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JOBS LOST, JOBS GAINED: WORKFORCE TRANSITIONS IN A TIME OF AUTOMATION

DECEMBER 2017

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Project teams are led by the MGI partners and a group of senior fellows, and include consultants from McKinsey offices around the world. These teams draw on McKinsey's global network of partners and industry and management experts. Advice and input to MGI research are provided by the MGI Council, members of which are also involved in MGI's research. MGI council members are drawn from around the world and from various sectors and include Andrés Cadena, Sandrine Devillard, Richard Dobbs, Tarek Elmasry, Katy George, Rajat Gupta, Eric Hazan, Eric Labaye, Acha Leke, Scott Nyquist, Gary Pinkus, Sven Smit, Oliver Tonby, and Eckart Windhagen. In addition, leading economists, including Nobel laureates, act as research advisers to MGI research.

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JOBS LOST, JOBS GAINED: WORKFORCE TRANSITIONS IN A TIME OF AUTOMATION

DECEMBER 2017

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PREFACE

Automation is not a new phenomenon, and fears about its transformation of the workplace and effects on employment date back centuries, even before the Industrial Revolution in the 18th and 19th centuries. In the 1960s, US President Lyndon Johnson empaneled a "National Commission on Technology, Automation, and Economic Progress." Among its conclusions was "the basic fact that technology destroys jobs, but not work."* Fast forward and rapid recent advances in automation technologies, including artificial intelligence, autonomous systems, and robotics are now raising the fears anew—and with new urgency. In our January 2017 report on automation, *A future that works: Automation, employment, and productivity*, we analyzed the automation potential of the global economy, the timelines over which the phenomenon could play out, and the powerful productivity boost that automation adoption could deliver.

This report goes a step further by examining both the potential labor market disruptions from automation and some potential sources of new labor demand that will create jobs. We develop scenarios that seek to address some of the questions most often raised in the public debate. Will there be enough work in the future to maintain full employment, and if so what will that work be? Which occupations will thrive, and which ones will wither? What are the potential implications for skills and wages as machines perform some or the tasks that humans now do?

The report is part of the McKinsey Global Institute's research program on the future of work, and is by no means the final word on this topic. The technology continues to evolve, as will our collective understanding of the economic implications. Indeed, we highlight some of the limitations of our analysis and scenarios, and areas for further research. The report builds on our previous research on labor markets, incomes, skills, and the expanding range of models of work, including the gig economy, as well as the potential impacts on the global economy of digitization, automation, robotics, and artificial intelligence.

The research was led by James Manyika, chairman and director of the McKinsey Global Institute and McKinsey senior partner based in San Francisco; Susan Lund, an MGI partner based in Washington, DC; Michael Chui, an MGI partner in San Francisco; Jacques Bughin, MGI director and McKinsey senior partner based in Brussels; and Jonathan Woetzel, MGI director and McKinsey senior partner in Shanghai. Parul Batra, Ryan Ko, and Saurabh Sanghvi headed the research team at different times over the course of the project. The team comprised Julian Albert, Gurneet Singh Dandona, Nicholas Fletcher, Darien Lee, Nik Nayar, Sonia Vora, and Rachel Wong.

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* *Technology and the American economy: Report of the National Commission on Technology, Automation, and Economic Progress*, US Department of Health, Education, and Welfare, February 1966.

Colleagues from around the world offered valuable insights into various aspects of our research. We thank Jens Riis Anderson, Jake Bryant, Richard Dobbs, Rajat Gupta, Kimberly Henderson, Tasuku Kuwabara, Meredith Lapointe, Jan Mischke, Anu Madgavkar, Deepa Mahajan, Mona Mourshed, Chandrika Rajagopalan, Jaana Remes, Jimmy Sarakatsannis, Katharina Schumacher, Jeongmin Seong, Bob Sternfels, and Eckart Windhagen.

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This report contributes to MGI's mission to help business and policy leaders understand the forces transforming the global economy, identify strategic locations, and prepare for the next wave of growth. As with all MGI research, this work is independent and has not been commissioned or sponsored in any way by any business, government, or other institution. While we are grateful for all the input we have received, the report and views expressed here are ours alone. We welcome your comments on this research at **MGI@mckinsey.com**.

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On Fifth Avenue, New York

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IN BRIEF

JOBS LOST, JOBS GAINED: WORKFORCE TRANSITIONS IN A TIME OF AUTOMATION

In our latest research on automation, we examine work that can be automated through 2030 and jobs that may be created in the same period. We draw from lessons from history and develop various scenarios for the future. While it is hard to predict how all this will play out, our research provides some insights into the likely workforce transitions that should be expected and their implications. Our key findings:

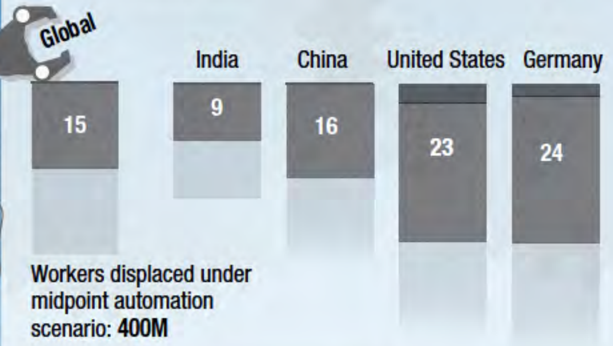
- Automation technologies including artificial intelligence and robotics will generate significant benefits for users, businesses, and economies, lifting productivity and economic growth. The extent to which these technologies displace workers will depend on the pace of their development and adoption, economic growth, and growth in demand for work. Even as it causes declines in some occupations, automation will change many more—60 percent of occupations have at least 30 percent of constituent work activities that could be automated. It will also create new occupations that do not exist today, much as technologies of the past have done.
- While about half of all work activities globally have the technical potential to be automated by adapting currently demonstrated technologies, the proportion of work actually displaced by 2030 will likely be lower, because of technical, economic, and social factors that affect adoption. Our scenarios across 46 countries suggest that between almost zero and one-third of work activities could be displaced by 2030, with a midpoint of 15 percent. The proportion varies widely across countries, with advanced economies more affected by automation than developing ones, reflecting higher wage rates and thus economic incentives to automate.
- Even with automation, the demand for work and workers could increase as economies grow, partly fueled by productivity growth enabled by technological progress. Rising incomes and consumption especially in developing countries, increasing health care for aging societies, investment in infrastructure and energy, and other trends will create demand for work that could help offset the displacement of workers. Additional investments such as in infrastructure and construction, beneficial in their own right, could be needed to reduce the risk of job shortages in some advanced economies.
- Even if there is enough work to ensure full employment by 2030, major transitions lie ahead that could match or even exceed the scale of historical shifts out of agriculture and manufacturing. Our scenarios suggest that by 2030, 75 million to 375 million workers (3 to 14 percent of the global workforce) will need to switch occupational categories. Moreover, all workers will need to adapt, as their occupations evolve alongside increasingly capable machines. Some of that adaptation will require higher educational attainment, or spending more time on activities that require social and emotional skills, creativity, high-level cognitive capabilities and other skills relatively hard to automate.
- Income polarization could continue in the United States and other advanced economies, where demand for high-wage occupations may grow the most while middle-wage occupations decline—assuming current wage structures persist. Increased investment and productivity growth from automation could spur enough growth to ensure full employment, but only if most displaced workers find new work within one year. If reemployment is slow, frictional unemployment will likely rise in the short-term and wages could face downward pressure. These wage trends are not universal: in China and other emerging economies, middle-wage occupations such as service and construction jobs will likely see the most net job growth, boosting the emerging middle class.
- To achieve good outcomes, policy makers and business leaders will need to embrace automation's benefits and, at the same time, address the worker transitions brought about by these technologies. Ensuring robust demand growth and economic dynamism is a priority: history shows that economies that are not expanding do not generate job growth. Midcareer job training will be essential, as will enhancing labor market dynamism and enabling worker redeployment. These changes will challenge current educational and workforce training models, as well as business approaches to skill-building. Another priority is rethinking and strengthening transition and income support for workers caught in the cross-currents of automation.

JOBS LOST GAINED CHANGED

Automation will bring big shifts to the world of work, as AI and robotics change or replace some jobs, while others are created. Millions of people worldwide may need to switch occupations and upgrade skills.

Scenarios for automation adoption, 2016–30

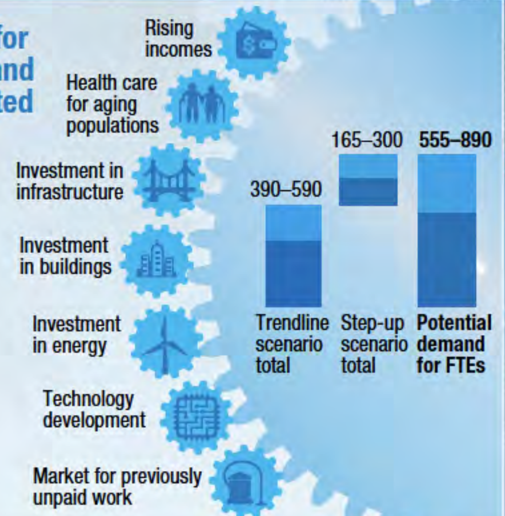
Under midpoint scenario, % of work hours with potential to be automated



Workers displaced under midpoint automation scenario: **400M**

Scenarios for labor demand from selected catalysts, 2016–30

Million FTEs, ranged low–high



Jobs of the future: some occupations will grow, others will decline, and new ones we cannot envision will be created

Workforce transitions

Our scenarios for automation and labor demand highlight challenges for workers

SWITCHING OCCUPATIONS...

75M–375M

Number of people who may need to switch occupational categories by 2030, under our midpoint to rapid automation adoption scenarios

...DEMANDING NEW SKILLS...

...CHANGING EDUCATIONAL REQUIREMENTS

Priorities for policy makers and business leaders

ECONOMIC GROWTH
Ensuring robust demand growth and economic dynamism; economies that are not expanding don't create jobs

SKILLS UPGRADE
Upgrading workforce skills, especially retraining midcareer workers, as people work more with machines

FLUID LABOR MARKET
The shifting occupational mix will require more fluid labor markets, greater mobility, and better job matching

TRANSITION SUPPORT
Adapting income and transition support to help workers and enable those displaced to find new employment

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Help wanted, Beverly Hills, California

SUMMARY OF FINDINGS

The technology-driven world in which we live is a world filled with promise but also challenges. Cars that drive themselves, machines that read X-rays, and algorithms that respond to customer service inquiries are all manifestations of powerful new forms of automation. Yet even as these technologies increase productivity and improve our lives, their use will substitute for some work activities humans currently perform—a development that has sparked much public concern.

This research builds on MGI's January 2017 report on automation and its impact on work activities.[1] We assess the number and types of jobs that might be created under different scenarios through 2030, and compare that to work that could be displaced by automation.[2] The results reveal a rich mosaic of potential shifts in occupations in the years ahead, with important implications for workforce skills and wages. The analysis covers 46 countries that comprise almost 90 percent of global GDP. We focus on six countries that span income levels (China, Germany, India, Japan, Mexico, and the United States). For each, we modeled the potential net employment changes for more than 800 occupations, based on different scenarios for the pace of automation adoption and for future labor demand. The intent of this research is not to forecast. Rather, we present a set of scenarios (necessarily incomplete) to serve as a guide, as we anticipate and prepare for the future of work. This research is by no means the final word on this topic; ongoing research is required. Indeed, in Box E2 at the end of this summary, we highlight some of the potential limitations of the research presented in this report.

Our findings suggest that several trends that may serve as catalysts of future labor demand could create demand for millions of jobs by 2030. These trends include caring for others in aging societies, raising energy efficiency and meeting climate challenges, producing goods and services for the expanding consuming class, especially in developing countries, not to mention the investment in technology, infrastructure, and buildings needed in all countries. Taken from another angle, we also find that a growing and dynamic economy—in part fueled by technology itself and its contributions to productivity—would create jobs. These jobs would result from growth in current occupations due to demand and the creation of new types of occupations that may not have existed before, as has happened historically. This job growth (jobs gained) could more than offset the jobs lost to automation. None of this will happen by itself—it will require businesses and governments to seize opportunities to boost job creation and for labor markets to function well. The workforce transitions ahead will be enormous. We estimate that as many as 375 million workers globally (14 percent of the global workforce) will likely need to transition to new occupational categories and learn new skills, in the event of rapid automation adoption. If their transition to new jobs is slow, unemployment could rise and dampen wage growth.

Indeed, while this report is titled *Jobs lost, jobs gained*, it could have been, *Jobs lost, jobs changed, jobs gained*; in many ways a big part of this story is about how more occupations will change than will be lost as machines affect portions of occupations and people increasingly work alongside them. Societal choices will determine whether all three of these coming workforce transitions are smooth, or whether unemployment and income inequality rise. History shows numerous examples of countries that have successfully ridden the wave of technological change by investing in their workforce and adapting policies, institutions, and business models to the new era. It is our hope that this report prompts leaders in that direction once again.

1 *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017.

2 We use the term "jobs" as shorthand for full-time equivalent workers (FTEs), and apply it to both work displaced by automation and to new work created by future labor demand. In reality, the number of people working is larger than the number of FTEs, as some people work part-time. Our analysis of FTEs covers both employees within firms as well as independent contractors and freelancers.

AUTOMATION COULD DISPLACE A SIGNIFICANT SHARE OF WORK GLOBALLY TO 2030; 15 PERCENT IS THE MIDPOINT OF OUR SCENARIO RANGE

In our prior report on automation, we found that about half the activities people are paid to do globally could theoretically be automated using currently demonstrated technologies.[3] Very few occupations—less than 5 percent—consist entirely of activities that can be fully automated. However, in about 60 percent of occupations, at least one-third of the constituent activities could be automated, implying substantial workplace transformations and changes for all workers. All this is based on our assessments of current technological capability—an ever evolving frontier (Exhibit E1).

Exhibit E1

Global workforce numbers at a glance

Technical automation potential

~50% of current work activities are technically automatable by adapting currently demonstrated technologies.

6 of 10 current occupations have more than **30%** of activities that are technically automatable

Impact of adoption by 2030[1]

% of workers (FTEs[2])	Slowest	Midpoint	Fastest
Work potentially displaced by adoption of automation, by adoption scenario	**0%** (10 million)	15% (400 million)	**30%** (800 million)
Workforce that could need to change occupational category, by adoption scenario[3]	**0%** (<10 million)	3% (75 million)	**14%** (375 million)

Impact of demand for work by 2030 from 7 select trends[4]

% of workers (FTEs)	Low	High
Trendline demand scenario	**15%** (390 million)	**22%** (590 million)
Step-up demand scenario	**6%** (165 million)	**11%** (300 million)
Total	**21%** (555 million)	**33%** (890 million)

In addition, of the 2030 workforce of 2.66 billion, 8–9% will be in new occupations[5]

1 "Slowest" and "fastest" adoption refer to the two extremes of the scenario range we used in our automation adoption modeling, the latest and earliest scenarios, respectively. See Chapter 1 for details.
2 Full-time equivalents.
3 In trendline labor-demand scenario.
4 Rising incomes; health care from aging; investment in technology, infrastructure, and buildings; energy transitions; and marketization of unpaid work. Not exhaustive.
5 See Jeffrey Lin, "Technological adaptation, cities, and new work," *Review of Economics and Statistics*, volume 93, number 2, May 2011.

SOURCE: McKinsey Global Institute analysis

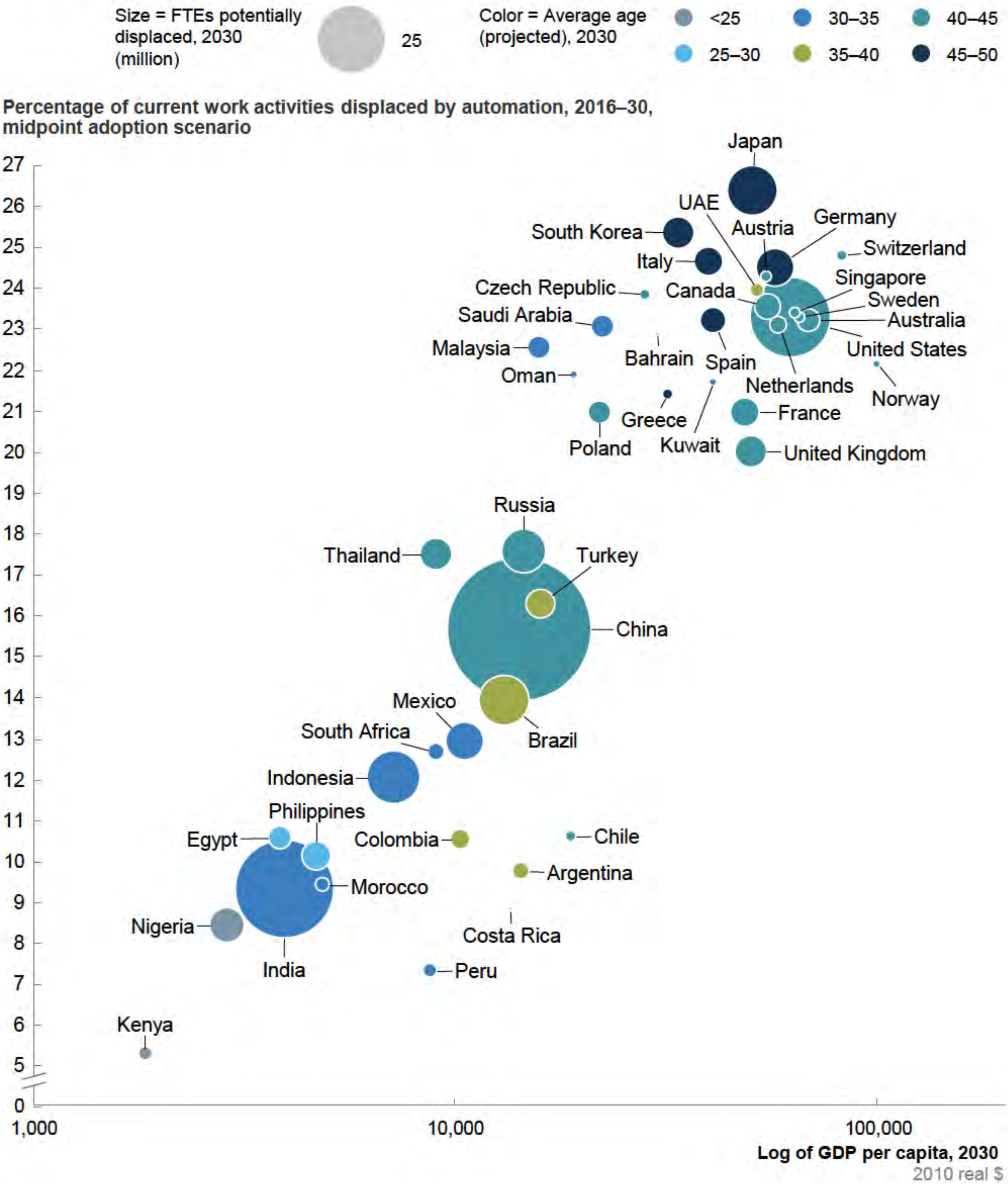
While technical feasibility of automation is important, it is not the only factor that will influence the pace and extent of automation adoption. Other factors include the cost of developing and deploying automation solutions for specific uses in the workplace, the labor market dynamics (including quality and quantity of labor and associated wages), the benefits of automation beyond labor substitution, and regulatory and social acceptance. Taking into account these factors, our new research estimates that between almost zero and 30 percent of the hours worked globally could be automated by 2030, depending on the speed of adoption. In this report we mainly use the midpoint of our scenario range, which is 15 percent of current activities automated. Results differ significantly by country, reflecting

[3] Our definition of automation includes robotics (machines that perform physical activities) and artificial intelligence (software algorithms that perform calculations and cognitive activities). Companies may adopt these technologies for reasons other than labor cost savings, such as improved quality, efficiency, or scale, although worker displacement could still be a consequence. A glossary of automation technologies and techniques is in the technical appendix.

the mix of activities currently performed by workers and prevailing wage rates. They range from 9 percent in India to 26 percent in Japan in the midpoint adoption rate scenario (Exhibit E2). This is on par with the scale of the great employment shifts of the past, such as out of agriculture or manufacturing (Box E1, "The historical evidence on technology and employment is reassuring").

Exhibit E2

Impact of automation varies by a country's income level, demographics, and industry structure



SOURCE: World Bank; Oxford Economics; McKinsey Global Institute analysis

Box E1. The historical evidence on technology and employment is reassuring

Technology adoption can and often does cause significant short-term labor displacement, but history shows that, in the longer run, it creates a multitude of new jobs and unleashes demand for existing ones, more than offsetting the number of jobs it destroys even as it raises labor productivity (Exhibit E3).[1] An examination of the historical record highlights several lessons:

- All advanced economies have experienced profound sectoral shifts in employment, first out of agriculture and more recently manufacturing, even as overall employment grew. In the United States, the agricultural share of total employment declined from 60 percent in 1850 to less than 5 percent by 1970, while manufacturing fell from 26 percent of total US employment in 1960 to below 10 percent today. Other countries have experienced even faster declines: one-third of China's workforce moved out of agriculture between 1990 and 2015.
- Such shifts can have painful consequences for some workers. During the Industrial Revolution in England, average real wages stagnated for decades, even as productivity rose.[2] Eventually, wage growth caught up to and then surpassed productivity growth. But the transition period was difficult for individual workers, and eased only after substantial policy reforms.
- New technologies have spurred the creation of many more jobs than they destroyed, and some of the new jobs are in occupations that cannot be envisioned at the outset; one study found that 0.56 percent of new jobs in the United States each year are in new occupations.[3] Most jobs created by technology are outside the technology-producing sector itself. We estimate that the introduction of the personal computer, for instance, has enabled the creation of 15.8 million net new jobs in the United States since 1980, even after accounting for jobs displaced. About 90 percent of these are in occupations that use the PC in other industries, such as call center representatives, financial analysts, and inventory managers.
- Robust aggregate demand and economic growth are essential for job creation. New technologies have raised productivity growth, enabling firms to lower prices for consumers, pay higher wages, or distribute profits to shareholders. This stimulates demand across the economy, boosting job creation.[4]
- Rising productivity is usually accompanied by employment growth, because it raises incomes which are then spent, creating demand for goods and services across the economy. When there has been a tradeoff between employment growth and labor productivity growth, it has been short-lived. In the United States, for example, our analysis shows that employment and productivity both grew in 95 percent of rolling three-year periods and 100 percent of rolling 10-year periods since 1960.
- Over the long term, productivity growth enabled by technology has reduced the average hours worked per week and allowed people to enjoy more leisure time.[5] Across advanced economies, the length of the average work-week has fallen by nearly 50 percent since the early 1900s, reflecting shorter working hours, more paid days off for personal time and vacations, and the recent rise of part-time work. The growth in leisure has created demand for new industries, from golf to video games to home improvement.

