
CHAPTER 3: NATIONAL OBJECTIVES, TECHNOLOGY CRITICALITY, AND TECHNOLOGY ASSESSMENT

There is bipartisan interest in investing in “critical technologies,” but the United States does not have an operational definition of “criticality,” let alone the data, intellectual foundations, or policy roadmap that could translate that definition into a recommended portfolio of policies and investments. Policymakers lack methods to evaluate the criticality of specific technologies for national objectives ranging from national and economic security to the social well-being of all citizens (in terms of health and the number, quality, and distribution of jobs, for example). And even if a critical technology is identified, consensus does not exist regarding mechanisms such as secrecy, openness, domestic capabilities, international alliances, and the role of government investment that can best promote their development in the United States while protecting against their exploitation by adversaries.

Unfortunately, past approaches to identifying critical technologies have proven inadequate. Reports and lists have often been little more than reflections of stakeholder interests, and have struggled to find their way to supporting meaningful policy (cf. Moguee 1991, Knezo 1993, Bimber and Popper 1994, Wagner and Popper 2003). Nonetheless, a number of entities (cf. CFR, OSTP, DOD) have produced recent lists of “critical” or “key” technologies (**box 3-1**), and the CHIPS and Science legislation mandates that NSF’s Directorate for Technology, Innovation, and Partnerships (TIP) annually update a list of 10 key technologies and how they might address US domestic and international challenges.

In the 1990 Defense Authorization Act (PL 101-189, signed into law in November 1989), Congress defined “critical technologies” as “essential for the United States to develop to further the long-term national security or economic prosperity.” As revealed during the pandemic, this definition

does not include public health or look beyond technology development to address related aspects such as product access.

For this project, we define a technology as critical with respect to three different but overlapping national missions (for detailed descriptions, see **appendix 3A**):

- US national security and that of our allies,
- US economic well-being, and
- US social well-being.

The Role of Technology in Advancing National Missions

Technological progress has long been considered central to all three missions. Technological superiority is considered a foundational element for the US military and warfighter (IMTI 2009). For example, the Allied victory in World War II has been attributed in part to the ability of the American (and Soviet) mass production industry to turn out military aircraft, tanks, and other weapons systems in unprecedented quantities thanks to inventions in materials, electricity, and the assembly line (Hounshell 1985). Today, uncrewed and autonomous systems—whether missiles, drones, or combat robots—have changed the nature of warfare, and AI more broadly is expected to continue to revolutionize conflict. One study concluded that, thanks to IT’s ubiquity (e.g., as a general purpose technology) and its regular performance improvements (Moore’s law), more than 90% of increases in total factor productivity in the 1990s in the United States and worldwide could be attributed to technological progress in microprocessors (Jorgenson et al. 2015).

Disruptive technologies can also transform the rules of the game in firm and national competition and international comparative advantage in ways

that transcend classic productivity measurements, as has been seen with the invention of the car, the internet, and wireless communication (box 3-2).

Finally, the social benefits of technological advances are so numerous and so transformative to daily life that they increase the quality of life in ways that can be hard for economists to measure. Such were the effects of electricity, pasteurization, and semiconductors; more modern examples might include mRNA vaccines, ubiquitous computing, and AI.

Strategies, Tradeoffs, and Wins for National Objectives

Predicting the future of technology is challenging, but it is possible to set desirable objectives, map out technology pathways that with high probability can help to achieve those objectives, and work to coordinate relevant actors. Well-defined and

transparent technology assessment methods can assist policymakers in developing strategies and identifying both tradeoffs and win-win solutions across national objectives for stakeholders with different values or weighting of national objectives.

Common methods in strategic analysis for technology policy include scenario analysis (Cornelius et al. 2005), wargaming (McHugh 1966, Rubel 2006), stress tests (Simchi-Levi and Simchi-Levi 2020, Ivanov and Dolgui 2022), and engineering analytic (technoeconomic) modeling (Busch and Field 1988, Morgan 2017), among others. The latter has shown promise in supporting the designation of commercialization pathways for emerging technologies, by identifying labor skill and quantity requirements as well as technology advances (such as improvements in process yields) required to lower costs (cf. Liu et al. 2021, Combemale et al. 2022).

