI competitiveness			
Workforce			
• Active labor market policies[ag] • AI hiring rate[d] • AI researchers[be] • AI study programs in English[d] • AI talent concentration[df] • AI-related PhDs[f] • AI-related post-doctoral students[f] • Answers related to AI questions on public websites[e] • Cooperation in labor-employer relations[g] • Cost to terminate redundant workers[g] • Data scientists and engineers[e]	• Diversity of workforce in AI[g] • Education of AI researchers[b] • Existing AI professionals[e] • Female STEM graduates[ac] • Flexibility of wage determination[ag] • Gender diversity of IT graduates[e] • Gender diversity of science graduates[e] • Gender equality in AI talent concentration[de] • Healthy life expectancy[g] • H-Index rating[e] • Hiring and firing practices[g]	• Information and communications technology skills[c] • IT graduates[e] • Job postings requiring AI-related skills[df] • Law or policy to enhance diversity in AI workforce[f] • National retention rate of AI scientists[e] • Number of data scientists, AI researchers, and engineers on employment platforms[e] • Pay and productivity[ag] • Population covered by social protection schemes[a] • Public reliance on professional management[g] • Questions related to AI on public websites[e]	• Ratio of wage and salaried female workers to male workers[g] • Relative AI skill penetration (i.e., self-reported prevalence and intensity of AI skills in the workforce)[df] • Share of current employees working as data scientists[f] • Skillset of graduates[ag] • STEM graduates[ace] • STEM graduates in tertiary education[f] • Top AI researchers[b] • Workers in firms adopting AI[b] • Workers in firms piloting AI[b] • Workers' rights, by international labor standards[g]

• Digital skills among active population[a]	• Information and communications technology graduates in tertiary education[f]		
Education			
• Activity on public code repositories[c] • AI courses in ethics for the general population[f] • Coursera data science score[ef] • Education programs including technical and ethical aspects of AI[f] • Extent of staff training in AI[g] • Gender breakdown of STEM graduates[f]	• Gender breakdown of STEM graduates expected to work as STEM professionals when they are 30[f] • Government strategy to improve digital skills in public sector[f] • Mean years of schooling[g] • Primary, lower secondary, and secondary students with access to computer[f] • Primary, lower secondary, and secondary students with access to internet[f]	• Public education expenditure[a] • Public perception of critical thinking in teaching[g] • Pupil-to-teacher ratio in primary education[g] • Quality of engineering and technology higher education[c] • Quality of vocational training[g] • School life expectancy[g] • Science literacy of 15-year-olds by gender[f] • Score on Human Capital Index[a]	• Share of top 100 computer science universities by country[e] • Skillset of graduates[a] • Technical AI courses for general population[f] • Tertiary education programs with 1+ module on ethics in AI[f] • Tertiary education programs dedicated to AI (or related field)[f] • Tertiary education programs with 1+ module in AI (or related field)[f]
Human Capital Mobility			
• Cost of visas for high-skilled tech workers[e]	• Ease of hiring foreign labor[g]	• Internal labor market mobility[ag]	• Net migration flow of AI skills[d]
Governance Indicators selected from other frameworks that analysts can use to measure governance related to AI competitiveness			
Collaboration & Partnerships			
• International co-inventions[g]	• Multistakeholder collaboration[g]	• Participation in International Organizational Standards (ISO) AI Committee[e]	• State of cluster development[g]
Laws, Regulations & Policies			
• Binding AI regulation or soft law[f] • Burden of government regulation[g] • Comprehensive framework for data management and publication[f] • Conflict of interest regulation[g] • Data protection and privacy laws[cf]	• Efficiency of legal framework in challenging regulations[g] • Efficiency of legal framework in settling disputes[g] • Freedom of Information Act[f] • Freedom of the press[g] • Government effectiveness (i.e., the quality of public services, civil service, and independence)[ac]	• Intellectual property protection laws[g] • Judicial independence[g] • Laws or policies on procurement of AI systems[f] • Laws or policies to integrate AI tools into the education system[f] • Laws to protect due process rights[f] • Legal framework's adaptability to digital business models[a]	• Level of data protection regulation[e] • Perception of incidences of corruption[g] • Protection of property rights[g] • Quality of land administration[g] • Regulatory barriers for available data to train and use AI systems[b] • Regulatory quality[c]
Responsible Practices			
• AI social media posts[d]	• Law or policy for educators to teach AI ethics[f]	• Policy for addressing impact of AI on the environment[f]	• Score on cybersecurity index (Kaspersky or Global Cybersecurity Index)[cef]