Although the historical record is largely reassuring, some people worry that automation today will be more disruptive than in the past. Technology experts and economists are debating whether "this time, things are different" (and we examine that debate starting on page 48 of this report). Our current view is that the answer depends on the time horizon considered (decades or centuries) and on the pace of future technological progress and adoption. On many dimensions, we find similarities between the scope and effects of automation today compared to earlier waves of technology disruption, going back to the Industrial

1 David H. Autor, "Why are there still so many jobs? The history and future of workplace automation," *Journal of Economic Perspectives*, volume 29, number 3, summer 2015.

2 Robert C. Allen, "Engels' pause: Technical change, capital accumulation, and inequality in the British industrial revolution," *Explorations in Economic History*, volume 46, number 4, October 2009.

3 This implies that 18 percent of the workforce today is employed in an occupation that essentially did not exist in 1980. Jeffrey Lin, "Technological adaptation, cities, and new work," *Review of Economics and Statistics*, volume 93, number 2, May 2011.

4 David Autor and Anna Salomons, "Does productivity growth threaten employment?" Working paper prepared for ECB Forum on Central Banking, June 2017.

5 For instance, see Mark Aguiar and Erik Hurst, "Measuring trends in leisure: The allocation of time over five decades," *The Quarterly Journal of Economics*, volume 122, issue 3, August 2007.

Box E1. The historical evidence on technology and employment is reassuring (continued)

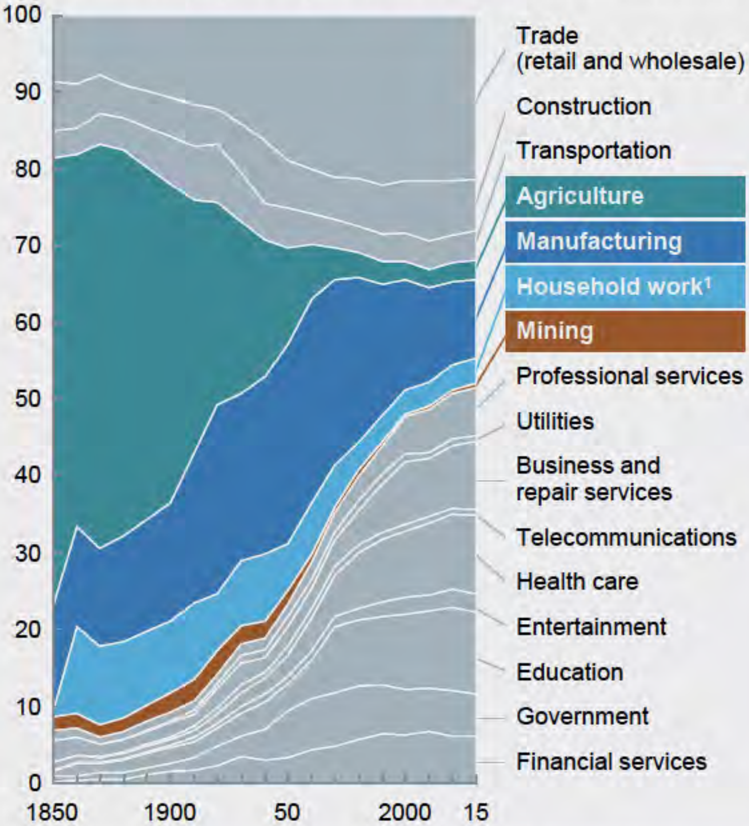
Revolution. However, automation going forward might prove to be more disruptive than in recent decades—and on par with the most rapid changes in the past—in two ways. First, if technological advances continue apace and are adopted rapidly, the rate of worker displacement could be faster. Secondly, if many sectors adopt automation simultaneously, the percentage of the workforce affected by it could be higher.

Exhibit E3

History shows that technology has created large employment and sector shifts, but also creates new jobs

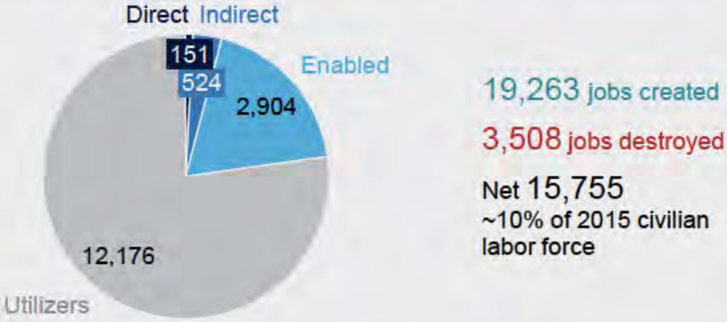
Large-scale sector employment declines have been countered by growth of other sectors that have absorbed workers

Share of total employment by sector in the United States, 1850–2015



Technology creates more jobs than it destroys over time, mainly outside the industry itself

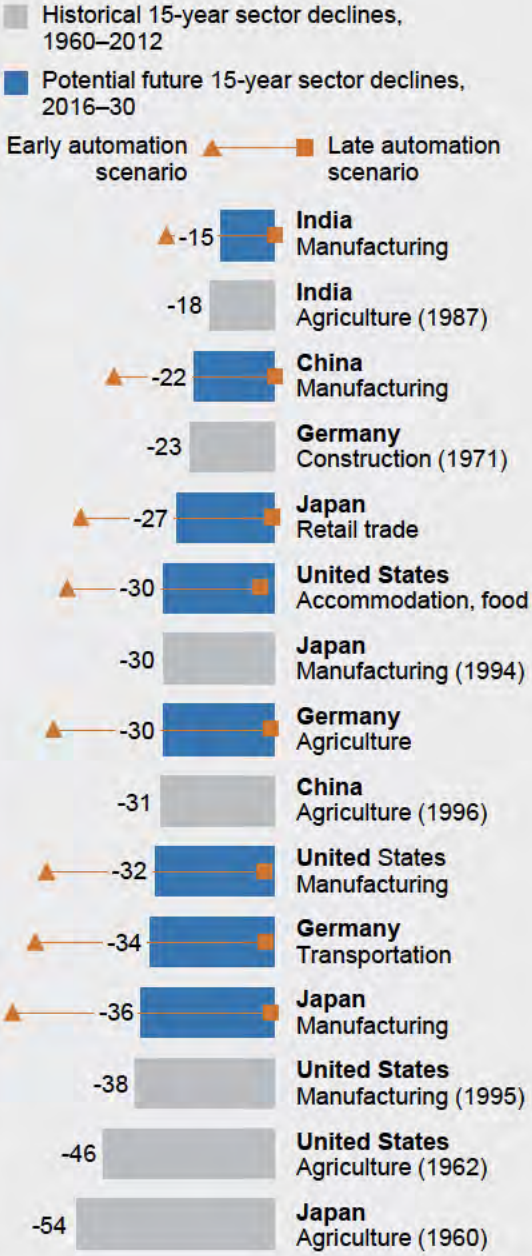
Example: Personal computers (total US jobs created, thousand)



Selected examples of large sector employment declines, past and future

% decline in sector employment

% of FTEs



1 Increase from 1850 to 1860 in employment share of household work primarily due to changes in how unpaid labor (slavery) was tracked.

NOTE: Numbers may not sum due to rounding.

SOURCE: IPUMS USA 2017; US Bureau of Labor Statistics; Groningen Growth and Development Centre 10-Sector Database; Moody's; IMPLAN; US Bureau of Labor Statistics; FRED; McKinsey Global Institute analysis

The potential impact of automation on employment varies by occupation and sector. Activities most susceptible to automation include physical ones in predictable environments, such as operating machinery and preparing fast food. Collecting and processing data are two other categories of activity that can increasingly be done better and faster with machines. This could displace large amounts of labor, for instance in mortgage origination, paralegal work, accounting, and back-office transaction processing. It is important to note, however, that even when some tasks are automated, employment in those occupations may not decline, but rather workers may perform new tasks. In addition, employment in occupations may also grow, if the overall demand for that occupation grows enough to overwhelm the rates of automation.

Automation will have a lesser effect on jobs that involve managing people, applying expertise, and those involving social interactions, where machines are unable to match human performance for now. Jobs in unpredictable environments—occupations such as gardeners, plumbers, or providers of child- and elder-care—will also generally see less automation by 2030, because they are difficult to automate technically and often command relatively lower wages, which makes automation a less attractive business proposition.

RISING INCOMES, INVESTMENTS IN INFRASTRUCTURE AND ENERGY, AND OTHER CATALYSTS COULD POTENTIALLY CREATE MILLIONS OF NEW JOBS

Up to
130M
new jobs in health care from aging and rising incomes by 2030

While automation's displacement of labor has been visible for many years, it is more difficult to envision all the new jobs that will be created. Many of these new jobs are created indirectly and spread across different sectors and geographies.

In this report, we model some potential sources of new labor demand that may spur job creation to 2030, even net of automation. We consider two scenarios, a "trendline" scenario based on current spending and investment trends observed across countries, and a "step-up" scenario that assumes additional investments in some areas. We calculate jobs (full-time equivalents) that could be created both directly and indirectly for more than 800 existing occupations. We do not consider the dynamic interactions between trends or across the economy (Exhibit E4). The results are not precise forecasts of future job growth, but rather are suggestive of where jobs of the future may be.

For three trends, we model only a trendline scenario. They are:

- **Rising incomes and consumption, especially in emerging economies.** Previous MGI research has estimated that 1 billion more people will enter the consuming class by 2025.[4] Using external macroeconomic forecasts, we estimate that global consumption could grow by $23 trillion between 2015 and 2030, and most of this will come from the expanding consuming classes in emerging economies. As incomes rise, consumers spend more on all categories. But their spending patterns also shift, creating more jobs in areas such as consumer durables, leisure activities, financial and telecommunication services, housing, health care, and education. The effects of these new consumers will be felt not just in the countries where the income is generated, but also in economies that export to those countries.[5] Globally, we estimate that 300 million to 365 million new jobs could be created from the impact of rising incomes.

- **Aging populations.** By 2030, there will be at least 300 million more people aged 65 years and above than there were in 2014. As people age, their spending patterns

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4 We define consuming classes or consumers as individuals with an annual income of more than $3,600, or $10 per day, at purchasing power parity, using constant 2005 PPP dollars. *Urban world: Cities and the rise of the consuming class*, McKinsey Global Institute, June 2012.

5 We assume that current patterns of global trade continue, at the same level relative to GDP as today. As a result, advanced economies also benefit from rising incomes in developing countries. The United States, for example, could gain up to 3 percent of net new jobs from rising incomes by 2030 from net exports. In Germany's case, that figure could be more than 40 percent.

shift, with a pronounced increase in spending on health care and other personal services. This will create significant demand for a range of occupations, including doctors, nurses, and health technicians, but also home health aides, personal care aides and nursing assistants in many countries, even as it reduces demand for pediatricians and primary-school teachers. Globally, we estimate heath care and related jobs from aging and rising incomes could grow by 80 million to 130 million by 2030.[6]

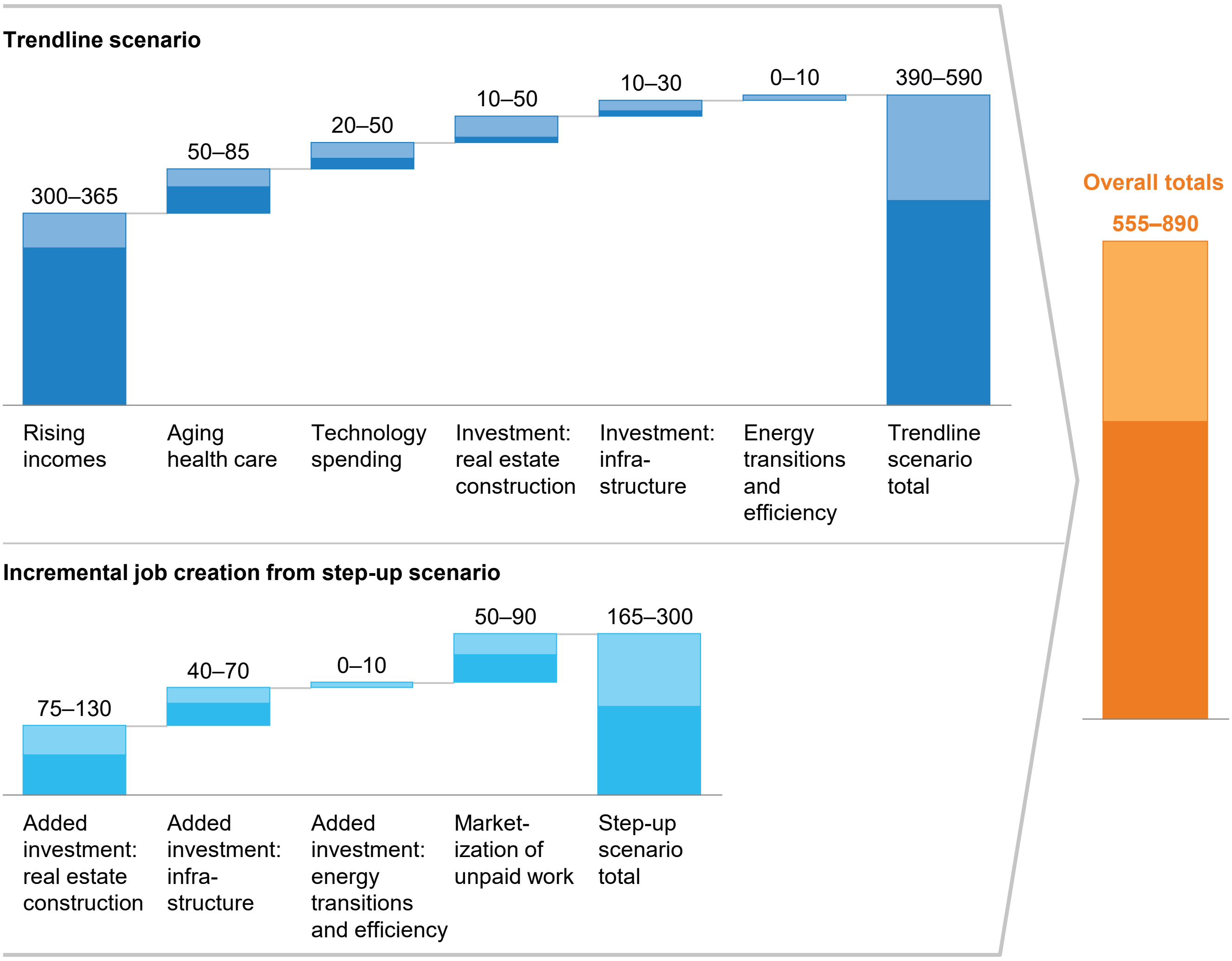
50M
new technology jobs by 2030

- **Development and deployment of technology.** Jobs related to developing and deploying new technologies may also grow. These jobs include computer scientists, engineers, and IT administrators. Overall spending on technology could increase by more than 50 percent between 2015 and 2030. About half would be on information technology services, both in-house IT workers within companies and external or outsourced tech consulting jobs. The number of people employed in these occupations is small compared to those in health care or construction, but they are high-wage occupations. By 2030, we estimate this trend could create 20 to 50 million jobs globally.

Exhibit E4

Rising consumer incomes are the largest source of job creation among our seven catalysts

Potential jobs created from seven catalysts of labor demand, midpoint automation, 2016–30[1]
Million FTEs, ranged low–high



1 Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: McKinsey Global Institute analysis

[6] We net out the effect of fewer health-care jobs related to children in this trend.

For three other trends, we model both a trendline scenario and a step-up scenario; the latter is based on explicit choices that could be made by governments, business leaders, and individuals to create additional jobs.

- **Investment in infrastructure and buildings.** Infrastructure and buildings are two areas of historic underspending that may create significant additional labor demand if action is taken to bridge infrastructure gaps and overcome housing shortages. MGI has estimated that the world needs to invest about 3.8 percent of GDP annually, or an average of $3.3 trillion per year to fill infrastructure gaps, compared with $2.5 trillion currently.[7] This includes both developing countries that are urbanizing and industrializing, and advanced economies that have underinvested in maintaining their infrastructure and buildings. Rising incomes also create demand for more and higher quality buildings. Both factors could create new demand, mainly in the construction sector, for up to 80 million jobs in the trendline scenario and, in some cases, potentially up to 200 million globally in the step-up scenario.[8] These jobs include architects, engineers, carpenters and other skilled tradespeople, as well as construction workers, machinery operators and other jobs with lower skill requirements.

- **Investments in renewable energy, energy efficiency, and climate adaptation.** Investments in renewable energy, such as wind and solar, energy efficiency technologies, and adaptation and mitigation of climate change may create new demand for workers in a range of occupations, including in manufacturing, construction, and installation. In our trendline scenario, we model future job growth based on already-announced policy intentions for energy efficiency and the required investment to meet these goals.[9] For a step-up scenario, we use more ambitious targets that countries will need to get closer to meeting commitments to the Paris climate accord.[10] These investments could create up to ten million new jobs in the trendline scenario, and up to ten million additional jobs globally in the step-up scenario.

20M
potential new jobs from energy investments in our step-up scenario

- **"Marketization" of previously unpaid domestic work.** The last trend we consider is the potential to pay for services that substitute for currently unpaid and primarily domestic work—including cooking, childcare, and cleaning. This so-called marketization of previously unpaid work is already prevalent in advanced economies, and rising female labor force participation worldwide could accelerate the trend. About 75 percent of the world's total unpaid care is undertaken by women and amounts to as much as $10 trillion of output per year, roughly equivalent to 13 percent of global GDP.[11] Individual decisions within the household to use paid services or government investment to provide universal childcare and pre-school could fuel this development. We consider this in the step-up scenario only, as its magnitude and timing is unclear. But we estimate that this shift could marketize 50 million to 90 million unpaid jobs globally, mainly in occupations such as childcare, early childhood education, cleaning, cooking, and gardening.

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7 *Bridging global infrastructure gaps*, McKinsey Global Institute, June 2016.

8 In the step-up scenario, we assume higher levels of run-rate infrastructure investment after countries have closed their respective infrastructure gap. We also assume that, at minimum, countries reach levels of commercial and residential real estate investment comparable to those in the United States.

9 Energy efficiency data from *World energy outlook 2016*, International Energy Agency, November 2016. See also *Beyond the supercycle: How technology is reshaping resources*, McKinsey Global Institute, February 2017.

10 While the United States has announced that it will withdraw from the Paris Agreement, other signatory countries have said they will continue to meet agreed emission reduction targets.

11 *The power of parity: How advancing women's equality can add $12 trillion to global growth*, McKinsey Global Institute, September 2015.

UP TO 375 MILLION PEOPLE MAY NEED TO SWITCH OCCUPATIONAL CATEGORIES, WITH THE HIGHEST SHARE IN ADVANCED ECONOMIES

When we look at the net changes in job growth and decline from the trends described above compared with the work that can be automated, a mosaic of shifts in occupations and job categories emerges (Exhibit E5).

Across all countries, the categories with the highest percentage job growth net of automation include health-care providers; professionals such as engineers, scientists, accountants, and analysts; IT professionals and other technology specialists; managers and executives, whose work cannot easily be replaced by machines; educators, especially in emerging economies with young populations; and “creatives,” a small but growing category of artists, performers, and entertainers who will be in demand as rising incomes create more demand for leisure and recreation. Builders and related professions will also grow, particularly in the step-up scenario that involves higher investment in infrastructure and buildings. Manual and service jobs in unpredictable environments will also grow, such as home health aides and gardeners.

Advanced economies may also see employment declines in occupations that are most susceptible to automation. These include office support occupations, such as record clerks, office assistants, and finance and accounting; some customer interaction jobs, such as hotel and travel workers, cashiers, and food service workers; and a wide range of jobs carried out in predictable settings, such as assembly line workers, dishwashers, food preparation workers, drivers, and agricultural and other equipment operators. Helping individuals transition from the declining occupations to growing ones will be a large-scale challenge.