BOX 3-1

History of Technology Criticality Designation and Listings

The concept of technology “criticality” has focused primarily on national security but at times expanded to include economic competitiveness and societal well-being, including public health. First came the notion of militarily critical technologies and, later, families of technology deemed critical for economic competitiveness. Early DOD compilations included lists and hundreds of pages of analysis. Early export control policies targeted sales of high-technology goods to the Soviet Union, Warsaw Pact countries, and China. High-performance computers, and their hardware components and software, were of particular concern as dual-use (military and civilian) technologies, especially given their role in calculations for early nuclear weapons. More recently, technologies such as semiconductors and software in end-systems essential to socioeconomic functioning (e.g., the internet, air traffic control, the electrical grid) as well as products associated with energy security have been considered critical. A 1976 Defense Science Board report (DOD 1976, pp. 1, 3) emphasized embedded (intangible) industrial knowledge, not just goods produced with such knowledge, stating that “Design and manufacturing know-how are the principal elements of strategic technology control,” adding “there is unanimous agreement that the *detail of how to do things* is the essence of the technologies” (emphasis in original). That said, most critical technology lists focus on products and technologies. They are usually developed by consensus committees, which face the challenges of quantifying criticality for different missions and balancing stakeholder interests inherent in agency missions as well as S&T expertise. **Table 3B1-1** summarizes three recent critical technology lists. Eleven of the 18 rows have significant overlap across the lists, which also share a focus on national security.

TABLE 3B1-1. Recent critical technology listings, 2022 and 2023

Governmentwide “Critical and Emerging Technologies”	DOD “Critical Technologies”	CHIPS and Science “Key Technologies”
Advanced computing	Advanced computing and software	High performance computing, semi-conductors, and advanced computer hardware and software
Advanced engineering materials	Advanced materials	Advanced materials science, including composites, 2D materials, other next-generation materials, and related manufacturing technologies
Advanced gas turbine engine technologies		
Advanced manufacturing		Robotics, automation, and advanced manufacturing
Advanced and networked sensing and signature management	Integrated network	Advanced communications technology and immersive technology
Communication and networking technologies	Systems-of-systems	Data storage, data management, distributed ledger technologies, and cybersecurity, including biometrics
Networked sensors and sensing	FutureG	
Advanced nuclear energy technologies		
Artificial intelligence	Trusted AI and autonomy	Artificial intelligence, machine learning, autonomy, and related advances
Autonomous systems and robotics		
Biotechnologies	Biotechnology	Biotechnology, medical technology, genomics, and synthetic biology
Directed energy Hypersonics	Directed energy, hypersonics	
Financial technologies		
Human-machine interfaces	Human machine interfaces	
Quantum information technologies	Quantum science	Quantum information science and technology (S&T)
Renewable energy generation and storage	Renewable energy generation and storage	Advanced energy and industrial efficiency technologies, such as batteries and advanced nuclear technologies, including but not limited to for the purposes of electric generation

Governmentwide “Critical and Emerging Technologies”	DOD “Critical Technologies”	CHIPS and Science “Key Technologies”
Semiconductors and microelectronics	Microelectronics	See top row
Space technologies and systems	Space technology	
		Natural and anthropogenic disaster prevention or mitigation
<p>NOTE: Entries appear as in the source documents (L to R columns): <i>Critical and Emerging Technologies List Update</i> (Executive Office of the President, Feb 2022), p. 2; <i>National Defense Science & Technology Strategy 2023</i> (Department of Defense [unclassified version released May 9]), p. 3; HR 4346 (“CHIPS and Science Act”), July 22, 2022, Sec. 10387, pp. 560–61.</p>		

In terms of quantifying tradeoffs, for example, one assessment showed that compulsory secrecy during World War II protected sensitive technology but also resulted in restricted commercialization and limited follow-on innovation, with effects persisting through at least 1960 (Gross 2019). In terms of identifying win-wins across national missions or stakeholders with different values, past assessments have shown, for example, that (i) for safety-critical robust semiconductors, improved access to raw materials and intermediate inputs can benefit both the economy (sales and jobs in the automotive sector) and national security (chips for missiles) (Berger et al. 2023); and (ii) in the case of high-end semiconductors for communications, research suggests that reshored manufacturing can enhance US technological leadership and increase both the number and quality of US jobs (Combe-male and Fuchs 2021, Combemale et al. 2022).

However, although scenarios can be cognitively compelling, they can also lead users to focus too narrowly on specific outcomes and ignore other potential futures. Various methods of horizon scanning are often important ways to make sure needed alternatives are analyzed, and are one of multiple places where LLM approaches may be particularly powerful.

Anticipating Future Technology Impacts

Technologies that are critical to each or all of the three missions can be readily identified. The challenge lies in anticipating which will be critical in the future. This requires thinking carefully and systematically about the various ways current and future technologies and their capabilities may evolve, and about the consequences of that evolution. **Box 3-3** discusses prior work and future opportunities.

Critical technology assessment is not, however, primarily about making predictions. Rather, it should acknowledge the ongoing challenge of decision making under uncertainty; provide analysis, tools, and data to support better-informed decisions in the face of inevitable uncertainty; and identify strategies that will increase the odds of realizing desired outcomes.

