United States–Japan Research Exchange on Artificial Intelligence

Proceedings from a Pair of Conferences on the Impact of Artificial Intelligence on Work, Health, and Data Privacy and on Disaster Prediction, Resilience, and Recovery

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Preface

Artificial intelligence (AI) and machine learning (ML—hereafter referred to as AI/ML) are being applied more and more widely across the globe, affecting how individuals work, pursue health, and protect their communities. These changes have implications for society, the economy, and data science. The experiences of the United States and Japan, two of the world's wealthiest and most technologically advanced liberal democracies, represent important leading indicators of how AI/ML affect human society now and will continue to do so. U.S. and Japanese experiences also carry lessons for each other about how the two sides of the Pacific might think about the policy impacts that AI/ML technologies can have and what policies might be necessary to effectively and safely employ learning algorithms. How are these two advanced countries thinking about and employing AI? What can they learn from each other's experiences and approaches? And are there areas for cooperation that might be pursued?

Given the importance of understanding the implications of AI/ML, the RAND Corporation convened a pair of public conferences at in Pittsburgh, Pennsylvania, and New Orleans, Louisiana, that brought together leading U.S. and Japanese experts on work, health, and data security (Conference I), and on international affairs, disaster response, and disaster modeling (Conference II) to exchange views on AI/ML technologies. At the first conference, on October 10, 2019, noted AI ethicist David Danks (L.L. Thurstone Professor of Philosophy and Psychology and Head of the Department of Philosophy at Carnegie Mellon University) gave a keynote speech in which he discussed decisionmaking and biases in AI and the concerns that these issues raise as they are employed on a widening scale. At the second conference, on February 18, 2020, Charles Sutcliffe (Chief Resilience Officer, Governor's Office of Coastal Activities) explained the challenges that Louisiana faces in protecting and preserving coastal wetlands and how the state employs a variety of forecasting and modeling technologies in an attempt to prevent erosion and minimize damaging weather events in an era of accelerating global warming and climate change. These conference proceedings capture insights from the two conferences, recount some of the exchanges among the participants at those sessions, and are built around the papers that the conference presenters submitted after the conferences concluded. The views articulated and expressed herein, including those about any technology or commercial product, are those of the participants and should not be construed as an endorsement by RAND or its research sponsors.

This effort was sponsored by the Government of Japan and conducted in the Community Health and Environmental Policy Program within RAND's Social and Economic Well-Being Division. RAND Social and Economic Well-Being is a division of the RAND Corporation that seeks to actively improve the health and social and economic well-being of populations and communities throughout the world. The Community Health and Environmental Policy Program focuses on such topics as infrastructure, science and technology, community design,

community health promotion, migration and population dynamics, transportation, energy, and climate and the environment, as well as other policy concerns that are influenced by the natural and built environment, technology, and community organizations and institutions that affect well-being. For more information, email chep@rand.org.

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Abbreviations

AI	artificial intelligence
APPA	Authorized Public Purpose Access
COVID-19	coronavirus disease 2019
DFFT	Data Free Flow with Trust
EHR	electronic health record
EOC	emergency operations center
G20	Group of 20
GDPR	General Data Protection Regulation
GEONET	Global Navigation Satellite System Earth Observation Network System
ML	machine learning
PeOPLe	Person-centered Open PLatform for well-being

CHAPTER ONE

Introduction

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How are technological advances associated with artificial intelligence (AI) likely to affect work, health, communications, and communities? Is AI likely to fuel a collapse of employment or spawn a boom in new fields of work? Or will it instead serve as a tool, helping doctors to identify disease earlier or enabling novel medical breakthroughs that save millions of lives? Will concerns about algorithmic bias and privacy—or worries about outright malicious use of personalized health information—lead to obstacles that slow or prevent the discovery of patterns in data that would lead to new policy solutions? And as natural disasters and anthropogenic climate change threaten coastal communities, how are advanced democracies, such as the United States and Japan, most likely to employ AI to respond effectively to assess threats ahead of time and prepare against them, evaluate them in real time as they are unfolding, and respond more quickly in the aftermath to save lives during recovery operations?

The RAND Corporation invited leading U.S. and Japanese experts in fields of work, health, data security and society, international affairs, disaster management, and risk modeling to participate in a pair of public conferences to answer these questions about AI technology impacts. The specialists who presented at the conferences that informed this volume come from backgrounds in academia, the think tank world, the nonprofit field, the private sector, and government. They reflect the growing interest in both the United States and Japan—as well as other countries around the world—in moving AI technologies from theory to application, in many cases through commercial, government, or military usage. The first conference addressed work, health, and data security; the second conference addressed disaster response and disaster modeling.

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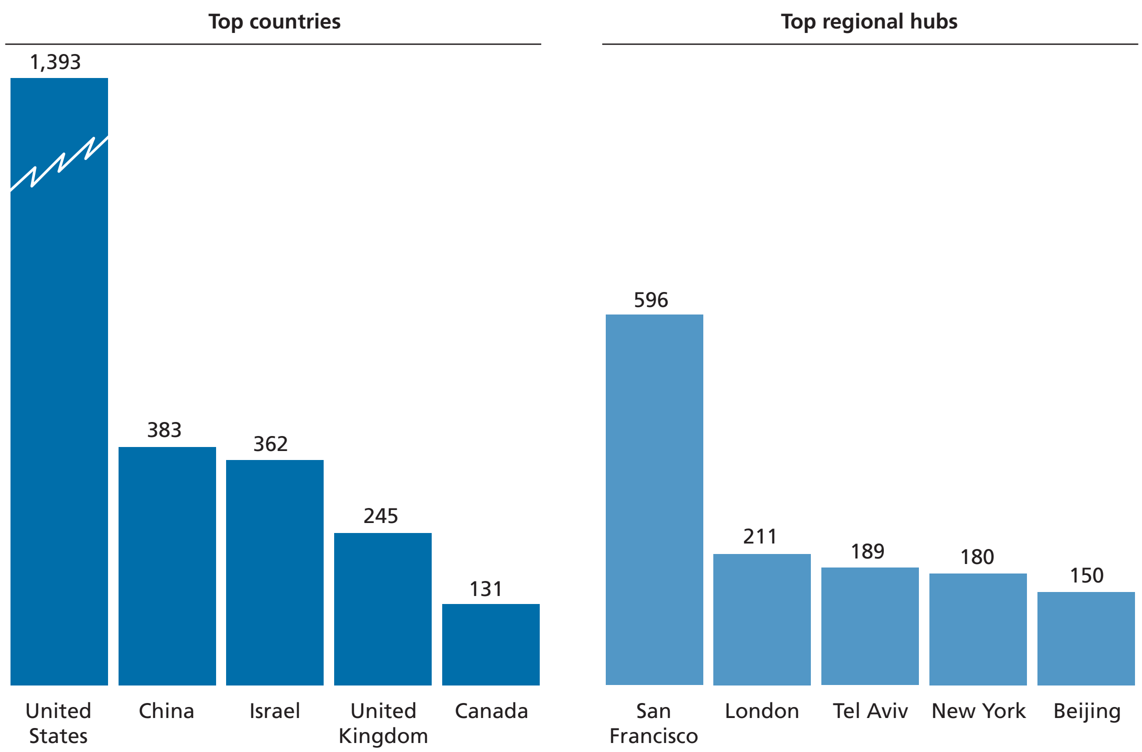
These conference proceedings capture insights from the two conferences, recount some of the exchanges among the participants at those sessions, and are built around the papers that the conference presenters submitted after the conferences concluded.

Shortly after these conferences, the coronavirus disease 2019 (COVID-19) pandemic exploded onto the world stage. In both the United States and Japan, AI has been a part of the effort to respond. For example, the National Institutes of Health has developed algorithms to detect, track, and diagnose COVID-19 and has employed AI in the formulation of personalized therapies.[1] Japan has sought to employ AI to reduce risks for on-site factory workers doing such jobs as quality control.[2] Many other applications have also been explored as part of the COVID-19 response, but these efforts generally occurred in the months after the conclusion of the conferences described in these conference proceedings, so they are not explored further here.

In recent years, there has been an explosion of interest in AI worldwide, including in the United States and in Japan. According to one report comparing countries, the United States has focused more on software; Japan has focused more on developing applications for robotics and hardware; and many European countries have focused heavily on applications for social services. For its part, China has raced ahead of both Japan and the European Union and now trails only the United States in AI start-ups (see Figure 1.1).[3]

Figure 1.1
The Race for Global Leadership in Artificial Intelligence Start-Ups



SOURCE: Roland Berger and Asgard, *Artificial Intelligence—A Strategy for European Startups: Recommendations for Policymakers*, Munich, Germany, 2018.

[1] National Institute of Biomedical Imaging and Bioengineering, National Institutes of Health, "NIH Harnesses AI for COVID-19 Diagnosis, Treatment, and Monitoring," press release, August 5, 2020.

[2] Naomi Tajitsu and Makiko Yamazaki, "Japan Looks to AI as Coronavirus Challenges Go-and-See Control Mantra," Reuters, August 30, 2020.

[3] Guillermo Garcia, *Artificial Intelligence in Japan: Industrial Cooperation and Business Opportunities for European Companies*, Brussels, Belgium: EU–Japan Centre for Industrial Cooperation, 2019.

For many experts in the field, the term "artificial intelligence" has been overused, misused, and abused, often for the purpose of attracting attention to an article or selling a book or product. To lay the groundwork for the discussion that follows in the rest of these conference proceedings, this introductory chapter lays out some basic terminology and a thumbnail history of the evolution of the field of AI; explains why AI is more widely applied today and why, as a consequence, the assessments offered up in these conference proceedings are likely to give some insights and indications of possible future trends; and identifies some of the relevant dimensions of U.S. and Japanese applications of AI going forward and policy issues associated with those applications.

A Brief History of Artificial Intelligence

One of the defining characteristics of human beings is their ability to use tools and technology to solve problems. Throughout history, people have sought ways to manipulate their environments, both manually and mentally, in ways that make work easier and lives healthier and safer. The industrial, quantum, and information revolutions that unfolded in the early to middle decades of the 20th century came together to produce a situation over the past seven decades in which it began to be possible to ask whether one could build a machine that could think independently. Mid-20th-century researchers—such as Alan Turing, Claude Shannon, John von Neumann, Marvin Minsky, and others—began thinking about what a computer program would need in terms of information, language processing, and programming capabilities to be able to program and reprogram itself responsively in light of new information. Such a machine would constitute an *artificial intelligence*, so labeled by researchers at a 1956 Dartmouth conference on advances in computing and information sciences. Turing later devised a test to evaluate whether a machine could truly think, arguing that it if could simulate responses to questions posed by a human to such a high degree of accuracy that the human interacting with it could not tell that it was a machine, then the computer could be said to have genuine intelligence (what later came to be described as *artificial general intelligence*, contrasted with AI that might supersede human capabilities, or *artificial superintelligence*).

The field entered a lull that is generally referred to as its first "AI winter" in the mid-1970s, after it failed to advance as quickly as some governments (particularly those of the United States and United Kingdom), funders, and research scientists had anticipated.

Coming out of the downturn in interest, those computer scientists who had stuck with the field throughout the 1970s and early 1980s sought to devise symbolic representations of the world, problems, and relationships, described as *symbolic AI* or *expert systems* approaches to the subject (sometimes described as *good old-fashioned AI*—or GOFAI—a term coined by John Haugeland in his 1986 book, *Artificial Intelligence: The Very Idea*[4]). Although these approaches initially appeared promising, they ultimately foundered on the recognition that top-down designs intended to model the world as a series of "if–then" statements cannot progress much farther than solving simple problems; they certainly cannot develop genuine reprogrammability and reconfigurability as truly autonomous and human-level intelligence requires. As a consequence, the field endured a second AI winter from the mid-1980s through the mid-1990s—funding streams again dried up, interest in the subject fell, and skepticism about its prospects surged.

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[4] John Haugeland, *Artificial Intelligence: The Very Idea*, Cambridge, Mass.: MIT Press, 1986.

By the late 1990s, researchers who stuck with AI through that second winter largely shifted from a top-down approach to a ground-up model of machine learning (ML) premised on the notion of surfacing relationships among data through trial and error modeled on neural networks intended to approximate the human brain. Some leading physicists, evolutionary biologists, and philosophers of mind also see this approach as promising.[5] By the early decades of the 21st century, AI was once again seen as having bright prospects, with continued improvements in semiconductor processing speeds and enormous growth in databases (*big data*) attendant on the networking of a wide variety of devices in an Internet of Things.[6] Some, however, point to the previous AI winters and caution against excessive expectations, expressing a preference for the terms ML or *augmented intelligence* as a way to signal that much work remains to be done before artificial general intelligence becomes even remotely realistic.[7] They note that AI/ML technologies usually require large, coded data sets; vast computing power; and a programmed set of relationships and weightings or distances to be measured between values in the data set, at which point an algorithm or algorithms (a mathematical equation or set of such equations) calculates a variety of interrelationships and seeks to identify previously unrecognized patterns in the data. For many such observers, it is most realistic to think of AI/ML as tools that humans will employ rather than "Life 3.0"—or, even more ominously, "our final invention."[8]

Many societies across the ages have harbored concerns about the impact of technology, worrying that it might lead to mass unemployment and job destruction. The Luddites of 19th-century England are among the most-prominent examples of opposition to blind faith in technology divorced from consideration of its social impact. Others have expressed fears about bias in data coding that might entrench pre-existing social discrimination and lend it a patina of scientific or "objective" authority. On a more cosmic scale, the telling of cautionary tales about technology that slips the bounds of control and turns malevolent can be found in myths (the Golem of Prague), children's fantasies (Disney's *The Sorcerer's Apprentice*); Hollywood films (*2001: A Space Odyssey*, *Tron*, *Her*, and *I Am Mother*), television series (HBO's *Westworld*—as evolved from the original novel by Michael Crichton and the movie with Yul Brynner), and novels (William Gibson's *Neuromancer* and Dan Simmons's *Hyperion Cantos*). Over the past decade, even leading thinkers, such as Stephen Hawking and Elon Musk, have warned about the risks posed by AI.[9] Where does the truth lie between these reassuring imaginings of AI as a technological savior and nightmare visions of a future of robotic AI overlords enslaving or exterminating humanity?[10]

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5 Max Tegmark, *Life 3.0: Being Human in the Age of Artificial Intelligence*, New York: Vintage Books, 2017; Daniel C. Dennett, *From Bacteria to Bach and Back: The Evolution of Minds*, New York: W. W. Norton & Co., 2017.

6 The *Internet of Things* refers networked devices embedded with technologies for the purpose of connecting and exchanging data over the Internet.

7 World Science Festival, "Making Room for Machines: Getting Ready for AGI," YouTube, March 27, 2020.

8 Tegmark, 2017; James Barratt, *Our Final Invention: Artificial Intelligence and the End of the Human Era*, New York: Thomas Dunne Books, 2013.

9 Rory Cellan-Jones, "Stephen Hawking Warns Artificial Intelligence Could End Mankind," BBC, December 2, 2014; Connor Forrest, "Musk: 'AI Is Far More Dangerous Than Nukes,' Needs Regulation," *TechRepublic*, March 12, 2018.

10 Discussions of AI in the popular media also frequently focus on concerns about ensuring that rules are in place to guard against the emergence of a technological singularity or superintelligence. For example, see George Dvorsky, "Preparing for Catastrophically Dangerous AI—And Why We Can't Wait," *Gizmodo*, December 5, 2018; and Stuart Russell, "How to Stop Superhuman A.I. Before It Stops Us," *New York Times*, October 17, 2019.

To ground the discussion in fact-based analysis, it is helpful to remember that the images, aspirations and fears in the aforementioned fictional works reflect not only society's debates about and past experiences with technology but also human relationships. For the United States and Japan, these debates have differed quite substantially, suggesting that a cross-national, sociological approach to understanding some of the policy issues and technology prospects associated with AI might be appropriate.

AI for Social Good

The debate continues about whether artificial minds, a technological *singularity* (the moment when a notional AI slips the bounds of human control),[11] or even superintelligence (AI capable of thought that vastly exceeds even the smartest human beings)[12] are on the horizon. Meanwhile, ML applications that are more practical (if more mundane) are being created and put to use today in ways that are already reshaping lives, with consequences that are both advantageous and, at times, destabilizing. In the view of AI ethicist David Danks of Carnegie Mellon University, the goal for society as it begins to employ AI more broadly and at a day-to-day level should not just be to increase productivity or profitability; to undertake routine, boring, or dangerous tasks; or to sort through volumes of data that human minds are incapable of processing to find valuable insights—the goal should be to do those things in a way that also enhances human well-being.[13] Such "AI for social good," as Anna Bethke, Head of AI for Social Good at Intel, has described it, aims to "positively impact the well-being of people, animals, or [even] the planet."[14] Bringing social justice concerns into the discussion enables a critical pivot away from speculative or highly technical questions about the future of the technology and life itself and toward issues more germane to solving real-world problems while avoiding catastrophically damaging democracy by transforming "work, wealth and the social order," as Barnhizer and Barnhizer have warned.[15]

A small sampling of recent developments finds AI being employed not merely to help identify music or books that one might wish to purchase or listen to next on a website but also to accelerate trades on Wall Street (with the consequence of eliminating high-paying finance jobs)[16] and to select parts for repair on air conditioning units in Japan (with consequences for lower-end mechanical repair positions).[17] It is being used for tasks as cosmological as classifying galaxy images from the Hubble Space Telescope and as down in the dirt as analyzing crop

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[11] Vernor Vinge, "The Coming Technological Singularity: How to Survive in the Post-Human Era," VISION-21 Symposium, conference proceedings, Westlake, Ohio: NASA Lewis Research Center and the Ohio Aerospace Institute, December 1, 1993.

[12] Nick Bostrom, *Superintelligence: Paths, Dangers, Strategies*, Oxford, United Kingdom: Oxford University Press, 2014.

[13] ITU, "AI for Good 2018 Interviews: David Danks, Professor, Carnegie Mellon University," YouTube, May 16, 2018.

[14] Anna Bethke, "What Do AI for Social Good Projects Need? Here Are 7 Key Components," *ITU News*, March 29, 2019.

[15] David Barnhizer and Daniel Barnhizer, *The Artificial Intelligence Contagion: Can Democracy Withstand the Imminent Transformation of Work, Wealth and the Social Order?* Atlanta, Ga.: Clarity Press, 2019.

[16] Jack Kelly, "Artificial Intelligence Is Superseding Well-Paying Wall Street Jobs," *Forbes*, December 10, 2019.

[17] Aki Fukuyama, "Air Conditioner Manufacturer Taps AI to Choose Parts for Repair," *Asahi Shimbun*, July 19, 2019.

yields and the best timing for precision watering, fertilization, and harvesting.[18] In Japan, AI is being employed in child care and elder care alike as a technical solution in support of an aging, shrinking population that is still uncomfortable with the prospect of substantially expanded immigration but needs more labor power.[19] In health care specifically, AI is increasingly being employed to scan basic radiology images; this frees radiology technicians to focus more closely on difficult cases in which too few examples of a disease exist for patterns to have formed in large data sets. AI is also used to accelerate early diagnoses of sepsis (the 11th leading cause of death in the United States, claiming up to 250,000 lives a year)—a condition in which the multiple factors at play can often stymie even the best doctors until it is too late.[20] In the field of disaster prediction, preparedness, and response, municipalities are increasingly turning to private-sector AI start-ups that promise to improve transparency and resource allocation. Whether such high-tech solutions to disaster response end up being too good to be true or simply improve over time remains to be seen; it is certainly true that deploying AI technologies in several arenas will require substantial policy regulations and supports to ensure safety and effectiveness.[21]

As these examples make clear, however, in some cases, AI will have varying effects. It will be a cause of job loss in some fields but will replace missing labor in other sectors of the workforce. It promises to improve or even save lives, enabling those who use it to be safer, more productive, and more effective. These technologies have matured to the point where they are beginning to affect the broad economies and societies of both the United States and Japan, and the two countries have moved to lay out clear policy visions and guidelines in these areas.

Japan was first out of the gate, publishing its national *Artificial Intelligence Technology Strategy* on March 31, 2017.[22] Noting that AI is beginning to reshape society and can help address human suffering, the strategy lays out a pathway to 2030 whereby these technologies will be used to "supplement human beings." Describing AI as part of a "Fourth Industrial Revolution," the report notes the prospect for impact on work (see Chapter Two of these conference proceedings), calls for a key focus on AI in health care (Chapter Three), and pays specific attention to issues data protection (Chapter Four). The Japanese strategy, which was an extension of the Strategic Council for AI Technology established in 2016, also called out the shortage in Japan's AI specialized workforce and identified three centers for Japan's AI revolution—the Center for Information and Neural Networks and the Universal Communications Research Institute at the National Institute of Information and Communications Technology, the Center for Advanced Intelligence Projects at the Institute of Physical and Chemical Research (RIKEN), and the Artificial Intelligence Research Center of the National Institute of Advanced Industrial Science and Technology.

Two years later, in February 2019, the United States put forward its own official policy document, *Artificial Intelligence for the American People*, which laid out the Trump adminis-

18 "AI Classifies Galaxies Using Hubble Space Telescope Images," Nvidia Developer News Center, April 24, 2018; Kathleen Walch, "How AI Is Transforming Agriculture," *Forbes*, July 5, 2019.

19 "With Help from Robots, Nursery Teachers Have More Time to Focus on Children," *Sankei Shimbun*, May 13, 2019; "Can AI Play a Useful Role in Nursing Care? This Tokyo Start-Up is Leading the Way," *Forbes*, December 19, 2018.

20 Mayo Clinic, "Artificial Intelligence in Medicine: Mayo Clinic Radio," November 10, 2019; Suchi Saria, "TedXBoston: Better Medicine Through Machine Learning," YouTube, October 12, 2016.

21 Sheri Fink, "This High-Tech Solution to Disaster Response May Be Too Good to Be True," *New York Times*, August 9, 2019.

22 Strategic Council for AI Technology, *Artificial Intelligence Technology Strategy*, Japan, March 31, 2017.

tration's vision of how to guide the development of AI technologies.[23] The very first sentence of that document began by noting that "the age of artificial intelligence has arrived, and is transforming everything from health care to transportation to manufacturing." The Executive Order on AI focused on an approach characterized as a "whole of government strategy in collaboration and engagement with the private sector, academia, the public and like-minded international partners." Noting the wide variety of public statements, panels, and studies on AI that have been issued over the past half-decade by the U.S. government, the policy particularly highlights the need for

> continued long-term investments in AI; effective methods for human-AI collaboration; understanding and addressing the ethical, legal, and societal implications for AI; ensuring the safety and security of AI; developing shared public data sets and environments for AI training and testing; measuring and evaluating AI technologies through standards and benchmarks; better understanding the National AI R&D workforce needs; and expanding public-private partnerships to accelerate AI advances.