The coming workforce transitions among occupations could be very large

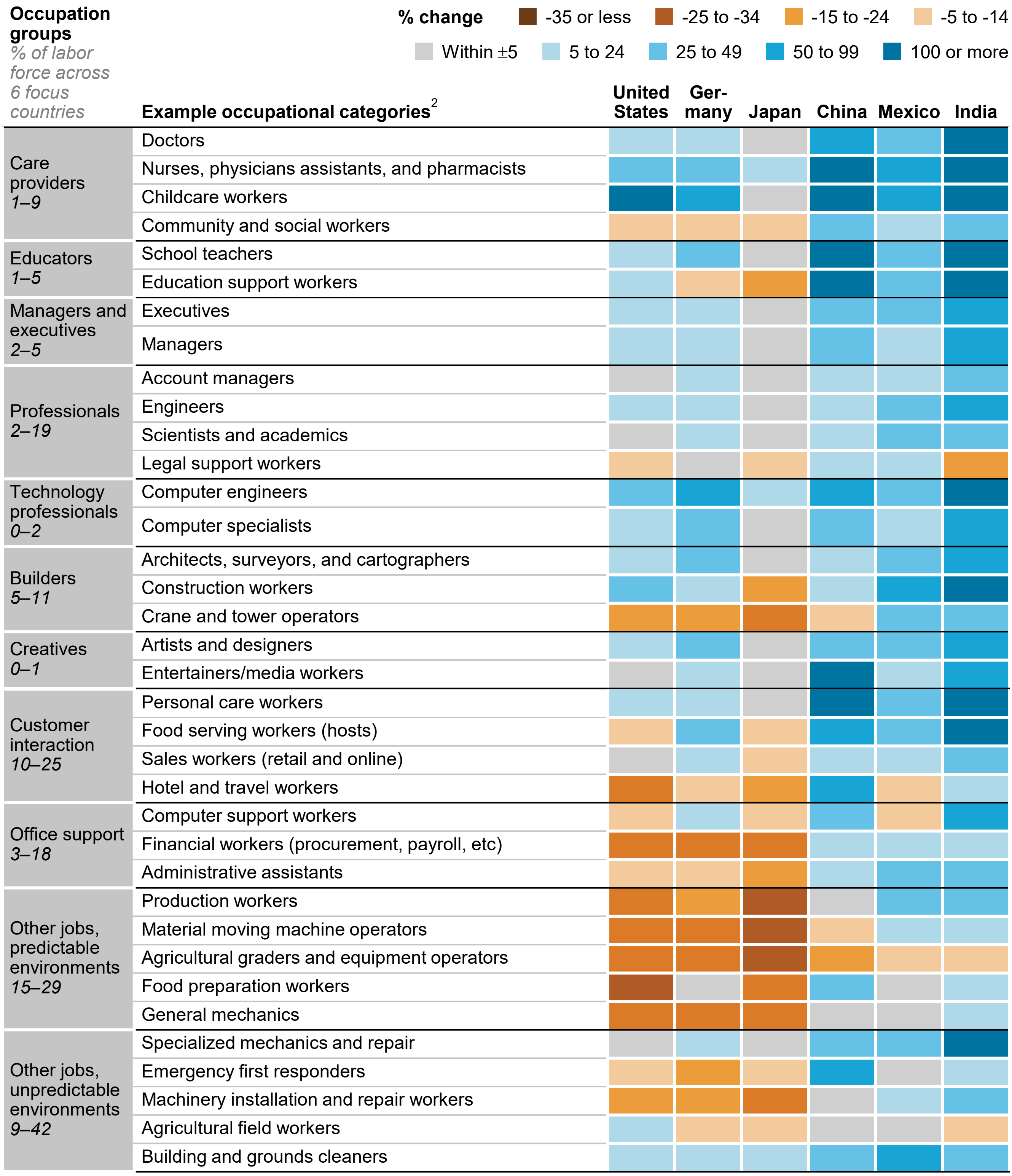
The changes in net occupational growth or decline imply that a very large number of people may need to shift occupational categories and learn new skills in the years ahead. The shift could be on a scale not seen since the transition of the labor force out of agriculture in the early 1900s in the United States and Europe, and more recently in China. But unlike those earlier transitions, in which young people left farms and moved to cities for industrial jobs, the challenge, especially in advanced economies, will be to retrain midcareer workers. There are few precedents in which societies have successfully retrained such large numbers of people. Frictions in the labor markets—including cultural norms regarding gender stereotypes in work and geographic mismatches between workers and jobs—could also impede the transition.[12]

[12] See Nicholas Eberstadt, *Men without work: America’s invisible crisis*, Templeton Press, 2016.

Exhibit E5

Jobs of the future: Employment growth and decline by occupation

Net impact of automation and seven catalysts of labor demand, 2016–30
% change (+/–), step-up labor demand, midpoint automation[1]



1 Midpoint of earliest and latest automation adoption in the "step-up" scenario (i.e., high job growth). Some occupational data projected into 2016 baseline from latest available 2014 data.
2 A complete version of this heat map with all occupation groupings is in Chapter 3.

SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

Up to

1/3

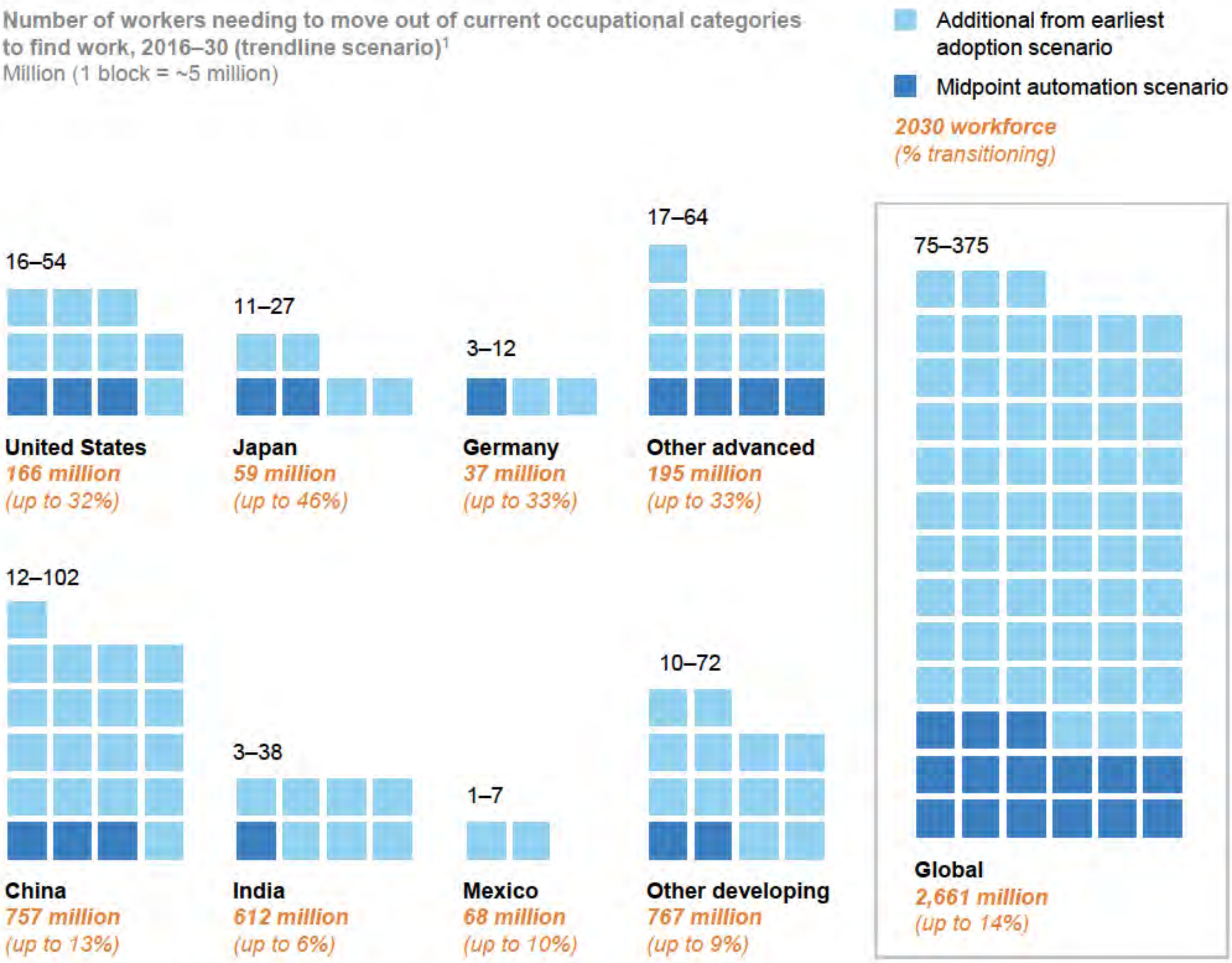
of workforce in the United States and Germany may need to find work in new occupations

We estimate that between 400 million and 800 million individuals could be displaced by automation and need to find new jobs by 2030 around the world, based on our midpoint and earliest (that is, the most rapid) automation adoption scenarios. We think demand for jobs will be there, based on our scenarios of future labor demand and the net impact of automation, as described in the next section. However people will need to find their way into these jobs. Of the total displaced, 75 million to 375 million may need to switch occupational categories and learn new skills, under our midpoint and earliest automation adoption scenarios (Exhibit E6).[13] Under the latest adoption scenario (that is, the slowest), this number would be far lower, below 10 million. Given the minimal impact on the workforce of this edge-case scenario, we have not highlighted it in the exhibits in this report. In absolute terms, China faces the largest number of workers needing to switch occupations—up to 100 million if automation is adopted rapidly, or 12 percent of the 2030 workforce—although this figure is relatively small compared with the huge shift in China out of agriculture in the past 25 years. For advanced economies, the share of the workforce that may need to learn new skills and find work in new occupations is much higher: up to one-third of the 2030 workforce in the United States and Germany, and nearly half in Japan.

Exhibit E6

Globally, up to 375 million workers may need to switch occupational categories

Number of workers needing to move out of current occupational categories to find work, 2016–30 (trendline scenario)[1]
Million (1 block = ~5 million)



1 Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: U.S. Bureau of Labor Statistics; McKinsey Global Institute analysis

[13] Analysis conducted by segmenting all US Bureau of Labor Statistics occupations into 58 occupational categories. See technical appendix.

WILL THERE BE ENOUGH WORK IN THE FUTURE?

Today there is growing concern about whether there will be enough jobs for workers given potential automation. History would suggest that such fears may be unfounded: over time, labor markets adjust to changes in demand for workers from technological disruptions, although at times with depressed real wages. We address this question about the future of work through two different sets of analyses: one based on modeling of a limited number of catalysts of new labor demand and automation described above, and one using a macroeconomic model of the economy that incorporates the dynamic interactions among variables. We also note that if history is any guide, we could expect 8 to 9 percent of 2030 labor demand will be in new types of occupations that have not existed before.[14] Both analyses lead us to conclude that, with sufficient economic growth, innovation, and investment, there can be enough new job creation to offset the impact of automation, although in some advanced economies additional investments will be needed as per our step-up scenario to reduce the risk of job shortages. But a larger challenge will be ensuring that workers have the skills and support needed to transition to new jobs. Countries that fail to manage this transition could see rising unemployment and depressed wages.

Future jobs lost and jobs gained vary by country, with the largest disruptions expected in advanced economies

The magnitude of future job creation from the trends described above and the impact of automation on the workforce vary significantly by country, depending on four factors:

- **Wage levels.** Higher wages make the business case for automation adoption stronger. However, low-wage countries may be affected as well, if companies adopt automation to boost quality, achieve tighter production control, move production closer to end consumers in high-wage countries, or other benefits beyond reducing labor costs. Some economists worry about "premature deindustrialization" in developing countries due to automation.[15]

- **Demand growth.** Economic growth is essential for job creation; economies that are stagnant or growing slowly create few if any net new jobs. Countries with stronger economic and productivity growth and innovation will therefore be expected to experience more new labor demand, although the amount and nature of job creation will vary depending on the sectors that drive growth.

- **Demographics.** Demographics affect both labor demand and labor supply. Countries with a rapidly-growing workforce, such as India, may enjoy a "demographic dividend" that boosts GDP growth—if young people are employed. Countries with a shrinking workforce, such as Japan, can expect lower future GDP growth, derived only from productivity growth. However, countries with a declining workforce need automation to offset their shrinking labor supply, while countries with growing workforces have greater job creation challenges.

- **Mix of economic sectors and occupations.** The automation potential for countries reflects the mix of economic sectors and the mix of jobs within each sector. Japan, for example, has a higher technical automation potential than the United States because the weight of sectors that are highly automatable, such as manufacturing, is higher. And within Japanese manufacturing, a larger proportion of jobs involve activities that can be more easily automated, such as production, than in the United States.

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14 Ibid. Jeffrey Lin, "Technological adaptation," May 2011.

15 For instance, see Dani Rodrik, "Premature deindustrialization," *Journal of Economic Growth*, volume 21, number 1, 2016.

These factors combine to create different outlooks for the future of work in each country (Exhibit E7). For instance, Japan is rich but its economy is projected to grow slowly to 2030. It faces the combination of slower job creation coming from economic expansion and a large share of work that can be automated as a result of high wages and the structure of its economy. However, Japan will also see its workforce shrink by 2030 by four million people. In the step-up scenario, and considering the jobs in new occupations we cannot envision today, Japan's net change in jobs could be roughly in balance.

Like Japan, the United States and Germany could also face significant workforce displacement from automation by 2030, but their projected future growth—and hence new job creation—is higher. The United States has a growing workforce and, in the step-up scenario, with innovations leading to new types of occupations and work, Germany's workforce will decline by three million by 2030, and it will have more than enough labor demand to employ all workers.

138M
Growth in India's labor force by 2030

At the other extreme is India: a fast-growing developing country with relatively modest potential for automation over the next 15 years, reflecting low wage rates. Our analysis finds that most occupational categories are projected to grow in India, reflecting its potential for strong economic expansion. However, India's labor force is expected to grow by 138 million people by 2030, or about 30 percent. Employing these new entrants in formal sector jobs will require job creation on a much larger scale than in the past. Automation will make this challenge more difficult; some fear "jobless growth."[16] However, our analysis suggests that India can create enough new jobs to offset automation and employ new entrants, if it undertakes the investments in our step-up scenario.

China and Mexico have higher wages than India, and so are likely to see more automation. China is still projected to have robust economic growth and will have a shrinking workforce; like Germany, China's problem could be a shortage of workers. Mexico's projected rate of future economic expansion is more modest, and its workforce will grow by 15 million by 2030. Like the United States and Japan, our results suggest that Mexico could benefit from the job creation in the step-up scenario plus innovation in new occupations and activities to make full use of its workforce.

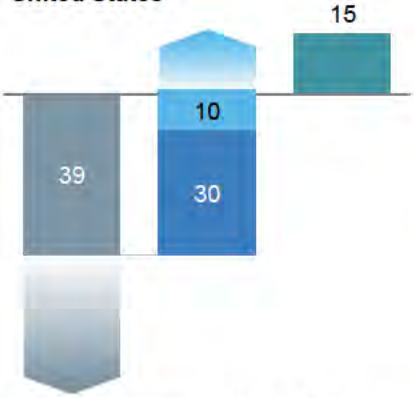
[16] See *India's labor market: A new emphasis on gainful employment*, McKinsey Global Institute, June 2017.

Exhibit E7

Jobs lost, jobs gained: Automation, new job creation, and change in labor supply, 2016–30

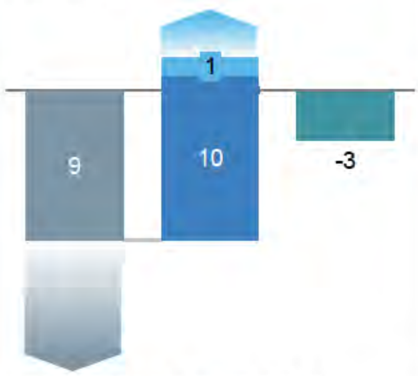
Range of automation scenarios and additional labor demand from seven catalysts

United States



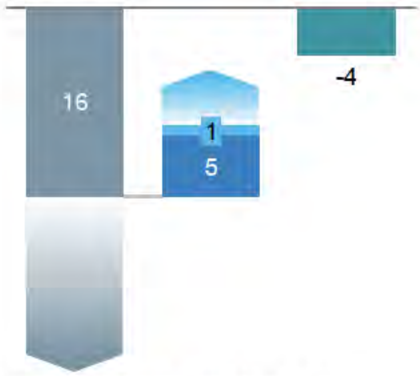
Enough jobs are created in the step-up scenario (along with growth in new occupations) to offset both automation and the growth in labor force

Germany



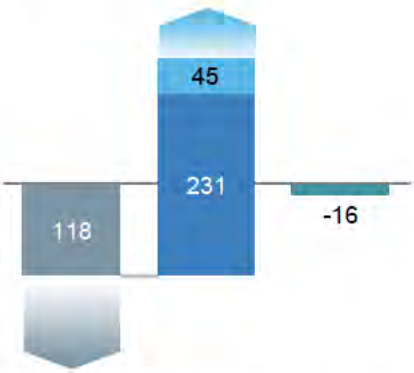
Enough jobs are created in the trendline scenario to offset effects of automation and the decline in the labor force

Japan



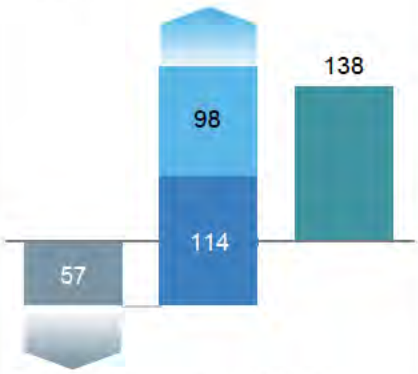
Enough jobs are created in the step-up scenario to offset automation and the decline in the labor force, if innovation creates sufficient new work activities

China



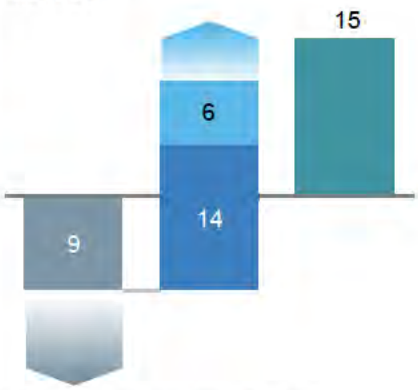
Enough jobs are created in the trendline scenario to offset effects of automation and the decline in labor force

India



Enough jobs are created in the step-up scenario to offset both automation and the growth in labor force

Mexico



Enough jobs are created in the step-up scenario to offset automation and the growth in labor force, given innovation in new work activities

1 Historical analysis suggests that we could expect 8–9% of 2030 labor supply will be in "new jobs," which is additional to labor demand we have estimated.

NOTE: We identified seven catalysts of labor demand globally: rising incomes, health-care spending, investment in technology, buildings, infrastructure, and energy, and the marketization of unpaid work. We compared the number of jobs to be replaced by automation with the number of jobs created by our seven catalysts as well as change in labor force, between 2016 and 2030. Some occupational data projected into 2016 baseline from latest available 2014 data. Not to scale.

SOURCE: McKinsey Global Institute analysis

If displaced workers are not reemployed quickly, countries will face rising unemployment and depressed wages

To model the impact of automation on overall employment and wages, we use a general equilibrium model of the economies of our six focus countries that takes into account the economic impacts of automation and dynamic interactions.[17] The model is not intended to forecast the future, but rather is a tool to explore the implications of different scenarios.

Automation has at least three distinct economic impacts. Most attention has been devoted to the potential displacement of labor. But automation also may raise labor productivity: firms only adopt automation when doing so enables them to produce more or higher-quality output with the same or fewer inputs (including material, energy, and labor inputs). The third impact is that automation adoption raises investment in the economy, lifting short-term GDP growth. We model all three effects.[18] We also create different scenarios for how quickly displaced workers find new employment, based on historical data.

The results reveal that across different rates of re-employment, our six countries could expect to be at or very near full employment by 2030. Consistent with the historical experience, labor markets adjust to technological shocks. However, the model also illustrates the importance of reemploying displaced workers quickly. If displaced workers are able to be reemployed within one year, our model shows automation lifting the overall economy: full employment is maintained in both the short and long-term, wages grow faster than in the baseline model, and productivity is higher. However, in scenarios in which some displaced workers take years to find new work, unemployment rises in the short- to medium-term. The labor market adjusts over time and unemployment falls—but with slower average wage growth. In these scenarios, average wages end up lower in 2030 than in the baseline model, which could dampen aggregate demand and long-term growth. The pace of reemployment will be influenced by the effectiveness of retraining, the capacity of companies to innovate and, in some sectors, the elasticity of demand.

WORKERS WILL REQUIRE DIFFERENT SKILLS, AND WAGE POLARIZATION IN ADVANCED COUNTRIES COULD CONTINUE

In all six of our focus countries, we find that in general, the current educational requirements of the occupations that may grow are higher than those for the jobs displaced by automation. In advanced economies, occupations that currently require only a secondary education or less see a net decline from automation, while those occupations requiring college degrees and higher grow. In India and other emerging economies, we find higher labor demand for all education levels, with the largest number of new jobs in occupations requiring a secondary education but the fastest rate of job growth will be for occupations currently requiring a college or advanced degree (Exhibit E8). For all countries, increasing investments in education and workforce training will be a priority.

Moreover, we find that workers of the future will spend more time on activities that machines are less capable of, such as managing people, applying expertise, and communicating with others. They will spend less time on predictable physical activities, and on collecting and processing data, where machines already exceed human performance. The skills and capabilities required will also shift, requiring more social and emotional skills, and more advanced cognitive capabilities, such as logical reasoning and creativity.