• AI-related social media conversations net sentiment[d] • Commitment to sustainability[g] • Conference submissions on responsible AI topics[d] • Digital health policy[f] • Ethical principles in AI[c] • Framework on notice or takedown for violating AI policies[f] • Government accountability (i.e., the extent to which a country's citizens participate in selecting their government)[c]	• Law or policy on impact of AI on social media[f] • Law or policy on remedying harm caused by AI[f] • Law or policy to reduce digital gender gap[f] • Law or policy to reduce digital socioeconomic or geographical gap[f] • Participation in standardization of AI and digital technologies[f]	• Policy on use of AI for preservation of cultural heritage[f] • Policy on use of AI for preservation of Indigenous languages[f] • Population that thinks AI is harmful[e] • Presence of right to explanation[e] • Prioritization of sectors that would benefit from AI[f] • Public trust in AI[f] • Public trust in government websites and applications[f]	• Score on the E-Participation Index (i.e., government use of online tools to engage citizens in policymaking)[fg] • Social capital (e.g., cohesion and engagement, family networks, and political participation)[g] • Social media share of voice on AI[d] • Strength of auditing and accounting standards[g] • Transparency in use of AI systems[f]
Vision & Leadership			
• Adoption of emerging technologies[c] • AI legislation passed[de] • AI mentions in legislative proceedings[de] • Dedicated AI strategy considers AI ethics[e] • Dedicated AI strategy on training or upskilling[e] • Dedicated AI strategy received external consultation[e]	• Dedicated AI Strategy signed by senior member of government[e] • Government adaptability (i.e., public perception of government stability, vision, and responsiveness to change)[g]	• Government has dedicated AI governmental body[e] • Government has dedicated AI minister[e] • Government has measurable AI targets[e] • Government responsiveness to change[c]	• Government/ministries responsible for AI governance[f] • National AI strategy[cdef] • Public Sector AI Skills Development[e] • Time scale of dedicated strategy[e] • Tracking of previous years' efforts on AI[e]

Economy Indicators selected from other frameworks that analysts can use to measure economic capabilities and capacity related to AI competitiveness			
Business Environment			
• Attitudes towards entrepreneurial risk[g] • Average days taken for patent office to provide approval[e] • Banks' regulatory capital ratio[g] • Border clearance efficiency[g] • Budget transparency[g]	• Debt dynamics (i.e., debt-to-gross domestic product ratio)[g] • Distortive effect of taxes and subsidies on competition[g] • Domestic credit to private sector[ag] • Extent of market dominance[g]	• Gross domestic product (GDP)[g] • Gross domestic product for computer programming and related activities[f] • High tech exports as a share of trade[f] • Inflation[g] • Insolvency recovery rate[g]	• Non-AI unicorns (i.e., private non-AI companies valued at over $1 billion)[c] • Non-performing loans[g] • Non-tariff barriers[ag] • Number of AI companies acquired[e] • Postal reliability index[a] • Soundness of banks[g]