In deploying such systems, the United States has also laid out a set of guiding principles or standards for AI that it is seeking to promote, including making sure that systems that employ AI are "reliable, robust, trustworthy, secure, portable, and interoperable." In seeking to advance the goal of transparency in AI decisionmaking, the Defense Advanced Research Projects Agency has launched a research program on *explainable artificial intelligence*, or AI that can account clearly for its outputs so that users can determine how an assessment, adjudication, or outcome was reached and whether any bias, error, or other problematic input was introduced, skewing the output.[24]

As the foregoing review makes clear, U.S. and Japanese researchers and policymakers are actively thinking about how to employ AI technologies, what the impact of such technologies is likely to be, how to channel or constrain such impacts to ensure that they produce the desired kind of society, and what supporting policies and regulations are necessary to ensure desired outcomes. There are substantial overlaps in the approaches taken by the U.S. government and the Japanese government—particularly in terms of prioritizing data security and privacy and in terms of recruitment and retention of AI talent. The approaches also have significant differences: One key area is the extent to which Japan's government envisions AI as leading to "Society 5.0," while the U.S. approach is focused on more-granular and less-grandiose questions of how to apply these new technologies. As the two countries' approaches evolve and interact, there are likely to be many areas of commonality and policy overlap where the two sides can learn from each other and possibly even work together.

The following chapters in these conference proceedings explore these questions in greater depth and offer opinions and analysis from leading U.S. and Japanese experts who spoke at the conferences that RAND organized on these subjects.

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[23] The White House, "Artificial Intelligence for the American People," webpage, 2019.

[24] Matt Turek, "Explainable Artificial Intelligence (XAI)," Defense Advanced Research Projects Agency, undated.

Chapter Summaries

In Chapter Two, Osonde Osoba of RAND argues that, rather than discussing the impact of AI and robotics on the "future of work,"[25] it might be more useful to think in terms of "tasks," with AI eliminating some, enhancing the effectiveness of human partners in others, and creating a need for new ones (and sometimes entire categories of jobs). Osoba notes that the reaction to AI and the national-level discussions about technologies can tend to be highly specific or historically embedded, even without participants' being aware that they are so—with the consequence that these outlooks can appear to be universal until one compares across societies. As a consequence of Western narratives about technology, for example, Americans have tended to be more concerned about negatives and downsides, whereas, in Japan, the emphasis has been more on technologies, including AI, as solutions to problems. Additionally, as Japan's working-age population declines, job loss to robots and algorithms might be less of a concern than in the United States, where fears of a disruption to the labor force, at least prior to the outbreak of COVID-19, tended to focus more on technological displacement.

Turning next to the impact of AI on health, in Chapter Three, Ritika Chaturvedi of the University of Southern California finds that the move to embrace electronic health records in recent years has enabled rapid growth in the kinds of codable data sets that AI/ML algorithms require to surface patterns in personal health information. This, in turn, is fueling an explosion of interest in personalized health treatments, or *precision medicine*. Although still in a nascent stage, such a shift would see the medical profession move away from an approach in which treatments are based on one-size-fits-all interventions that work for the average patient and toward a regime in which medical interventions will be precisely tailored to the specific individual. For a true shift to precision medicine to come about in the coming decade, however, issues of cost-effectiveness, equity and diversity, clinical adoption and accessibility, implementation, data and privacy, and evaluation will need to be worked through.

In Chapter Four, Suga Chizuru of the Davos World Economic Forum on the Fourth Industrial Revolution Japan picks up on the theme of data, privacy, and the public good. She argues that taking fullest advantage of the opportunities for advancing human well-being that AI presents requires development of a framework for managing data flows and sharing needs. She examines one such potential policy guide for balancing concerns about privacy with the need for aggregated (if depersonalized) data to achieve social good (a Japanese government initiative called Data Free-Flow with Trust), arguing that this approach holds great promise to protecting and balancing individual equities, leveraging private-sector incentives, and achieving positive social outcomes.

Employing AI for disaster prediction, resilience, and recovery is yet another application that could see major advances in the coming decade. In Chapter Five, Greg Brunelle of the technology firm One Concern describes the challenges that risk assessors, disaster managers, and first responders must address. Many firms and institutions might secure their own systems but struggle to understand the extent to which their broader security is dependent on a series of underlying extended and interrelated networks that are not under their control, such as electric power grids, wastewater treatment systems, and transportation networks. He describes how the rise of big data about storms, systems of critical infrastructure, and person-level information and behavior patterns has allowed properly configured AI algorithms to enhance prediction, improve asset alloca-

[25] Darrell M. West, *The Future of Work: Robots, AI, and Automation*, Washington, D.C.: Brookings Institution Press, 2018.

tion for preparedness, use incoming data to adapt on the fly during an unfolding disaster, and increase the likelihood of more-effective and accelerated recovery after disaster.

In Chapter Six, Jeffrey Hornung of RAND looks at the experience of Japan during the March 11, 2011 earthquake, tsunami, and nuclear disaster, and identifies several ways that AI might be usefully employed in a similar situation in Japan or the United States in the future. Mindful of the fact that much of the damage caused by the "triple disaster" was in the form of the tsunami that slammed ashore in the wake of the earthquake, he explores specific applications of AI to managing large-scale water disasters. Other coastal communities—such as New Orleans (Hurricane Katrina in 2005), New York (Hurricane Sandy in 2012), Houston (Hurricane Harvey in 2017), and Puerto Rico (Hurricanes Irma and Maria in 2017)—have suffered similar flooding disasters in the form of storm surges and/or broken levees. If AI can be married with real-time atmospheric and oceanographic sensors, dynamic forecasting models, and profiles of local persons (and perhaps even reinforced with data sets from wearable Wi-Fi–enabled technology), it might be possible to quickly and effectively update alert zones, open pathways for first responders, find and prioritize response efforts, and save lives. Such advances could be particularly welcome in such coastal states as Louisiana, where RAND, in the wake of Hurricane Katrina in 2005, set up its Gulf States Policy Institute in New Orleans and has subsequently done substantial work aimed at helping support the state's flood risk and resilience program.[26]

In Chapter Seven, Shunichi Koshimura of Tohoku University and RTi-cast adds valuable insights from Japan's own experience of leveraging AI/ML technologies to forecast propagation of tsunamis resulting from undersea earthquakes along the coast of Japan. Noting that real-time forecasting using AI/ML algorithms has advanced rapidly in recent years, he calls attention to the particular danger of a massive quake along the Nankai Trough near Tokyo and Yokohama and urges the Japanese government to focus more resources on preparing against such a catastrophe, including by engaging such firms as RTi-cast.

Chapter Eight concludes these conference proceedings with a review of some of the key issues identified in the papers and in the presentations at the two conferences, highlighting important themes for future analysis by policy researchers interested in understanding the questions that decisionmakers must address in seeking to leverage AI for social good.

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[26] RAND Corporation, "About the RAND Gulf States Policy Institute," webpage, undated; David G. Groves, Kenneth Kuhn, Jordan R. Fischbach, David R. Johnson, and James Syme, *Analysis to Support Louisiana's Flood Risk and Resilience Program and Application to the National Disaster Resilience Competition*, Santa Monica, Calif.: RAND Corporation, RR-1449-CPRA, 2016.

CHAPTER TWO

AI and Labor Automation: A Cross-Cultural Assessment

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Technology creation (loosely speaking, involving toolmaking and tool use) has been a defining aspect of society. Societies and their embedded technologies co-evolve in the sense that societies adopt technologies and are, in turn, shaped by them. The fortunes of various civilizations changed substantially as they progressed from the Stone Age through the Iron Age as a result of technological creation and innovation. History is replete with examples of transformational technologies that had deep consequences for the societies that adopted them, ranging from agriculture and crop cultivation to the wheel, the printing press, gunpowder, and nuclear power. Some of these technologies were radical shifts that produced hard-to-predict downstream societal impacts.[1]

At the moment, the deployment of a broad class of advanced information processing technologies, broadly grouped under the label of *artificial intelligence*, or AI, is in the process of modifying operations and decisionmaking in almost every dimension of human society.[2] AI technologies have been deployed in fields as varied as health and medical technology, education, defense, and transportation.[3] It is, again, hard to predict the downstream effects of this technology-

1 Joel Mokyr, Chris Vickers, and Nicolas L. Ziebarth, "The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different?" *Journal of Economic Perspectives*, Vol. 29, No. 3, 2015.

2 I resist the temptation to attempt a crisp definition of AI beyond suggesting that it consists of simple or complex artificial tools for solving intelligence and/or information tasks. Some recent works that offer more-detailed discussions of AI definitions include Marvin Minsky, *Proceedings of the IRE [Institute of Radio Engineers]*, Vol. 49, No. 1, January 1961; Nils J. Nilsson, *Artificial Intelligence: A New Synthesis*, San Francisco, Calif.: Morgan Kaufmann Publishers, 1998; Stuart J. Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach*, Kuala Lumpur, Malaysia: Pearson Education Limited, 2016; and Osonde A. Osoba and William Welser IV, *The Risk of Artificial Intelligence to Security and the Future of Work*, Santa Monica, Calif.: RAND Corporation, PE-237-RC, 2017.

3 Varun Gulshan, Lily Peng, Marc Coram, Martin C Stumpe, Derek Wu, Arunachalam Narayanaswamy, Subhashini Venugopalan, Kasumi Widner, Tom Madams, Jorge Cuadros, et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," *Journal of the American Medical Association*, Vol. 316, No. 22, 2016; Robert F. Murphy, *Artificial Intelligence Applications to Support K–12 Teachers and Teaching: A Review of Promising Applications, Challenges, and Risks*, Santa Monica, Calif.: RAND Corporation, PE-315-RC, 2019; Danielle C. Tarraf, William Shelton, Edward Parker, Brien Alkire, Diana Gehlhaus, Justin Grana, Alexis Levedahl, Jasmin Leveille, Jared Mondschein, James Ryseff, Ali Wyne, Dan Elinoff, Edward Geist, Benjamin N. Harris, Eric Hui, Cedric Kenney, Sydne Newberry, Chandler Sachs, Peter Schirmer, Danielle Schlang, Victoria M. Smith, Abbie Tingstad, Padmaja Vedula, and Kristin Warren, *The Department of Defense Posture for Artificial Intelligence: Assessment and Recommendations*, Santa Monica, Calif.: RAND Corporation, RR-4229-OSD, 2019; Maria Lopez Conde and Ian Twinn, *How Artificial Intelligence Is Making Transport Safer, Cleaner, More Reliable and Efficient in Emerging Markets*, Washington, D.C.: International Finance Corporation, Emerging Markets Compass No. 75, November 2019.

induced structural shift in our complex societies. But this prediction task is precisely what is needed if our aim is to assure the welfare of individuals and the stability of our societies.

What is the effect on the future supply of human jobs if AI and automation become increasingly capable of doing human work? Concerns about the *future of work* are pressing because most societies are organized around citizens earning their sustenance and livelihoods through either manual or mental labor (or both). In addition to the purely economic calculus, a separate dimension of the problem is that many people derive a substantial degree of meaning and self worth from the work that they do. In light of these considerations, questions about the impact of AI and automation on the future of work begin to take on existential hues.

Some economists have argued that, left unresolved, future-of-work issues will tend to spill over and affect political stability. For example, Alice Rivlin of the Brookings Institution has opined that the failure to account for job losses resulting from technology changes was partially responsible for the public's outrage in the 2016 elections.[4] Others, ranging from leading academic economists to candidates for the U.S. presidency, have suggested modifying the social contract that ties individual welfare so tightly to gainful employment and put forward such strategies as a universal, unconditional basic income as a mechanism for this decoupling.[5]

Hans Moravec illustrates the concern with a metaphor of mountains and valleys: He imagines intelligence tasks lying on a notional landscape in which the cognitive difficulty of tasks is reflected by its altitude in that terrain.[6] Here, the rising competence of modern AI is akin to a rising flood. Over time, AI systems will grow to be competent at many lowland and hilltop tasks. Will they reach the mountain peaks? Are there tasks in this landscape that will always require human skill? In short, is there any refuge for humans in this rising flood of machine intelligence?

This chapter provides an examination of three aspects of the future-of-work question:

1. What does the literature suggest about the overall interaction between the landscape of occupations and automation?
2. What are the distributional impacts of job automation likely to be?
3. How do publics in different countries perceive and react to labor automation concerns (with reference to the United States and Japan as two advanced industrial democracies)?

A More Careful Examination

Let us first take a closer critical look at the AI labor automation concern. One key observation, however banal, is that concerns about the implications of technology for job supply are very old.[7] Carl Benedikt Frey, an economic historian, gives examples of policymakers keen to prevent new technologies from automating human jobs that reach as far back as the Roman

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[4] Alice M. Rivlin, "Seeking a Policy Response to the Robot Takeover," Brookings, May 2, 2017.

[5] These run the gamut from Milton Friedman and Charles Murray to the technologist and politician Andrew Yang.

[6] Hans Moravec, "When Will Computer Hardware Match the Human Brain?" *Journal of Evolution and Technology*, Vol. 1, No. 1, March 1998.

[7] Carl Benedikt Frey, *The Technology Trap: Capital, Labor, and Power in the Age of Automation*, Princeton, N.J.: Princeton University Press, 2019; Erik Brynjolfsson and Andrew McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, New York: W. W. Norton & Company, 2014; Frank Levy and Richard J. Murnane, *The New Division of Labor: How Computers are Creating the Next Job Market*, Princeton, N.J.: Princeton University Press, 2012.

Empire under Vespasian.[8] The Luddite movement (1811–1816) is another example of social automation anxiety. Around the same time or shortly thereafter, Queen Victoria espoused protectionist policies during the Industrial Age to save human jobs.[9] A more recent, but still historical, set of concerns had to do with occupations likely to be lost in response to the spread of computers and automation.[10]

Many such historical responses reveal a propensity to focus on job displacement in basic future-of-work analyses. Both words in that phrase—*job* and *displacement*—are key concepts that require parsing. There is a focus on which *whole* jobs or occupations are at risk of (or susceptible to) automation,[11] along with an assumption that automation necessarily leads to human workers being displaced. For example, when researchers report that new AI systems can perform medical image diagnosis better than humans, the natural follow-up under this mental model is an analysis of how many radiologists will be displaced. However, this default mental model elides many important questions and details about how technology affects the supply of jobs for people. Next, we explore a few sources to update this mental model of the future-of-work question.

A Task-Based Reframing

Jobs or occupations are almost never conceptual monoliths. Most jobs require the exercise of diverse faculties in the execution of a diverse array of tasks.[12] Furthermore, contemporary models of automation (especially via AI or machine learning) do not tend to perform the full set of subtasks in an occupation.[13] Thus, models of automation's effects on jobs that conceive of occupations as monoliths are unlikely to be sufficiently detailed to capture all the relevant degrees of freedom and impacts on employment. Many occupations also feature an inarticulable task coordination function—i.e., rules for when and how to switch among subtasks. This coordination or planning function renders occupations more than just the sum of their subtasks. Other unarticulated aspects of occupations are interpersonal trust, accountability, or liability roles. Human agents often have legally sanctioned roles as bearers of accountability in many occupations (e.g., a doctor or civil engineer). Technological artifacts, specifically AI systems, cannot yet bear legal responsibility in any meaningful way,[14] and it is unclear whether or when they ever will be able to do so.

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[8] Frey, 2019.

[9] Brynjolfsson and McAfee, 2014.

[10] Paul Armer, *Computer Aspects of Technological Change, Automation, and Economic Progress*, Santa Monica, Calif.: RAND Corporation, P-3478, 1966.

[11] For example, see Carl Benedikt Frey and Michael A. Osborne, "The Future of Employment: How Susceptible Are Jobs to Computerization?" *Technological Forecasting and Social Change*, Vol. 114, 2017; Jae Hee Chang, Gary Rynhart, and Phu Huynh, *ASEAN in Transformation: How Technology Is Changing Jobs and Enterprises*, Switzerland: Bureau for Employers' Activities, International Labour Office, Working Paper No. 10, 2016.

[12] David H. Autor, "The 'Task Approach' to Labor Markets: An Overview," *Journal for Labour Market Research*, Vol. 46, 2013; Osoba and Welser, 2017.

[13] Andrew Ng, "What AI Can and Can't Do," *Harvard Business Review*, November 9, 2016.

[14] Joanna J. Bryson, Mihailis E. Diamantis, and Thomas D. Grant, "Of, For, and By the People: The Legal Lacuna of Synthetic Persons," *Artificial Intelligence and Law*, Vol. 25, No. 3, 2017.

Other Modes of Occupational Impact

Labor displacement is not the only way in which technology and automation can affect the labor market. Acemoglu and Restrepo highlight a few alternative modes of effect, noting that, besides displacement, technology can improve the productivity of workers, create completely new tasks and occupations, and/or modify the value of some human tasks.[15] For example, the advent of the personal computer might have displaced some typists or secretaries, but it also improved the productivity of a wider set of workers. Similarly, the rise of AI has created novel jobs, such as AI researchers, data scientists, and even gig workers supported by tech-powered platforms. The rise of AI has also increased the value of human cognition tasks—e.g., data labeling tasks on Amazon's Mechanical Turk or reCAPTCHA vision tasks.[16]

The expanded view of the effects of automation paints the outcome less as a zero-sum game between tech and workers and more as a potentially positive-sum game. This model also has more historical explanatory power. We have yet to see the widespread runaway unemployment that a displacement-only model would predict, given the explosion of technologies in the past half-century.

Differential Population Effects

Developing a better understanding of how occupations are constituted is important because it gives us better insight into how work evolves in response to rising AI-enabled automation. Also important is understanding how impending labor market shifts differentially affect workers in different parts of society. A positive-sum future-of-work outcome can still be destabilizing (even disastrous) if the benefits in jobs and income are disproportionately distributed in ways that fuel social strife.

The evidence suggests that automation has not and will not affect all societal strata equally. Scholarship over the past decade and a half has highlighted two trends relevant to distribution outcomes. The first is the question of job polarization.[17] When jobs are displaced by automation or lost during economic decline, the job losses are not equally borne across the skill spectrum; rather, there is a differential susceptibility to job loss, with middle skill jobs being the most susceptible to loss and most resistant to recovery. Research suggests that such middle-skill job loss is primarily because of direct displacement by technology.[18]

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[15] Daron Acemoglu and Pascual Restrepo, *Artificial Intelligence, Automation and Work*, Cambridge, Mass.: National Bureau of Economic Research, Working Paper 24196, 2018.

[16] CAPTCHA is a somewhat forced acronym for "completely automated public Turing test to tell computers and humans apart." It refers to a type of challenge–response test to determine whether the user is human. reCAPTCHA is a version of a CAPTCHA service offered by Google.

[17] Nir Jaimovich and Henry E. Siu, *The Trend Is the Cycle: Job Polarization and Jobless Recoveries*, Cambridge, Mass.: National Bureau of Economic Research, Working Paper 18334, 2012; David H. Autor, Lawrence F. Katz, and Melissa S. Kearney, "The Polarization of the U.S. Labor Market," *American Economic Review*, Vol. 96, No. 2, 2006.

[18] Autor, 2013.

The second differential effect is the declining share of returns to labor compared with returns to capital.[19] This suggests more than just that firms are replacing workers with tech (i.e., capital); it implies that capital owners will capture a growing share of any economic growth.

Another differential effect of growing concern is related to the status and protection of the growing gig-working class. Discussions of gig work point to such trends as the growing gig-working population and fewer legal protections for gig workers than for standard workers. For example, Cherry examines the novel legal issues associated with *virtual work*, a subset of gig work that focuses on episodic labor engagements executed away from direct supervision (e.g., workers on the Amazon mechanical Turk platform and virtual gold farmers).[20] Irani explores the differentiation in social valuation of work for *microworkers* (crowdsourced temporary labor, including virtual labor) compared with those who are regularly employed.[21] More recently, Wood and colleagues surveyed gig workers across two continents and reported the exposure of these workers to insecurity resulting from an absence of labor regulations and rights.[22]

The United States and Japan: The Role of Culture in Explaining Reactions to AI

Many of the points in the preceding sections reflect a particularly U.S.-centric perspective. Rising competent and intelligent automation is a global phenomenon, and different societies have not necessarily responded to these phenomena in the same way that U.S. society has. Some interesting insights can be gained by comparing the differences between the debates over AI in the United States and in Japan.

First, demographic considerations represent an important context for how the two societies are responding to the potential impact of AI on work. Japan is an aging society with one of the highest life expectancies in the world. The total fertility rate is below the replacement rate of 2.1 percent. The United States has a slightly higher total fertility rate (though still sub-replacement) that it augments with a relatively high immigration rate. However, the United States features a shorter life expectancy. There is also significantly more ethnic diversity in the United States. Overall, U.S. society is younger and more diverse than Japanese society. Furthermore, the United States experiences generally higher levels of unemployment. The combination of lower unemployment and an older population might help explain the comparatively lower levels of job displacement anxiety in Japan.[23]

A separate difference worth noting is in public perspectives about technology and automation. The last AI winter of the 1980s in the United States was an important critical juncture:[24]

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[19] Loukas Karabarbounis and Brent Neiman, "The Global Decline of the Labor Share," *Quarterly Journal of Economics*, Vol. 129, No. 1, 2013.

[20] Miriam A. Cherry, "A Taxonomy of Virtual Work," *Georgia Law Review*, Vol. 45, No. 4, 2010.

[21] Lilly Irani, "The Cultural Work of Microwork," *New Media & Society*, Vol. 17, No. 5, 2015.

[22] Alex J. Wood, Mark Graham, Vili Lehdonvirta, and Isis Hjorth, "Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy," *Work, Employment and Society*, Vol. 33, No. 1, 2019.

[23] Gillian Tett, "Why Japan Isn't Afraid of Robots," *Financial Times*, June 12, 2019; Christopher Mims, "Why Japanese Love Robots (And Americans Fear Them)," *MIT Technology Review*, October 12, 2010.