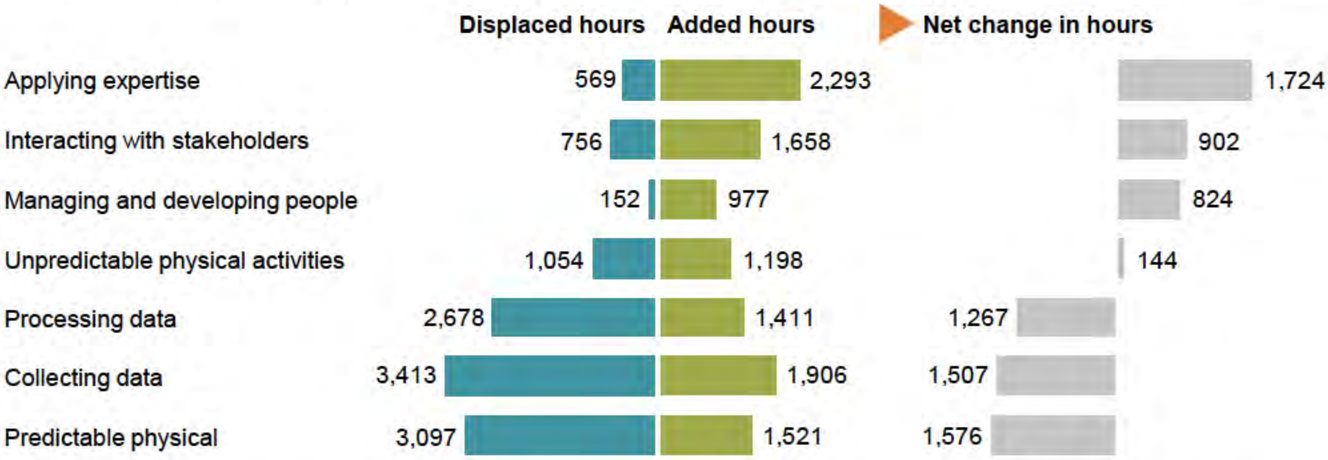
17 We used McKinsey & Company's Global Growth Model, a supply-side general equilibrium macroeconomic model that covers more than 100 countries with data from 1960 through 2015.

18 We obtain data for labor displacement and required firm investment from MGI's automation model, at the midpoint adoption scenario. We make a conservative assumption on the productivity impact of automation, that firms produce the same value of output as prior to automation but with fewer workers. See technical appendix for more detail.

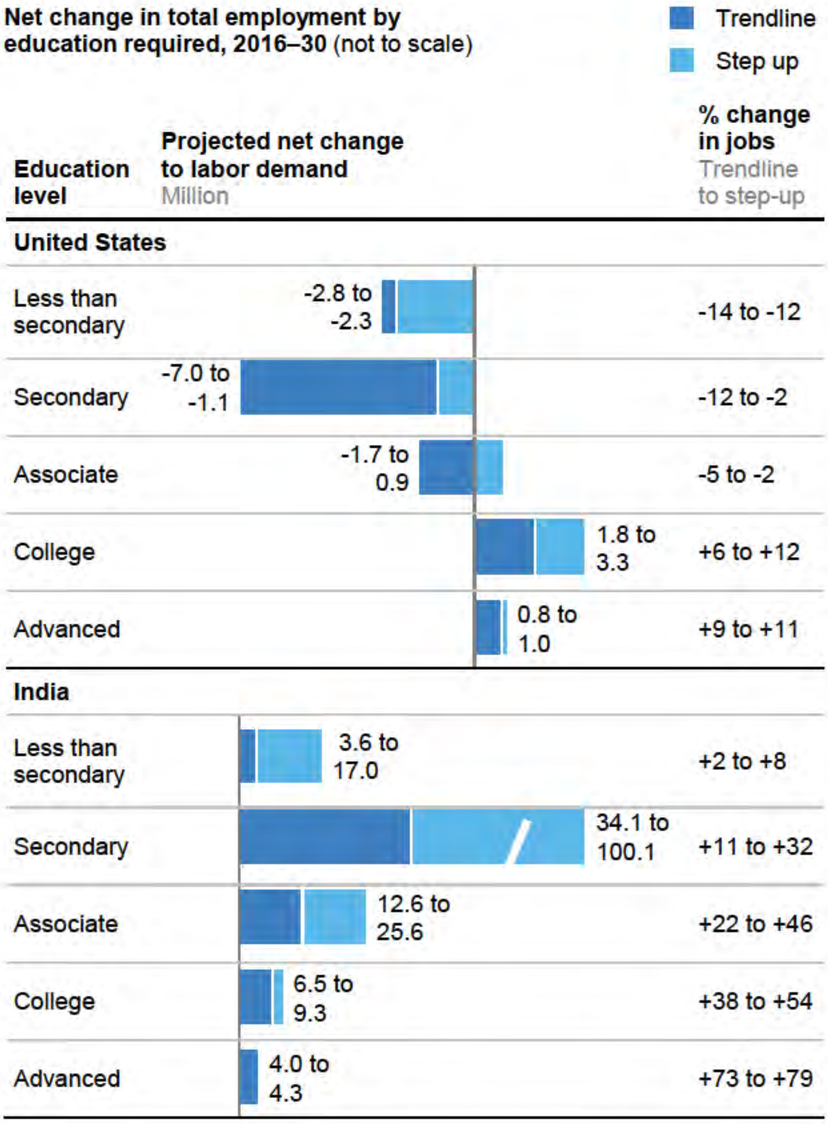
Exhibit E8

Potential shifts for activities, educational requirements, and wages

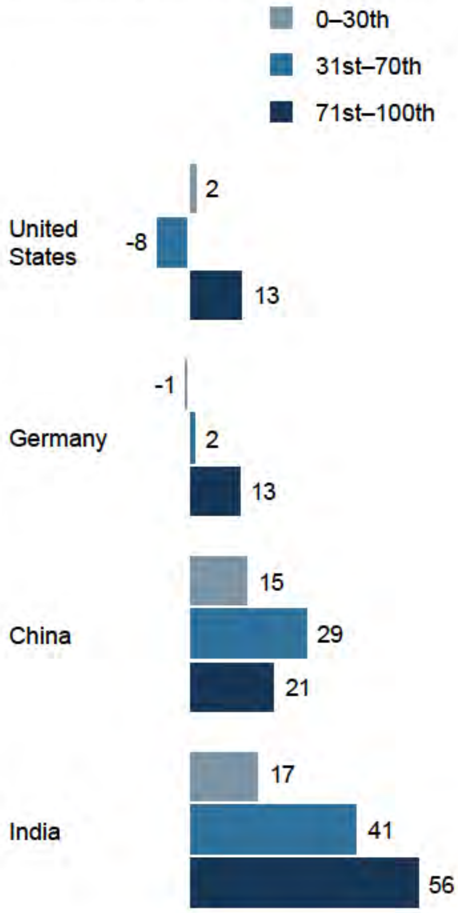
Net growth in work will involve more application of expertise, interaction, and management: Germany example
Total work hours by activity type, 2016–30 (Midpoint automation, step-up demand) (million)



Net change in total employment by education required, 2016–30 (not to scale)



Middle-wage jobs may fare well in emerging economies but lose out in advanced economies
Net job change by wage tercile, step-up scenario
% ± change from 2030 labor supply due to automation and labor demand catalysts



NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: ONET skill classification, US Bureau of Labor Statistics; McKinsey Global Institute analysis

Wage polarization could be exacerbated in advanced economies but developing countries will see a growing middle class

Wages may stagnate or fall in declining occupations. Although we do not model shifts in relative wages across occupations, the basic economics of labor supply and demand suggests that this should be the case for occupations in which labor demand declines. Since 1980, most advanced economies have seen an overall declining share of national income being captured by labor (compared with capital). Recent academic work suggests that technological change is one reason for this decline.[19]

Our analysis, looking at changes in employment by occupation at today's relative wage levels, shows that most job growth in the United States and other advanced economies will be in occupations currently at the high end of the wage distribution. Some occupations that are currently low-wage, such as nursing assistants and teaching assistants, will also increase, while a wide range of middle-income occupations will have the largest employment declines. These results suggest that income polarization could continue. Policy choices we identified in our step-up scenario, such as increasing investments in infrastructure, buildings, and energy transitions could help create additional demand for middle-wage jobs such as construction workers in advanced economies.

The wage trend picture is quite different in emerging economies such as China and India, where our scenarios show that middle-wage jobs such as retail salespeople and teachers will grow quickly as these economies develop. This implies that their consuming class will continue to grow in the decades ahead. However, our analysis comes with several important caveats (see Box E2, "What could overstate or understate the impact scenarios assessed in this research—and what we have not considered").

BUSINESSES AND POLICYMAKERS WILL NEED TO ACT TO KEEP PEOPLE WORKING AS AUTOMATION IS ADOPTED

The benefits of AI and automation to users and businesses, and the economic growth that could come via their productivity contributions, are compelling. They will not only contribute to dynamic economies that create jobs, but also help create the economic surpluses that will enable societies to address the workforce transitions that will likely happen regardless. Faced with the scale of worker transitions we have described, one reaction could be to try to slow the pace and scope of adoption in an attempt to preserve the status quo. While this may limit the workforce transitions, it would affect the contributions that these technologies make to business dynamism and economic growth, via the contribution to productivity growth, and which in turn leads to jobs growth and prosperity. We should embrace these technologies but also address the workforce transitions and challenges they bring. In many countries, this may require an initiative on the scale of the Marshall Plan involving sustained investment, new training models, programs to ease worker transitions, income support, and collaboration between the public and private sectors.

Achieving the benefits of deploying automation, such as productivity growth, while addressing its challenges, is not impossible. During the transition out of agriculture, for example, the United States made a major investment in expanding secondary education, and for the first time required all students to attend. Called the High School Movement, this raised the rate of high school enrolment of 14- to 17-year-olds from 18 percent in 1910

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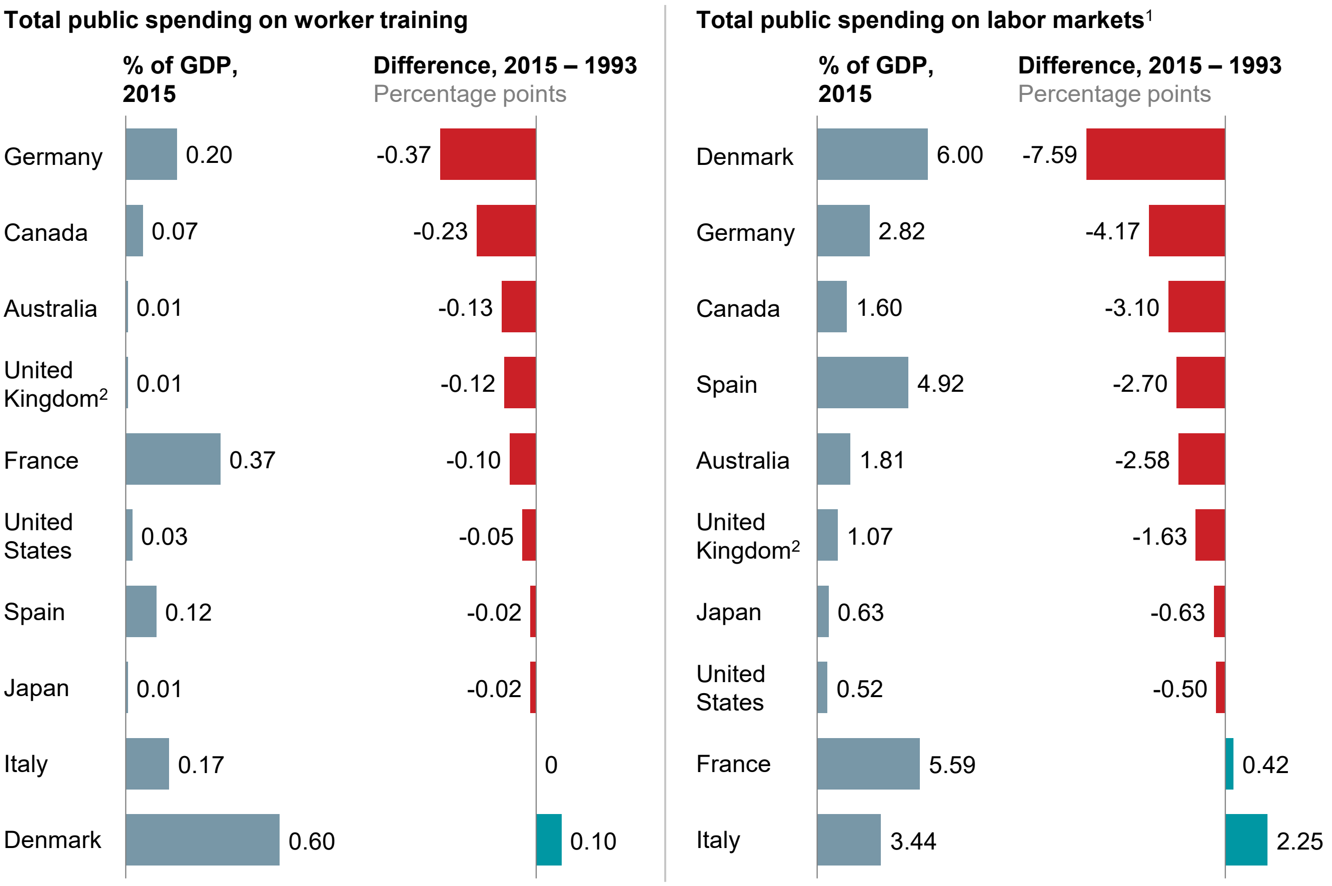
19 See Lawrence H. Summers, "Economic possibilities for our children," The 2013 Martin Feldstein Lecture, *NBER Reporter Online*, number 4, 2013; Laura Tyson and Michael Spence, "Exploring the effects of technology on income and wealth inequality," in *After Piketty: The agenda for economics and inequality*, Heather Boushey, J. Bradford DeLong, and Marshall Steinbaum, eds, Harvard University Press, May 2017; Loukas Karabarbounis and Brent Neiman. "The global decline of the labor share," *The Quarterly Journal of Economics*, volume 129, number 1, February 2014.

to 73 percent in 1940, making the US workforce among the best-educated and most productive in the world, and enabling the growth of a vibrant manufacturing sector.[20]

Policy makers, business leaders, and individual workers all have constructive and important roles to play in smoothing workforce transitions ahead. History shows that societies across the globe, when faced with monumental challenges, often rise to the occasion for the well-being of their citizens. Yet over the last few decades, investments and policies to support the workforce have eroded. Public spending on labor force training and support has fallen in most OECD countries, and corporate spending on training has declined in the United States (Exhibit E9). Educational models have not fundamentally changed in 100 years; we still use systems designed for an industrial society to prepare students for a rapidly-changing knowledge economy. It is now critical to reverse these trends, with governments making workforce transitions and job creation a more urgent priority.

Exhibit E9

Most OECD countries have been spending less on worker training and labor markets over the past 20+ years



1 Public spending on employment incentives; startup incentives; direct job creation; out-of-work income maintenance and support; early retirement; public employment services and administration; and sheltered and supported employment and rehabilitation (excluding worker training).
2 2011 data used for United Kingdom.
NOTE: Countries where 1993 data was not available omitted. Not to scale.

SOURCE: OECD; *Labour market policy expenditure and the structure of unemployment*, Eurostat, 2013; McKinsey Global Institute analysis

[20] John Bound and Sarah Turner, "Going to war and going to college," *Journal of Labor Economics*, volume 20, number 4, October 2002.

Today, while policy choices will vary by country, all societies will need to address four key areas to smooth the looming workforce transitions:

- **Maintaining robust economic growth to support job creation.** Sustaining robust aggregate demand growth is critical to support new job creation, as is support for new business formation. Fiscal and monetary policies that ensure sufficient aggregate demand, as well as support for business investment and innovation, will be essential. Targeted initiatives in certain sectors could also help, including by increasing investment in infrastructure and energy transitions, as well as policies to enable a shift of unpaid household work such as childcare to the market, as discussed in our step-up scenario.

- **Scaling and reimagining job retraining and workforce skills development.** Providing job retraining and enabling individuals to learn marketable new skills throughout their lifetimes will be a critical challenge—and for some countries, the central challenge. Midcareer retraining will become ever more important as the skill mix needed for a successful career changes. A range of initiatives in countries from Sweden to Singapore may point the way to new approaches to improving skills or teaching new ones, including to older workers. Governments can play an important role here, as the US government did in previous eras with the GI Bill, which enabled just under eight million veterans returning from war to go to college or be retrained.[21] Programs that can more quickly retool the labor force by focusing on re-training and credentialing at the level of skills in demand rather than multi-year degrees could be important. Business can take a lead in some areas, including with on-the-job training and providing opportunities to workers to upgrade their skills, both through in-house training and partnerships with education providers.

- **Improving business and labor market dynamism including mobility.** Greater fluidity will be needed in the labor market to manage the difficult transitions we anticipate. This includes restoring now-waning geographic mobility in advanced economies including the United States. Digital talent platforms and the rise of the "gig" economy can foster fluidity, by matching workers and companies seeking their skills, and by providing a plethora of new work opportunities for those open to taking them.[22] Policy makers in countries with relatively inflexible labor markets can learn from others that have deregulated, such as Germany, which transformed its federal unemployment agency into a powerful job-matching entity. Governments may also update labor market regulations to ensure that gig economy jobs are not subject to discrimination, and that remaining uncertainties about worker benefits are resolved.

- **Providing income and transition support to workers.** Income support and other forms of transition assistance to help displaced workers find gainful employment will be essential. Beyond retraining, a range of policies can help, including unemployment insurance, public assistance in finding work, and portable benefits that follow workers between jobs. We know from history and from our analysis that wages for many occupations can be depressed for some time during workforce transitions. More permanent policies to supplement work incomes might be needed to support aggregate demand and ensure societal fairness. Possible solutions to supplement incomes, such as more comprehensive minimum wage policies, universal basic income, or wage gains tied to productivity, are all being explored.

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21 Claudia Goldin, "America's graduation from high school: The evolution and spread of secondary schooling in the twentieth century," *Journal of Economic History*, volume 58, number 2, June 1998.

22 See *A labor market that works: Connecting talent with opportunity in the digital age*, McKinsey Global Institute, June 2015.

Business leaders have much to gain by early adoption of automation technologies, enabling performance benefits such as quality and speed, as well as greater efficiency and productive use of all factors of production. Businesses will be on the front lines of the workplace as it changes. That will require them to both retool their business processes and re-evaluate their talent strategies and workforce needs, carefully considering which individuals are needed, which can be redeployed to other jobs, and where new talent may be needed. Many companies are finding it is in their self-interest—as well as important for societal responsibility—to train and prepare workers for a new world of work.

Individuals, too, will need to be prepared for a rapidly evolving future of work. Acquiring new skills that are in demand and resetting intuition about the world of work will be critical for their own well-being. There will be demand for human labor, but workers everywhere will need to rethink traditional notions of where they work, how they work, and what talents and capabilities they bring to that work. Ultimately, we will all need creative visions for how our lives are organized and valued in the future, in a world where the role and meaning of work start to shift.

•••

Automation represents both hope and challenge. The global economy needs the boost to productivity and growth that it will bring, especially at a time when aging populations are acting as a drag on GDP growth. Machines can take on work that is routine, dangerous, or dirty, and may allow us all to use our intrinsically human talents more fully. But to capture these benefits, societies will need to prepare for complex workforce transitions ahead. For policy makers, business leaders, and individual workers the world over, the task at hand is to prepare for a more automated future by emphasizing new skills, scaling up training, especially for midcareer workers, and ensuring robust economic growth.

Box E2. What could overstate or understate the impact scenarios assessed in this research—and what we have not considered

We analyze scenarios for the net impact of automation and future labor demand on employment, skills, and wages. Most of them suggest that, while there will be enough work to maintain full employment in the long term, ensuring that displaced workers have the skills and support needed to obtain the new jobs will be critical. If workers are not re-employed quickly, the impact on wage growth could be negative. This conclusion could overstate or understate the impact.

On the one hand, the future disruption could be smaller than we anticipate for several reasons:

- Adopting automation requires significant investments and redesign of business processes, and companies have been slow to adopt digital technologies, let alone recent forms of AI and automation.[1] In our slowest automation adoption scenario, less than 5 percent of work is automated by 2030, so the overall impact on the economy could be minimal.
- In our analysis, we make the strong assumption that every hour of work that is automated results in one hour less of work for a full-time equivalent employee. But companies often choose to redefine occupations, or redeploy some workers instead. For instance, after the introduction of the ATM, the number of bank tellers in the United States continued to grow for many years, even as the activities they performed changed.[2]
- Our model of the seven catalysts of labor demand does not take into account dynamic effects within the economy, and they represent only a partial list of future sources of labor demand. If automation adoption is rapid, future productivity growth could be higher than we model, and this could raise incomes and result in more job creation than we anticipate. This could offset the labor displacement, even during the transition.

On the other hand, the impact of automation on work could be more disruptive than we anticipate for several reasons:

- The development of automation technologies, including AI, could accelerate or break through new frontiers. AI researchers today say that machine learning has unlocked more rapid improvements in the technology than could have been imagined even a few years ago. Improvements in machine capabilities in areas such as natural language understanding and generation could mean that more work might be automated more rapidly than we estimate here.
- While we assume that wage levels will play a major role in determining automation adoption, companies may also adopt these technologies for other reasons, including their capacity to exceed human performance capabilities in some areas. This would mean more rapid automation adoption than we model, particularly in low-wage economies and for low-wage work in advanced economies.
- Displaced workers might not find new work quickly, or at all, because they lack the skills or educational requirements, or because other barriers such as cultural preferences or geographic mobility stand in their way. There are few examples of large-scale retraining and redeployment of midcareer workers. Moreover, labor markets may not work as well as they need to do to help displaced workers find new employment.
- The assumptions we make on future consumption growth and spending on infrastructure and buildings might be too optimistic. In the past decade, actual GDP growth in nearly all advanced economies has been lower than forecast. Continued sluggish growth, rising geopolitical tensions, or a new recession could make our future job creation scenarios too optimistic.