Measuring Policy Impacts

Measuring the impact of specific policies designed to address critical technologies presents at least two challenges. First, given the length of the innovation pipeline, it may take 10–30 years or more to know whether the desired outcome has been achieved. This time horizon is much longer than political cycles.

The Role of Technology in Competitiveness

The US balance of trade in goods and services has been negative for the past half-century. US-based firms in multiple industries including steel, semiconductors, and automobiles have struggled, sometimes successfully and sometimes not, as international rivals eroded their positions. These industries differ in their structure, work systems, supply networks, and technologies. Government policies on cross-border trade, foreign investment, and industrial supports and subsidies also vary. All these factors influence competitive outcomes for individual firms, either at the margins or centrally. To be competitive, technologies must be introduced at meaningful scale in products or processes—in a word, commercialized. In the United States this is the work of private firms, which may be manufacturers or providers of intangible outputs such as financial services and health care.

Two cases illustrate the impacts of technology use, one benefiting a US industry, the other advantaging international competitors. The US petrochemicals industry adopted technological innovations and plants grew in size because of steady improvements in process modeling, advances in catalysis, and computerized process controls. In microelectronics, foreign semiconductor firms gained advantages in high-volume production by fine-tuning their processes, superseding US capabilities in quality and reliability and thus cutting into the once-dominant market shares of US-based manufacturers. Impacts were initially felt in commodity devices such as memory chips, and later in the leading process nodes for the most advanced chips. Many services also benefit from technological innovation. For example, hospitals are using onsite 3D printers to create lifesize models of organs for the development and practice of complex surgeries and to create dental implants and prosthetics. Businesses pursue technical knowledge for product and process innovation in part through internal R&D—in 2022 Alphabet spent nearly \$40 billion on R&D and Amazon some \$73 billion¹—and in part through strategic funding, search, and leverage of technology from outside sources, whether Silicon Valley startups, spinoffs from academic research, defense R&D and procurement, or from overseas. Technological advances are not without costs, however. Impacts of trade and technology on workers have been widely documented, although detailed analysis of how different technologies may have different impacts and the specific implications for training have been challenging to obtain because of the aggregate level of public data, the siting of necessary knowledge in firms, and the significant technical and product expertise needed. Implementing the necessary training is also resource-intensive.²

¹ From 10-K reports filed with the Securities and Exchange Commission, online. Amazon terms its entry “technology and content,” but it is the same accounting category as for the R&D spending reported by other firms.

² See <https://data.oecd.org/socialexp/public-spending-on-labour-markets.htm>. Over the years the United States has spent less on worker training than other members of the Organization for Economic Cooperation and Development, excepting only Mexico. More generally, see, e.g., Barnow and Smith (2015).

Second, it can be particularly difficult to set up policy experiments that have a counterfactual, especially for singular large-scale investments such as developing a new aircraft or building a particle accelerator.

Notwithstanding these challenges, it is essential to learn from past policies and to set up as effective a system as possible and then retrospectively assess

the efficacy of policy actions (Manski 2013). In some cases, it may be possible to obtain focused or short-term metrics—such as the net short-term change in employment resulting from a program. Well-designed policies for critical technologies can be expected to also have synoptic or longer-term consequences. In this case, while it may be possible to show correlation, controlling for large numbers

of other changes can make it difficult or impossible to demonstrate causation. Examples of the two types of metrics in the three domains of criticality are shown in **appendix table 3A-1**.

Demonstrating Critical Technology Assessment

The 1-year NNCTA pilot focused on demonstrating the potential for analytics to inform national RD&D investment and other policy issues for critical technologies in four technology areas:

- artificial intelligence (AI),
- semiconductors (chips),
- biopharmaceuticals (generic drugs), and
- energy storage (batteries) and critical materials

Developing measures of criticality was not the primary objective, but demonstration efforts in each of the four areas ended up providing a variety of short-term quantitative and qualitative measures. **Appendix tables 3A-2** and **3A-3** show the domains of criticality addressed by each area.

BOX 3-3

Forecasting Technology Outcomes

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In the world of technology, as in human affairs more generally, the future is deeply uncertain. Technology forecasts involve complex technological and social systems whose interactions and outcomes can be difficult to predict. The high-profile case of solar energy demonstrates the challenge, where the price in 2019 was lower than expert assessments of cost in 2030 (Savage et al. 2021) (**figure 3B3-1**) and then cost estimates based on experience curve analysis (Candelise et al. 2013). For useful predictions to be possible, stable patterns must exist (Makridakis et al. 1998). When the pattern does change, as happens with some major innovations—solid-state electronics in place of vacuum tubes, jet engines in place of reciprocating powerplants, fiber-optic communications in place of digital electronics—prediction will at best be suggestive and highly uncertain until some new pattern has emerged and been validated.