• Buyer sophistication[g] • Competition in services[g] • Complexity of tariffs[g] • Cost of starting a business[g] • Credit gap[g]	• Employer willingness to delegate authority[g] • Free movement of people and capital[a] • Government promotion of investment in emerging technologies[c]	• Insolvency regulatory framework[g] • Insurance premium[g] • Labor tax rate (i.e., taxes and mandatory contributions on labor paid by businesses)[g] • Mean tariff rate[a]	• Time spent dealing with government regulations[c] • Time to start a business[g] • Trade tariffs[g] • Use of mobile phone for online transactions[a] • Value of AI companies acquired[e]
Investment & Financing			
• AI firms with $1M+ in funding[b] • AI merger and acquisition investment[d] • AI minority stake investment[d] • AI private investment[d] • AI public offering investment[d] • Average funding of AI company[e]	• Average startup funding[e] • Company expenditure on AI R&D[f] • Company expenditure on AI services as share of intermediate consumption[f] • Company investment in emerging technologies[c] • Computer software spending[c] • Dedicated spending on AI[e]	• Dedicated spending on public AI compute infrastructure[e] • Financing of small- and medium-sized enterprises[g] • Funding of AI startups[e] • Government has publicly dedicated money to AI[e] • Government investments in public AI compute infrastructure[e] • Government investments in the training of national AI foundation model[e]	• Newly funded AI companies[d] • Spend period of dedicated governmental AI budgets[e] • Total funding of AI companies[e] • Venture capital availability[cg] • Venture capital and private equity deals[b] • Venture capital and private equity funding[b]
Business Activities			
• Acquisitions of AI firms[b] • AI companies[e] • AI companies on country's stock exchange[e] • AI market capitalization[g] • AI startups[be]	• AI unicorns (companies valued at over $1 billion)[ce] • Businesses using AI[e] • Employee perceptions of companies embracing disruptive ideas[g]	• Exports of semiconductor devices and parts[d] • Growth of innovative companies[g] • Imports of AI goods and services[g] • Listed AI companies (in public stock exchanges)[e]	• Shareholder governance[g] • Value of trade in information and communication technology services[c] • Value of trade in information and communication technology goods[c]

Source: GAO analysis of literature. | GAO-26-107624

Note: This is a list of indicators from frameworks developed by other organizations and offers suggestions for analysts choosing drivers and signals. Analysts are not limited to indicators identified in these frameworks. The superscripts for each indicator direct analysts to the relevant frameworks, which often include information about data sources.

[a]Mauro Cazzaniga, Florence Jaumotte, Longji Li, Giovanni Melina, August J. Panton, Carlo Pizzinello, Emma Rockall, and Marina M. Tavares, *Gen-AI: Artificial Intelligence and the Future of Work* (Washington, D.C: International Monetary Fund, 2024), https://doi.org/10.5089/9798400262548.006.

[b]Daniel Castro and Michael McLaughlin, *Who is Winning the AI Race: China, the EU, or the United States?* 2021 Update (Washington, D.C.: Information Technology and Innovation Foundation, 2021), https://www2.datainnovation.org/2021-china-eu-us-ai.pdf.

[c]Pablo Fuentes Nettel, Emma Hankins, Richard Stirling, Giulia Cirri, Gonzalo Grau, Sulamaan Rahim, and Eddie Crampton, The *Government AI Readiness Index 2024* (United Kingdom: Oxford Insights, 2024), https://oxfordinsights.com/wp-content/uploads/2024/12/2024-Government-AI-Readiness-Index-2.pdf.

[d]Loredana Fattorini, Nestor,Maslej, Ray Perrault, Vanessa Parli, John Etchemendy, Yoav Shooham, and Katrina Ligett, *The Global AI Vibrancy Tool 2024* (Stanford, CA: Stanford University, 2024), https://hai.stanford.edu/assets/files/global_ai_vibrancy_tool_paper_november2024.pdf.

[e]Serena Cesaro and Joe White, *The Global Artificial Intelligence Index 2024* (London, England: Tortoise Media, 2024), https://www.tortoisemedia.com/2024/09/18/the-global-artificial-intelligence-index-2024.

[f]United Nations Educational, Scientific and Cultural Organization (UNESCO), *Readiness Assessment Methodology: A Tool of the Recommendation on the Ethics of Artificial Intelligence* (Paris, France: UNESCO, 2023), https://unesdoc.unesco.org/ark:/48223/pf0000385198.

[g]Klaus Schwab, *The Global Competitiveness Report 2019* (Geneva, Switzerland: World Economic Forum, 2019), https://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf.

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