A number of other caveats to our findings should also be noted. We have not made assumptions in our modeling about sector trends, such as the growth of ecommerce in retailing, or the impact of fiscal constraints on public sector employment. We also do not model changes in work structure, such as the growth of the gig economy, or activities within an occupation that could change as a result of technological innovation. Our analysis of wage trends is based on current average wages for each occupation in each country, and we do not model wages over time by occupation based on the dynamics of labor supply and demand. Finally, we do not model changing skill requirements for occupations or analyze the "skill bias" of automation technologies, that is, whether they will enable high-skill workers at the expense of low-skill ones, or vice-versa.[3]

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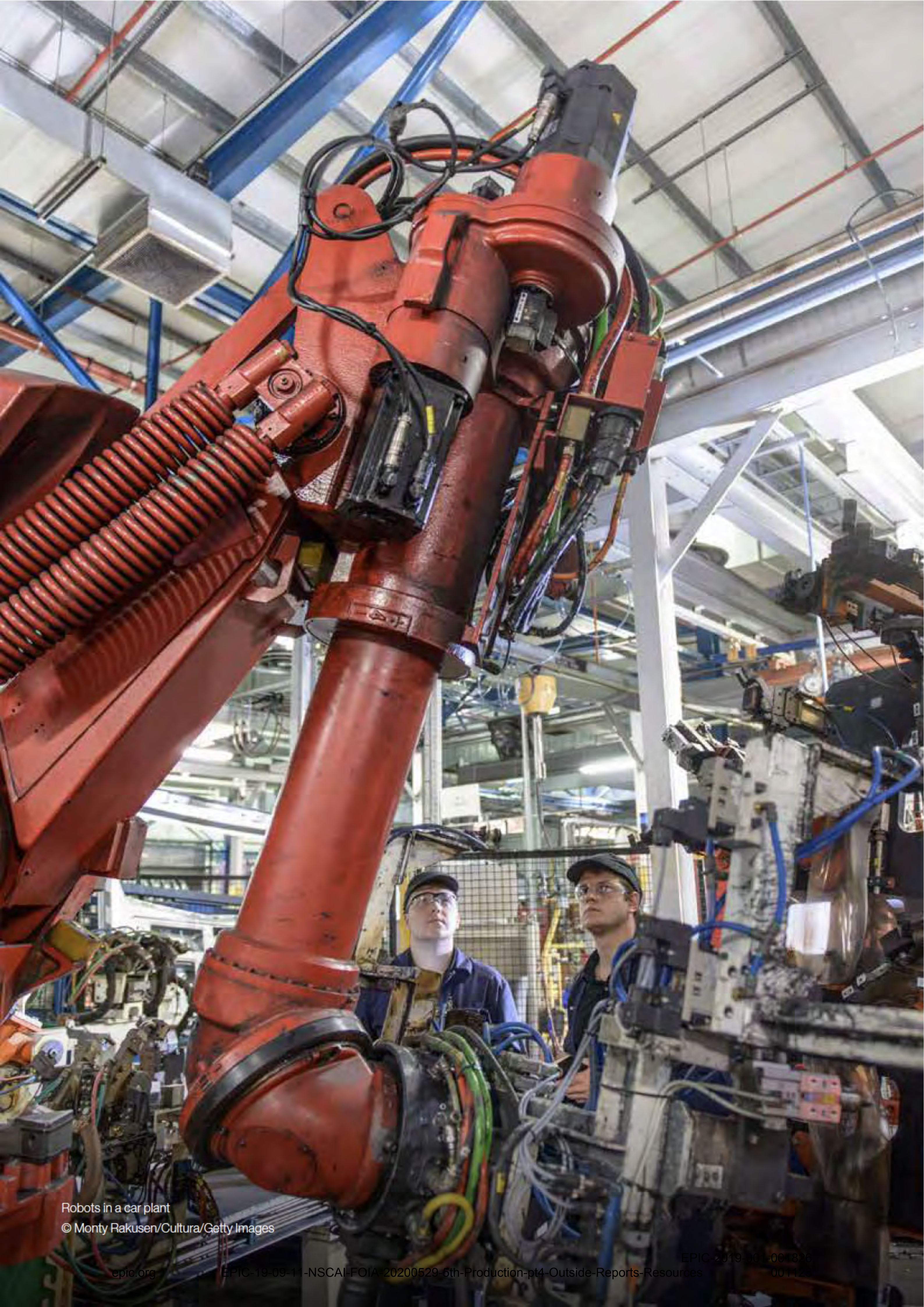
1 See *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017; *Digital America: A tale of the haves and have-mores*, McKinsey Global institute, December 2015, and *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June 2016.

2 James Bessen, *Learning by doing: The real connection between innovation, wages, and wealth*, Yale University Press, 2015.

3 For a discussion of skill bias, see David H. Autor, Frank Levy, and Richard J. Murnane, "The skill content of recent technological change: An empirical exploration," *The Quarterly Journal of Economics*, volume 18, number 4, November 2003.



Robots in a car plant
© Monty Rakusen/Cultura/Getty Images

1. JOBS LOST, JOBS CHANGED: IMPACT OF AUTOMATION ON WORK

We live in an age when machines answer customer inquiries, help doctors understand X-rays, lip-read better than human professionals, and sort trash into compost and recyclables—an age, too, when the public debate about automation and its impact on the workplace raises anxious questions. First is the existential one about the future of work itself. Given rapid advances in technologies including robotics and artificial intelligence, will there be enough work to ensure full employment? Second is the question about what those jobs will be, and which skills will be needed for them. The third is what all this could mean for wages.

We seek to address these questions in this report through, first, an analysis of automation potential and scenarios about the extent of adoption of current work activities by 2030 and, second, an analysis of potential future labor demand. We looked at 46 countries, representing almost 90 percent of global GDP. To illustrate the potential impact at a country level, we use six as exemplars of countries that vary by sector and occupation mix, GDP per capita growth, wage rates, and demographics: China, Germany, India, Japan, Mexico, and the United States.[23]

In this chapter, we focus on automation's potential to transform the workplace. Building on our previous automation work, we create a range for the number of hours that could be displaced by automation by 2030, and seek to identify the work activities, occupations, and sectors that are most—and least—susceptible to being automated (see Box 1, "Automation's rapid advances and its limitations—for now").[24]

Among the findings of our new research are that as much as 30 percent of the hours worked globally could be automated by 2030, depending on the speed of adoption, with 15 percent of current work activities being automated in our midpoint scenario. The speed of adoption depends on factors including technical feasibility, the pace of technology development, costs, and social and regulatory acceptance. These results differ significantly by country, reflecting the mix of activities currently performed by workers and prevailing wage rates, ranging from 9 percent in India to 26 percent in Japan in the midpoint adoption rate scenario.

[23] See the technical appendix for details of our modeling.

[24] See *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017.

Box 1. Automation's rapid advances and its limitations—for now

Automation is not a new phenomenon; industrial robots have been a fixture on factory floors for several decades, and software algorithms help logistics companies optimize the route planning of deliveries in a faster and more efficient manner than human route planners could.

Recent developments in robotics, artificial intelligence, and machine learning are noteworthy for the advances they represent, however. We are on the cusp of a new automation age in which technologies not only do things we thought only humans could do, but can increasingly do them at a superhuman level. In just the past year, a project by Google's DeepMind and the University of Oxford has applied deep learning to a huge data set of BBC programs to create a lip-reading system that is substantially more proficient than a professional human lip-reader.[1] Researchers at Stanford University have developed a deep learning system that is able to diagnose pneumonia from chest x-rays better than expert radiologists working alone.[2] Robot "skin" made of a piezotronic transistor mesh developed by the Georgia Institute of Technology and covered in thousands of mechanical hairs can "feel" textures and find objects by touch.[3] Companies are using advanced facial analysis to monitor emotional responses to advertisements and other digital media content, via a webcam.[4]

AI is already being deployed in synthetic biology, cancer research, climate science, and material science. For example, researchers at Vanderbilt university have used computers to exceed the human standard in predicting the most effective treatment for major depressive disorders and eventual outcomes of breast cancer patients.[5]

Three factors are driving the technological advances:

- Machine-learning algorithms have progressed in recent years, especially through the development of deep learning and reinforcement-learning techniques based on neural networks.
- Computing capacity is increasing exponentially and has become available to train larger and more complex models much faster. Graphics processing units, originally designed to render the computer graphics in video games, have been repurposed to execute the data and algorithm crunching required for machine learning at speeds many times faster than traditional processor chips. This computing capacity has been aggregated in hyper-scalable data centers and made accessible to users through the cloud.
- Vast amounts of data that can be used to train machine learning models are being generated, for example through daily creation of billions of images, online click streams, voice and video, mobile locations, and sensors embedded in the Internet of Things.

Formidable technical challenges still lie ahead. While machines can be trained to perform a range of cognitive tasks, they remain limited. They are not yet good at putting knowledge into context, let alone improvising, and they have little of the common sense that is the essence of human experience and emotion. They struggle to operate without a pre-defined methodology. They can replicate fugues in the style of Bach, but cannot yet understand sarcasm or love.[6]

One of the biggest remaining technical challenges is mastery of natural language processing—understanding and generating speech. These capabilities are indispensable for numerous work activities but, despite great progress in areas such as machine translation, machines still have far to go to achieve human levels of performance.

Beyond the development of technology, much work remains to be done integrating different capabilities into holistic solutions in which everything works together seamlessly. Combining a range of technologies will be essential for workplace automation, but engineering such solutions—whether for hardware or software—is a difficult process.

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1 Hal Hodson, "Google's DeepMind AI can lip-read TV shows better than a pro," *New Scientist*, November 21, 2016.
2 Taylor Kubota,"Stanford algorithm can diagnose pneumonia better than radiologists," *Stanford News*, November 15, 2017.
3 Klint Finley, "Syntouch is giving robots the ability to feel textures like humans do," *Wired*, December 17, 2015.
4 Molly Reynolds, "How facial recognition is shaping the future of marketing innovation," *Inc.*, February 16, 2017.
5 Xia Li et al., "An algorithm for longitudinal registration of PET/CT images acquired during neoadjuvant chemotherapy in breast cancer: preliminary results," *EJNMMI Research*, December 2012.
6 Dave Gershgorn, "You probably can't tell the difference between Bach and music written by AI in his style," *Quartz*, December 15, 2016. A sample of harmonization in the style of Bach generated using deep learning, posted by Sony CSL, can be listened to on YouTube at https://www.youtube.com/watch?v=QiBM7-5hA6o.

About
50%
of the time spent on work activities in the global economy could theoretically be automated by adapting currently demonstrated technologies

AUTOMATION CAN RAISE THE PRODUCTIVITY OF THE GLOBAL ECONOMY BUT WILL AFFECT EMPLOYMENT: A BRIEF RECAP OF OUR PRIOR RESEARCH

In our January 2017 report, *A future that works: Automation, employment, and productivity*, we noted that automation technologies such as advanced robotics and artificial intelligence are powerful drivers of productivity and economic growth which can help create economic surpluses and increase overall societal prosperity. Key findings of that report include:

- Automation could accelerate the productivity of the global economy by between 0.8 and 1.4 percent of global GDP annually, assuming that human labor replaced by automation rejoins the workforce and is as productive as it was in 2014. Automation on its own will not be sufficient to achieve long-term economic growth aspirations across the world; for that, additional productivity-boosting measures will be needed, including reworking business processes or developing new products and services. Nonetheless, the productivity growth enabled by automation can ensure continued prosperity in aging nations and provide an additional boost to fast-growing ones.[25]

- For companies, the deployment of automation can deliver benefits in the form of labor cost savings, but also in myriad other performance-enhancing ways. It can enable firms to get closer to customers and predict maintenance needs, sharply reducing the cost of operations in some activities and extending the life of existing capital assets. Automation can also increase scale and speed. Nissan, for example, has halved the time it takes to move from final product design to production thanks to an automated system, while BMW has reduced machine downtime by 30 to 40 percent—effectively generating fresh economies of scale with minimal investment—through AI-enabled condition-based maintenance.[26] Exhibit 1 compares the estimated potential performance and labor cost reduction benefits from automation for a number of key processes within some sectors. These findings are based on estimates of potential in case studies informed by our work with industry.

- Overall, our analysis suggested that roughly 50 percent of the time spent on activities that people are paid almost $15 trillion to do in the global economy have the theoretical potential to be automated by adapting currently demonstrated technology—in other words, the technical capabilities already exist, although an integrated solution to automate each particular activity might not yet have been developed nor deployed. We estimated the potential for technology to automate the more than 2,000 work activities in about 800 occupations across the economy, by adapting currently demonstrated technologies. (We examined work activities individually rather than whole occupations, since occupations consist of a range of activities with different potential for automation). Certain categories of activity are more susceptible to automation than others.[27] While less than 5 percent of occupations can be fully automated, about 60 percent have at least 30 percent of activities that can technically be automated (see illustration, "Automation: A global force that will transform economies and the workforce").

- Our automation analysis found significant variation among sectors of the economy, and among the occupations within those sectors. For example, almost one-fifth of the time spent in US workplaces involves predictable physical activity and is prevalent in such sectors as manufacturing and retail trade. Accordingly, these sectors have a relatively high technical potential for automation by adapting currently demonstrated technologies. Even within sectors, there is considerable variation. In manufacturing, for

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25 Even at historical rates of productivity growth, economic growth could be nearly halved as a result of this aging trend. *Global growth: Can productivity save the day in an aging world?* McKinsey Global Institute, January 2015.

26 For details and further examples, see Michael Chui, Katy George, and Mehdi Miremadi, "A CEO action plan for workplace automation," *McKinsey Quarterly*, July 2017.

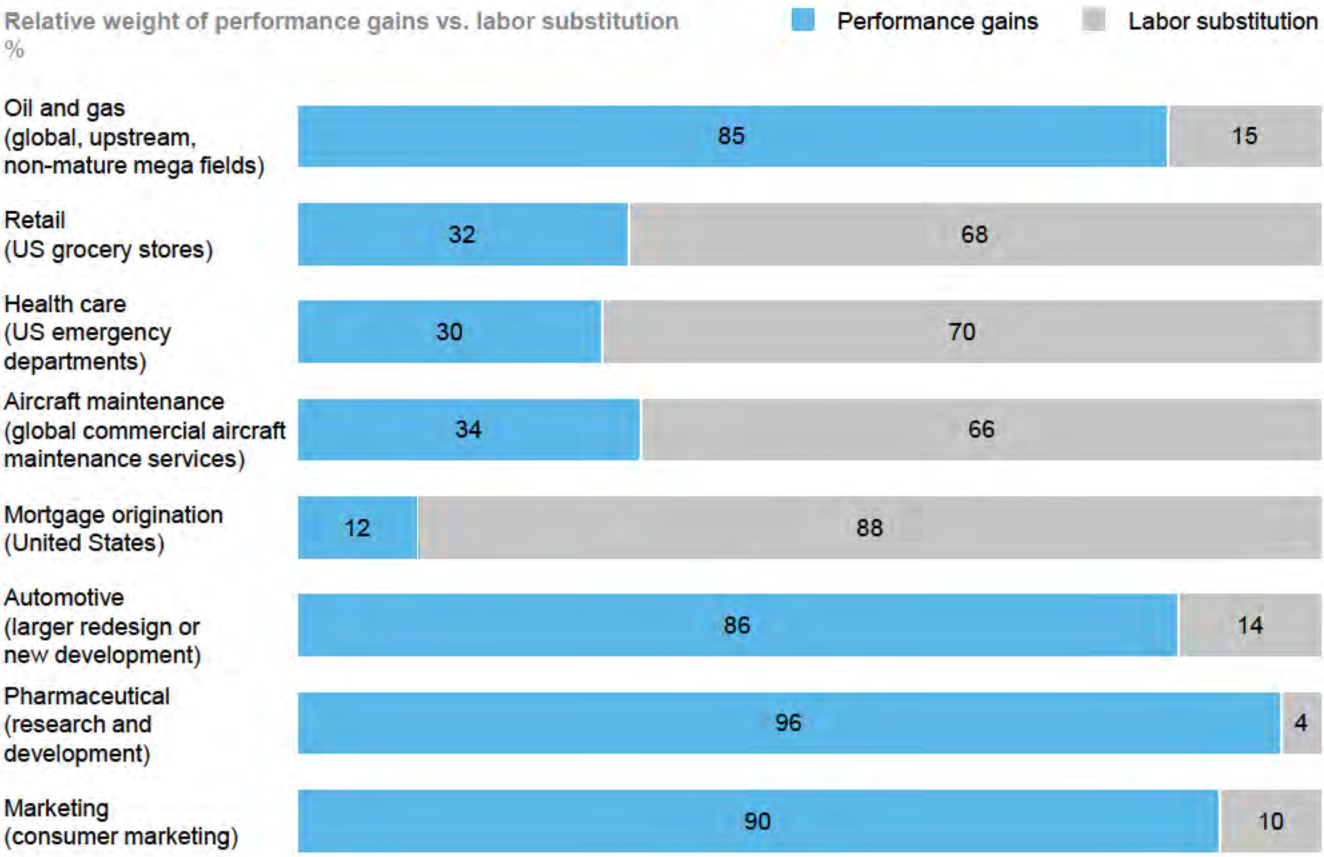
27 Ibid.

example, occupations that have a large proportion of physical activities in predictable environments such as factory welders have a technical automation potential above 90 percent, whereas for customer service representatives that potential is less than 30 percent.

- Technical feasibility is an essential element of automation but four other factors also influence the timing, which explains in part why our overall analysis of automation adoption and the impact on employment to 2030 can vary among countries. The other factors are economic and social: the cost of developing and deploying automation solutions for the workplace—that is actually developing integrated solutions for specific use cases; labor market dynamics including the supply, demand, and cost of human labor; the net economic benefits of automation, which include performance benefits beyond labor substitution such as higher throughput, raised productivity, and heightened safety; and regulatory and social acceptance. Labor market dynamics in particular plays an important role in the national variations around automation adoption, since wage rates vary widely by country, even for similar occupations. The relative cost of automation compared with the cost of labor will affect adoption: if qualified workers are in abundant supply and significantly less expensive than automation, this could be a decisive argument against automation in that situation. Consequently, in the period to 2030, we expect advanced economies, with wage levels that are relatively higher, to adopt automation earlier than many emerging economies, especially if adoption requires expensive hardware solutions. That said, our automation modeling does consider the continuing improvement in automation technologies' capabilities over time, as well as decreasing costs.

Exhibit 1

Automation improves corporate performance in ways beyond simple labor substitution



SOURCE: McKinsey Global Institute analysis

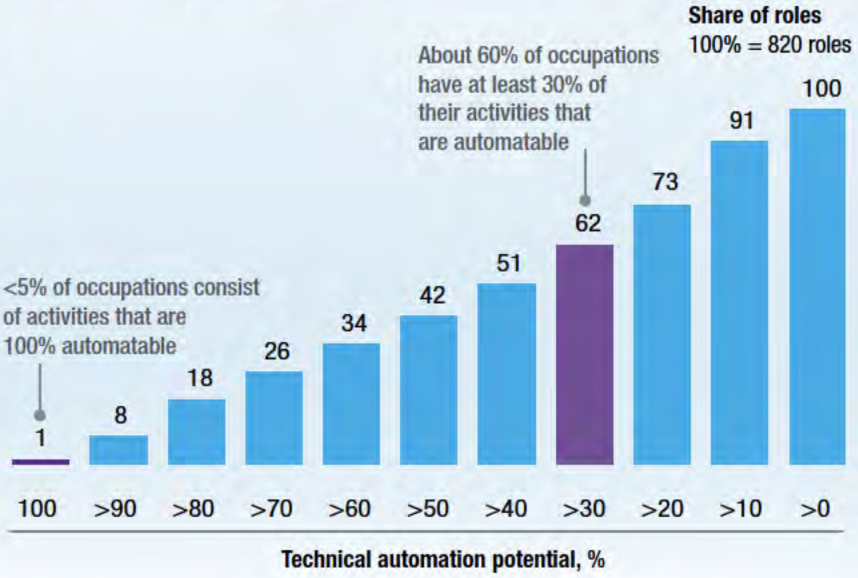
From the January 2017 MGI report, *A future that works: Automation, employment, and productivity*

AUTOMATION

A global force that will transform economies and the workforce

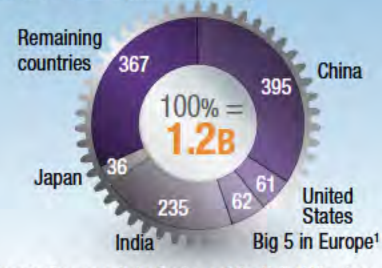
Technical automation potential by adapting currently demonstrated technologies

While few occupations are fully automatable, 60 percent of all occupations have at least 30 percent technically automatable activities



Wages associated with technically automatable activities
$ trillion

Labor associated with technically automatable activities
Million full-time equivalents (FTEs)

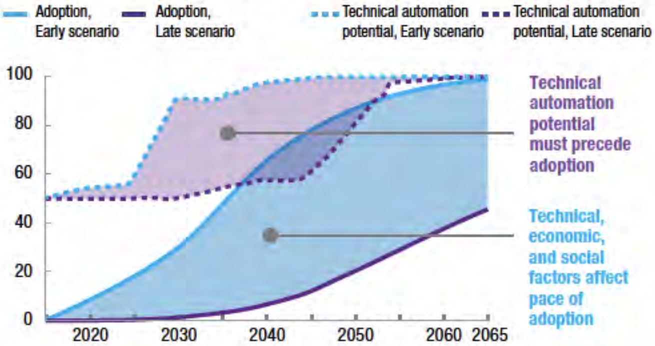


[1] France, Germany, Italy, Spain, and the United Kingdom.