[24] Drew McDermott, M. Mitchell Waldrop, B. Chandrasekaran, John McDermott, and Roger Schank, "The Dark Ages of AI: A Panel Discussion at AAAI-84," *AI Magazine*, Vol. 6, No. 3, 1985; James Hendler, "Avoiding Another AI Winter," *IEEE Intelligent Systems*, Vol. 3, No. 2, 2008, pp. 2–4.

Funding and research activity on AI technologies dried up, arguably partially as a result of the U.S. Defense Advanced Research Projects Agency (DARPA, the key U.S. AI research funder at the time) being less than satisfied with the returns on its research investments. However, this AI winter was *not* an international retrenchment on all AI activities. For example, while the AI environment in the United States languished in the wake of DARPA's drawdown on funding, researchers in the Soviet Union pressed on with foundational AI research.[25] Some important players in the Soviet space at the time were Yakov Tsypkin, Vladimir Vapnik, Alexey Chervonenkis, and Alexander Galushkin.[26]

At the same time, Japan did more than press on during the 1980s: It doubled down on AI by making huge investments on a strategic vision referred to as the "fifth-generation computer," which was envisioned to be based on symbolic AI.[27] Japan went on to become a world leader in the implementation of cutting-edge symbolic AI systems (e.g., fuzzy logic systems). Many of the electronics it would go on to export to the United States contained fuzzy logic intelligence, and Japanese control systems for trains also used these innovations.

Unfortunately, symbolic expert AI systems proved limited in performance compared with the neural network–based (or connectionist[28]) systems that are now the basis of deep-learning systems. Symbolic systems do not scale as easily, and they are more expensive to train because they rely on access to appropriately elicited direct human expertise. Neural network systems, on the other hand, scale as fast as the computing technology will allow and depend mostly on access to cheaper data for training. Computing has grown at an exponential rate so far, and the growth of the data ecosystem has also been prodigious.

Japan's continued engagement with AI and automation appears to have fostered a more-positive perspective on AI and automation in the Japanese public. Japanese pop culture is replete with positive images of helpful robots and beneficial AI (e.g., such animated stories as *Ghost in the Shell*, *Neon Genesis Evangelion*, *Escaflowne*, and even the children's character Doraemon, a giant robot cat). In U.S. pop culture, by contrast, AI has been the subject of a virtually unbroken string of negative portrayals, from HAL9000 in Stanley Kubrick's *2001: A Space Odyssey* to portrayals of malevolent AI in *The Terminator*, *The Matrix*, *Ex Machina*, or *Avengers: Age of Ultron*. Such images undoubtedly reflect popular suspicions about and anxieties regarding AI and automation, and might even help foster them.

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[25] Donald Wunsch II, "Neural Networks in the Former Soviet Union," AIAA 9th Computing and Aerospace, conference proceedings, San Diego, Calif.: American Institute of Aeronautics and Astronautics (AIAA), October 19–21, 1993.

[26] Tsypkin, Vapnik, and Chervonenkis in particular are known for extensive work on the fundamental principles and bounds of learning systems.

[27] Edward A. Feigenbaum and Pamela McCorduck, *The Fifth Generation*, London, United Kingdom: Pan Books, 1984. In some sense, this strategic vision is similar in scale and audacity to China's recent push to become the leading AI innovation power by 2030. Japan was aiming to counter accusations similar to those leveled against China more recently: that it only copies foreign innovations and contributes nothing new (Ehud Y. Shapiro, "The Fifth Generation Project—A Trip Report," *Communications of the ACM*, Vol. 26, No. 9, 1983). The failure of the fifth-generation computer initiative also highlights a potential vulnerability in a centrally planned or directed tech innovation strategy. Such innovation strategies might not be sufficiently responsive to the limitations of the technology or the constraints of the market.

[28] The term *connectionist* refers to the fact that neural networks consist of connected collections of processing units. Furthermore, the power and efficacy of neural networks depends on the number of such connected processing units.

Potential Attitude Attributions and Further Questions

It is infeasible to extract a robust comparative theory to account for cross-cultural differences in attitude from the history of just two cases. We cannot be sure that we have a complete characterization of all relevant societal features. Even if we did, the trajectory of both societies in time (however complete) is just a single historical instance that gives us little to no (counterfactual) insight on how changes in details might have changed the outcome.[29]

We can, however, mine the historical record for insights about which variables have the most influence on attitude differences. The following factors seem potentially relevant:

1. **A Central Innovation Strategy:** Centrally directed strategies on technology innovation have a mixed record of success. Japan's Fifth Generation initiative was a failure by some accounts because it did not lead to an early economic advantage in deep learning. Closer to home, the earliest U.S. adventures in space, although nominally successful, initially served only a limited purpose: national pride. The economic windfall of space innovation (e.g., such economically valuable innovations as the Global Positioning System and tempur foam mattresses) were almost an afterthought. Supposed success or failure notwithstanding, innovation programs seem to be instrumental in socializing the public to the relevant technologies (i.e., different types of automata, space travel). Socializing the public can be useful if it leads to public discourse that is less based on fear and more informed.
2. **The Influence of Media:** Related to the function of socializing the public, the preceding section pointed out some positive depictions of AI-based automata in the Japanese media. It is also suggestive that while the U.S. media was popularizing the idea of space exploration and adventure from the 1960s through the 1980s with such television shows as *Star Trek* and *Lost in Space* and such box-office blockbusters as the *Star Wars* franchise, this was also a period when critically acclaimed films emerged that painted AI-enabled automata in a less-than-favorable light—notably such films as *2001: A Space Odyssey*, *Terminator*, and *Robocop*. Such media influenced the popular imagination considerably, and it stands to reason that negative media depictions of technology might have fueled persistent negative public images associated with AI technology in the United States today, perhaps akin to the way *Jaws* is widely credited with having shaped (and inflated) a generation of Americans' impressions of the threat posed by sharks.
3. **Philosophical Cultures:** The robot ethics scholar Naho Kitano argued that Japan's predominant spiritual tradition, Shintoism, predisposes adherents to believe in the immanence of spirits in all things—including inanimate objects, such as robots.[30] There is a greater willingness to look beyond the robot's inanimate façade for an animating spirit that can be connected with. Kitano contrasts this perspective with the focus on the primacy of humanity in Western philosophical cultures. By this account, U.S. and Japanese predispositions toward automation are unsurprising: We see a general distrust of robots in the United States and a more trusting disposition in Japan.

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[29] Feigenbaum and McCorduck, 1984.

[30] Naho Kitano, "'Rinri': An Incitement Towards the Existence of Robots in Japanese Society," *International Review of Information Ethics*, Vol. 6, 2006.

Each of these factors is only potentially (and partially) explanatory. There is more work to be done in teasing apart the factors underlying the divergence in public opinion. The stakes of such research include not only cross-cultural understanding but also culturally sensitive policymaking.

Conclusion

This chapter aimed to cast some clarifying light on the popular anxieties around the future-of-work response to AI-enabled automation. We started off with an examination, based on the current literature, of the effects of automation on the labor market. That discussion highlighted the importance of developing a more detailed picture of what occupations are (e.g., collections of subtasks, a coordination function over said tasks, a repository of human accountability). The discussion suggested that it is historically justifiable to expect positive-sum outcomes from labor automation. Assuming that outcome, what about the distribution of positive and negative impacts across a society? In response to this question, we briefly examined the differential impacts labor automation might have in a society.

There is significant nuance beyond this limited discussion on the interaction among labor, automation, and culture. For example, Sato and Morita examine how technology innovations have differentially affected Japan and the United States between 1960 and 2004.[31] They highlight key demographic differences between the two populations during the period in question, including a declining and aging population in Japan compared with a growing population in the United States. On the question of labor, Sato and Morita use models and empirical data to support their argument that much of the economic growth that Japan experienced over the period in question was attributable more to tech innovation ("quality") than to labor growth. In contrast, much of the economic growth over that period in the United States was attributable more to labor growth ("quantity") than to tech innovation. However, the findings of Sato and Morita give a limited view of the reality on the ground. For example, the two countries had very different policy responses to systemic labor concerns (e.g., how to construct safety net structures to support the unemployed and how the private sector responded to labor supply problems). Furthermore, those policy responses are arguably a reflection of differences in regulatory cultures, as argued by such scholars as Knoke and colleagues and Ebbinghaus.[32]

Finally, this chapter concludes with a comparison of attitudes toward labor automation across cultures, specifically in the United States and in Japan. The comparison is intended to cast some light on the different trajectories that technology policy concerns can take in different jurisdictions. The aim is not to present definitive findings or conclusions from the exploration. We only highlight some interesting possible factors that might have colored the public's concerns over labor automation: central innovation strategies, local media, and local philosophical cultures. Much more research is needed to qualify the contributions (if any) of factors such as these to technology policy concerns, such as labor automation.

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[31] Ryuzo Sato and Tamaki Morita, "Quantity or Quality: The Impact of Labour Saving Innovation on U.S. and Japanese Growth Rates, 1960–2004," *Japanese Economic Review*, Vol. 60, No. 4, 2009.

[32] David Knoke, Franz Urban Pappi, Jeffrey Broadbent, and Yutaka Tsujinaka, *Comparing Policy Networks: Labor Politics in the U.S., Germany, and Japan*, Cambridge, United Kingdom: Cambridge University Press, 1996; Bernhard Ebbinghaus, *Reforming Early Retirement in Europe, Japan and the USA*, Oxford, United Kingdom: Oxford University Press, 2006.

CHAPTER THREE

Artificial Intelligence, Big Data, and Precision Medicine

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Artificial intelligence (AI) provides computers with the ability to learn without being explicitly programmed, relying on algorithms to find patterns and insights from existing pools of data, which are subsequently applied to new data sets to make better and more-accurate decisions and predictions. Today, the health care industry is uniquely positioned to benefit from AI. The recent widespread adoption of electronic health records (EHRs) and low-cost genetic and biomolecular sequencing has created a wealth of medical information waiting to be mined. Combining such data with wearable devices and biosensors, patient health portals, social media, financial information, and census-based demographic data presents opportunities for hyper-personalization of prevention, treatment, and diagnosis paradigms. Many companies are beginning to recognize such untapped potential and are in the process of developing AI tools that have the potential to revolutionize many facets of biomedical research, health care delivery, and logistics, from triage decisions (Automated Nurse), to diagnostic tools (Google DeepEye), from radiological image analysis to clinical decision support (IBM Watson), from robotic surgery to emergency medical support positioning and deployment using predictive analytics, and from management to follow-up care (AiCure, NextIT). Some industry analysts have predicted that the AI in health care market will to expand from $2.1 billion in 2018 to $36.1 billion in 2025, representing a staggering compound annual growth rate of approximately 50 percent.[1] In this chapter, I will briefly discuss the concept of precision medicine (also referred to as *precision health*), the role of AI, key drivers of growth, and the policy implications that must be grappled with on the horizon.

Many Terms, One Overarching Goal

Today, the terms *personalized medicine*, *precision medicine*, *precision health*, and even *precision public health* are all widely used, often leading to confusion. This section discusses the evolution of the terms and nuances in their meanings and applications.

[1] *Artificial Intelligence in Health Care Market by Offering, Technology, End User and Geography—Global Forecast to 2025*, India: Markets and Markets, December 2018.

Personalized Medicine

The successful mapping of the entirety of the human genome promised to open an entirely new approach to health care: using individual discrepancies in gene sequences to identify the root causes of disease and developing therapeutics to overcome those root causes. The term *personalized medicine* began to be used around 1997 to encompass this concept.[2] However, it became clear as time passed that analyzing genetic sequences alone was a gross oversimplification of the mechanisms underlying all but the most-heritable diseases. Today, diseases that are associated with single gene defects are considered quite rare, affecting less than 1 percent of the human population.[3] Consequently, the number of personalized medicines that were developed during the first decade of the 21st century numbered in the single digits—an underwhelming result for a predicted revolutionary scientific advance.[4]

The vast majority of diseases with high medical and economic burdens affecting the world population today are chronic, noncommunicable diseases that arise from a complex, multisystem interplay among genes, environments, and behaviors.[5] Genome-wide sequencing studies demonstrated that the most-common diseases and disorders worldwide (such as diabetes, obesity, heart disease, and various forms of cancer) were associated with multiple defective genes, and that simply having copies of defective genes was not necessarily predictive of disease development.[6] Furthermore, it became increasingly apparent that the interaction between such defective genes, the complexity of human behavior, and environment were responsible for many diseases. This realization led to the *multi-omic* (e.g., genomics, transcriptomics, proteomics, metabolomics, microbiomics, behavioromics, enviromics) approach to studying disease, highlighting the need for a multisystem, data-driven approach to understanding individual disease risk.[7]

Precision Medicine

Given the perceived early failures of personalized medicine, *precision medicine* (defined as an emerging approach for disease prevention and treatment that takes into account people's individual variations in genes, environment, and lifestyle) emerged as essentially a rebranding of

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2 Marc Wortman, "Medicine Gets Personal," *MIT Technology Review*, Vol. 104, No. 1, 2001, p. 72.

3 Heidi Chial, "Rare Genetic Disorders: Learning About Genetic Disease Through Gene Mapping, SNPs, and Microarray Data," *Nature Education*, Vol. 1, No. 1, 2008.

4 Geoffrey S. Ginsburg and Kathryn A. Phillips, "Precision Medicine: From Science to Value," *Health Affairs*, Vol. 37, No. 5, 2018.

5 Martin McKee, Andy Haines, Shah Ebrahim, Peter Lamptey, Mauricio L Barreto, Don Matheson, Helen L Walls, Sunia Foliaki, J. Jaime Miranda, Oyun Chimeddamba, et al., "Towards a Comprehensive Global Approach to Prevention and Control of NCDs," *Globalization and Health*, Vol. 10, October 28, 2014.

6 R. Pranavchand and B. M. Reddy, "Genomics Era and Complex Disorders: Implications of GWAS with Special Reference to Coronary Artery Disease, Type 2 Diabetes Mellitus, and Cancers." *Journal of Postgraduate Medicine*, Vol. 62, No. 3, 2016.

7 Sophia Miryam Schüssler-Fiorenza Rose, Kevin Contrepois, Kegan J. Moneghetti, Wenyu Zhou, Tejaswini Mishra, Samson Mataraso, Orit Dagan-Rosenfeld, Ariel B. Ganz, Jessilyn Dunn, Daniel Hornburg, et al., "A Longitudinal Big Data Approach for Precision Health." *Nature Medicine*, Vol. 25, 2019.

personalized medicine concepts in the age of big data and large-scale analytics.[8] The term was first coined in 2011 in a National Academies report and later popularized by President Barack Obama's State of the Union speech in 2015, which announced the National Institutes of Health Precision Medicine Initiative.[9] Precision medicine was described as a paradigm shift in health care—one that would take advantage of new data-driven technologies to predict disease risk and develop preventative and therapeutic strategies tailored to appropriately targeted populations with an overall focus on proactive prevention and individualized treatment.

The overarching goal of precision medicine is to fix shortcomings in the U.S. health care system, including tendencies toward reactiveness and disease management rather than toward proactive prevention. Additionally, U.S. health care has traditionally focused on "one size fits all" strategies for managing disease at symptom onset and seeking cures after illness has struck. Such strategies, called *standards of care* (SoC), rely on population averages to increase the probability of achieving the best clinical outcomes for the average patient. However, strategies for the average patient often do not work for individuals, and inherent patient heterogeneity (e.g., demographic, environmental, behavioral, biological) limits the effectiveness of SoC, resulting in a large number of patients who do not respond to a given treatment; the SoC approach also leads to adverse events, poorer clinical outcomes, and increased costs.[10] The top ten highest-grossing drugs in the United States—spanning treatment of schizophrenia, arthritis, heartburn, high cholesterol, depression, and asthma—are effective in only 4–25 percent of their respective patient populations.[11]

Precision (Public) Health

Precision health, or *precision public health*, takes the idea of precision medicine and applies it to theories of social determinants of health. Racial or ethnic minorities, socioeconomically disadvantaged individuals, and discriminated-against populations continue to experience disproportionate levels of adverse health outcomes in the United States,[12] despite decades of research correlating health to individual social determinants—such as demographics (e.g., age, gender, race), social or population characteristics (e.g., employment, neighborhood, housing), and associated behaviors (e.g., diet, exercise, drug or alcohol use).[13] Although social determinants account for 60 percent of factors that influence an individual's lifetime health trajectory, interventions and/or public health policies based on social determinants have produced mixed results.[14] Precision

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8 Francis S. Collins and Harold Varmus, "A New Initiative on Precision Medicine," *New England Journal of Medicine*, Vol. 372, No. 9, 2015.

9 National Research Council, *Toward Precision Medicine: Building a Knowledge Network for Biomedical Research and a New Taxonomy of Disease*, Washington, D.C.: National Academies Press, 2011; Barack Obama, "The Precision Medicine Initiative," Washington, D.C.: The White House, January 30, 2015.

10 U.S. Food and Drug Administration, "Paving the Way for Personalized Medicine: FDA's Role in a New Era of Medical Product Development," October 28, 2013.

11 Nicholas J. Schork, "Personalized Medicine: Time for One-Person Trials," *Nature*, Vol. 520, No. 7549, April 29, 2015.

12 Michael Marmot, "Social Determinants of Health Inequalities," *The Lancet*, Vol. 365, No. 9464, 2005.

13 Shawn Dolley, "Big Data's Role in Precision Public Health," *Frontiers in Public Health*, Vol. 6, No. 68, March 2018.

14 Xinzhi Zhang, Eliseo J. Pérez-Stable, Phillip E. Bourne, Emmanuel Peprah, O. Kenrik Duru, Nancy Breen, David Berrigan, Fred Wood, James S. Jackson, David W. S. Wong, et al., "Big Data Science: Opportunities and Challenges to Address Minority Health and Health Disparities in the 21st Century," *Ethnicity & Disease*, Vol. 27, No. 2, Spring 2017, p. 95.

public health emerged in response to a large body of subgroup-specific research suggesting that various health interventions are not broadly effective and that stratified approaches might be necessary to improve equity.[15] The precision public health approach, therefore, aims to develop targeted health and social interventions to address unique needs of specific populations.[16]

Key Drivers of Precision Medicine

Technology is central to precision medicine. The -omics revolution, novel health technologies, big data, automation, and AI are major drivers of precision medicine, providing an unprecedented opportunity to understand the relationships among individual heterogeneity, health, and disease. The rise in cheaply obtainable genetic sequencing information, wearable technologies, the Internet of Things, and the broad adoption of EHRs has led to an explosion of data—providing the essential substances for AI-based analyses into the determinants of health and disease.[17] Maturation of analytical techniques (AI, machine learning, deep learning, neural networks) that have arisen in the age of big data are also major drivers of the promise of precision medicine.

The Need for New Methods

Historically, the practice of medicine and public health has relied on methods that are increasingly viewed as overly simplistic and reductive rather than holistic. Traditional hypothesis-driven research relies on coarse time-scale research instruments (e.g., periodic longitudinal surveys) designed to isolate changes in a dependent variable (e.g., obesity) based on manipulation of an independent variable (e.g., access to housing). This limits our ability to understand recursive, multilevel, and network effects in real time.[18] Additionally, classical approaches use population averages to create "one size fits all" interventions to increase the probability of achieving the best outcomes for an average person.[19] Such strategies are limited by inherent population heterogeneity in number, magnitude, interplay, and amplification or exacerbation of various stressors (e.g., system effects on obesity of education, income, housing, genetics, and diet). As a result, multi-factoral causes of diverse health outcomes for diverse individuals remain unaddressed, and poor health outcomes persist—particularly among the disadvantaged. Data science approaches, including AI, allow researchers to move beyond coarse timescales and single-

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[15] Collins and Varmus, 2015.

[16] Dolley, 2018.

[17] Fei Jiang, Yong Jiang, Hui Zhi, Yi Dong, Hao Li, Sufeng Ma, Yilong Wang, Qiang Dong, Haipeng Shen, and Yongjun Wang, "Artificial Intelligence in Healthcare: Past, Present and Future," *Stroke and Vascular Neurology*, Vol. 2, No. 4, 2017.

[18] Pamela DeGuzman, Paige Altrui, Aubrey L. Doede, Marcus Allen, Cornelia Deagle, and Jessica Keim-Malpass, "Using Geospatial Analysis to Determine Access Gaps Among Children with Special Healthcare Needs," *Health Equity*, Vol. 2, No. 1, 2018; Dolley, 2018; Muin J. Khoury and John P. A. Ioannidis, "Big Data Meets Public Health," *Science*, Vol. 346, No. 6213, 2014; Travis B. Murdoch and Allan S. Detsky, "The Inevitable Application of Big Data to Health Care," *JAMA*, Vol. 309, No. 13, 2013; and Zhang et al., 2017, p. 95.

[19] Margarita Alegria, Marc Atkins, Elizabeth Farmer, Elaine Slaton, and Wayne Stelk, "One Size Does Not Fit All: Taking Diversity, Culture and Context Seriously," *Administration and Policy in Mental Health and Mental Health Services Research*, Vol. 37, No. 1–2, 2010; Paula A. Braveman, Catherine Cubbin, Susan Egerter, David R. Williams, and Elsie Pamuk, "Socioeconomic Status in Health Research: One Size Does Not Fit All," *JAMA*, Vol. 294, No. 22, 2006.

level effects to refined, multi-timescale, multidimensional, and intersectional analyses that better account for interactions among various stressors, genetics, behaviors, and health.

Data Explosion

Data silos and interoperability issues aside, the health care and life sciences industries are virtual goldmines of data waiting to be unearthed to improve health. Here, I describe the value of large-scale biomolecular, clinical, and behavioral data and their utility for precision medicine and health.

Biomolecular: The -omics revolution began with the sequencing of the human genome, and genomics continues to lead the way by bringing revolutionary technologies to researchers and providing an anchor on which all other -omics layers are built. Costs of gene sequencing have plummeted, enabling routine and large-scale sequencing to power association studies between genes and phenotypes. In addition to the human genome, the genomes of our gut flora are now under the spotlight, revealing important links to health and metabolism. Beyond such conventional traits as height and binary disease status, genome-wide association studies can now provide insight into the pharmacokinetics and pharmacodynamics of prescribed pharmaceutical compounds as traits displaying individual variabilities. In addition, the advancement of high-throughput technologies has generated unprecedented amounts and varied types of -omics data. Comprehensive molecular profiling has been conducted to profile biological samples on different layers of genomic activities, such as mRNA (transcriptomics; how DNA is converted into RNA), protein assembly and structure (how RNA is converted into protein), and DNA methylation (how DNA is modified in situ). Collectively, holistic large-scale biomolecular data sets offer a wealth of information to be mined by data science approaches.