This sort of uncertainty poses a fundamental problem for critical technology assessment. Major or radical innovations—“breakthroughs”—are a chief goal of innovation policy. Although rare, when they emerge the existing pattern is dissolved, rendering the future unknowable. Until a new pattern is established, guesses or at best informed technical judgment will be the sole basis for anticipating future trends.

How long the period of high uncertainty will last is usually also unknowable. For high-temperature superconductivity, for example, no new pattern is visible despite decades of advances in both theoretical understanding and experimental demonstration. Similarly, no one can reasonably predict if and when lithium-ion electric vehicle batteries will be superseded by some alternative electrochemical family. Moore’s law, on the other hand, was put forward in 1975, quickly accepted, and by about 1980 the only question was how long the newfound trend would last and what would come next.

In thinking about technological forecasting, it is important to not conflate the idea of *identifying relevant technology directions and their potential implications* with the idea of *predicting exactly when a specific technical advance will occur*.³

³ National technology strategy benefits greatly from knowledge of the potential directions to be taken. For example, it is quite useful to learn from experts—even if the timing and exact uses are not yet clear—that more general versions of AI large language models will be trained on vast quantities of videos and not just text, and that this training may revolutionize systems for video surveillance and self-driving vehicle technology.

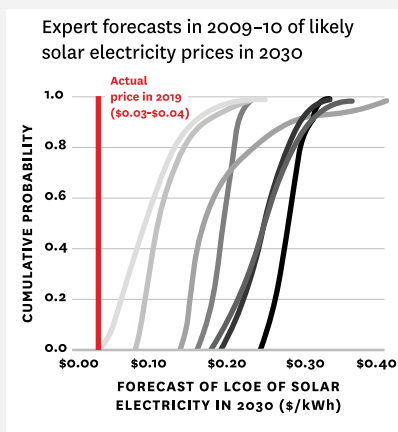


FIGURE 3B3-1. Underestimation of progress in reducing the future levelized cost of a technology (solar electricity) is illustrated by these cumulative distribution functions of the cost of solar photovoltaics in 2030 as assessed by seven energy experts in 2009–10. None of the forecasts included the actual price a decade later in 2019 (far left). Adapted from Savage et al. (2021).

2021, Ziegler et al. 2021, Makridakis et al. 2023), including work in decision sciences demonstrating that certain individuals (or “superforecasters”) can be consistently more accurate than experts or the general public (e.g., Tetlock and Gardner 2015). It’s also too early to tell how advances in machine learning and natural language processing may be able to improve prediction capabilities, and research is needed to understand how and where they can contribute to technology prediction. To date, however, both technological enthusiasts and policy promoters habitually underestimate the technical obstacles that must be overcome before commercialization and therefore the time from demonstration of a new technology to its practical realization. As Simon Kuznets (1972, p. 437), 1971 Nobel laureate in economics for work including pioneering studies of innovation, explained: “a major technological innovation requires a long period of sustained improvement, and many significant complementary innovations (some of them also major but derivative) before its ramified and significant effects...are realized.” This truth is part of the basis for evolutionary theories of innovation (Nelson and Winter 1982, Mokyr 1996), and it has substantial implications for forecasting and policy.

In summary, regardless of method, technological forecasting of exact times of precise technical developments is in general extremely difficult, should always include a range of uncertainty, and should not be the primary focus of near-term critical technology assessment efforts.⁴ However, predictions of the general direction(s) in which technology will change and analyses of what will be the gating factors in these technological advances (and therefore policy actions that can make a difference) require much less precision and, taken with appropriate caution, can be of great use in providing insight and guidance to decision makers.

⁴ For additional readings on the challenges of predicting technology outcomes see Albright (2002), Alic (1999), Apreda et al. (2019), Halal (2013), Kott and Perconti (2018), Fye et al. (2013), and Jaxa-Rozen and Trutnevte (2021).

A generalized sense of the directions of technological advances that are likely to have substantial impacts on society and the economy underlies the many critical technologies lists put forward in recent years, as well as individual policies such as those embodied in the CHIPS and Science Act pieces of legislation and documents intended as guides to policy thinking (e.g., the *National Artificial Intelligence Research and Development Strategic Plan: 2023 Update*, released by the White House in May 2023). The sounder the grasp of policymakers and policy influencers concerning factors and forces likely to affect technological directions and the pace of advance, along with possible constraints such as resource availability (e.g., for lithium-ion electric vehicle batteries) or the availability of skilled labor (e.g., for quality control in the manufacture of COVID vaccines), the more likely their decisions and actions will have positive effects on the economy, the labor force, and the population as a whole. This sort of forecasting is far easier than attempting to predict the timing of technological, production, or cost advances.

There is important ongoing research into other technological forecasting methods and applications (Nagy et al. 2013, Meng et al. 2021, Trancik