Five factors affecting pace and extent of adoption

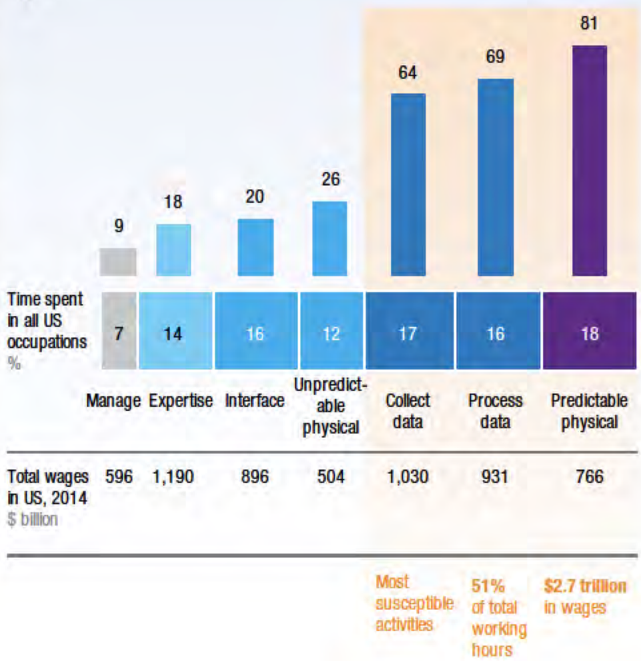
1. **TECHNICAL FEASIBILITY** Technology has to be invented, integrated, and adapted into solutions for specific case use
2. **COST OF DEVELOPING AND DEPLOYING SOLUTIONS** Hardware and software costs
3. **LABOR MARKET DYNAMICS** The supply, demand, and costs of human labor affect which activities will be automated
4. **ECONOMIC BENEFITS** Include higher throughput and increased quality, alongside labor cost savings
5. **REGULATORY AND SOCIAL ACCEPTANCE** Even when automation makes business sense, adoption can take time

Scenarios around time spent on current work activities, %



Three categories of work activities have significantly higher technical automation potential

Time spent on activities that can be automated by adapting currently demonstrated technology
%



MCKINSEY GLOBAL INSTITUTE

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AUTOMATION COULD REPLACE 9 TO 26 PERCENT OF THE WORK HOURS IN OUR SIX FOCUS COUNTRIES BY 2030

15% of work could be displaced by automation by 2030 in our midpoint adoption scenario

Our automation model applies the factors listed above to a range of scenarios, bookended by two scenarios around the earliest adoption and latest adoption we modeled. It is not our intention to predict the timing but to provide a range, and these two edge case scenarios may turn out to be extreme. However, they do enable us to model a spectrum of outcomes.

While about half of all work activities globally have the technical potential to be automated by adapting currently demonstrated technologies, according to our prior research on automation, this will not happen overnight. Taking into account the technical, economic and social factors affecting the pace and extent of automation, described above, the proportion of work actually displaced by 2030 will likely be lower. We estimate that up to 30 percent of current work activities could be displaced by 2030, with a midpoint of 15 percent, or the hours of about 400 million full-time equivalents. Indeed, the range of outcomes is particularly wide in 2030 in our model; in the event of late automation adoption, the percentage of work activities displaced by 2030 would be close to zero. Among countries, too, especially between advanced economies and emerging ones, the range is wide. Exhibit 2 highlights both how we arrived at our range of automation scenarios, and the modeling we used for estimating scenarios for future labor demand, which we describe in detail in the following chapter.

Exhibit 2

Automation adoption and new labor demand: Arriving at our scenarios

Automation adoption

Technical potential for automation

Determined using currently available technologies, with future technical progress modeled along S-curves

Today (2016), 50% of work activities globally could be automatable by adapting currently demonstrated technologies

Automation adoption scenarios

Firm adoption of automation depends on technical feasibility, implementation costs, labor costs, economic benefits, and regulatory and social acceptance

By 2030, adoption of automation technology could lead to 15% of work activities being automated in our midpoint adoption scenario (up to 30% in early scenario and close to zero in a late scenario)

Jobs lost, jobs gained

Catalysts of future labor demand

Two scenarios: trendline (trends in spending and employment across countries) and step-up (further societal and policy choices)

Seven trends: rising incomes; health-care spending from aging; technology adoption; spending on infrastructure, building, and energy; and marketization of unpaid work

Key outputs—new labor demand by
- Occupation
- Work activities
- Capabilities required
- Current educational requirements
- Current wage levels

Dynamic macroeconomic model

Our Global Growth Model, a general equilibrium macroeconomic model by country

Key inputs—effects of automation on
- Labor displacement
- Capital investment
- Productivity impact of automation
- Range of reemployment rates

Key outputs
- Unemployment rate
- GDP growth rate
- Aggregate average wages

SOURCE: McKinsey Global Institute analysis

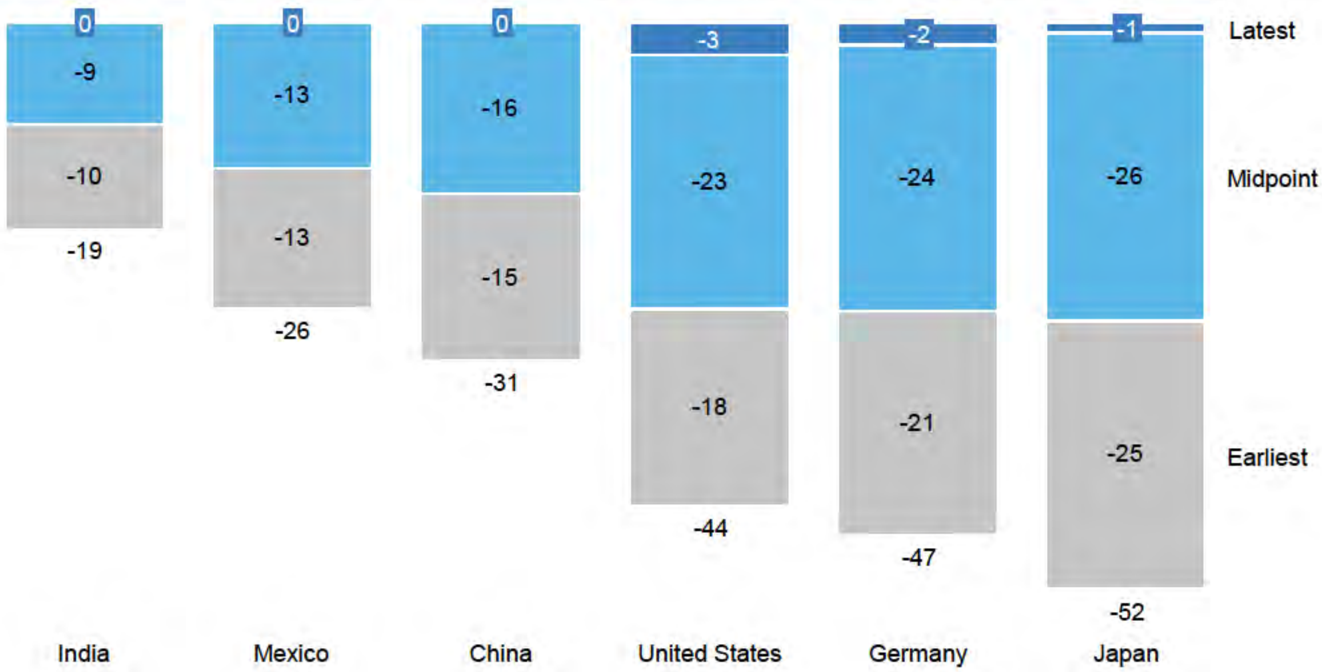
For the six countries we use as exemplars in this report, the hours that could be automated by 2030 in the midpoint adoption case range from 26 percent of the hours worked in Japan to 9 percent in India (Exhibit 3). Developed countries Germany (24 percent) and the United States (23 percent) are not far behind Japan, followed by China (16 percent) and Mexico (13 percent). In general, wage rates are the biggest determinant of the difference in automation scenarios among countries; higher wage rates make automation more economically attractive. In addition, the mix of activities, which is related to the mix of sectors and occupations, also affects the modeled rate of automation. Among the main differences between emerging and advanced economies is the importance of agriculture in the former. In Germany and Japan, manufacturing also has high automation potential. That said, emerging economies could leverage automation technologies aggressively in an effort to leapfrog their economic development. China, for example, has fewer robots per worker than the global average, but received nearly one-third of all robot shipments in 2016.[28]

At the other extreme of the scenarios we modeled, in our latest adoption scenario, less than 0.5 percent of work hours globally will be automated by 2030, and advanced economies will account for the large majority of them.

Exhibit 3

By 2030, in the midpoint adoption scenario, automation could replace up to 9–26% of current work in our focus countries, as high as 19–52% in the earliest adoption scenario and as low as 0–3% in the latest adoption scenario

Projected impact on total employment in midpoint automation scenario, 2016–30
% of FTE hours with potential to be automated, midpoint scenario (range of automation scenarios, latest to earliest)



NOTE: Numbers may not sum due to rounding.

SOURCE: McKinsey Global Institute analysis

[28] Grace Donnelly, "Robots have been taking jobs at a blistering pace in China," *Fortune*, August 23, 2017.

Automation will displace workers with different educational attainment across a wide range of occupations

Just as there is a wide variation in automation's impact on countries and sectors, so, too, its effect on specific occupations will vary. Those professions highly dependent on the work activities we identified as most susceptible to automation—physical work in a predictable environment, or data collection and processing—are likely to be the most affected, especially if automation adoption occurs earlier, which we anticipate to be the case in countries with high wages such as Japan, Germany, and other advanced economies. By comparison, occupations that require application of expertise, interaction with stakeholders, management and coaching of others, or a high degree of social and emotional response will be less susceptible to automation in the period to 2030.

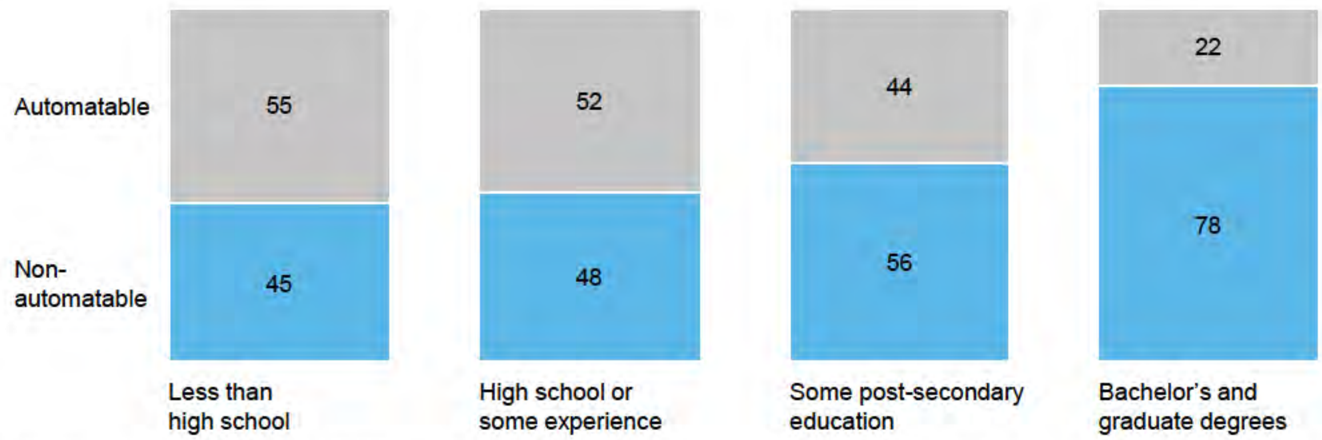
Occupations incorporating significant amounts of physical work in predictable environments including production workers and building and grounds cleaners, as well as office support (such as clerks and administrative assistants), are likely to face significant displacement of their activities by automation, while doctors, health aides, and other care providers and professionals including engineers and business specialists are less likely to experience as much displacement.

The current level of educational requirements for occupations tends to be correlated with the likelihood that their activities can be automated. The technical automation potential for occupations requiring less than a high school diploma is 55 percent, whereas for those with a college degree, that potential is far lower, at just 22 percent. Occupations requiring some post-secondary education generally include work activities that are less automatable than those requiring a high school diploma and some experience, and so on (Exhibit 4).

Exhibit 4

Occupations requiring higher levels of education and experience have lower automation potential

Technical automation potential of work activities by job zone in the United States
%



Example occupations	Less than high school	High school or some experience	Some post-secondary education	Bachelor's and graduate degrees
	▪ Logging equipment operators ▪ Taxi drivers	▪ Stock clerks ▪ Travel agents ▪ Dental lab technicians ▪ Firefighters	▪ Nursing assistants ▪ Web developers ▪ Electricians ▪ Legal secretaries	▪ Lawyers ▪ Doctors ▪ Teachers ▪ Statisticians ▪ Chief executives

NOTE: We define automation potential according to the work activities that can be automated by adapting currently demonstrated technology.

SOURCE: US Bureau of Labor Statistics; O*Net; McKinsey Global Institute analysis

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Countries and companies have compelling reasons to embrace automation, since the technologies will give a much-needed boost to productivity in the global economy. Depending on the pace of adoption, however, automation technologies in the workplace could displace workers in a wide range of sectors; in our most aggressive scenario for early adoption, almost one-third of work hours in the global economy could be automated by 2030—although other, later adoption scenarios have less dramatic outcomes in that time frame. Economic and social factors beyond technical feasibility affect adoption, and these could lead to strong variations in adoption rates among sectors and countries. Under these circumstances, what will be the future of work? Will the global economy create enough additional jobs to offset those lost to automation, regardless of when adoption takes place? And if so, what sort of jobs will those be, requiring which skills, and paying what wages? In the next two chapters, we highlight findings of our analysis of future labor demand and the complex workforce transitions that automation will likely set in motion.

An automated wool factory in France, circa 1949

2. LESSONS FROM HISTORY ON TECHNOLOGY AND EMPLOYMENT

For centuries, the arrival of new technology in the workplace has sparked workers' fears—and, sometimes, violent backlash. Already in 1589, England's Queen Elizabeth I refused to grant a patent to a stocking frame invented by William Lee because she was supposedly concerned about the effect on hand knitters.[29] In the early 19th century, textile workers in Britain and France smashed automated looms in their factories and printers struck to protest the arrival of steam-powered presses.[30]

Leading thinkers in the past, from David Ricardo to Karl Marx and John Maynard Keynes, raised concerns about the effect of technological change on employment, and opinion polls show that anxiety has come to the fore again, amid rapid advances in robotics and artificial intelligence.[31] A number of prominent academics and technologists argue that the latest wave of automation technologies, including artificial intelligence and machine learning, will be particularly disruptive to the workforce.[32]

In this chapter, we examine the historical impact of technology on employment, skills, and wages. History does not necessarily repeat itself, but it does provide valuable context and possible lessons for the future of labor demand in a time of automation. Among those lessons are that technological innovation in the past has enabled the creation of many more new jobs than it has destroyed, raising productivity, spurring sustained increases in living standards, and bringing about a shift in the balance of work and leisure. However, the transition has not always been smooth: for example, real wages stagnated for nearly 50 years in 19th century England during the Industrial Revolution there, and only picked up again at a time of substantial social policy reforms. Charles Dickens among other novelists used the harsh realities of everyday life for displaced and other workers as material for his works. History also shows that robust aggregate demand and economic growth are essential for job creation. New technologies have raised productivity growth, enabling firms to lower prices for consumers, pay higher wages, or distribute profits to shareholders. This stimulates demand across the economy, boosting job creation.

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29 R. L Hills, "William Lee and his knitting machine," *Journal of the Textile Institute*, volume 80, number 2, July 1989.

30 The most celebrated anti-technology protests were conducted by "Luddites" in Nottingham, England, in 1811, but they were not alone. French textile workers staged an uprising in a silk factory in Lyons in 1831 known as the revolt of the Canuts. Fernand Rude, *La Révolte des canuts 1831–1834*, La Découverte, 2001. A strike by *Times of London* newspaper printers in 1814 linked to the introduction of steam presses was quelled only after the paper's owners promised to keep on printers. Elizabeth L. Eisenstein, *The printing press as an agent of change*, Cambridge University Press, 1980.

31 Political economist David Ricardo worried in the early 19th century that machines would make labor redundant, while Karl Marx in the 1850s foresaw an era when the means of labor would be transformed by "an automatic system of machinery." In 1930, John Maynard Keynes coined the term "technological unemployment" to describe a situation in which innovation that economized on the use of labor outstripped the pace at which new jobs could be created, in a "temporary phase of maladjustment." David Ricardo, *On the principles of political economy and taxation,* 1817; Karl Marx, *Grundrisse: Foundations of the critique of political economy*, 1858; John Maynard Keynes, "Economic possibilities for our grandchildren," in *Essays in Persuasion*, Macmillan 1933.

32 Erik Brynjolfsson and Andrew McAfee, *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*, W.W. Norton, 2014,

25
Percentage point decline in share of US agricultural employment between 1880 and 1920

LARGE-SCALE SECTOR EMPLOYMENT DECLINES HAVE BEEN MORE THAN OFFSET BY OTHER SECTORS EMPLOYING WORKERS

Since the First Industrial Revolution began in England in the 18th century, the economies of Europe, the United States, and other countries have undergone two profound waves of structural change. Mechanization enabled a revolution in agriculture and in industry, prompting a migration of workers from the countryside to cities. A second structural shift has occurred in the past 60 years as the share of manufacturing employment has declined in some countries even as growth in service sectors accelerates.[33]

The employment shifts accompanying this process of structural transformation have been very large. In the United States, for instance, the agriculture share of employment declined from 58 percent of total employment in 1850 to 2.5 percent of employment today (Exhibit 5). In just 40 years, between 1880 and 1920, the share of agricultural employment declined 25 percentage points. During the same decades, other sectors were being transformed by mechanization and electrification as well: the share of miners and household workers, for example maids and servants, also declined, although these shifts affected fewer workers. Since 1960, when the second wave of structural transformation began, manufacturing fell from 27 percent of total US employment to 9 percent today, as automation and global trade transformed manufacturing and as demand for services exploded.

The patterns are broadly similar in other countries, although there are some notable differences in the pace. China's shifting sector mix in recent years has been especially rapid: agricultural employment fell as a share of total employment by 32 percentage points in just 25 years, from 60 percent in 1990 to 28 percent in 2015.[34] In Mexico, the agriculture share of employment declined from 52 percent in 1960 to 13 percent in 2015, although in contrast with China, the decline has been gradual and continuous across decades. In Japan, agricultural employment declined from a 31 percent share of total employment in 1960 to 3.5 percent in 2015, while manufacturing's share of total employment dropped from its peak in 1973 of 25 percent to 13 percent in 2015.

Throughout these large shifts of workers across occupations and industries, overall employment as a share of the population has generally continued to grow. New industries and occupations emerged to absorb workers displaced by technology, although as we discuss below, the transition has not always been smooth.

Magnitude of potential job dislocation from automation through 2030 is not unprecedented

When we compare historical sector employment to potential labor displacement from our automation model, we see that even in the earliest automation scenario, future rates of labor displacement from automation within specific sectors are not unprecedented. For example, our analysis shows that a number of sectors in different countries, including agriculture in China, Germany, and Japan, and manufacturing in the United States, have declined by 30 percent and more over a period of 15 years. Our analyses of scenarios of automation displacement over the 15 years from 2016 to 2030 are within the same range (Exhibit 6).

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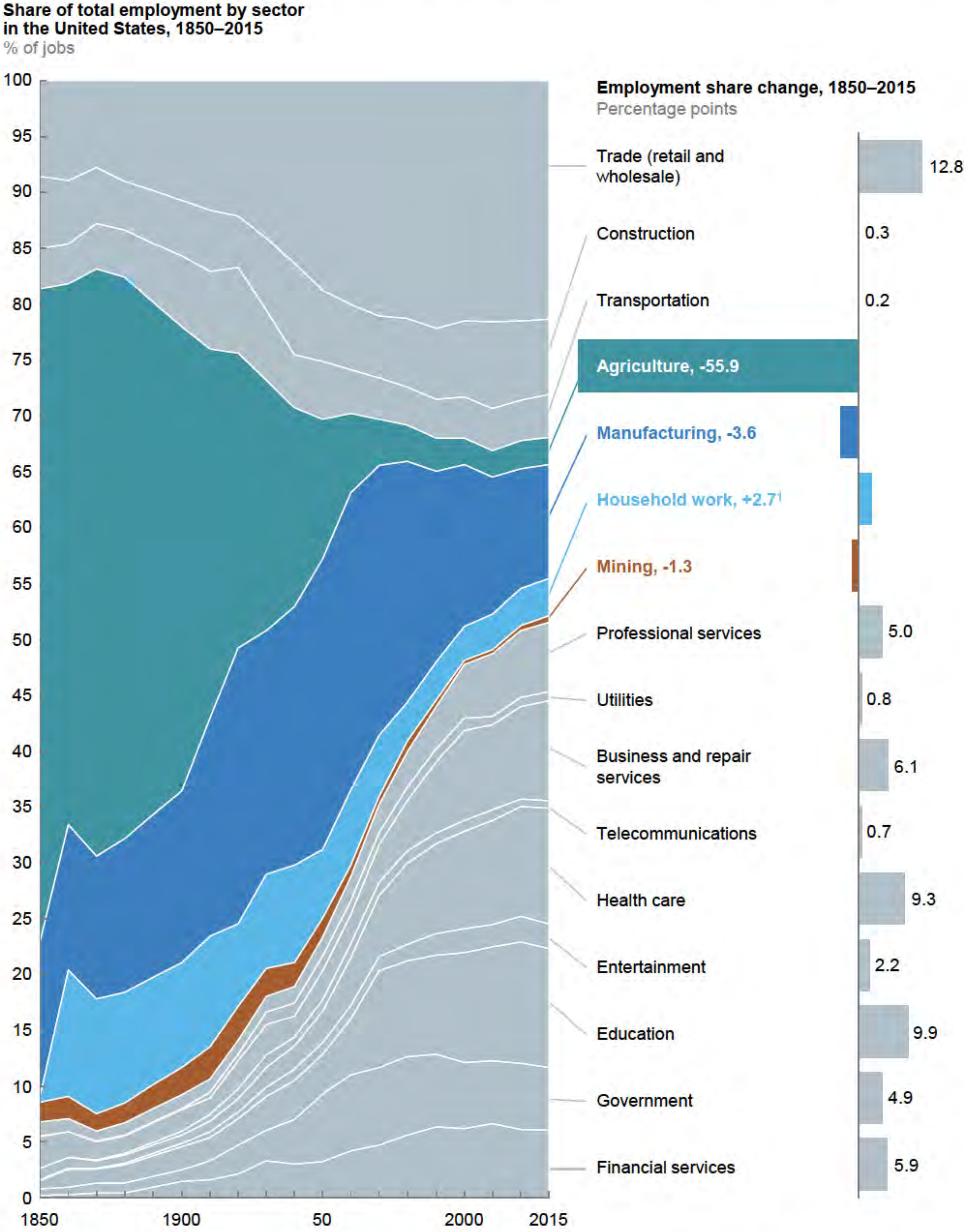
[33] See Berthold Herrendorf, Richard Rogerson, and Ákos Valentinyi, "Growth and structural transformation," in *Handbook of Economic Growth*, Philippe Aghion and Steven N. Durlauf, eds., volume 2, Elsevier, 2014; Benjamin N. Dennis and Talan B. İşcan, "Engel versus Baumol: Accounting for structural change using two centuries of U.S. data," *Explorations in Economic History*, volume 46, number 2, April 2009.