Clinical: Incentives from the Health Information Technology Act of 2009 in the United States have, in part, led to an adoption rate approaching 80 percent of certified EHRs in acute care hospitals.[20] EHR adoption rates have also increased worldwide.[21] It has been suggested that, in the United States alone, there will soon be 1 billion patient visits documented per year in EHR systems.[22] In addition to the patient data housed in EHRs, the amount of additional data available about medical conditions, underlying genetics, medications, and treatment approaches is substantial.

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[20] Office of the National Coordinator for Health Information Technology, Index for Excerpts from the American Recovery and Reinvestment Act, HealthIT.gov, 2009.

[21] Nigam H. Shah, "Translational Bioinformatics Embraces Big Data," *Yearbook of Medical Informatics*, Vol. 7, No. 1, 2012; Oliver Heinze, Markus Birkle, Lennart Köster, and Bjöern Bergh, "Architecture of a Consent Management Suite And Integration Into IHE-Based Regional Health Information Networks," *BMC Medical Informatics Decision Making*, Vol. 11, No. 58, October 4, 2011; Antonio Tejero and Isabel de la Torre, "Advances and Current State of The Security and Privacy in Electronic Health Records: Survey from a Social Perspective," *Journal of Medical Systems*, Vol. 36, No. 5, 2012; Alexander Mense, Franz Hoheiser-Pförtner, Martin Schmid, and Harald Wahl, "Concepts for a Standard Based Cross-Organisational Information Security Management System in the Context of a Nationwide EHR," *Studies in Health Technology Informatics*, Vol. 192, 2013; Arild Faxvaag, Trond S. Johansen, Vigdis Heimly, Line Melby, and Anders Grimsmo, "Healthcare Professionals' Experiences with EHR-System Access Control Mechanisms," *Studies in Health Technology Informatics*, Vol. 169, 2011; and Dustin Charles, Jennifer King, Vaishali Patel, and Michael F. Furukawa, *Adoption of Electronic Health Record Systems Among U.S. Non-Federal Acute Care Hospitals: 2008–2012*, Washington, D.C., Office of the National Coordinator for Health Information Technology, ONC Data Brief No. 9, March 2013.

[22] George Hripcsak and David J. Albers, "Next-Generation Phenotyping of Electronic Health Records," *Journal of the American Medical Informatics Association*, Vol. 20, No. 1, 2013.

Behavioral: Low-cost, consumer-facing digital technologies (such as mobile devices and wearable sensors) are ubiquitous, generating data on multiple aspects of individual lifestyles and behaviors that are critical for understanding the interplay among social determinants, lived experiences, and overall health. Today, there are an estimated 75 billion active digital technologies, generating 2.5 quintillion bytes of data daily on environment, transportation, geolocation, diet, exercise, biometrics, social interactions, and everyday human lives.[23] These person-generated health data (PGHD) allow for continuous in situ monitoring of health—in real time and over time, outside (or in addition to) intermittent monitoring in clinical settings.[24] PGHD are especially powerful for precision medicine and health, allowing for data-driven correlations between multiple social determinants and behaviors to uncover complex relationships between acute and chronic stress and overall health. The Fitbit, for example, has been used across more than 500 health studies and 171 clinical trials,[25] accounting for 80 percent of digital technology research.[26] It is considered low-cost, user-friendly, and unobtrusive, and is capable of producing relatively accurate, continuous, multivariate PGHD (e.g., heart rate, step count, sleep cycles, energy expenditure).[27] Its utility has been studied across a variety of issues—such as mental health,[28] obesity,[29] cardiovascular conditions,[30] and sleep[31]—and across populations, such as older adults and individuals with chronic conditions.[32]

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26 Stephen P. Wright, Scott R. Collier, Tyish S. Brown, and Kathryn Sandberg, "An Analysis of How Consumer Physical Activity Monitors are Used in Biomedical Research," *FASEB Journal*, Vol. 31, 2017.

27 Ara Jo, Bryan D. Coronel, Courtney E. Coakes, and Arch G. Mainous, "Is There a Benefit to Patients Using Wearable Devices Such as Fitbit or Health Apps on Mobiles? A Systematic Review," *American Journal of Medicine*, Vol. 132, No. 12, 2019.

28 John A. Naslund, Kelly A. Aschbrenner, and Stephen J. Bartels, "Wearable Devices and Smartphones for Activity Tracking Among People with Serious Mental Illness," *Mental Health and Physical Activity*, Vol. 10, 2016.

29 Julie B. Wang, Lisa A. Cadmus-Bertram, Loki Natarajan, Martha M. White, Hala Madanat, Jeanne F. Nichols, Guadalupe X. Ayala, and John P. Pierce, "Wearable Sensor/Device (Fitbit One) and SMS Text-Messaging Prompts to Increase Physical Activity in Overweight and Obese Adults: A Randomized Controlled Trial," *Telemedicine Journal and E-Health*, Vol. 21, No. 10, 2015.

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31 Janna Mantua, Nickolas Gravel, and Rebecca M. C. Spencer, "Reliability of Sleep Measures from Four Personal Health Monitoring Devices Compared to Research-Based Actigraphy and Polysomnography," *Sensors*, Vol. 16, No. 5, May 5, 2016.

32 Nicola Straiton, Muaddi Alharbi, Adrian Bauman, Lis Neubeck, Janice Gullick, Ravinay Bhindi, and Robyn Gallagher, "The Validity and Reliability of Consumer-Grade Activity Trackers in Older, Community-Dwelling Adults: A Systematic Review," *Maturitas*, Vol. 112, 2018; James Weatherall, Yurek Paprocki, Theresa M. Meyer, Ian Kudel, and Edward A. Witt, "Sleep Tracking and Exercise in Patients with Type 2 Diabetes Mellitus (Step-D): Pilot Study to Determine Correlations

New Methods, Large-Scale Data, and Advanced Analytics Could Fundamentally Revolutionize the Study and Delivery of Health Care

Large-scale biomolecular, clinical, and behavioral data combined with novel data science analyses provide a major opportunity to develop individualized interventions to improve health and well-being for all. In addition to traditional statistics, modern data science (including AI and machine learning) is emerging to recognize patterns in and make predictions based on large, empirical data sets. Unlike hypothesis-driven designs, data science allows for networked, multilevel correlations of multiple variables on health outcomes to develop complex risk predictions.[33] Data science enables identification of multivariate indicators of health for a broad variety of health outcomes that can be used to monitor, influence, and maintain healthy behaviors in real time. For example, data science applications of Fitbit data can accurately predict changes in loneliness or depression among college students,[34] hospital readmission,[35] and blood sugar management for diabetes.[36] Collectively, such studies highlight a major opportunity to create a synergistic feedback loop for health engagement among researchers, health professionals, and patients via digital technologies. In the first step, consumers share health data with researchers. Researchers then develop indicators (e.g., sleep duration) of health (e.g., cardiometabolic risk). Such indicators are then used to personalize interventions that are pushed back to consumers (e.g., missing a target bedtime last week means that a reminder will be sent this week to begin a wind-down routine before bedtime). Finally, providers and researchers assess compliance via indicators (e.g., did they increase time in bed?) and evaluate the effects of interventions on health (e.g., did extra time in bed or a reminder for wind-down routine result in incremental increases in sleep duration?), allowing for iterative improvement of interventions over time.

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36 Soo Lim, Seon Mee Kang, Kyoung Min Kim, Jae Hoon Moon, Sung Hee Choi, Hee Hwang, Hye Seung Jung, Kyong Soo Park, Jun Oh Ryu, and Hak Chul Jang, "Multifactorial Intervention in Diabetes Care Using Real-Time Monitoring and Tailored Feedback in Type 2 Diabetes," *Acta Diabetologica*, Vol. 53, No. 2, 2016.

Key Policy Considerations Required to Enable Success of Precision Medicine and Health

The U.S. health care system is one of the largest and most complex in the world. The United States is the only developed country without nationalized health care, and the health care system it does have functions through a fragmented combination of public and private stakeholders who individually manage pieces of the health care life cycle—from research and development to public health, patient care, and health care delivery to financing and reimbursement. A new health care paradigm (such as precision medicine and health) faces daunting challenges in terms of value demonstration, achievement of acceptance and trust, implementation, and evaluation.

Precision medicine and precision health exist largely as thought experiments—there are few studies demonstrating whether precision strategies have the intended effects of improving health outcomes and decreasing costs when implemented broadly. The adoption of precision medicine into clinical practice has been highlighted as a primary strategic priority by the major players in the global health community in the United States, China, the European Union, India, Norway, and Japan. Market forecasting experts expect the global precision medicine therapeutic market to rise to $141.7 billion by 2026.[37] From a public health and policy perspective, the implementation of health technologies are only justified if their benefits to population health exceeds their opportunity cost. Here, I describe some overarching policy questions in precision medicine and precision health that are critical to its overall success.

Cost Effectiveness: Do the benefits derived from precision medicine–based interventions justify the development and implementation costs? Do precision medicine–based interventions improve overall health outcomes in a cost-effective manner? What are the trade-offs between investing in precision medicine and in lower-tech prevention and population health strategies?

Equity and Diversity: How can precision medicine–based strategies ensure equitable delivery of health care across a diverse and heterogeneous population? What are recruitment strategies that can ensure inclusion and retention of historically underserved populations, including individuals who might not have access to required mobile devices and other critical technologies? What incentives are required for industry to develop precision medicine strategies for small population segments?

Clinical Adoption and Acceptability: What is the role of algorithms in clinical decisionmaking? How should risk probabilities be translated into clinical decisions and management by providers? What kind of provider training and education is required to make use of technology-based health care solutions?

Implementation: How should precision medicine be introduced into health care settings? What kinds of equipment, technology, and specialized training are required? What is required for adoption and trust in technology? What is required for adequate reimbursement by payers?

Data and Privacy: How should sensitive data be managed, collected, processed, and stored to ensure patient safety and privacy? Who owns and controls access to data? What pre-

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[37] Visiongain, "Global Precision Medicine Market Forecast 2018–2028—Visiongain Report," press release, PR Newswire, March 29, 2018.

cision medicine–related standards need to be set (data components, data systems, mobile apps, other internet-enabled technologies)? When, by whom, and how?

Evaluation: How must clinical trial paradigms change as patient populations become smaller as a result of precision medicine stratification? What metrics should be used to evaluate success of precision medicine and health?

U.S., Japanese Experiences Show Precision Medicine Requires Policy Support to Fully Maximize Technology Solutions

The policy issues listed in the previous section must be considered in the context of the unique needs of each country and its respective health care environment. The United States, for example, must balance a privatized and decentralized health care system with the need for broad information-sharing—no easy task. In addition, the lack of modernized privacy legislation might not only lead to potential discrimination on genetic or behavioral data and but also might reduce trust among populations, thus decreasing sharing of personal data and the overall availability of data for research use. Digital contact tracing to understand the spread of coronavirus disease 2019 provides an example of how a potentially powerful pandemic mitigation tool might be less effective in the United States than in Asian countries, such as Japan and Singapore; public reporting suggests that Americans are less likely to trust digital technology companies and data-sharing than their Asian counterparts.[38] This is because of both cultural paradigms, such as the emphasis on individual freedoms and privacy in the United States over more socially minded Asian countries, and legal issues related to privacy.

For its part, the Government of Japan has made precision medicine a strategic priority in the Japan Revitalization Strategy 2016 and the Healthcare Policy Strategy.[39] Key Japanese ministries—such as the Cabinet Office; the Ministry of Health, Labor, and Welfare; the Ministry of Education, Culture, Sports, Science, and Technology; and the Ministry of Economy, Trade, and Industry—have developed goals and associated performance metrics for precision medicine. Japan plans to initially target rare diseases, insurable diseases, cancer, infectious diseases, dementia, undiagnosed diseases, and pharmacogenomics.[40] To supplement these initiatives, Japan is collecting genomic data through three biobanks (Bio Bank Japan, Tohoku Medical Megabank, and National Center Bio Bank Network) that collectively aim to sequence genomes of at least 500,000 individuals.[41]

Because the public health insurance of Japan does not use cost-effectiveness as a metric to determine insurance coverage, the main policy issue that Japan is grappling with is how to evaluate coverage decisions of potential precision medicine interventions to balance care and

38 Carroll Doherty and Jocelyn Kiley, "Americans Have Become Much Less Positive About Tech Companies' Impact on the U.S.," Pew Research Center, July 29, 2019.

39 Hokuto Asano, *Personalized and Precision Medicine in Japan*, Stanford, Calif.: Stanford Asia Health Policy Program, Working Paper No. 43, July 2017.

40 Headquarters for Healthcare Policy, "Ideas of Target Diseases for Genomic Medical Care [ゲノム医療実現に向けた対象疾患の考え方(案)]," Cabinet Secretariat, February 15, 2017.

41 Cancer Genome Medicine Promotion Consortium Roundtable, *Toward the Construction of Public Participation Type Cancer Genomic Medicine* [国民参加型がんゲノム医療の構築に向けて], Japanese Ministry of Health, Labour, and Welfare, draft report, undated.

effectiveness with total health care expenditures: Japan already has extensive public debt and its health care expenditures are expected to rise as its population ages.

Conclusion

As AI technologies continue to evolve and large data sets of health information proliferate, new opportunities for pursuing personalized health and precision medicine are poised to come online that could dramatically improve the speed and effectiveness of health care, all while lowering costs and improving outcomes. Such a result is not preordained, however, and key policy questions will need to be addressed in the course of the integration of AI technologies into the health field's development. The experiences of the United States and Japan suggest a need for serious thought about how to balance privacy, effectiveness, cost, equity, and other key issues. Exchanges of ideas and approaches among the United States, Japan, and other countries might be a fruitful way to test, refine, and advance each country's understanding of the trade-offs among the various equities at stake.

CHAPTER FOUR

Artificial Intelligence and the Problem of Data Governance: Building Trust in Data Flows for the Benefit of Society

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To maximize the impact of artificial intelligence (AI) on health and social well-being, large data sets of sensitive personally identifiable information or personal health information are required, but managing privacy and security for these data has proven challenging. How should nations regulate flows of increasingly crucial data to balance privacy concerns, social impact, and value? This chapter focuses on an examination of one aspect of the critical input factors that supports AI—social policy for data management. It argues that Japan's preferred framework—Data Free Flow with Trust—carries distinct advantages that help balance divergent equities and ensure all stakeholders' interests.

Data have been called "the new oil"—the crucial fuel that powers the modern, digital economy.[1] Interest and debate around data is growing in many fields—including health care, as the World Health Organization noted in April 2019 in its recommendations on digital interventions.[2] At the 2019 Group of 20 (G20) summit in Osaka, Japan, world leaders discussed how to deal with the rapidly expanding digital economy and agreed about the creation of a negotiating framework—called the Osaka Track—for the development of international rules for data flows.[3] The framework is based on a proposal made by Japanese Prime Minister Shinzo Abe at the annual meeting of the World Economic Forum in Davos-Klosters in January 2019.[4] As outlined in the G20 leaders' declaration, Japan intends to take the lead in establishing international rules regarding the protection of personal information and other data and in establishing a system that will allow the free flow of data across borders.

Until now, health data have been owned by companies, hospitals, and the government, and individuals have had only limited access. In Europe, the General Data Protection Regulation (GDPR), which came into effect in 2019, established the principle of an individual's right to access his or her data.[5] Individuals are becoming the axis around which data circulate. At

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1 For example, see "The World's Most Valuable Resource Is No Longer Oil, But Data," *The Economist*, May 6, 2017.

2 World Health Organization, "WHO Guideline: Recommendations on Digital Interventions for Health System Strengthening," Geneva, Switzerland: 2019.

3 Group of 20, Osaka declaration on digital economy, Tokyo, Japan: Ministry of Foreign Affairs of Japan, 2019.

4 Shinzo Abe, "Defeatism About Japan Is Now Defeated: Read Abe's Davos Speech in Full," World Economic Forum, 2019.

5 Charlotte J. Haug, "Turning the Tables—The New European General Data Protection Regulation," *New England Journal of Medicine*, Vol. 379, No. 3, 2018.

the same time, we are beginning to observe the limits of the concept of data ownership. The idea that data are fixed, exclusively owned assets similar to oil is misleading and increasingly difficult to treat as credible. For example, unlike oil, the value of data increase as they are distributed and connected with other data; by adding data from one patient to that of 10,000 other patients, we can provide that one patient with the care that they require. Seen in this alternative view, data are considered a sharable good—and, in some ways, a public commodity.

Japan's Proposed Information Management Solution

It is in this context that Japan proposed the idea of Data Free Flow with Trust (DFFT) at the Osaka G20 meeting in 2019. DFFT seeks to balance openness with the need for trusted mechanisms of exchange and control.[6] In the field of health care and medicine, there are growing expectations for the use of data under the principle of DFFT, which the Government of Japan is promoting as a framework for handling nonperson-level data. In medicine, however, there is also a demand for trustworthy methods of handling personal data to improve the provision of care. Three key elements—respect for human rights, specific public interests, and considerations for data holders—are at the core of the DFFT conceptual framework (Figure 4.1).

The first element is respect for human rights. In Europe, GDPR (as a product of Articles 7 and 8 of the Charter of Fundamental Rights of the European Union) treats the protection of personal data as a fundamental human right. Among GDPR's basic presumptions regarding the handling of personal information is the idea that trust is centered on the individual (sometimes described by the concept of "privacy as trust").[7]

Both GDPR and DFFT prioritize human rights. Obtaining consent, preferably in an opt-in manner, is crucial in accurately reflecting the will of individuals and respecting their right to privacy. In the stricter versions of respect for privacy, obtaining consent once might not suffice; dynamic consent might be required to note the changes in individuals' situations and choices over time.[8]

The second element is related to the value that is created when data are used. To whom does that value accrue, and under what circumstances? DFFT recognizes that data should be used to further the interests of individuals, companies, countries, and the public at large. In some cases, data might even be used without explicit individual consent if a collective consensus exists regarding the appropriate purpose and circumstances for such a use.

The World Economic Forum has proposed the principle of Authorized Public Purpose Access (APPA) as an approach to ensuring data use with a high degree of trust that does not rely exclusively on opt-in consent.[9] Under APPA, the requirements for consent and anonymization might be waived for certain data, purposes, or users if (1) data are recognized to be important

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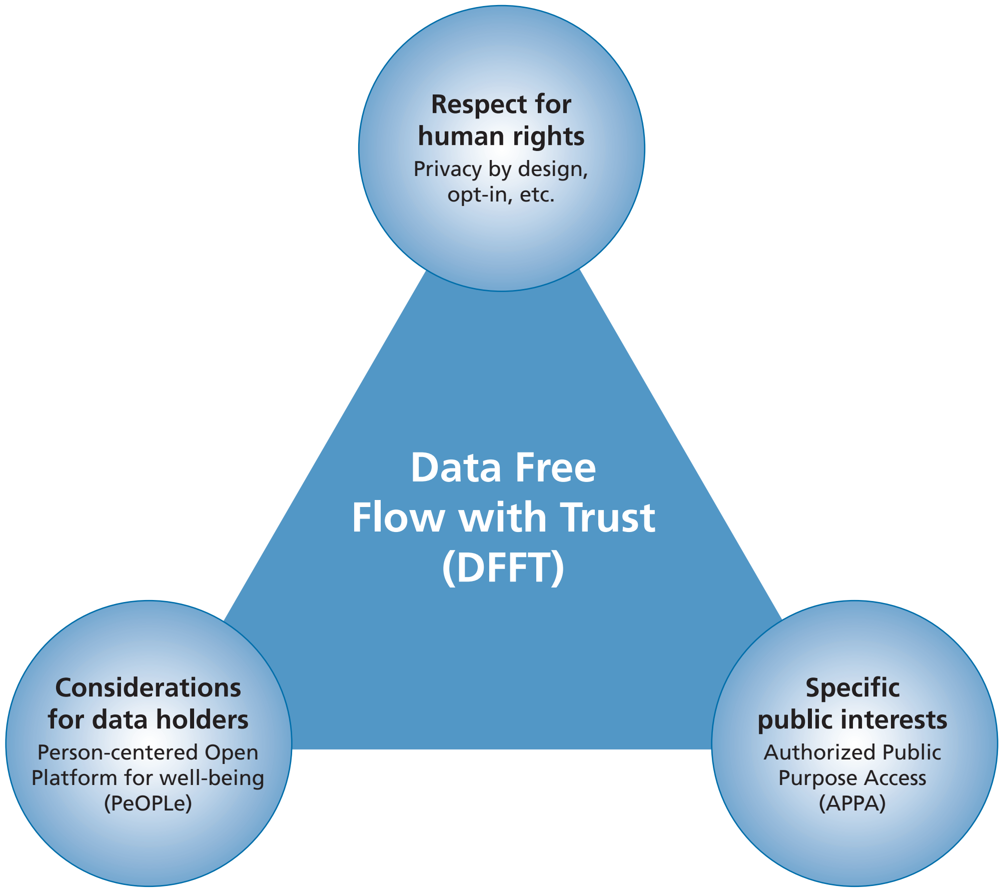
6 G20 Japan Digital, "How Can :Data Help You Get Medical Treatment Tailored to You?" webpage, undated.

7 Ari Ezra Waldman, *Privacy as Trust: Information Privacy for an Information Age*, New York: Cambridge University Press, 2018.

8 Jane Kaye, Edgar A. Whitley, David Lund, Michael Morrison, Harriet Teare, and Karen Melham, "Dynamic Consent: A Patient Interface for Twenty-First Century Research Networks," *European Journal of Human Genetics*, Vol. 23, No. 2, 2015.

9 World Economic Forum, *APPA—Authorized Public Purpose Access: Building Trust into Data Flows for Well-Being and Innovation*, Geneva, Switzerland, December 2019.

Figure 4.1
Key Factors in Data Governance Under the Proposed DFFT Concept



for public safety or protection of human life, and (2) handling the data under the APPA principle will provide clear benefits to all members of society. Even if personal consent is absent, APPA proposes that data can still be used contingent on the following criteria: (1) importance of the purpose, (2) method and/or level of anonymization, or (3) identity of the data user.