[34] 10-sector database, Groningen Growth and Development Centre.

Exhibit 5

Throughout history, large-scale sector employment declines have been countered by growth of new sectors that have absorbed workers



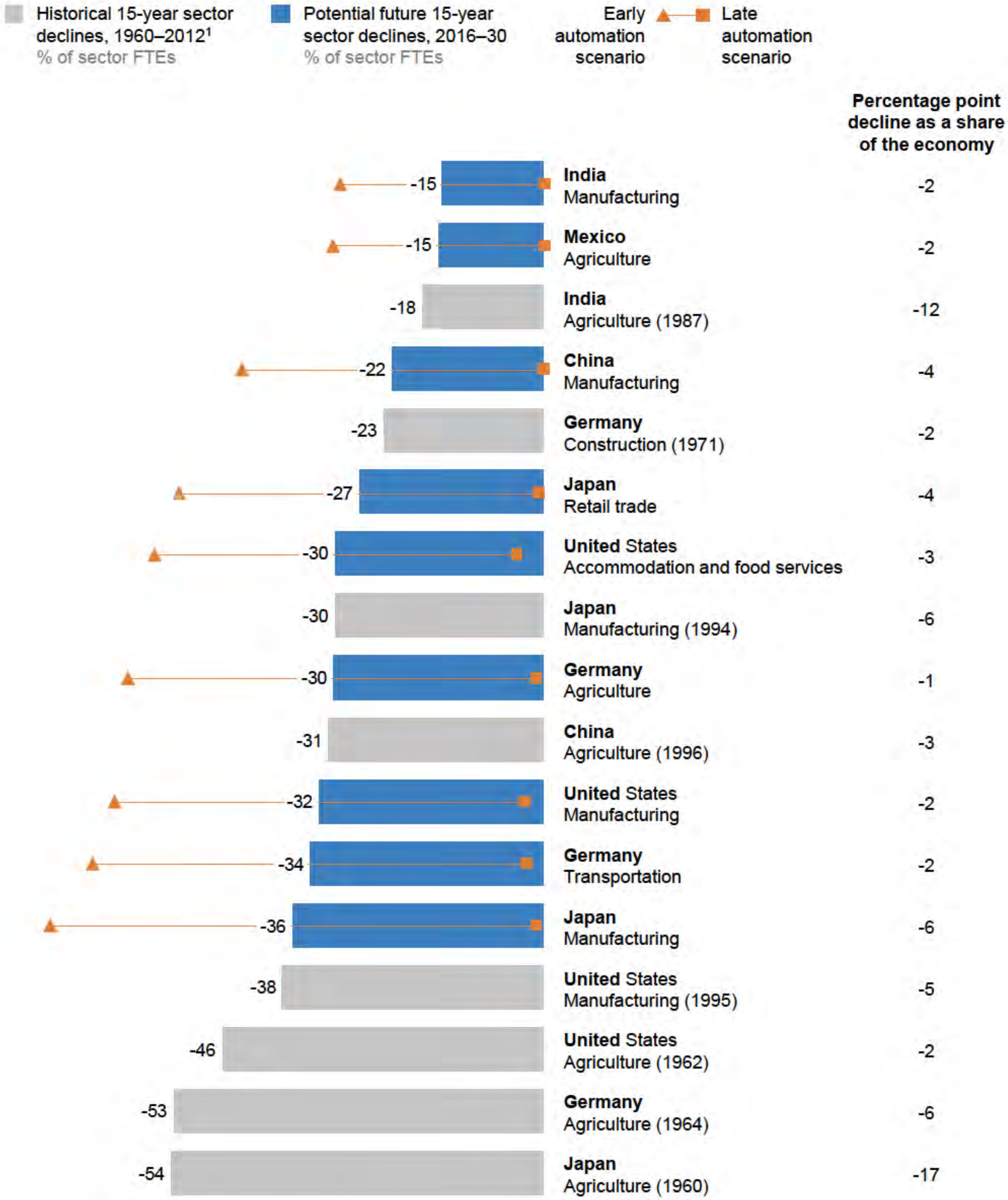
1 Increase from 1850 to 1860 in employment share of household work primarily due to changes in how unpaid labor (slavery) was tracked.

SOURCE: IPUMS USA 2017; US Bureau of Labor Statistics; McKinsey Global Institute analysis

Exhibit 6

Future sector declines from automation are largely expected to be within range of historical declines on a sector basis, but smaller as a share of the overall economy

Selected examples of large sector employment declines vs. potential impact of automation
% decline in sector



1 Sector declines, as a share of the economy, were calculated along a 15-year moving window between 1960 and 2012. Sectors shown here are the largest percentage decline within the 1960-2012 time frame.

SOURCE: Groningen Growth and Development Centre 10-Sector Database; McKinsey Global Institute analysis

2x

Growth of female employment in the United States as a proportion of working-age women, from 1950 to late1990s

TECHNOLOGICAL CHANGE SPARKS RISING PRODUCTIVITY AND AGGREGATE EMPLOYMENT

History shows that the adoption of technological innovation can act as a powerful stimulus on the economy and jobs. The overall effect of mechanization has been to create jobs on an unprecedented scale. Machines allow workers to produce more, thereby raising productivity and (eventually) wages, and lowering the price of goods for consumers. These twin effects unleash new demand for all goods and services. In addition, as firms gain scale, they require more managers, accountants, and other office workers.

This dynamic is the reason that aggregate employment has grown over the long term, even as the size of the workforce has grown. In the United States, for example, female employment almost doubled as a proportion of working-age women from 32 percent in 1950 to 60 percent in the late 1990s before falling back to 57 percent today. Yet this major shift did not reduce overall employment. Indeed, employment grew: the total number of people employed in the United States more than doubled from 65 million in 1960 to 152 million in 2017, according to data from the US Bureau of Labor Statistics. Similar trends have occurred in other countries.

Technology enables productivity growth, raises incomes, and stimulates new consumer demand

Evidence of the economy-wide positive correlation among technology, productivity, and employment can be seen in the aggregate data across countries. Within an industry, machines and automation can sometimes contribute to employment declines. For instance, in the United States, one recent study found that every industrial robot deployed results in the reduction of six human workers within the surrounding metropolitan area.[35] However, when looking at the total economy, we see the opposite effect: rising productivity (often from technology) is usually accompanied by employment growth, not decline. This is because automation raises productivity, which in turn increases incomes of workers and/or shareholders. Higher incomes are spent, creating demand for goods and services across the economy.[36]

When there has been a tradeoff between employment growth and labor productivity growth, it has been short-lived. Looking at the United States since 1960, for example, our analysis shows that employment and productivity both grew in 79 percent of individual years, while productivity grew while employment declined in 12 percent of years. But both employment and productivity grew in 95 percent of rolling three-year periods and 100 percent of rolling 10-year periods. This phenomenon is also seen in other countries. In China, employment and productivity both increased in 77 percent of individual years but 98 percent of the 10-year periods between 1960 and 2016. In Germany, which saw unemployment rise after reunification, employment and productivity grew in 68 percent of individual years but 81 percent of rolling 10-year periods (Exhibit 7).

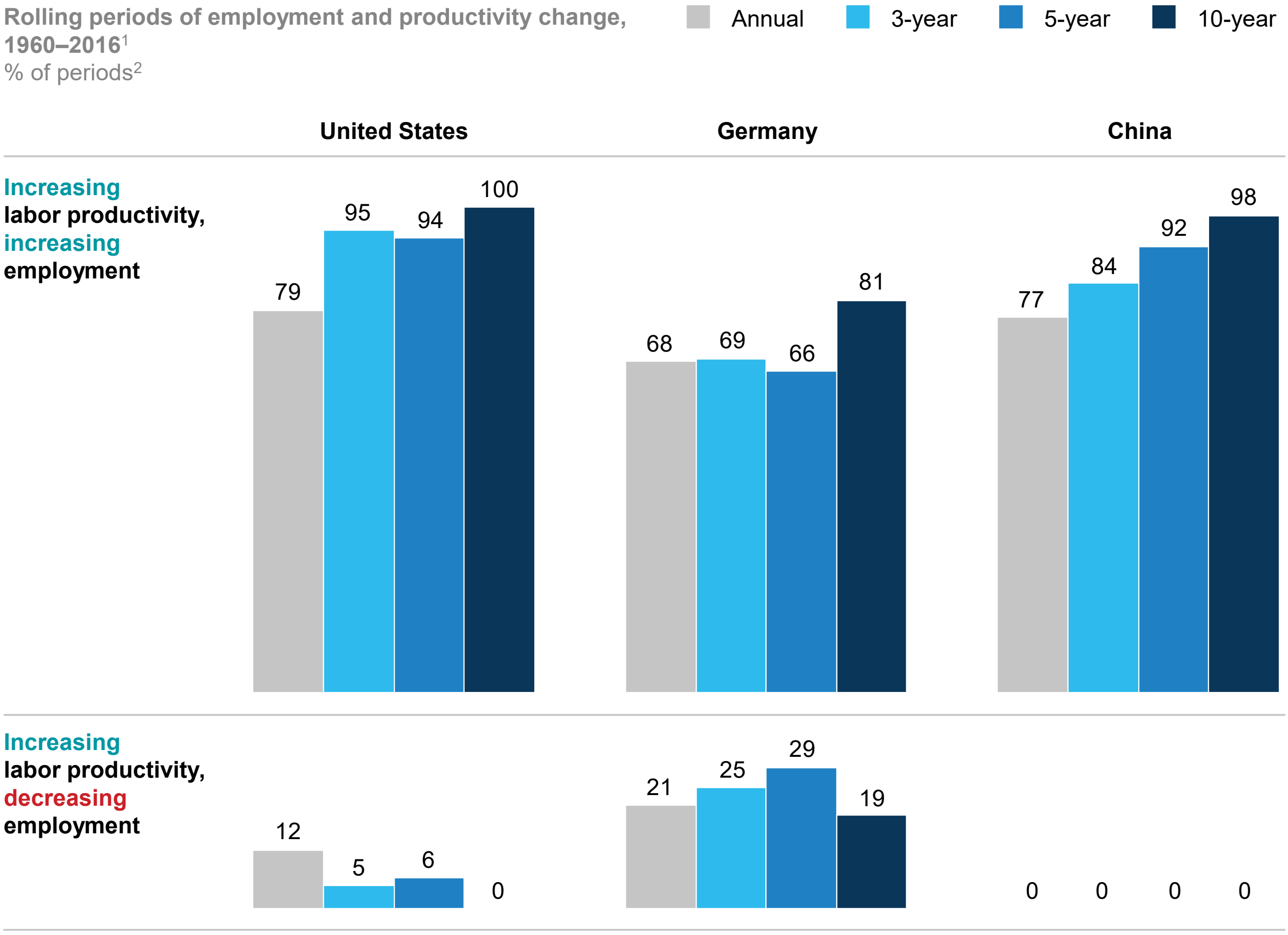
[35] Daron Acemoglu and Pascual Restrepo, *Robots and jobs: Evidence from US labor markets*, NBER working paper number 23285, March 2017.

[36] Ibid. David Autor and Anna Salomons, "Does productivity growth threaten employment?" June 2017.

Exhibit 7

Productivity growth and employment across the entire economy go hand-in-hand—especially when viewed over longer time periods

Rolling periods of employment and productivity change, 1960–2016[1]
% of periods[2]



1 Employment, persons; productivity, GDP per person, 2015 $.
2 Periods categorized into four different scenarios: Increasing productivity and employment, increasing productivity and decreasing employment, decreasing productivity and increasing employment, and decreasing productivity and employment.

SOURCE: The Conference Board Total Economy Database 2016; McKinsey Global Institute analysis

Even as productivity growth leads to rising incomes, technological innovation can also reduce prices and increase the quality of goods and services.[37] This combination can cause demand for a product to soar, resulting in higher employment even within the sector itself. The Ford Model T provides one historical example. The assembly line dramatically improved the productivity of the process of manufacturing automobiles. Exhibit 8 shows that over a six-year period, the number of Model Ts produced per worker annually nearly tripled, from eight to 21. The surge in productivity, combined with increasing economies of scale, enabled Ford to reduce the price from $950 in 1909 to $440 in 1915. As a result, the number of cars sold increased 30-fold, and employment rose from 1,655 to 18,892.[38]

[37] Ibid. David H. Autor, "Why are there still so many jobs?" summer 2015.

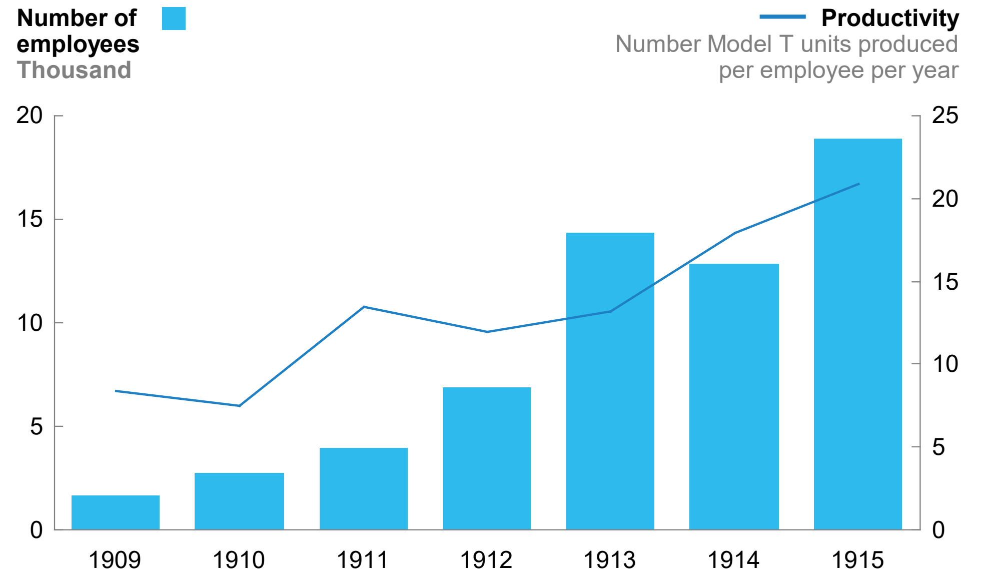
[38] David Hounshell, *From the American system to mass production 1800-1932: The development of manufacturing technology in the United States*, JHU Press, 1985.

Exhibit 8

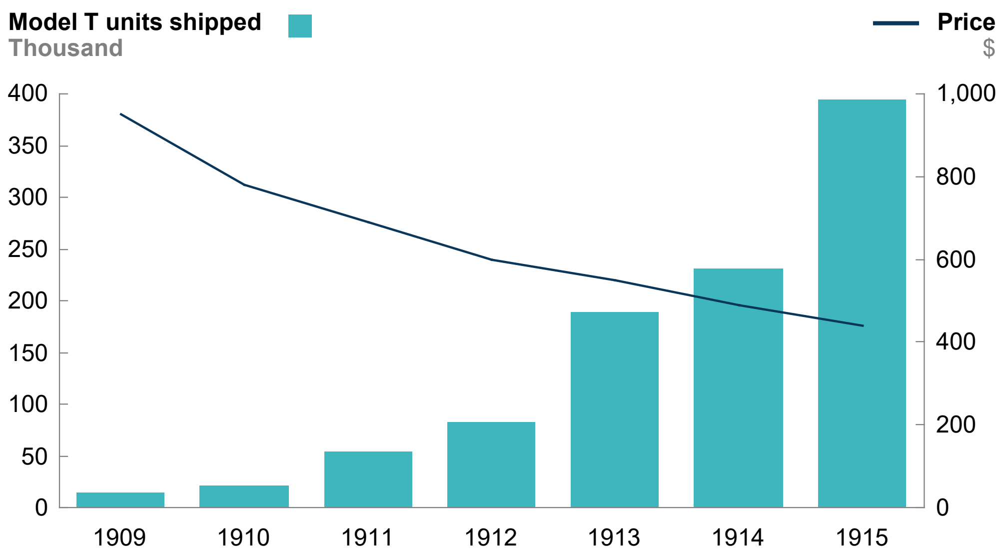
Automation can stimulate employment by lowering the price of a good and unleashing latent demand

Example: Ford Model T assembly line

Assembly line improved productivity and number of employees…



… as prices fell and sales rose



SOURCE: US Bureau of Labor Statistics; FDIC; David Hounshell, *From the American system to mass production 1800–1932: The development of manufacturing technology in the United States*, Baltimore, JHU Press, 1985; Bernard C. Beaudreau, *ICT: The industrial revolution that wasn't*, Lulu, May 2008; McKinsey Global Institute analysis

TECHNOLOGY DISPLACES SOME WORK BUT CREATES NEW JOBS, SOMETIMES IN UNFORESEEN WAYS

It is easy to see which jobs are being destroyed by technology, but difficult to imagine which jobs will be created by it. Telephone switchboard operators have gone the way of lamplighters in the 19th century, but how many of them, lamenting the loss of their jobs, could have imagined the development of the smartphone—and the huge global industry employing tens of millions of people that has sprung up around it? More than 50 years ago, Joseph Schumpeter coined the phrase "creative destruction" to describe this age-old phenomenon in which the emergence of new technology "destroys" jobs by rendering them obsolete, and "creates" new jobs in their wake.[39]

[39] Joseph Schumpeter, *Capitalism, socialism, and democracy*, Routledge, 1942.

Not only does technology create new occupations, it can also change existing occupations in unpredictable ways. After ATMs were introduced in the United States, for example, the number of bank tellers actually rose, as banks competed to provide higher-quality services to customers and the role of tellers changed from dispensing cash to providing broader advice and services. The reduction in the number of tellers per branch enabled banks to open more branches and make retail banking more convenient for customers, which drove the demand for more tellers.[40] From 1991 to 2007, the number of ATMs and tellers in the United States both increased. However, that trend reversed as Internet banking and the 2008 financial crisis resulted in cutbacks in bank branches and tellers.

To better understand the pattern of job creation and destruction, we conducted case studies of two technologies in the United States—personal computers and automobiles—to estimate the number and types of jobs lost to the new technology and the number of new jobs created. In both cases, our research reveals that while some work activities declined, sometimes rapidly, new types of work activities were created. The net impact of both technologies was highly positive, creating new jobs that made up 10 percent of total employment over four decades.

The personal computer enabled the creation of 15.8 million net new jobs since 1980, accounting for 10 percent of employment

Computer-related industries such as computer and data processing services and computer and related equipment manufacturing have been growing rapidly since the 1970s. Microsoft and Apple were founded in that decade. Laptop computers came on the market in the early 1980s, and this century has seen the rapid rise of smartphones and tablets.

The growth of computers has generated significant employment: in the United States, we estimate that computers have enabled the net creation of 15.8 million jobs since 1970 (Exhibit 9). We arrive at this figure by tallying employment gains and losses in different sectors and occupations. We find that in total, we can identify 3.5 million jobs destroyed by the introduction of computers, including those in typewriter manufacturing, secretarial work, and bookkeeping. But at least 19.3 million were created in a wide range of occupations and industries.

When digital editing made it easier and more efficient for authors to type and then directly edit their own work, computers eliminated the need for people specialized in editing and re-typing documents. Employment for typists and secretaries fell significantly, by 1.4 million between 1990 and 2015, even as the overall US workforce grew. The number of bookkeeping clerks also declined, by an annual average of 3 percent in the same period, as accounting moved from physical books to accounting software, resulting in nearly 900,000 fewer jobs.

But many new jobs were also created. These include jobs in the computer manufacturing industry and supplier industries (such as semiconductors), as well as employment in occupations enabled by computers (IT systems administrators, computer scientists in other industries), and in occupations that use computers (customer service call centers, which barely existed before computers, and ecommerce). Of this total, only about 1 percent of net new jobs came directly from the computer manufacturing industry and only 3 percent came from supplier industries.

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40 Ibid. James Bessen, *Learning by doing*, 2015.