Data managed under an APPA-based framework might be accessed not only by public-sector entities but also by trusted private companies or scientists. The goal of APPA is not to treat data as indiscriminately shared assets but to define, from the perspective of data distribution architecture, how to secure trust and ensure the protection of individual human rights and societal interests. The goal of APPA shares similarities with the concept of "privacy by design."[10]

Finally, the third element, consideration for data holders, will also be important for DFFT. The U.S.-Japan Digital Trade Agreement reached last year builds on the DFFT initiative. It ensures the free cross-border transfer of data, including personal information, and prohibits both data localization requirements and the transfer of (and access to) source codes and algorithms. These measures secure the reasonable interests of data holders and ensure financial sustainability. Data should not be made available without the holder's consent or requests from the data subjects. A people-centric open platform requires balancing respect for human rights with the

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[10] Ann Cavoukian, *Privacy by Design: The 7 Foundational Principles*, Zurich, Switzerland: Internet Architecture Board, 2009.

realization of value. Building a PeOPLe on which data can be created, linked, and used broadly and openly will ensure that person-centered data can be used across industries, government, and academic boundaries.[11] Such an approach is premised on the notion that, with the proper handling of personal information, it is possible to achieve high-trust use contingent on the particular consent conditions of each individual.

Are Such Concepts Workable?

What are the benefits of introducing these ideas? First, obtaining appropriate consent is required under GDPR, and the concept has already gained worldwide acceptance. The acquisition of dynamic consent is already practiced in biobanks and will be an important element in personal health records or personal data storage where data are primarily handled by individuals.[12]

APPA is the key to realizing data value in situations in which consent cannot be obtained. Some types of emergency access to health-related personal information are already permitted under the laws of different jurisdictions, including the GDPR in the European Union and the California Consumer Privacy Act in the United States.[13]

APPA draws on the Findable, Accessible, Interoperable, Reusable (FAIR) Data Principles.[14] These permit access to personal medical data that are required to save lives during a natural disaster and to information regarding infected patients that is required to prevent a disease pandemic. Under APPA, the FAIR principles can be extended to make it easier to use data in drug development for rare diseases, precision-medicine treatments for rare cancers, or services to protect elderly people with dementia. Broadening these concepts on a global scale will offer benefits to individual countries, create new value in supporting underserved communities, and help secure human rights that transcend borders. It should be noted that the term *public purpose* does not necessarily indicate that the government is always allowed to access and use people's data. For instance, this concept can be useful in addressing the question about how to handle data related to refugee assistance.

A PeOPLe architecture can provide suggestions for rethinking the use of data in areas beyond health care. The development of "smart cities" is at the forefront of implementing data distribution systems and the new framework to ensure trust in data distribution should make it possible to use data for the well-being of society. For such an approach to succeed, it must be premised on what Sen has characterized as "values that could be expected to gain wider adherence and support when open discussion is allowed, when information about other societies becomes more freely available, and when disagreements with the established views can be expressed and defended without suppression and fear."[15]

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[11] ICT Utilization Promotion Advisory Panel in the Healthcare Field, *Towards the Construction of a Next Generation Health Care System Utilizing ICT* [*ICT*を活用した「次世代型保健医療システム」の構築に向けて], Tokyo, Japan: Ministry of Health, Labor and Welfare of Japan, October 19, 2016.

[12] Kaye et al., 2015.

[13] Californians for Consumer Privacy, homepage, undated.

[14] Future of Research Communications and e-Scholarship, "The Fair Data Principles," webpage, undated.

[15] Amartya Sen, "Elements of a Theory of Human Rights," *Philosophy and Public Affairs*, Vol. 32, No. 4, Fall 2004.

Putting the three elements into practice is not easy. Opt-in or dynamic consent systems can have disadvantages. Constant requests for consent can lead to the problem of consent fatigue and can be costly for data owners. Additionally, it might not always be possible to obtain consent. For instance, after the Great East Japan Earthquake in 2011, it was impossible for medical and emergency services to share information about the whereabouts of dialysis patients, thus resulting in life-threatening risks. In Japan, there have been instances of misunderstandings and overcautiousness regarding the use of personal data; some people in Japan believe that no data whatsoever can be used without explicit individual consent, even in instances where the law allows it. In the case of children and the elderly, the capacity to consent during emergency situations might be compromised. Therefore, it might be more important to achieve group consensus regarding the handling of personal information rather than individual consent, similar to data regarding genomic or infectious diseases.

In light of these concerns, the concept of APPA might be attractive. However, what should constitute a sufficient public purpose under APPA? One answer might be the achievement of sustainable development goals, particularly the third goal of "good health and well-being."[16] There is also the question of who should qualify for exceptions from standard data access and exchange rules under APPA, and the criteria on which this decision should be based. With regard to the balance of human rights, it is important to clarify when opt-in consent is necessary and when to require an increasingly appropriate consent acquisition method that considers individuals' differing abilities to provide consent. It is also necessary to establish rules for the shared use of and access to data. The World Economic Forum favors a thorough discussion of this issue with a wide variety of stakeholders, including the community of scientists.

PeOPLe, as a concept, also faces many challenges. Considering the principles of interoperability, data portability, and open application programming interfaces,[17] PeOPLe could become a standard platform for the future if it wins sufficiently widespread support and acceptance. Importantly, the function of this platform should be to control access rights, not providing data.

Many issues remain to be solved, such as who should manage the platform, how to identify data accessed from trusted parties with legitimate purposes, how the platform's components and processes should be standardized, and how the architecture agreed on for APPA should function. Some issues might be solved through computer science technology. Regarding the issue of legitimate public purposes, there is a need for further discussion about fundamental values, such as fairness and justice, and how they are accepted and interpreted internationally. To implement data use under APPA, it is necessary to confirm compliance with international rules, similar to GDPR and the Asia-Pacific Economic Cooperation organization's Cross-Border Privacy Rules, as well as legal compliance in each country, such as the Health Insurance Portability and Accountability Act and the California Consumer Privacy Act in the United States.[18]

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[16] United Nations, Department of Economic and Social Affairs, "Goals: 3: Ensure Healthy Lives and Promote Well-Being for All at All Ages," webpage, undated.

[17] An application programming interface defines the calls or requests that can be made among software intermediaries and how to make them.

[18] Cross-Border Privacy Rules System, homepage, undated.

Conclusion

In the digital age, innovation requires connectivity for various types of data. The DFFT approach promotes the necessary free flow of data in a form that protects human rights and secures trust. It does so not only because privacy and other rights are important but also because it recognizes that a system that ignores those rights will not be sustainable. As a values-based philosophy, DFFT gives shape to concrete governance mechanisms and architectures, including the ideas described here, specifically (1) APPA as a framework for managing access to sensitive personal information that seeks to balance individual rights, the interests of data holders, and the public good; and (2) PeOPLe, a human-centric platform for creating, connecting, and broadly using data. Therefore, DFFT is a strong contender for the best approach to balancing individuals' privacy concerns with society's need for information, to the long-term benefit of everyone.

CHAPTER FIVE

Building Resilience: AI/ML Technologies and Natural Disaster Risk Assessment

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What roles can artificial intelligence (AI) and machine learning (ML—hereafter AI/ML in this chapter) play in helping societies manage the threats of natural disasters? Especially as risk becomes more diverse, public- and private-sector enterprises are challenged to gain a comprehensive understanding of the threats and hazards that their businesses and services face. Risk diversity has increased as organizations have come to rely on just-in-time inventories, global supply chains, and increasingly complex but fragile technologies and communications systems that underlay their operations. Historically, risk management enterprise efforts focused on physical hazards and threats to their infrastructure; although that view remains foundational and critically important, threats to external partners' systems and the critical infrastructure that they rely on are new and growing sources of risk. Furthermore, major natural disasters and other disruptive events have laid bare the exposure that companies and governments face as a result of using interdependent systems. To mitigate against, prepare for, respond to, and recover from disruptive events in a timely, effective and cost-conscious manner, risk and emergency managers must understand the interconnectedness of all of the systems that provide the foundation for their enterprise. Furthermore, risk transfer via insurance and other solutions (such as outsourcing) have become an increasingly popular and fiscally sound approach to limiting risk and the financial vulnerabilities that accompany it. To procure appropriate levels of insurance (e.g., business disruption insurance), or determine which processes can safely be outsourced, companies and governments must be able to complete an accurate and holistic analysis of risk across the entire enterprise. One approach that has shown promise is the mating up of big data with AI/ML. Utilizing several patented technologies, including several related to AI/ML, One Concern Inc. is a private-sector firm that employs AI/ML for disaster response and risk assessment or mitigation commercially.[2] This chapter describes the evolution of the disaster management field in recent years and shares insights from how one private-sector firm that is engaged in disaster prediction, resilience, and recovery has employed AI/ML technologies.

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1 The views presented in this chapter are solely those of the author and should not be construed as an endorsement of any specific technology or product by RAND or any of its research sponsors.

2 Other firms in this sector include Descartes Labs, Google, Hypergiant, and IBM; see Selene Cee, "Using Big Data to Predict Natural Disasters," *Deep Tech Wire*, March 18, 2019.

Existing Modeling Solutions: Data and Technology

One of the foundational shortcomings of conventional technologies and existing risk-management models—a shortcoming that induces significant uncertainty in outcomes and leaves risk managers unable to render actionable information to decisionmakers—is the limited set of relevant past events on which these models are calibrated. Hazard and risk modelers have to wait for the occurrence of new events (often natural disasters) to understand how existing systems performed and to update their models in laborious efforts that still provide only limited accuracy. If no events have occurred in the recent past for a given region, a very limited understanding of that region's risk profile, interconnected systems, and key point vulnerabilities exists.

It is for these reasons that existing flood models, for example, tend to provide only a broad-brush analysis with very limited accuracy and resolution.[3] This hinders the ability of disaster managers and elected leaders to make targeted and timely decisions in an accurate manner for life-saving activities, such as alerts and warnings, evacuations, and logistics management. Likewise, when such models are used to create policy and prioritize infrastructure hardening, significant damage still occurs and lives are lost if and when unexpected areas are affected or areas expected to be affected are struck to a degree that was not anticipated.

Advances in AI/ML-based solutions offer an opportunity to overcome these challenges and provide risk managers with tools that are faster, more efficient, and more accurate. To support analysis at the macrolevel (e.g., business enterprises, large complex geographics, or such complex systems as global logistics supply chains), field testing and deployment of these emerging solutions should take place at a local level, providing analysis of limited geographies and systems. This will allow AI/ML engineers the ability to validate and adjust algorithms, assess existing data sets for usefulness and accuracy, and make adjustments based on those findings.[4] Applying early solutions to the field of emergency management allows for field testing as described and immediate support to life-critical situations.

Emergency Management and Data Analytics

No two disasters are exactly the same. They are highly dependent on the initial conditions that exist at the time the disaster strikes. For instance, a typhoon that strikes a city this year will do so in a way that is at least a slightly different—and perhaps very different—from any previous

3 Scholarly work on improving decisionmaking under deep uncertainty through research on robust decisionmaking modeling and its applications in theory and practice (especially as related to climate change, flooding, and infrastructure planning) can be found in Kelly Klima, "Decision-making Under Deep Uncertainty: Climate Change and Infrastructure Management," in W. Tad Pfeffer, Joel B. Smith, and Kristie L. Ebi, eds., *The Oxford Handbook of Planning for Climate Change Hazards*, Oxford, United Kingdom: Oxford University Press, 2018; V. A. Marchau, Warren Walker, Pieter J. Bloemen, and Steven W. Popper, *Decision Making Under Deep Uncertainty: From Theory to Practice*, Zurich, Switzerland: Springer Nature Switzerland AG, 2019; and Steven W. Popper, "Robust Decision Making and Scenario Discovery in the Absence of Formal Models," *Futures & Foresight Science*, Vol. 1, No. 3–4, September–December 2019.

4 Data scientists at One Concern have been researching how to validate existing data sets (typically those that exist in government files) and how to compensate for data gaps and inaccuracies. An example of their research was recently presented at a conference hosted by the Southern California Earthquake Center (Abhineet Gupta, Todd MacDonald, and Debbie Weiser, "Applications of and Considerations for Using Machine Learning and Deep Learning Tools in Earthquake Engineering, with Focus on Soft Story Building Identification," 2019 SCEC Annual Meeting Poster, #298, August 2019).

storm. Even minor variations in the strength of the storm surge, wind, and amounts of rainfall can result in significant changes in the amount of inundation, wind damage, and structural impacts across a community. Additionally, conditions within the community and the local environment will, to one degree or another, all be different than they were in previous events. The local environmental conditions, such as the amount of water in the rivers and the moisture content of the soil, might be different as well. These dependent conditions also include the status of the community (whether it is a workday, whether the hospitals are already full of patients) and the status of the city's infrastructure (construction on a major road). These community conditions affect the potential societal impacts and, by extension, the decisionmaking by emergency managers as they prepare for and respond to the crisis.

It's also important to note that cities change frequently. New buildings are erected; roads are changed; infrastructure, such as dams and drainage systems, is expanded. As a result, if the emergency management team is using static risk maps that do not account for those changes, then the risk assessment portrayed by that map is going to be inaccurate. Emergency managers must have the most up-to-date understanding of their risk possible if they want to accurately plan for what they will have to do when disaster strikes.

Disaster professionals prepare for the next crisis by considering what might happen when a natural event, such as a flood or earthquake, occurs. Typically, they do this by looking at past events. Drawing on the experience of the previous disasters—what happened, what actions worked, what actions could have been done better—these professionals attempt to reinforce actions that worked and correct for actions that did not work as well as they could have. Learning from previous disasters is very important and provides the disaster managers with the ability to serve their citizens more effectively—saving lives, reducing suffering, and recovering from the disaster faster. However, examining past disasters does not account for the variability that comes with every new disaster.

For instance, perhaps alerting the public early (i.e., three days before a typhoon struck) proved to be an effective way to get people to evacuate with plenty of time. Because of that positive outcome, emergency managers will plan to use that time frame again. But what if the next typhoon is moving faster and does not allow for three days of notice? How do disaster responders know when to issue the warning?

Another example is mass care. For example, there was not enough food for everyone who went to shelters in a previous disaster. Planners will figure out the difference between how much food they had (e.g., in storage or a stockpile) and how much they actually needed. Using those figures, they can ask for funds to buy more food for storage for future crises. But is that enough food for the worst-case scenario? And during the next disaster, which might not be a worst-case scenario, should they take all the food out of storage or just some of it? Determining how much is needed requires the emergency manager to calculate, based on their best guess, how many people will be evacuated, how many will need to be sheltered, and for how long. Without accurate data, their calculations could be quite wrong. Additionally troubling is the amount of time it takes to complete these calculations, particularly when the situation might be changing frequently.

Emergency managers are not done assessing the situation when they complete that single calculation. There are dozens of nuanced components of every disaster response that must be planned for. For example, the timing of the disaster will affect the issuing of evacuation directives. The extent of the geographic impact—including the specific types of critical infrastructure threatened, such as health care facilities and power and water stations—will determine

what external support resources are needed to compensate for lost or damaged local capabilities. If key decisionmakers do not have a realistic scenario or prediction of the crisis with which to consider these many issues, then it becomes very difficult to make sound planning assumptions and operational decisions. Using the most-accurate tools that provide a realistic, scenario-specific understanding of what could happen (or what is about to happen) gives the disaster team the best chance to make the right decisions that will best serve their citizens.

Making a decision in the best circumstances—when there are no time constraints, all information can be gathered, and a variety of outcomes can be considered—can be difficult. In times of crisis, government leaders must be prepared to make decisions during times of incredible stress using incomplete information, knowing that the outcomes of their decisions will directly affect people's safety and livelihoods. To bridge the gap between these circumstances, emergency managers seek to ensure that they have timely, accurate, and complete information available during a crisis. Modern technology has led to a significant increase in the amount and accuracy of the information available, but it also has created a new problem: the amount of raw data and information available.[5]

There is rarely (if ever) a single question or answer that provides the basis for an operational decision during a crisis. Rather, dozens of data points must be collected and collated into coherent information streams. Each of these streams are then combined to provide the best, most-accurate and comprehensive situational awareness for decisionmakers. From that standpoint, emergency managers make the best decisions possible.

Often, however, there are gaps in the data and information available. These gaps might be missing data or—more challenging—inaccurate information. To overcome the challenge of inadequate and inaccurate data, the emergency management profession has spent extensive time and resources over the years increasing the amount of data and information being provided to their operations centers during emergencies.[6] Examples of how they have augmented their access to data include adding television news feeds, procuring additional computers to monitor relevant websites (e.g., weather service, news service), incorporating traffic and closed-circuit cameras, accessing imagery of the disaster location (e.g., by satellite or drones) and monitoring social media sites.[7] Additionally, many emergency operations centers (EOCs) have established telephone numbers and social media pathways for the public to report information in real time.[8] All of this additional material being provided to the EOCs is good. It uncovers

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[5] RAND researchers have looked at this problem in detail for the U.S. Navy. See Isaac R. Porsche III, Bradley Wilson, Erin-Elizabeth Johnson, Shane Tierney, and Evan Saltzman, *Data Flood: Helping the Navy Address the Rising Tide of Sensor Information*, Santa Monica, Calif.: RAND Corporation, RR-315-NAVY, 2014.

[6] An extensive literature has explored efforts by disaster managers to determine what they need to know, how they can capture that information quickly and accurately, what technology exists to aid in these efforts, and what technology can be used to analyze and integrate data and information in a usable format. For example, see Shannon Riess, "New Technologies Aiding States' Disaster Response," Council of State Governments, July–August 2017; Eric Holdeman, "Technology Plays an Increasing Role in Emergency Management," *Government Technology*, June 26, 2014; National Research Council, *Improving Disaster Management: The Role of IT in Mitigation, Preparedness, Response and Recovery*, Washington, D.C.: National Academies Press, 2007.

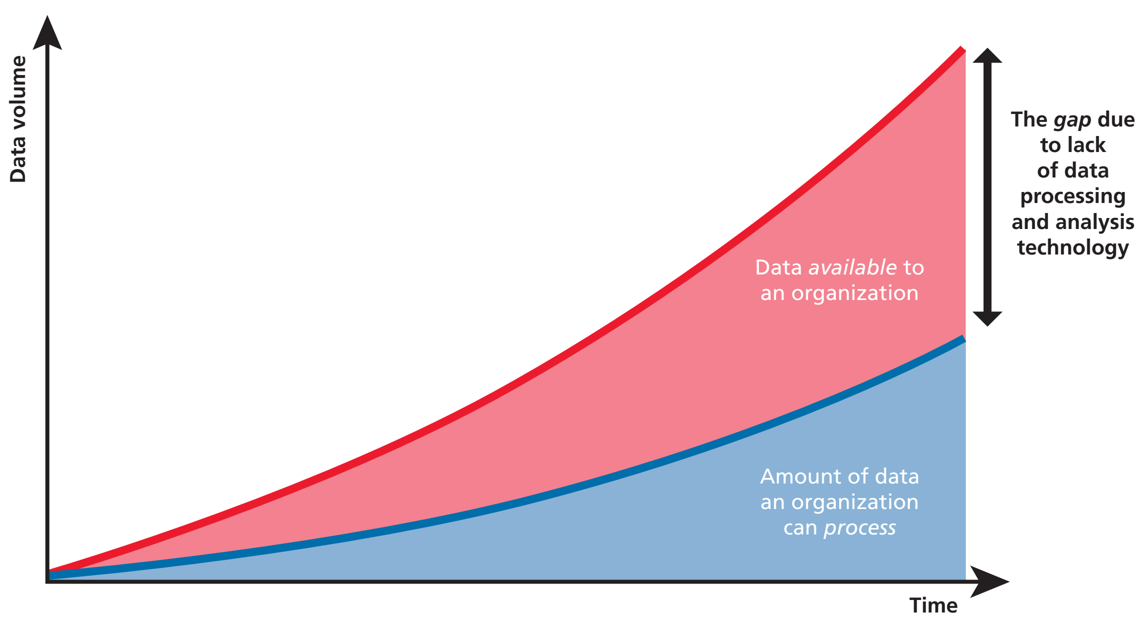
[7] Space and Naval Warfare Systems Center Atlantic, *Innovative Uses of Social Media in Emergency Management*, Washington, D.C.: U.S. Department of Homeland Security, Science and Technology Directorate, 2013.

[8] David F. Merrick and Tom Duffy, "Utilizing Community Volunteered Information for Disaster Situational Awareness," in T. Comes, F. Fiedrich, S. Fortier, J. Geldermann and T.Müller, eds. *Proceedings of the 10th International Conference on Information Systems for Crisis Response and Management*, Baden-Baden, Germany, May 2013.

previously existing blind spots, broadens the view that decisionmakers have of their communities, and supports inclusion of critical infrastructure sectors that previously might have been marginalized. However, too much information presents a different but still major challenge (see Figure 5.1).

Every data point and every information stream that enters an EOC must be assessed by a person working to manage the crisis. This happens in very much the same way that a computer processes information, but the human brain is far more limited in its ability to do so. There is only so much information that a person can receive, interpret, process, and then develop and use to offer possible solutions. Although everyone has, at one time or another, felt overwhelmed by information, this assumption is not merely anecdotal. Research in the fields of psychology and neurology have found that there are limits to the amount of raw data that humans can effectively process in a timely manner; in addition, a variety of cognitive biases lead to systematic errors in human judgement.[9] Even with dozens of disaster management professionals working together in the same EOC, the amount of data and information they are managing during a crisis still might be beyond their collective ability to process and manage. EOCs have had to compensate by adding many additional staff members to their operations to collate, validate, process, and integrate the volume of data.[10] This redirects personnel from other important functions, increases demand for space, and can slow the ability to create a common

Figure 5.1
Gap in Organizational Data Processing Capacity Versus Overall Data Availability



9 George A. Miller, "The Magical Number Seven: Plus or Minus Two," *Psychological Review*, Vol. 63, No. 2, 1956. Miller reports that the number of data points that most humans can hold in their short-term memory at any one time is about seven. It is from short-term memory that most immediate decisionmaking is processed, particularly when the decision is predicated on new information (as would be the case during a crisis).

10 Tanya Roscorla, "5 Reasons Why Emergency Operations Are Going Virtual," *Government Technology*, April 29, 2014.

operating picture from which operational and executive decisions can be made. Fortunately, advances in predictive analysis software solutions are beginning to provide an answer.[11]

For a very long time, humans have been using various tools for prediction. For instance, a barometer measures changes in atmospheric pressure. People learned that such changes can broadly but relatively accurately indicate that a change in the weather is about to occur. In modern times, government weather services provide predictions about upcoming weather conditions using observational and visual data and information they gather from gauges, atmospheric monitoring tools, and satellite images. As more data and information became available to these experts, they were able to develop models that predict changes in the weather, when and where storms will develop, and the path of a typhoon that is deep in the Pacific Ocean and thousands of miles from land. Depending on the situation, the accuracy of these predictions can vary a great deal. Regardless, absent any other solution, community leaders and emergency managers rely on these predictions to determine what actions they should take to protect their residents.

Emergency managers work with many other scientific disciplines to predict what will happen as a result of the next disaster as well. For instance, building engineers provide predictive analysis of how certain types of buildings will withstand a future earthquake. They do this by looking at past earthquakes and conducting experiments in laboratories; using the resulting information, they can identify what types of buildings in their communities are the most vulnerable and make a general prediction as to where the most damage might occur if an earthquake hits. Using whatever data sources their community might have on hand, emergency managers can also figure out how many people live in the buildings that are most vulnerable to damage and then assess how many resources they will need to conduct such response operations as search and rescue, sheltering, and feeding. Gathering and collating these disparate data sets can be very laborious and time-consuming. Additionally, the underlying data sets (e.g., building construction, number of residents in a building) change often. A building might be retrofitted to better withstand an earthquake, and people frequently move from one neighborhood to another, with the result that predictions based on outdated information could become inaccurate. Regardless, that sort of material is typically all that emergency managers have available to them as they work to protect their communities.

Over the past two decades, several advances in technology have led to improvements in prediction. The first was the major increase in available computational power. Not only have individual computers become much more powerful, but access is also now available to thousands or even millions of computers that can quickly undertake data-heavy computational tasks. The second advancement is in the fields of AI/ML. The ability for data scientists to create algorithms that solve highly complex problems has become much easier. Alongside these two technologies is a significant increase in understanding and research in the areas of engineering, atmospheric science, geologic science, and disaster management. Taken all together, emergency managers now have access to much more accurate and faster predictive modeling solutions that can consider thousands of data points about a city, neighborhood, or building—and what the impacts during the next natural disaster might be.

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[11] Oladapo Kayode, "An Overview of Data Analytics in Emergency Management," *International Journal of Computer Trends and Technology*, Vol. 63, No. 1, September 2018; Ari Vivekanandarajah, "Managing Natural Disasters with Predictive Data Analytics," *Selerity*, December 6, 2018.

One Concern Solutions: AI/ML for Disaster Resilience

Founded in California in 2015, One Concern is an applied technology company focused on using AI/ML to model disasters and improve resilience through risk-mapping.[12] It applies a combination of natural sciences and machine learning to generate risk maps that integrate data from structural and earthquake engineering, fluid mechanics, atmospheric sciences, and dozens of other subjects.

For example, during a flood, One Concern's models combine traditional flood models, flood gauge data, and atmospheric river models to predict with a high degree of accuracy the extent of inundation and the velocity of water flow on the ground at higher resolution than is typically available in standard geographic information system–based flood modeling solutions. The firm then applies structural engineering models, using data at the building level together with AI/ML algorithms, and matches these against weather, hydrology, and hydrodynamics models. From this, an understanding of the impending damage and impacts is generated along with an immersive, real-time picture of what is happening.

Natural disasters are extreme events and cause permanent deformations in the physical environment. Rivers will change course or combine, stream banks will reorganize, and debris will change water depth and direction. If the model output is based on static data, as is the case in conventional models, the model could diverge substantially from ground truth at any point. One Concern's approach in employing AI/ML technology seeks not only to update models as new data come in but also to work with local governments and businesses to update underlying data quickly.

Regardless of how robust a community's mitigation efforts have been, not every disaster or disruptive incident can be avoided. Emergency managers and their partner stakeholders within the community heavily invest their time and limited funds in planning for disasters and in training and exercising to be ready when one inevitably occurs. One Concern's simulations allow emergency personnel to plan within a framework of highly accurate disaster scenarios. By providing accurate impact predictions, One Concern's preparedness solution ensures that plans developed before a disaster are usable and effective during one.

One of the key lessons learned from past disasters is that direct losses, although the most visible and often heartbreaking, are merely the first wave of impact to a community following a natural disaster. The economic impacts caused by the second- and third-order effects of the primary incident can be crippling to a community for years after.[13] Most jurisdictions underestimate the degree to which their critical infrastructure—even that which proves to be physically well protected—is heavily dependent on external systems.

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[12] One Concern, homepage, undated.

[13] The discipline of disaster studies recognizes that impacts from disasters are not limited to the physical damage caused by the primary hazard. For example, a tornado causes physical damage to buildings, homes, and components of critical infrastructure, such as power substations. A *second-order effect* would be loss of business within the community caused by the loss of physical structures. A *third-order effect* would be migration of residents from the community to areas unaffected by the disaster where they can find work. These cascading consequences can take many months or years to develop fully and have long-lasting impacts on the affected community. Extensive research has been done regarding the long-term economic impacts of a natural disaster. One recent article that summarizes contemporary models and studies is W. J. Wouter Botzen, Olivier Deschenes, and Mark Sanders, "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies," *Review of Environmental Economics and Policy*, Vol. 13, No. 2, Summer 2019.

For example, even if a hospital is built to the highest building safety codes, it still depends on external sources of inputs, such as energy, fuel, water, supplies, and personnel. Advanced AI/ML modeling can provide emergency managers and community leaders with predictive and real-time accurate modeling not just of physical damage to critical infrastructure but also of the interdependencies on which their community's critical infrastructure rests. This information provides government officials and private-sector actors with a multidimensional view of their operating environment, thus allowing for timely, efficient, and more-accurate investments in mitigation, capital improvements, and operational decisionmaking—thus advancing their risk management programs.

Operational decisionmaking during a crisis is critical to saving lives and property, but the best and most cost-effective manner to mitigate against loss of operations, lives, and property is to invest in sound risk mitigation strategies before disaster strikes. Emerging AI/ML for disaster prediction and resilience technologies provide risk managers with the ability to simulate natural disasters' effects on their infrastructure and to produce fine-grained understandings of the impacts on both physical property and the critical infrastructure's individual components that they rely on but might not themselves own and operate, such as power and water supply. With access to such information, risk managers are then able to understand vulnerabilities to external fragilities that might undercut the ability to return to normal operations after the incident. Such information also enables risk managers to better assess the financial impacts to business and government operations, thus empowering more-efficient investment in risk transfer tools, such as business disruption insurance.

Comprehensive Resilience: Measuring Today, Planning for Tomorrow

Risk management solutions that use even the most-basic capabilities of emerging AI/ML technology can greatly advance a community's or business's resilience. Each risk-specific solution is augmented by the ability for emergency managers, utility officials, community planners, and elected leaders to engage in more-accurate and efficient mitigation, community and economic development planning, disruption and loss avoidance, crisis and continuity planning, and long-term recovery. Not only can AI/ML approaches support executive decisionmaking, they also allow leaders to reduce the likelihood of—or, in some cases, even prevent—disruptions from occurring, thus saving time, money, and lives.

Building holistic resilience allows communities to avoid or lessen the impacts of disasters and facilitates informed decisionmaking when uncertainty is at its greatest. Government and business leaders should seek end-to-end, comprehensive solutions for hazard assessment, data aggregation, impact prediction, collaboration, training, monitoring, action analysis, and prioritization, even if those emerging technologies are not yet fully matured. Only by working together with researchers and private-sector AI/ML software companies can governments and businesses ultimately field solutions that will allow them to meet the incredibly complex challenge of achieving resilience in a dynamic and interconnected world.

CHAPTER SIX

Natural Disasters in the United States and Japan: Where Could AI Be Most Helpful?

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As New Orleans' Hurricane Katrina in 2005 and Japan's March 2011 earthquake and tsunami showed, the destruction caused by earthquakes and hurricanes comes not just from the ground and air, but also—and most destructively—from the sea. The flooding that occurred in the wake of both disasters was catastrophic. Earthquakes and hurricanes will always happen, and there are tremendous human and financial costs associated with such events. Although there are many differences between northern Japan and the Gulf Coast, the prospect of employing artificial intelligence and machine learning (AI/ML) to help deal with future disasters holds out a common promise for both areas. A well-known Japanese proverb says one should always strive to "turn a disaster into good fortune."[1] How to predict, respond to, and mitigate the damage caused by earthquakes and hurricanes is a major challenge and an opportunity for Japan and the United States. This chapter offers an examination of problems that both countries experienced following devasting natural disasters and of prospects for future employment of AI/ML to save lives and reduce property damage, with a specific focus on issues associated with Hurricane Katrina and Japan's March 2011 disasters.

The Disasters

Hurricane Katrina hit New Orleans on August 29, 2005, as a Category Three storm characterized by heavy winds and rain. These eventually caused the breaching and overtopping of the system of protective levees, flooding approximately 80 percent of the city and submerging some areas more than 10 feet.[2] According to the U.S. Census Bureau, 1,833 died as a result of the storm.[3] The destruction caused the population of the metropolitan New Orleans area to fall by 254,502 people (comparing July 2006 figures with those of April 2000), a loss of more than one-half of the population.[4] It is estimated the storm caused $135 billion in damages.[5] Finally, 134,000 hous-

1 The Japanese phrasing is 禍を転じて福と為す.

2 Allison Plyer, "Facts for Features: Katrina Impact," The Data Center, August 26, 2016.

3 U.S. Census Bureau, "Facts for Features: Hurricane Katrina 10th Anniversary: Aug. 29, 2015," Release Number CB15-FF.16, July 29, 2015.

4 Plyer, 2016.

5 Plyer, 2016.

ing units in New Orleans—fully 70 percent of all occupied units—suffered damage from the hurricane and subsequent flooding.[6] In total, the hurricane displaced more than a million people across the Gulf Coast region, and up to 600,000 households were still displaced a month after the hurricane.[7]

Six years after Hurricane Katrina, Japan experienced the strongest earthquake in its recorded history on March 11, 2011, when a magnitude-9.0 temblor struck off the east coast of northern Japan in the Tōhoku region.[8] The earthquake was destructive in its own right; in addition to the immediate destruction it caused, it also generated a tsunami—a wall of water roughly 30 feet high moving at the speed of a commercial jetliner—that smashed into the coast and flooded an area of 216.6 square miles (561 square km) across eastern Japan, including the Fukushima Dai-Ichi nuclear power plant.[9] The combined earthquake and tsunami was costly, resulting in approximately $156 billion (¥16.9 trillion) in damages.[10] According to Japan's official estimate, the human toll was 15,883 deaths and 2,676 missing persons across 12 prefectures.[11] Additionally, hundreds of thousands of people were forced to evacuate, with roughly 130,000 homes destroyed and about 260,000 homes seriously damaged.[12]

Disaster Prediction

One of the biggest problems experienced with Hurricane Katrina had to do with accurate prediction. Until three days prior to making landfall in Louisiana, New Orleans was not considered likely to be at substantial risk; instead, it was at the margin of Katrina's projected path, and the main concern was the Florida Panhandle.[13] Most forecasts predicted a broad area, some 500 miles of the Gulf Coast, from Eastern Louisiana eastward.[14] But within 12 hours, the path

6 Plyer, 2016.

7 Plyer, 2016.

8 Cabinet Office of Japan, *General Situation of Measures Taken Regarding Disaster Management-Fiscal Year Heisei 23 Plan for Disaster Management* [防災に関してとった措置の概況—平成２３年度の防災に関する計画], Tokyo, Japan: Government of Japan, 2011, p. 3.

9 Cabinet Office of Japan, 2011, p. 14.

10 Cabinet Office of Japan, Emergency Disaster Counter-Measure Headquarters, *Regarding the 2011 Tohoku Region Pacific Ocean Earthquake (Great East Japan Earthquake)* [平成23 年（2011 年）東北地方太平洋沖地震（東日本大震災)について], Tokyo, Japan: Government of Japan, March 5, 2018, p. 42. Of that ¥16.9 trillion, the breakdown was as follows:

- buildings, etc. (housing, offices, plants, machinery, etc.): ¥10.4 trillion
- lifeline utilities (water service, gas, electricity, and communication and broadcasting facilities): ¥1.3 trillion
- social infrastructure (river, road, harbors, drainage, and airport, etc): ¥2.2 trillion
- other (agriculture, forestry and fisheries, social welfare facilities, schools, libraries): ¥3.0 trillion.

11 Cabinet Office of Japan, *General Situation of Measures Taken Regarding Disaster Management-Fiscal Year Heisei 25 Plan for Disaster Management* [防災に関してとった措置の概況—平成２５年度の防災に関する計画], Tokyo, Japan: Government of Japan, 2013, p. 39.

12 Cabinet Office of Japan, *General Situation of Measures Taken Regarding Disaster Management-Fiscal Year Heisei 24 Plan for Disaster Management* [防災に関してとった措置の概況—平成２４年度の防災に関する計画], Tokyo, Japan: Government of Japan, 2012, p. 4.

13 Jon Erdman, "Hurricane Katrina: The Day the Forecast Shifted," Weather Channel, August 26, 2015.

14 Greg Allen, "Katrina Sparked Push to Improve Hurricane Forecasting," NPR, August 31, 2015.

shifted 175 miles west, putting New Orleans directly in Katrina's path.[15] Uncertainty over the storm's trajectory made authorities hesitant to issue evacuation orders for New Orleans, likely dooming thousands to remain trapped in the city as the storm bore down on them.

In addition to predicting hurricane paths, meteorologists also find it difficult to predict storm strengths; here again, Katrina is instructive. On August 28, Katrina reached its peak intensity, with top sustained winds of 175 mph, making it a Category Five storm.[16] Yet less than 24 hours before it made landfall, forecasters were surprised to see it drop to a Category Three storm, with sustained winds of just 125 mph. This is typical of the challenges that forecasters face in accurately modeling storm scale and strength.

Although accurate prediction of hurricane paths and intensity is challenging, the science does appear to have improved in recent decades. By contrast, scientists have a much more highly circumscribed ability to predict the specific location and intensity of earthquakes.[17] Despite routinely experiencing earthquakes and tsunamis and scientists generally understanding where earthquakes are most likely to occur along known fault lines, no one predicted the enormity of Japan's March 2011 earthquake or the destructive tsunami it generated. Not only was the magnitude-9.0 earthquake the strongest that Japan ever recorded, it generated a devastating tsunami, with a run-up height in the ocean observed at 132.5 feet (40.5 meters)—the highest ever recorded in Japan—that made landfall at a height of 30.5 feet (9.3 meters).[18] This earthquake and tsunami affected 227 municipalities across nine prefectures along hundreds of miles of coastline.[19] If that were not enough, after the initial earthquake, Tōhoku was hit in the subsequent year by hundreds of aftershocks, all powerful in their own right. Six of these were of magnitude 7 or greater, 97 of magnitude 6 or greater, and 594 of magnitude 5 or greater.[20] These aftershocks were expected, but there was no ability to predict where they would occur or what their degree of intensity would be.

For societies that must deal with the threats posed by hurricanes, earthquakes, and tsunamis, better technology might hold the potential for better prediction. New technology has already improved the accuracy of hurricane-tracking. Since Katrina, faster computers, improved modeling, and a network of geosynchronous stationary and polar-orbiting satellites have been able to provide forecasters with better data that have reduced the margin of error in predicting a hurricane's path.[21] The average seasonal tracking error in a 48-hour forecast of where a storm would go was 110 nautical miles in 2005; by 2020, it had been reduced to 65 miles.[22] If AI/ML can help further narrow such projection windows, there would be numerous benefits. Rather than overly broad areas that make it difficult for governments to adequately prepare and issue evacuation orders, AI-enabled storm-tracking projections could lead to smaller areas

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[15] Erdman, 2015.

[16] National Oceanic and Atmospheric Administration, "Katrina: Forecasting the Nation's Most Destructive Storm," May 12, 2017.

[17] Allen, 2015; Michael Casey, "How Hurricane Forecasts Have Improved Since Katrina," CBS News, August 25, 2015.

[18] Cabinet Office of Japan, 2011, p. 2.

[19] Naomi Aoki, "Adaptive Governance for Resilience in the Wake of the 2011 Great East Japan Earthquake and Tsunami," *Habitat International*, Vol. 52, 2016, p. 21.

[20] Government of Japan, *Road to Recovery*, Tokyo, Japan, March 2012, p. 3.

[21] Casey, 2015.

[22] Casey, 2015.

with longer warning times, helping to reduce errors and put populations on alert in time to evacuate. This would avoid the need to issue evacuation orders to larger areas than necessary—and that, in turn, could minimize traffic jams that put people in danger of being stuck on the road when hurricanes hit. AI/ML systems also could help manage traffic signals during such crises, enabling states to clear paths for first responders and reroute evacuees to less-congested escape routes, making both evacuation and response less chaotic.

Similarly, technology has helped improve predictions of hurricane intensity. Since Katrina, the National Weather Service has taken initiatives that led to the adoption of new technology, such as drones, upgraded weather satellites, and better data-gathering instruments on the aircraft that fly into hurricanes.[23] AI/ML could use the growing number of data sources about a hurricane to project a storm's strength as it approaches the shore: Signals from measurements from the core of a hurricane collected by crewed or unmanned fixed-wing airframes; data collected by ships at sea, from sonobuoys, via satellite, through coastal wind sensors, and by sea level sensors; readings of oceanic temperatures; and other sources could be integrated to produce more-accurate models that integrate and run tens of thousands of variant projections. These could help produce more-accurate predictions on hurricane strength and trajectory, enabling coastal communities to prepare for storms more effectively and governments to issue evacuation orders that are timely and accurate.

Predicting initial earthquakes might be challenging: Without a widespread network of sensors in the ground and ocean, there are insufficient data for computer algorithms to process. Still, there might be benefits in other areas. For example, if AI/ML systems could be trained with the help of seismic data to analyze the magnitude and patterns of an initial earthquake (or collection of previous earthquakes), they might be able to predict the likely location of future earthquakes and their aftershocks, enabling governments to start evacuation operations to safer locations.[24] Similarly, if such technologies can be used to communicate with transportation services (such as Japan's high-speed rail network) and with energy and industrial facilities, governments and the private sector could better enable quick closures of vulnerable systems and avoid large-scale losses of life. In the case of tsunamis, networked technology with detection buoys already provides warnings that are more accurate and timely than in the past, allowing governments to issue tsunami warnings and provide some prior notification. If AI/ML can be used to forecast the likelihood of a tsunami location, projected wave height, and expected immersion depth, authorities will have a better understanding of the scope of damage in areas expected to be hit, which could aid not only in issuing more-accurate evacuation orders but also in determining safe locations to build residential areas, energy infrastructure, and escape routes to mitigate likely damage and loss of life from flooding.[25]

Damage Assessment and Disaster Response

In the immediate aftermath of any disaster, governments need accurate damage assessments to initiate rescue operations. Not only are lives at stake, but critical needs must be met for survi-

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[23] Allen, 2015.

[24] Naveen Joshi, "How AI Can and Will Predict Disasters," *Forbes*, March 19, 2019.

[25] Magdalena Osumi, "Japanese Team Developing AI-Based System to Forecast Chance of Tsunami and Scale of Damage," *Japan Times*, August 16, 2019.

vors, including provision of food, water, medicine, supplies, and shelter. The bigger the disaster, the more complicated these demands become. Without accurate damage assessments, any government's ability to respond becomes increasingly hampered.

In New Orleans, getting an accurate understanding of the scope of the disaster proved difficult, largely because of the lack of manpower and communications. The National Guard was crippled in the early days by a shortage of troops. When Katrina hit, 4,000 Louisiana Guards members were on duty, including 1,250 in New Orleans and surrounding parishes; by the next day, all 5,700 available Guard members were called up and dispersed around the state.[26] These troops were critical not only for response efforts but also for gathering situational awareness. Given the scale of the disaster, however, reinforcements from other states were needed. Arrival of these reinforcements was slowed by the logistics and red tape involved in summoning troops from civilian jobs and moving them thousands of miles, resulting in large numbers of reinforcements not arriving until the fourth day after the storm struck.[27] The eventual military response climbed to 35,000 Guard members and active-duty troops, but by the time most of these had arrived, valuable recovery time had been lost.[28]

Further complicating New Orleans' assessment and response was the fact that the federal disaster response plan hinged on transportation and communication, but National Guard officials had no contingency plan if these were disrupted; they had only one satellite phone for the entire Mississippi coast.[29] With land lines, cell phones and many satellite phones out of action, the frequencies used by the functioning radios were often jammed.[30] The complete devastation of the communications infrastructure left emergency responders and citizens without a reliable network across which they could coordinate.[31] A U.S. House of Representatives' report found there was "a complete breakdown in communications that paralyzed command and control and made situational awareness murky at best."[32] This compounded problems at the federal level, where the architecture of command and control mechanisms failed to perform because of unclear (and often overlapping) roles and responsibilities that made coordinating the disparate activities of federal departments and agencies difficult and, according to the White House, prevented federal-level authorities from getting "real-time, accurate situational awareness of both the facts from the disaster area as well as the on-going response activities of the Federal, State, and local players."[33] The different levels of authorities could not effectively communicate with each other to get an accurate understanding of the scope of the disaster, where priorities existed, and what lines of efforts were being pursued.

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[26] Scott Shane and Thom Shanker, "When Storm Hit, National Guard Was Deluged Too," *New York Times*, September 28, 2005.

[27] Shane and Shanker, 2005.

[28] Shane and Shanker, 2005.

[29] Susan B. Glasser and Michael Grunwald, "The Steady Buildup to a City's Chaos," *Washington Post*, September 11, 2005.

[30] Shane and Shanker, 2005.

[31] White House, "Chapter Five: Lessons Learned," *The Federal Response to Hurricane Katrina: Lessons Learned*, Washington, D.C., 2006.

[32] Select Bipartisan Committee to Investigate the Preparation for and Response to Hurricane Katrina, *A Failure of Initiative: Final Report*, U.S. House of Representatives, February 15, 2006, p. 359.

[33] White House, 2006.

One of the major failures was the disaster response. According to the White House,

> Federal resource managers had great difficulty determining what resources were needed, what resources were available, and where those resources were at any given point in time. Even when Federal resource managers had a clear understanding of what was needed, they often could not readily determine whether the Federal government had that asset, or what alternative sources might be able to provide it.[34]

The difficulty extended to pre-disaster planning too. Despite the pre-positioning of some emergency supplies, there were nowhere near enough supplies in the places that needed them. For example, the Federal Emergency Management Agency (FEMA) had stockpiled for immediate distribution 2.7 million liters of water, 1.3 million meals ready to eat, and 17 million pounds of ice, but Louisiana received only a small portion of the supplies; Alabama got more than five times as much water for distribution.[35] Once the disaster struck, supplies were dispatched to reach those in need, but FEMA's lack of a real-time asset-tracking system left federal managers in the dark regarding the status of resources once they were shipped.[36] The difficulty in tracking supplies became evident in the disaster response. FEMA, for example, delivered millions of pounds of ice to holding centers in cities far away from the Gulf Coast.[37] Meanwhile, places that needed supplies—such as the Superdome—had to wait days to receive them.[38] This proved disastrous: for example, FEMA sent only seven trailers of food and water to the Superdome—enough to provide only two days of food for as many as 22,000 people and only three days of water for 30,000.[39]

Like the United States during Hurricane Katrina, Japan had many difficulties in its early assessment and response to the March 11 disasters. With many of its communication networks destroyed, Japan used satellites to get a better understanding of the damage sites. To get more-detailed information, however, Japan asked U.S. forces to deploy airborne assets, such as the RQ-4 *Global Hawk* unmanned aerial vehicle, to establish greater situational awareness for Tōkyō. This proved critical because it helped provide near–real time imaging of survivors, disaster-affected areas, and infrastructure that was used to assess damage and helped officials evaluate priorities.[40] Still, assessment was difficult because of the enormity of the disaster, which affected 227 municipalities across nine prefectures along hundreds of kilometers of coastline.[41] In addition to the geographic scope, the scale of the damage was massive: The

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[34] White House, 2006.

[35] Glasser and Grunwald, 2005.

[36] White House, 2006.

[37] Chris Edwards, "Hurricane Katrina: Remembering the Federal Failures," *Cato at Liberty*, Cato Institute blog post, August 27, 2015.

[38] Edwards, 2015.

[39] Glasser and Grunwald, 2005.

[40] Tony Capaccio, "Northrop Drone Flies over Japan Reactor to Record Data," Bloomberg, March 17, 2011; Pacific Air Forces Public Affairs, "Air Force Officials Use Global Hawk to Support Japan Relief Efforts," press release, March 16, 2011; Seth Robson, "Global Hawk Invaluable After Japan Disasters," *Stars and Stripes*, September 12, 2011.

[41] Aoki, 2016, p. 21.

earthquake and tsunami left Japan with more than 27 million tons of debris, accounting for approximately 14 years of waste for the Tōhoku region.[42]

Japan's disaster response also encountered difficulties. Authorities were challenged by the enormity of the destruction. Searching for survivors and helping the injured was an extremely slow process because of the large number of damaged structures. Responders had to check every house individually, which took time and was extremely dangerous because of the damage. Japanese responders were further challenged by the sheer number of people and organizations helping the response efforts. Japan received help from hundreds of countries and philanthropic organizations. For example, at the peak of the crisis, more than 200 nongovernmental organizations alone operated within affected areas providing supplies, shelter, and medical care to Japanese citizens.[43] Within the first three weeks of the disaster, the Japanese Red Cross had received more than $1 billion in donations, and more than 68 search-and-rescue teams from 45 countries were standing by to assist.[44] Although life-saving, the international assistance was overwhelming for Japanese authorities who had lost critical communication infrastructure, resulting in difficulties obtaining an accurate situational awareness of what response efforts were being undertaken, where supplies had been delivered, and where supplies were needed. This led the United Nations Disaster Assessment and Coordination team to ask organizations to limit unsolicited contributions.[45]

As these snapshots of challenges in damage assessment and response demonstrate, the larger the disaster, the more difficult it becomes to obtain accurate situational awareness and to coordinate disaster response. Obtaining a complete picture of the situation is difficult because incoming information is often incomplete, sporadic, and difficult to collect into a coherent whole. Could technology offer answers to some of the challenges that these authorities faced? For example, could AI/ML enable authorities to get damage assessments to first responders faster through automatic analysis and automatic data provision?[46] AI can be used for image recognition, so could AI-enabled systems use remote sensing images after a disaster to compare with pre-disaster images to help governments better assess damage to areas?[47] If so, that could help create real-time mapping and damage assessment that would help locate survivors in inaccessible locations far faster than ground-based rescue teams.[48]

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[42] Terri Norton, "Lessons Learned in Disaster Debris Management of the 2011 Great East Japan Earthquake and Tsunami," in Vicente Santiago-Fandino, Shinji Sato, Norio Maki, and Kanako Iuchi, eds., *The 2011 Japan Earthquake and Tsunami: Reconstruction and Restoration*, Cham, Switzerland: Springer International, 2018, p. 68.

[43] Jennifer D. P. Moroney, Stephanie Pezard, Laurel E. Miller, Jeffrey Engstrom, and Abby Doll, *Lessons from Department of Defense Disaster Relief Efforts in the Asia-Pacific Region*, Santa Monica, Calif.: RAND Corporation, RR-146-OSD, 2013, p. 103.

[44] This number had increased to 138 countries or regions and 39 international organizations by April 2011. Center for Excellence in Disaster Management & Humanitarian Assistance, "Japan Earthquake and Tsunami Update," press release, April 20, 2011, p. 2; Liz Ford and Claire Provost, "Japan Earthquake: Aid Flows in from Across the World," *The Guardian*, March 14, 2011; Julie Makinen and Kenji Hall, "Red Cross Hasn't Reached Japan Quake Victims," *Los Angeles Times*, April 3, 2011; Stephanie Nebehay, "Japan Requests Foreign Rescue Teams, UN Says," Reuters, March 11, 2011.

[45] Moroney et al., 2013, p. 89.

[46] Prime Minister's Office of Japan, "How Japan is Using Space Technology in Natural Disasters," YouTube, March 3, 2019.

[47] Microsoft, "How AI Can Help After Disaster," YouTube, September 26, 2018.

[48] Peter H. Diamandis, "AI and Robotics Are Transforming Disaster Relief," *Singularity Hub*, April 12, 2019.

Similarly, for disaster response, AI/ML systems could be leveraged to help responders. Understanding where supplies are needed and having information on what has already been delivered to a given location and where gaps remain are all critical needs that can prove daunting if authorities are overwhelmed. Drones, such as those used in Japan, can be used to provide accurate information about damaged areas, thereby making rescue efforts safer and less time-consuming—but they only provide macrolevel situational awareness, not the details needed for finding survivors in collapsed structures. If small, AI-connected robots could be deployed to quickly enter damaged buildings, search for survivors, and make note of survivors and victims, this could save precious time during immediate response efforts. If AI is given access to cell phone locations in a crisis, it might be possible to provide greater awareness for authorities. Moreover, using AI/ML for response efforts could help governments and relief agencies by enabling them to "parse through large volumes of complex, fragmented data to generate useful information that they can act on more quickly than before."[49] If this technology could be paired with assets that are capable of delivering supplies, that could be used to help officials distribute supplies both to inaccessible areas and to areas where people are staying in shelters and large assembly areas (rather than where they were in their individual communities).[50]

Disaster Mitigation

Effective disaster mitigation relies on critical details regarding expected threats so that authorities responsible for building infrastructure that is resistant to future disasters can make accurate land-use plans and project designs that incorporate hazard protections, community placement, and land adjustments while retaining some sense of community for residents. The two cases show different strategies for disaster mitigation and possible areas where technology can help.

For New Orleans, federal, state, and local governments have spent more than $20 billion on the construction or repairs of 350 miles of levees, flood walls, gates, and pumps that now encircle the city.[51] This consisted of several steps. The first was to repair the broken levees and flood walls to match pre-storm levels of infrastructure. The second was for the Army Corps of Engineers to develop a plan to offer interim protection against storms that would cause a once-in-100-years flood.[52] Despite experts calling for protection against the kind of storm that might show up once in 5,000 years, the heights for a once-in-100-years flood were adopted as the benchmark for construction; some experts say this is insufficient because New Orleans remains below sea level and is expected to endure more-powerful storms in the future as the climate continues to warm.[53] Knowing that the flood walls and earthen levees were not high enough to stop another Katrina-like storm surge, other features were built, such as deeper pilings to keep the walls upright and gates to keep Lake Pontchartrain from pouring into the city.

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[49] Jeff Catlin, "Artificial Intelligence for Disaster Relief: A Primer," Lexalytics, December 6, 2018.

[50] Catlin, 2018.

[51] John Schwartz and Mark Schleifstein, "Fortified but Still in Peril, New Orleans Braces for Its Future," *New York Times*, February 24, 2018.

[52] Schwartz and Schleifstein, 2018.

[53] Schwartz and Schleifstein, 2018.

There are concerns about likely storm surges and future floods, given that parts of the city are sinking, its coastal buffer is shrinking, and rising sea levels threaten even the new defenses.[54] One report, by the National Academy of Engineering and the National Research Council, said that levees and flood walls alone can never be large or sturdy enough to fully protect New Orleans from another disaster similar to Katrina.[55] Instead, voluntary relocation of people and neighborhoods from areas that are vulnerable to flooding should be considered, as should elevating the first floor of buildings if relocation is not possible and establishing a comprehensive evacuation program that features well-designed and tested evacuation plans.[56]

Following the March 11 disasters, Japan has also focused on stronger defenses. Municipalities focused on seawalls but also raised low-lying land and conducted group relocation of communities to higher ground.[57] Taking into consideration that much of the devastation caused by the tsunami, municipalities had two guiding frameworks with which to plan. The first was by Japan's central government, which recommended that municipalities reconstruct breakwaters and seawall embankments against a Level-One (L1) tsunami, one caused by a magnitude-8 earthquake.[58] Understanding that Level-Two (L2) tsunamis—generated by an earthquake of magnitude 9 or greater—will overspill existing levees and are expected to cause flooding at 6½ feet and higher, the government recommended a combination of structural and nonstructural measures that featured land use and building regulations accounting for the risks of inundation, land readjustment and raising, parallel embankment construction, and embankment raising.[59] The land use and building regulations included restrictions from being used for residential purposes or other vulnerable uses, such as hospitals or schools. To determine these vulnerable areas, the government conducted a survey and computer simulations that showed which areas were vulnerable to L1 or L2 tsunamis. The second guiding framework was by prefectural governments that were responsible for deciding sea embankment heights. For the sake of simplicity, prefectures decided that embankments would be built at the same height without considering the actual conditions of the coast (e.g., mouth of a bay versus inner parts of a bay) or the expected population or density of buildings that would live behind these embankments.[60] Municipalities developed the reconstruction plans for their communities using the central government guidelines and the results of the simulations and wall heights set by the prefectures.

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54 David Uberti, "Is New Orleans in Danger of Turning into a Modern-Day Atlantis?" *The Guardian*, August 24, 2015.

55 "Levees Cannot Fully Eliminate Risk of Flooding to New Orleans," *News from the National Academies*, April 24, 2009.

56 "Levees Cannot Fully Eliminate . . . ," 2009.

57 Kayo Murakami and David Murakami Wood, "Planning Innovation and Post-Disaster Reconstruction: The Case of Tohoku, Japan," *Planning Theory and Practice*, Vol. 15, No. 2, 2014, p. 238.

58 Central Disaster Management Council, *Report of the Committee for Technical Investigation on Countermeasures for Earthquakes and Tsunamis Based on the Lessons Learned from the "2011 off the Pacific Coast of Tohoku Earthquake,"* Tokyo, Japan: Government of Japan, September 28, 2011.

59 Michio Ubaura, "Changes in Land Use After the Great East Japan Earthquake and Related Issues of Urban Form," in Vicente Santiago-Fandino, Shinji Sato, Norio Maki, and Kanako Iuchi, eds., *The 2011 Japan Earthquake and Tsunami: Reconstruction and Restoration*, Cham, Switzerland: Springer International, 2018, pp. 185–187.

60 Yasuaki Onoda, Haruka Tsukuda, and Sachi Suzuki, "Complexities and Difficulties Behind the Implementation of Reconstruction Plans After the Great East Japan Earthquake and Tsunami of March 2011," in Vicente Santiago-Fandino, Shinji Sato, Norio Maki, and Kanako Iuchi, eds., *The 2011 Japan Earthquake and Tsunami: Reconstruction and Restoration*, Cham, Switzerland: Springer International, 2018, p. 5.

Although both New Orleans and Japan have largely completed their efforts at disaster mitigation, it is useful to consider whether AI/ML have the potential of helping other governments prepare against future disasters from the sea. For example, Professor Shunichi Koshimura of Japan's Tōhoku University has developed technology to help provide the Japanese government with a real-time estimate of how far inland a tsunami could penetrate a coastal area and the number of people who could be affected by it.[61] If similar technology can be used to predict where a disaster will hit hardest, which defensive systems are likely to fail, and which communities are in the most danger, governments can create more-accurate hazard maps and inundation zones, thereby enabling more-informed decisionmaking when it comes to issuing building permits, building codes, and designating evacuation routes and emergency shelters.[62] Technology could also potentially be used to refresh these hazard maps on a frequent basis to ensure up-to-date information on land use.[63] This would better position governments to advise communities of potential risks and even issue evacuation orders, if necessary.[64] Another area where AI might prove useful is the potential to monitor aging infrastructure. In the event of a future hurricane, earthquake, or tsunami, it is expected that there would be significant damage not just to critical infrastructure—such as electricity, gas, and water—but also to buildings themselves. If AI systems can be used to detect structural deformations, this would help governments know what infrastructure needs urgent repairs and reduce the damage caused by collapsing buildings and bridges.[65] A final application for AI might be in the large-scale modeling of long-term recovery, where the initial cause of the disaster—whether storm, earthquake, or other hazard—has passed and populations suffer more from challenges in recovery and restoration than from the proximate cause of an incident. Every disaster is different, but after the initial crisis they all involve periods of clean-up and restoration during which at least some lives might be lost and many economic and psychological stresses occur.

Conclusion

How to predict, respond, and mitigate the damage caused by earthquakes and hurricanes is both a major challenge and an opportunity. The disasters that the United States and Japan experienced changed forever the lives of countless families and communities. Studying these disasters could provide lessons on how to leverage technology to mitigate the loss of lives in the future. This chapter described areas where AI/ML have the potential to improve the ability to predict, respond, and mitigate damage caused by natural disasters.

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[61] Alfred Siew, "In Japan, Technology Is Helping to Predict a Tsunami, Recycle Water for Affected Citizens," *Techgoondu*, February 27, 2019.

[62] Noah Rue, "The Life-Saving Potential of AI in Disaster Relief," *Medium*, January 9, 2019.

[63] Bill Gourgey, "How Artificial Intelligence Could Prevent Natural Disasters," *Wired*, July 10, 2018.

[64] Prime Minister's Office of Japan, 2019.

[65] Joshi, 2019.

CHAPTER SEVEN

How AI-Enabled Modeling and Simulation Can Improve Coastal Communities' Preparation, Defense, and Recovery from Disaster: Real-Time Tsunami Inundation Forecasting

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The 2011 Great East Japan earthquake and tsunami revealed many problems in Japan's disaster management policies, and these have undergone reforms in the years since to promote initiatives for building national resilience with the aim of creating safe and secure regions and improve society's strength and flexibility in confronting any future disasters. One of the key challenges in the aftermath of any tsunami is identifying its impact and prioritizing disaster response and relief activities. Because of the widespread damage to infrastructure and communications networks, the impacted regions were hampered in addressing the overall damage, sometimes for months. This experience highlighted the need to develop technologies to forecast the regional impact of tsunamis. Recent advances in high-performance computing and large data sets comprising observations of tsunami emergence, propagation, and effects hold out the promise of dramatically improving our understanding of the whole picture of tsunami-affected areas in real time.

Three approaches to real-time tsunami inundation forecasting methods have been proposed in Japan. The first is the so-called "Tsunami Scenario Bank" approach: searching tsunami forecast data from a pre-computed database connected with offshore tsunami observation posts.[2] Once a tsunami is observed offshore, the pre-computed database starts searching for the best matching pair of offshore tsunami heights that fits the observations, then projects the tsunami inundation scenarios most likely to correctly forecast coastal tsunami heights.

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[1] The views presented in this chapter are solely those of the author and should not be construed as an endorsement of any specific technology or product by RAND or any of its research sponsors.

[2] Aditya Riadi Gusman, Yuichiro Tanioka, Breanyn T. MacInnes, and Hiroaki Tsushima, "A Methodology for Near-Field Tsunami Inundation Forecasting: Application to the 2011 Tohoku Tsunami," *Journal of Geophysical Research—Solid Earth*, Vol. 119, No. 11, 2014; Yasuhiko Igarashi, Takane Hori, Shin Murata, Kenichiro Sato, Toshitaka Baba, and Masato Okada, "Maximum Tsunami Height Prediction Using Pressure Gauge Data by a Gaussian Process at Owase in the Kii Peninsula, Japan," *Marine Geophysical Research*, Vol. 37, 2016; Naotaka Yamamoto, Shin Aoi, Kenji Harata, Wataru Suzuki, Takashi Kunugi, and Hiromitsu Nakamura, "Multi-Index Method Using Off-Shore Ocean-Bottom Pressure Data for Real-Time Tsunami Forecast," *Earth, Planets and Space*, Vol. 68, No. 128, 2016.

The second is a "data assimilation" approach that assimilates tsunami wave field data using dense offshore tsunami observation networks.[3] This method estimates the tsunami wave field (tsunami height and tsunami velocity) in real time by repeatedly assimilating dense tsunami data into a numerical simulation. Both are highly dependent on the configuration of offshore tsunami sensors.

The third is the "real-time forward simulation" approach that runs simulations in real time with given tsunami source models based on seismic and geodetic observations. The real-time forward approach has the most advantages in simulating tsunami inundation on land—if reliable tsunami source model information is obtained. None of the three methods was developed before the 2011 Great East Japan Earthquake. The "Tsunami Scenario Bank" method is now being tested in some coastal areas, and the "real-time forward simulation" method is now in operation as a part of the Japanese central government's emergency response effort. In this chapter, I discuss my team's development of the third, "real-time forward simulation," model.[4]

We established a method of real-time tsunami inundation forecasting and damage estimation to predict the impact of a tsunami. The method has been verified through case studies of the 2011 Tohoku earthquake tsunami with regard to its forecasting reliability and capability.[5] After the verification, in 2017, the system started operation as a critical component of the tsunami response system in the Cabinet Office of the Government of Japan. Additionally, a newly founded technology firm, RTi-cast, is taking a role in offering and operating real-time tsunami inundation damage forecasting services across Japan. This chapter aims to provide some background discussion of real-time tsunami inundation forecasting and forward-looking discussion of perspectives for enhancing the use of real-time tsunami inundation forecasting information.

Real-Time Tsunami Inundation Forecasting with Forward Simulation

The vector-parallel supercomputers SX-ACE and SX-Aurora served as the core simulation architectures for the real-time forward simulation approach. SX-ACE are installed at both Tohoku and Osaka Universities and are operated independently to enhance redundancy in the event of an emergency. A simulation management system that achieves optimal allocation of jobs between nodes has recently been established. This enables SX-ACE to support urgent tasks, executing tsunami inundation simulation at the highest priority and suspending other active jobs, then automatically resuming them as soon as the urgent simulation completes.[6]

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[3] Takuto Maeda, Kazushige Obara, Masanao Shinohara, Toshihiko Kanazawa, and Kenji Uehira, "Successive Estimation of a Tsunami Wavefield Without Earthquake Source Data: A Data Assimilation Approach Toward Real-Time Tsunami Forecasting," *Geophysical Research Letters*, Vol. 42, No. 19, 2015; Yuchen Wang, Kenji Satake, Takuto Maeda, and Aditya Riadi Gusman, "Data Assimilation with Dispersive Tsunami Model: A Test for the Nankai Trough," *Earth, Planets and Space*, Vol. 70, No. 131, 2018.

[4] This research was partly supported by JST CREST (JPMJCR1411) and JSPS Grants-in-Aid for Scientific Research 17H06108.

[5] Shunichi Koshimura, Ryota Hino, Yusaku Ota, and Hiroaki Kobayashi, "Advances of Tsunami Inundation Forecasting and Its Future Perspectives," IEEE OCEANS 2017 Aberdeen conference and workshop, Aberdeen, Scotland, June 19–22, 2017.

[6] Akihiro Musa, Osamu Watanabe, Hiroshi Matsuoka, Hiroaki Hokari, Takuya Inoue, Yoichi Murashima, Yusaku Ohta, Ryota Hino, Shunichi Koshimura, and Hiroaki Kobayashi, "Real-Time Tsunami Inundation Forecast System for Tsunami Disaster Prevention and Mitigation," *Journal of Supercomputing*, Vol. 74, 2018.

The priority target for forecasting is the Nankai Trough and its vicinity, a region where tsunami-generating earthquakes are likely to occur (Figure 7.1). A large-scale Nankai Trough earthquake is estimated to occur in the next 30 years with 70–80 percent probability, according to long-term evaluations of seismic activity in Japan.[7] The forecasting area encompasses the 6,000-km coastline from Kagoshima to Shizuoka prefectures. In our assessment, we verify the capability of the new real-time tsunami inundation forecasting, damage mapping, and response system for stakeholders and responders through the case studies of the 2011 event.

Activating the tsunami propagation and inundation forecasting system requires receipt of seismic information from the Earthquake Early Warning service of the Japan Meteorological Agency, which can happen just a few tens of seconds after initial observation of seismic waves. More-precise information is then provided by real-time analysis of GEONET (Global Navigation Satellite System Earth Observation Network System) data that are supposed to be transmitted within ten minutes of an earthquake occurring. We use the fault rupture estimation derived by the RAPiD and REGARD algorithms, which provide the estimates of the moment magnitude, fault geometries, focal mechanisms, and slip distributions.[8] Given the tsunami source information, the system moves on to model tsunami propagation and inundation simulations running on SX-ACE and SX-Aurora together with offshore and coastal tide gauges to determine tsunami travel and arrival times, the extent of the inundation zone, the maximum flow depth distribution, and potential losses. The implemented model is based on nonlinear, shallow-water equations discretized by using a staggered, leap-frog finite difference method. Using SX-ACE, we accomplished a “10-10-10 challenge,” completing tsunami source determination in ten minutes and tsunami inundation modeling in ten minutes at 10-m grid resolution (Figure 7.1). The simulations are now optimized to be more efficient, using a new nested grid system and its MPI-parallelization and running on other HPC processors to expand its capability to other areas and users (Figure 7.2).[9]

Damage Estimation and Mapping

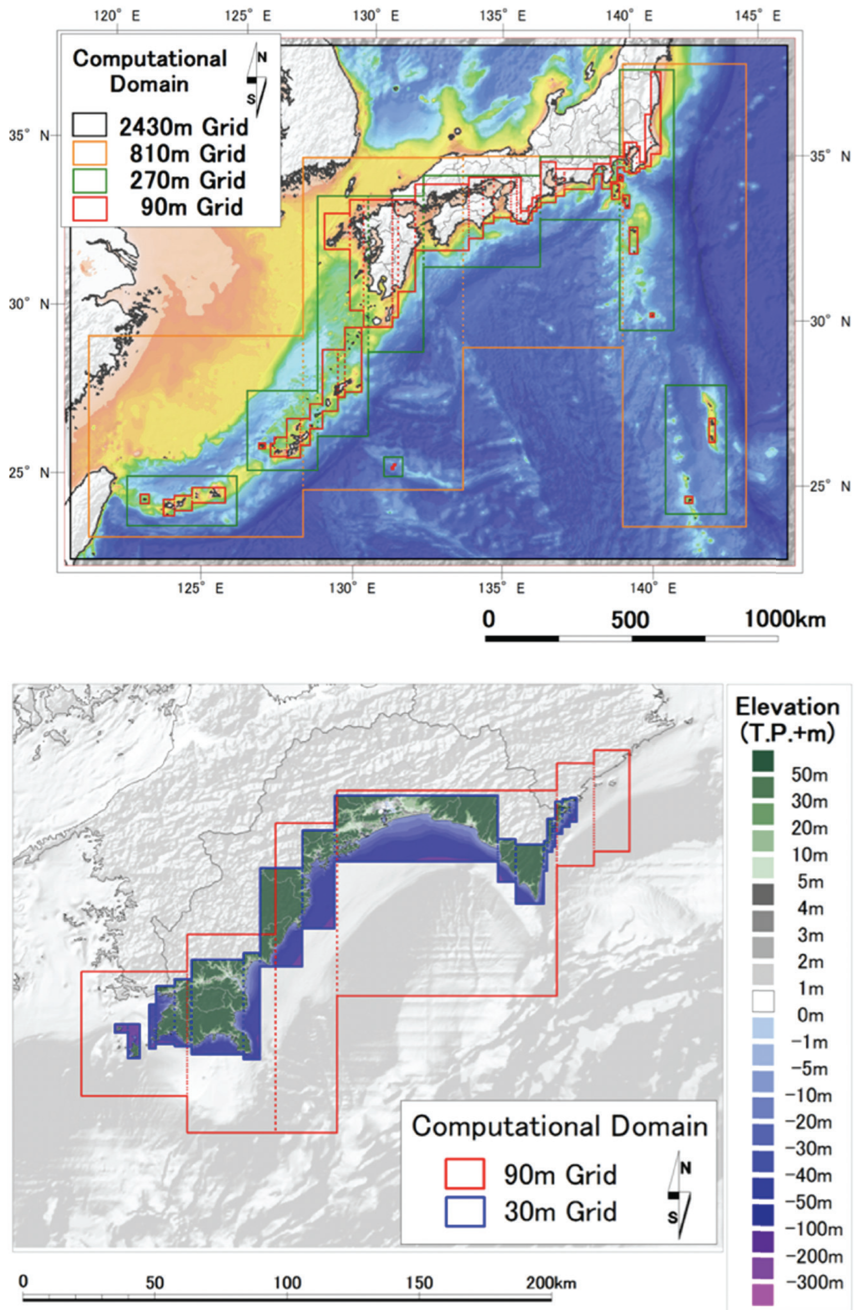
Identifying a tsunami’s impact and determining which areas are most likely to be devastated by it is critical for disaster response, recovery, and relief activities. Given the maximum flow depth distribution, the system performs geographic information systems analysis to determine

7 “A Disaster to Dwarf 3/11? The Predicted Nankai Quake,” *Nippon*, June 7, 2019.

8 Yusaku Ohta, Tatsuya Kobayashi, Hiroaki Tsushima, Satoshi Miura, Ryota Hino, Tomoji Takasu, Hiromi Fujimoto, Takeshi Iinuma, Kenji Tachibana, Tomotsugu Demachi, et al., “Quasi Real-Time Fault Model Estimation for Near-Field Tsunami Forecasting Based on RTK-GPS Analysis: Application to the 2011 Tohoku-Oki Earthquake (Mw 9.0),” *Journal of Geophysical Research—Solid Earth*, Vol. 117, No. B2, 2012; Satoshi Kawamoto, Yusaku Ohta, Yohei Hiyama, Masaru Todoriki, Takuya Nishimura, Tomoaki Furuya, Yudai Sato, Toshihiro Yahagi, and Kohei Miyagawa, “REGARD: A New GNSS-Based Real-Time Finite Fault Modeling System for GEONET,” *Journal of Geophysical Research—Solid Earth*, Vol. 122, No. 2, 2017.

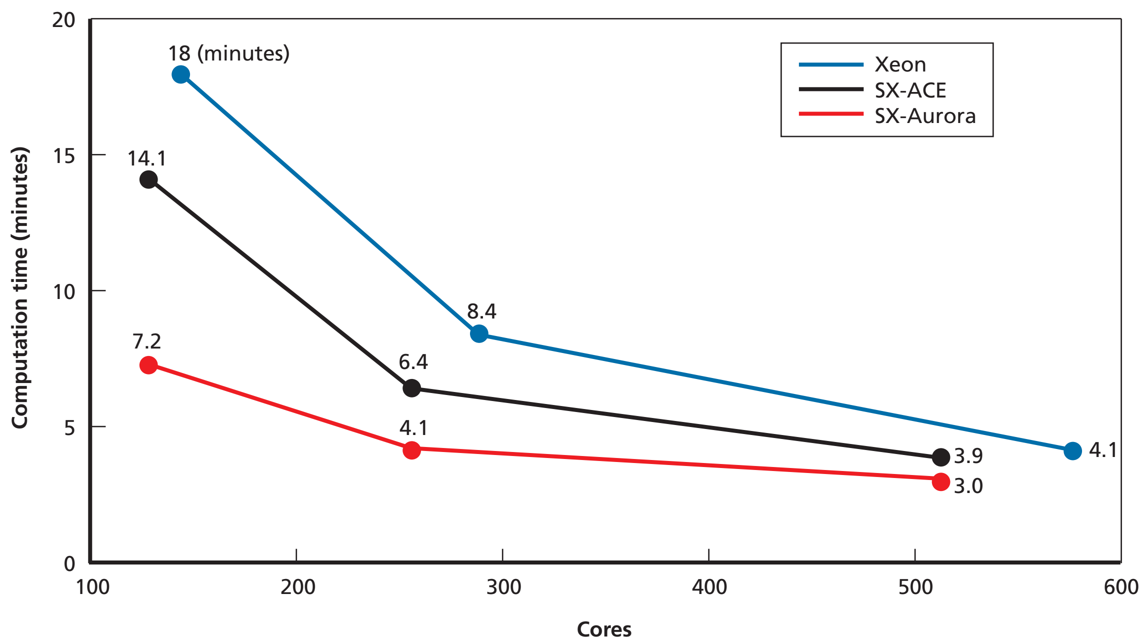
9 Takuya Inoue, Takashi Abe, Shunichi Koshimura, Akihiro Musa, Yoichi Murashima, and Hiroaki Kobayashi, “Development and Validation of a Tsunami Numerical Model with the Polygonally Nested Grid System and Its MPI-Parallelization for Real-Time Tsunami Inundation Forecast on a Regional Scale,” *Journal of Disaster Research*, Vol. 14, No. 3, 2019; Akihiro Musa, Takashi Abe, Takumi Kishitani, Takuya Inoue, Masayuki Sato, Kazuhiko Komatsu, Yoichi Murashima, Shunichi Koshimura, and Hiroaki Kobayashi, “Performance Evaluation of Tsunami Inundation Simulation on SX-Aurora TSUBASA,” in João M. F. Rodrigues, Pedro J. S. Cardoso, Jânio Monteiro, Roberto Lam, Valeria V. Krzhizhanovskaya, Michael H. Lees, Jack J. Dongarra, and Peter M. A. Sloot, eds., *International Conference on Computational Science, 2019—Proceedings, Part I*, New York: Springer, 2020.

Figure 7.1
Computational Domains for Nankai Trough Earthquake Tsunami



SOURCE: Inoue et al., 2019.
NOTE: The image on the top is a nested grid system; the image on the bottom illustrates grid configurations for Kochi Prefecture.

Figure 7.2
Performance of Real-Time Tsunami Inundation Forecasts with Multicomputational Platforms



SOURCE: Musa et al., 2020.
NOTES: The graphic shows the relationship of computational time to complete our six-hour inundation forecast and the number of the processor cores used in different computing platforms (Intel Xeon, NEC SX-ACE, and NEC SX_Aurora). It implies that the vector supercomputer SX-Aurora has the best performance out of three.

the size of the exposed population and structures using census data; it then estimates the numbers of potential deaths and damaged structures. The result is a tsunami fragility curve, which represents structural damage probabilities as a function of tsunami flow depth (Figure 7.3).[10]

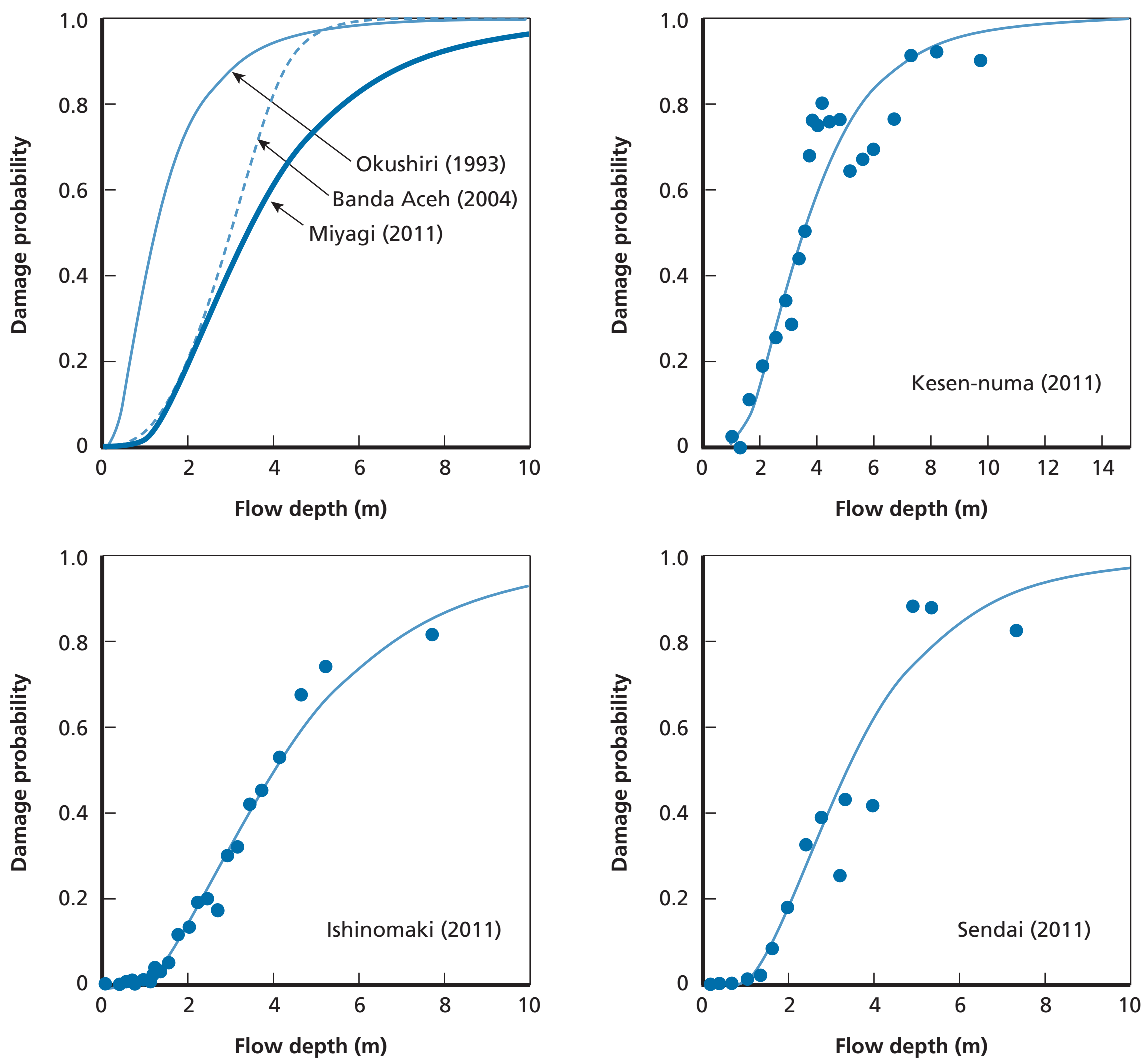
The results are disseminated as mapping products (Figure 7.4) to responders and stakeholders (e.g., national, regional, and municipal authorities and private-sector actors) for use in their emergency response activities (e.g., identifying the scale of the exposed population; assessing the potential damage to houses, road networks, and other critical infrastructure; search-and-rescue and recovery).

The projections are being used to enable governments and first responders to assess potential losses and decide how best to allocate scarce resources for efficient and timely response, relief, and recovery. In the future, the next step will be to expand the forecasting model's capability to respond during an emergent event to facilitate real-time evacuation and rescue efforts. For instance, the fusion of real-time mobile sensors (e.g., mobile phones, internet-enabled vehicles, or other types of Wi-Fi–connected devices) with tsunami inundation, traffic simulation, and pedestrian simulation models run by multiagent systems could provide dynamic solutions, helping identify how people should move to escape a tsunami and how many people are actually waiting to be rescued.[11]

[10] Shunichi Koshimura and Nobuo Shuto, "Response to the 2011 Great East Japan Earthquake and Tsunami Disaster," *Philosophical Transactions of the Royal Society A*, Vol. 373, No. 2053, October 2015.

[11] Takehiro Kashiyama, Yoshihide Sekimoto, Masao Kuwahara, Takuma Mitani, Shunichi Koshimura,"Hybrid System for Generating Data on Human Flow in a Tsunami Disaster," *Journal of Disaster Research*, Vol. 13, No. 2, 2018.

Figure 7.3
Tsunami Fragility Curves for Estimating Structural Damage

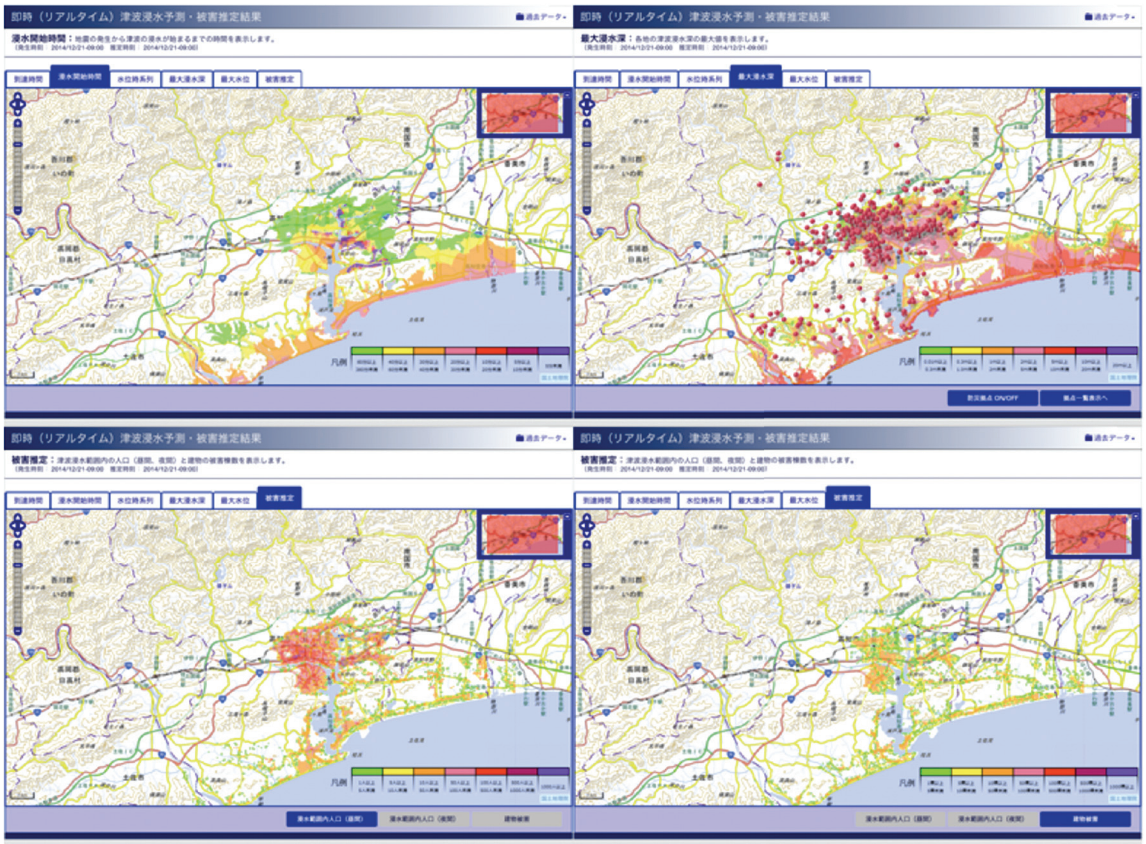


SOURCE: Koshimura and Shuto, 2015.
NOTES: The fragility curve shown in the figure indicates the damage probabilities of structural destruction equivalent to the flow depth that were obtained as empirical relations from coastal communities. Structures were especially vulnerable when the local flow depth exceeded 2 meters; flow depths above 6 meters typically cause total devastation.

Conclusion

With use of modern computing power and advanced monitoring capabilities, we have established a new system of real-time tsunami inundation forecasting and damage estimation and mapping to enhance society's resilience in the aftermath of a major tsunami disaster. If an earthquake is triggered along Nankai Trough, the tsunami source estimation will be performed using earthquake early warning information and GEONET data analysis, and the process is designed to complete the tsunami source estimate within ten minutes. Then, the real-time tsunami inundation forecasting system will be activated to execute the jobs on vector super computer SX-ACE within the next ten minutes. The spatial resolution of the tsunami inundation

Figure 7.4
Tsunami Inundation and Damage Forecast Results



NOTES: Top left: tsunami arrival time in number of minutes after quake occurs; top right: maximum flow depth in meters; bottom left: structural damage assessed in terms of the number of destroyed or washed-away buildings; bottom right: exposed populations in the inundation zone.

forecasting is up to 10 meters to perform precise tsunami inundation forecasting and damage estimation using tsunami fragility curves. The results are disseminated as mapping products to responders and stakeholders (e.g., national, regional, and municipal governments) to be used for their emergency response activities. The system started operation in November 2017 as a part of the tsunami disaster response system of the government of Japan. Enhancing the speed and reliability of tsunami inundation forecasting technology can improve tsunami warning by projecting survival information.

The technology of real-time forecast using forward simulation with high-performance computing infrastructure can be applied to hydrological and coastal hazards, such as storm surge. The damage forecast information can be used for decisionmakers both before and after an event to facilitate evacuation, relief, and recovery efforts by estimating exposed populations, potential deaths, required amounts of emergency supplies, impacts on road networks, likely amounts of debris generated, and the need and location sites for deployment of heavy construction equipment. Given the prospect of infectious disease outbreaks in the aftermath of a disaster, it might be extremely important to use forecasting information to understand population exposure risks by leveraging census data, dynamic mobile sensing data, and other valuable information to identify facilities needed for sheltering and recovery.

CHAPTER EIGHT

Conclusions

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As is clear from presentations made at the pair of conferences and the foregoing chapters of these conference proceedings, some aspects of the American and Japanese experiences of artificial intelligence and machine learning (AI/ML) technologies are quite similar, while also differing in certain key respects. Both societies face concerns about how to ensure that AI is used for social good. Both are striving to balance privacy concerns and (as presenters at the first conference noted) to encourage programmers to identify and confront bias in weightings. Like the United States, Japan is seeking transparency and intelligibility from the decision algorithms of its AI/ML tools as these are increasingly adopted by busy decisionmakers. Like Japan, the United States is eager to avoid losing out on the benefits of AI/ML by avoiding them altogether or by regulating them in ways that reflect an imbalanced concern for preventing harms that might not be realistic. Japan, even more than the United States, is in a position where it must work harder to train, attract, cultivate, and retain the AI/ML workforce of the future. And Japan has thought hard about how to protect data flows securely, something the United States is also exploring.

The two sides of the Pacific differ somewhat in their reactions to AI/ML technology. Japan, a less litigious society and one often characterized (perhaps somewhat simplistically) as more techno-optimistic, expresses fewer concerns about the potential negative effects of AI/ML, and the debates there appear less focused on potential existential AI threats. By contrast, the United States, with its greater emphasis of a legalistic regulatory framework and a stronger cultural emphasis on imagining worst-case scenarios (including in fiction and film), has been more techno-pessimistic. Japan's declining labor force makes technology a welcome addition; in the United States, many observers worry about job loss, though such concerns are mitigated in certain sectors where AI/ML technologies might free up scarce labor to focus on higher-value inputs and relieve workers of jobs that no one else would want. Examples of the latter in the United States include radiologic technologists, farm workers, and security guards; in Japan, a noted example has been administrative staff in child care.[1]

For both Washington, D.C., and Tokyo, it will be important that policies aimed at facilitating the rollout of AI/ML technology (e.g., by supporting such tools through appropriate regulatory frameworks that help ensure AI-enabled decisions) are explicable, free from bias, replicable, and (where required) justiciable. Steps to support standardization of legal culpability frameworks, build out infrastructures that enable the Internet of Things through reliable fifth-generation Wi-Fi, and ensure secure cloud computing will also facilitate the use of these new

1 "With Help from Robots . . . ," 2019.

technologies on a broader scale with greater social buy-in and support. Japan has been moving to expand its use of the Internet of Things and big data among small and medium-scale enterprises; as it continues to digitize its economy—a development that the coronavirus pandemic is likely to accelerate—it will become an even more attractive partner for the United States to cooperate with on AI/ML technologies.[2] Scoping the policy questions, educational and work force requirements, legal dimensions, technology issues, and international relations norms that will permit an extension of the power that AI/ML tools bring to work for the benefit of society is a promising area of cooperation between the United States and Japan—as well as with other allies, partners, and like-minded actors— and it will remain so for many years to come.[3]

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[3] James L. Schoff, *U.S.–Japan Technology Policy Coordination: Balancing Technonationalism with a Globalized World*, Washington, D.C.: Carnegie Endowment for International Peace, 2020.

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