Exhibit 9

Technology drives the creation of many more jobs than it destroys over time, mainly outside the industry itself

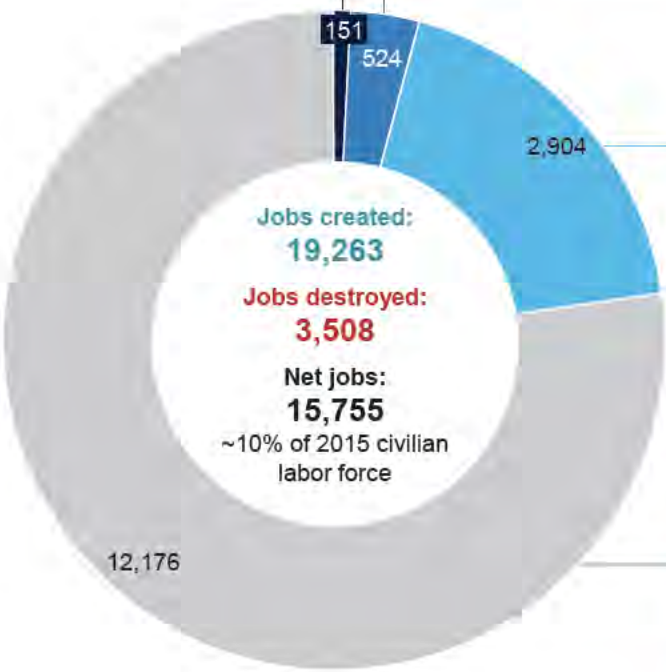
Example: Personal computers

Total US jobs created and destroyed by personal computers (examples listed are not comprehensive)

Thousand jobs

Direct Computer equipment manufacturing, 1970–2015	
▲ Assorted managers and administrators	31
▲ Computer software developers (in-industry equipment)	27
▲ Computer scientists	18
▼ Office machine manufacturers (typewriters)	-61

Indirect Computer suppliers, 1970–2015	
▲ Managers	42
▲ Semiconductor manufacturing occupations	31
▲ Printed circuit assembly occupations	26
▼ Typewriter indirect occupations	-79



Enabled Computer software and service industries, 1970–2015	
▲ Software developers (software and apps)	768
▲ Computer scientists	686
▲ Managers	416
▼ Typewriter repair	-32

Utilizers Computer-utilizing industries, 1980–2015	
▲ Customer service reps	3,205
▲ Computer scientists (not in computer industry)	1,873
▲ Stock and inventory clerks	1,517
▼ Bookkeepers and auditing clerks	-881
▼ Secretaries	-823
▼ Typists	-562

SOURCE: IPUMS; Moody's; IMPLAN; US Bureau of Labor Statistics; FRED; McKinsey Global Institute analysis

A larger share of employment gains has come in professions enabled by computers (18 percent of net employment created). This includes the entire computer software and services industry, with companies such as Oracle, IBM, and Microsoft. This industry employs three million people in the United States, including software and app developers, computer scientists, and managers and office workers.

Because of the multitude of applications of the computer, over 75 percent of net employment generated has been in occupations that use computers. For example, employment of computer scientists in finance, manufacturing, business services, and other industries grew rapidly, by an annual average of about 7 percent, between 1980 and 2015. In the same period, employment of financial managers and specialists able to use spreadsheets to track and analyze large amounts of company data grew by about 3 percent annually on average (see Box 2, "The impact of personal computer and Internet technologies on information analysts").

Box 2. The impact of personal computer and Internet technologies on information analysts

In theory, at least, many information analysts might have been replaced by the rise of the Internet, which makes collecting data and information vastly more efficient, and computers that enable rapid and complex computations. After all, much of their work in the 1980s, before these technologies were widespread, has since been automated.[1]

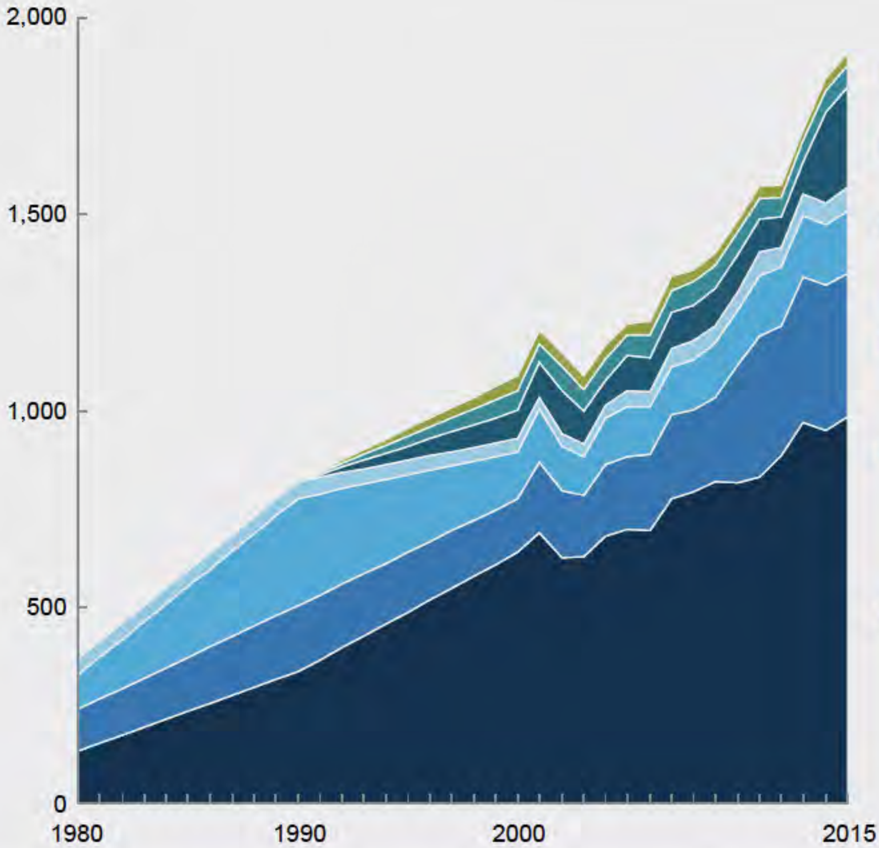
In fact, the opposite has happened. Computers and the Internet automated activities such as basic mathematics and information gathering, yet the number of information analysts soared nonetheless. As computers became more efficient, the cost of obtaining high-quality information dropped. Rather than decreasing demand for analysts, this stimulated the appetite for more insightful and low-cost analysis, and the number of analysts quintupled from around 400,000 in 1980 to about two million today (Exhibit 10).

The jobs of analysts have changed as well. With information and data more easily accessible, analysts can focus on making sense of—and sharing—information rather than gathering it.

Exhibit 10

The personal computer and Internet might have reduced employment for information analysts, but instead it soared as quality improved

Employment in analyst occupations, 1980–2015
Thousand



	Total employment, 2015 Thousand
Credit analysts	31
Budget analysts	55
Financial analysts	255
Statisticians	59
Operations research analysts	159
Economists, market researchers, and survey researchers	364
Management analysts	985
Total	1.9 million

1 Computer, operations, and management analysts were only recorded beginning 1980; credit, financial, and budget analysts were included post-2000.

SOURCE: IPUMS; McKinsey Global Institute analysis

[1] Under information analysts we have included the following Bureau of Labor Statistics occupations: credit analysts, budget analysts, financial analysts, operations research analyst, economists, market researchers and survey researchers, and management analysts.

As computer adoption increased, computer use was correlated with higher wages; employees in these occupations often acquired new skills to use computers, and could demand higher wage premiums.[41] For example, graphic designers took over the jobs of typesetters and started doing a wider range of tasks. Wages increased accordingly as they learned how to use new software and developed higher value skills.[42]

The automobile's largest employment effect has been in enabled industries

The introduction of the automobile created 6.9 million net new jobs in the United States between 1910 and 1950, based on our estimates.[43] This is equivalent to 11 percent of the US workforce in 1950. This includes 7.5 million jobs created, and 623,000 jobs destroyed. Workers displaced by the automobile include manufacturers of wagons, carriages, harnesses and saddles, and of railroad equipment and carriages, as well as supplier industries such as horse breeders and metal work occupations, and enabled industries such as livery services and message boys.

Ten times as many jobs were created in a host of new occupations. About 10 percent were within the auto manufacturing industry (Exhibit 11). Three times as many jobs were in the automotive supply chain, including metal parts manufacturers, warehouses and logistics, and wholesalers. An even larger share of jobs was created in enabled industries and occupations that use the automobile. Enabled industries include auto dealerships, auto repair, gas stations, and convenience stores, and these account for around 30 percent of net new jobs created. Utilizer industries, meanwhile, include transportation and logistics occupations, and account for about 25 percent of employment generated.

If we had extended our analysis beyond 1950, we would have seen the continuing transformative impact of the automobile on the economy and society. Building of the US interstate highway system began in the 1950s, transforming logistics networks. This in turn gave rise to the concept of the "family vacation," long-haul car trips and demand for roadside attractions, motels, and campgrounds. Drive-in movies and restaurants, shopping malls on the edges of towns, and parking lots sprang up. The automobile also enabled growth in suburbs, as workers could commute to jobs from locations outside urban public transportation networks.

THE NUMBER OF HOURS WORKED HAS DECLINED, WHILE LEISURE TIME HAS RISEN

50%
Approximate reduction in working hours in Germany, Sweden, United Kingdom, and United States since 1870

While past technological disruptions did not reduce the amount of work available to people, they nonetheless had one significant effect: a decline in the average number of hours worked per week—and conversely an increase in the amount of leisure enjoyed by individuals. Already in 1930, John Maynard Keynes predicted the advent of greater leisure: "For the first time since his creation man will be faced with his real, his permanent problem—how to use his freedom from pressing economic cares, how to occupy the leisure, which science and compound interest will have won for him, to live wisely and agreeably and well."[44]

In hindsight, Keynes was right: the average number of hours worked each week by employed workers has declined significantly in the past 150 years, giving workers more time for leisure. In 1870, workers in Germany, Sweden, and the United States averaged between 62 and 70 hours each week; in the United Kingdom, which was already shifting

41 James Bessen, *How computer automation affects occupations: Technology, jobs, and skills*, Boston University School of Law, law and economics research paper number 15-49, 2016.

42 Ibid. James Bessen, *Learning by doing*, 2015.

43 Data from Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek, *Integrated Public Use Microdata Series: Version 6.0* (dataset),University of Minnesota, 2015; Bureau of Economic Analysis; US Census 1900, 1914, 1910.

44 Ibid. John Maynard Keynes, "Economic possibilities for our grandchildren," 1963.

from agriculture to industry, the average worker put in 57 hours per week (Exhibit 12). By 2015, these figures had fallen by roughly half, to around 35 hours in Germany, Sweden, and the United Kingdom and 38.6 hours in the United States. Hours worked have continued to decline as the workforce shifted from manufacturing to services in the past 50 years. In OECD countries, the average hours work declined to 36 hours in 2015 from 42 hours between 1960 and 1980.[45] This trend is especially pronounced in Australia, Denmark, Germany, Ireland, the Netherlands, and Sweden.

Exhibit 11

The automobile created millions of jobs in suppliers and automobile-enabled industries

Example: Automotive

Total US jobs created and destroyed by automobiles (examples listed are not comprehensive)

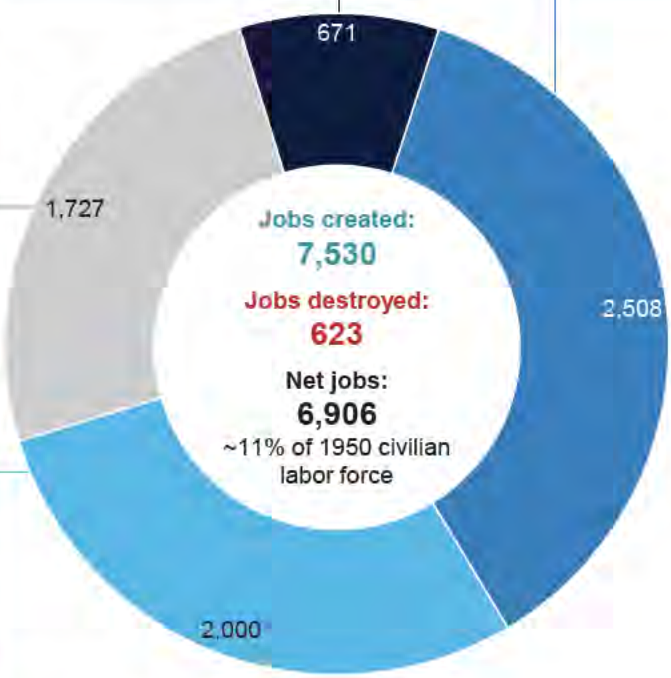
Thousand jobs

Direct: Automobile manufacturing, 1910–50	
▲ Operative and kindred workers	380
▲ Laborers	56
▲ Clerical and kindred workers	55
▼ Railroad and railway occupations	-194
▼ Wagon and carriage factory occupations	-83
▼ Harness and saddle factory occupations	-15

Automobile manufacturing supplier industries, 1910–50	
▲ Primary metals occupations	428
▲ Wholesale trade occupations	233
▲ Transportation and warehousing	220
▼ Textile mills occupations	-13
▼ Primary metals occupations	-13
▼ Transportation and warehousing occupations	-12

Automotive-utilizing industries, 1900–50	
▲ Truck and tractor drivers	1,241
▲ Deliverymen	154
▲ Mail carriers	128
▼ Messengers and office boys	-24

Automotive-enabled industries, 1910–50	
▲ Automobile mechanics	533
▲ Managers (e.g. dealerships, service centers)	452
▲ Automotive service and parking attendants	253
▼ Rail equipment	-150
▼ Livery stable industry	-34



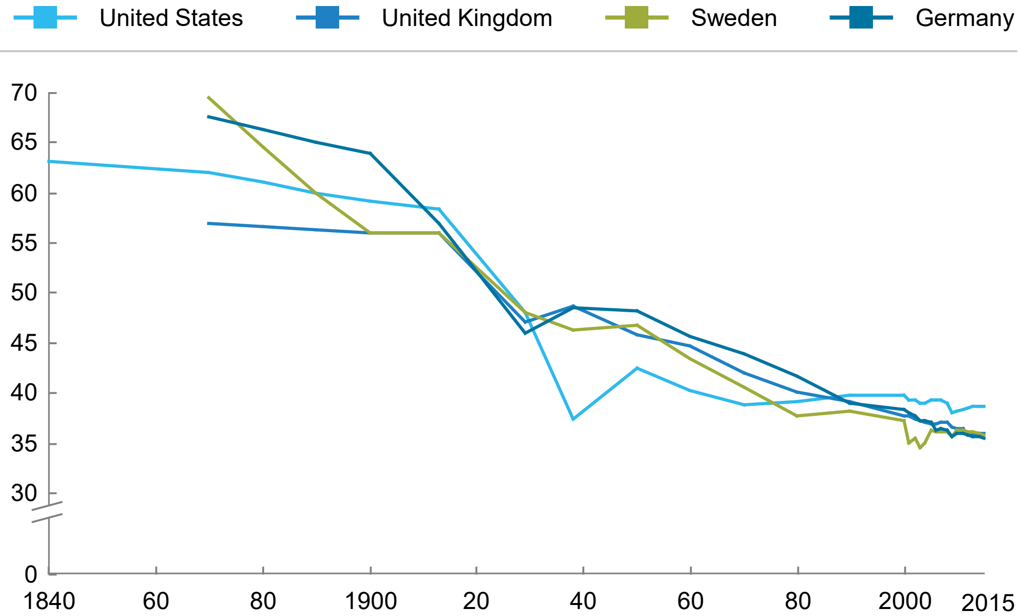
SOURCE: IPUMS; Moody's; IMPLAN; US Bureau of Labor Statistics; FRED; McKinsey Global Institute analysis

[45] Jeremy Reynolds, "You can't always get the hours you want: Mismatches between actual and preferred work hours in the U.S.," *Social Forces*, volume 81, number 4, June 2003; Michael White, *Working hours: Assessing the potential for reduction*, International Labour Organization, December 1987; Robert E. Hall, *Wages, income and hours of work in the U.S. labor force*, Massachusetts Institute of Technology, working paper number 62, August 1970.

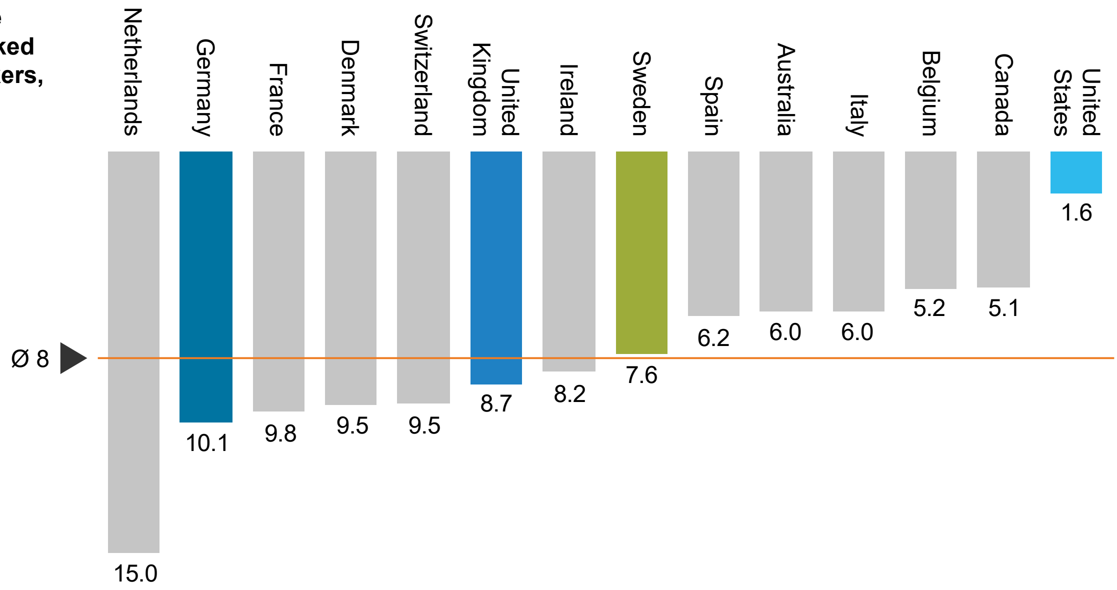
Exhibit 12

Average hours worked weekly have declined sharply since the mid-1800s

Average hours worked weekly by employed workers, 1840–2015



Decline in average weekly hours worked by employed workers, 1960–2015



NOTE: These workweek numbers take into account paid time off and holidays.

SOURCE: Michael Huberman and Chris Minns, "The times they are not changin': Days and hours of work in Old and New Worlds, 1870–2000," *Explorations in Economic History, 2007*; ILO; US Bureau of Labor Statistics; ONS Labor Force survey; McKinsey Global Institute analysis

The decline in average hours worked reflects the productivity improvements that have compounded over the years, allowing people to work less per week and yet still support growing economies. Differences between countries reflect different labor policies and social institutions governing the number of expected hours of work per week and vacation days. In the early 20th century, labor unions in the United States and in Europe pushed for national policies to cap the work week at 40 hours (which eventually became an International Labour Organization standard). In European countries such as France and Germany, a second wave of working-hour reductions took place in the 1980s and 1990s; in France, the government lowered the official work week to 35 hours—and today there is some evidence that French people would work more if they could.[46] Since 1960, the total hours worked has declined by 26 percent in Germany, 8 percent in Italy, and 7 percent in France.

The decline in average hours worked also reflects the steady rise of part-time employment across countries. The highest proportion of part-time work is in the Netherlands (39 percent of employed persons), the United Kingdom (24 percent), and Germany and Japan (22 percent).[47] Part-time work is often preferred for a variety of reasons by students, caregivers, and people nearing retirement, but also by some employers in markets where rigid labor market policies make full-time hiring economically unattractive. In the past decade, the number of people in the United States and Europe who earn money in the independent workforce—as freelancers, independent contractors, self-employed, and workers in the "gig" economy—has grown, to an estimated 162 million.[48] Many of these individuals work less than a full-time schedule.

As leisure time increases, people spend money on hobbies, entertainment, and other personal services, giving rise to entire new industries that in turn create jobs. Skiing, golfing, tourism, crafting, and do-it-yourself home projects are a just a few industries that have sprung from the new leisure economy. The number of jobs involved is significant: globally, as many as 292 million people are employed directly or indirectly by tourism—one in every ten jobs on the planet.[49]

THE IMPACT OF TECHNOLOGICAL CHANGE ON WAGES AND SKILLS

For some English workers during the early 19th century, wages stagnated or fell for

50 YRS

Adjusting the economy to new technological disruptions may take time, and can have significant repercussions for both skills and wages. In the first half of the 19th century, during the First Industrial Revolution in England, the steam engine and other technologies increased the productivity of unskilled workers and enabled them to undertake work previously carried out by higher-skill, and higher-paid, workers including craftsmen and artisans. Across the economy, mechanization raised output per worker. However, real wages stagnated for roughly 50 years, from 1790 until 1840 (Exhibit 13). During this period, first noted by economist Friedrich Engels in 1845, profits as a share of national income rose and the labor share of income declined.[50] After 1850, real wages began rising in line with productivity increases, and by the late 1800s wage growth exceeded productivity growth. But for nearly half a century, wage growth was nil and real living standards of workers declined. The plight of some workers provided material for Charles Dickens's bleak depictions in his novels, and led the English poet William Blake to decry factories as "dark, satanic mills."[51] The turnaround in the relationship between wages and output came at a time of substantial reform of existing structures including the right to unionize, limitations on

46 An MGI survey of 16,000 Europeans in eight countries showed that a majority was willing to make tradeoffs, including working more hours per week in exchange for more income and better services. This willingness to increase working hours was especially pronounced in France, where the workweek was officially lowered to 35 hours from 2000. *A window of opportunity for Europe*, McKinsey Global Institute, June 2015.

47 Arne L. Kalleberg, "Nonstandard employment relations: Part-time, temporary and contract work," *Annual Review of Sociology*, volume 26, August 2000; Chris Tilly: "Reasons for continuing growth of part-time employment," *Monthly Labor Review*, March 1991; Rachel A. Rosenfeld and Gunn Elisabeth Birkelund, "Women's part-time work: A cross-national comparison," *European Sociological Review*, volume 11, number 2, September 1995.

48 Our research has found that 20 to 30 percent of the working-age population in the United States and Western Europe works independently, including many who do so part-time. The majority, 70 percent, say they do so out of choice, with the remainder doing so out of necessity. *Independent work: Choice, necessity and the gig economy*, McKinsey Global Institute, October 2016.

49 *World economic impact*, World Travel and Tourism Council, 2017.

50 Ibid. Robert Allen, "Engels' pause," October 2009; for a discussion of historical wage trends, see also Gregory Clark, "The condition of the working class in England, 1209-2004," *Journal of Political Economy*, volume 113, number 6, 2005.

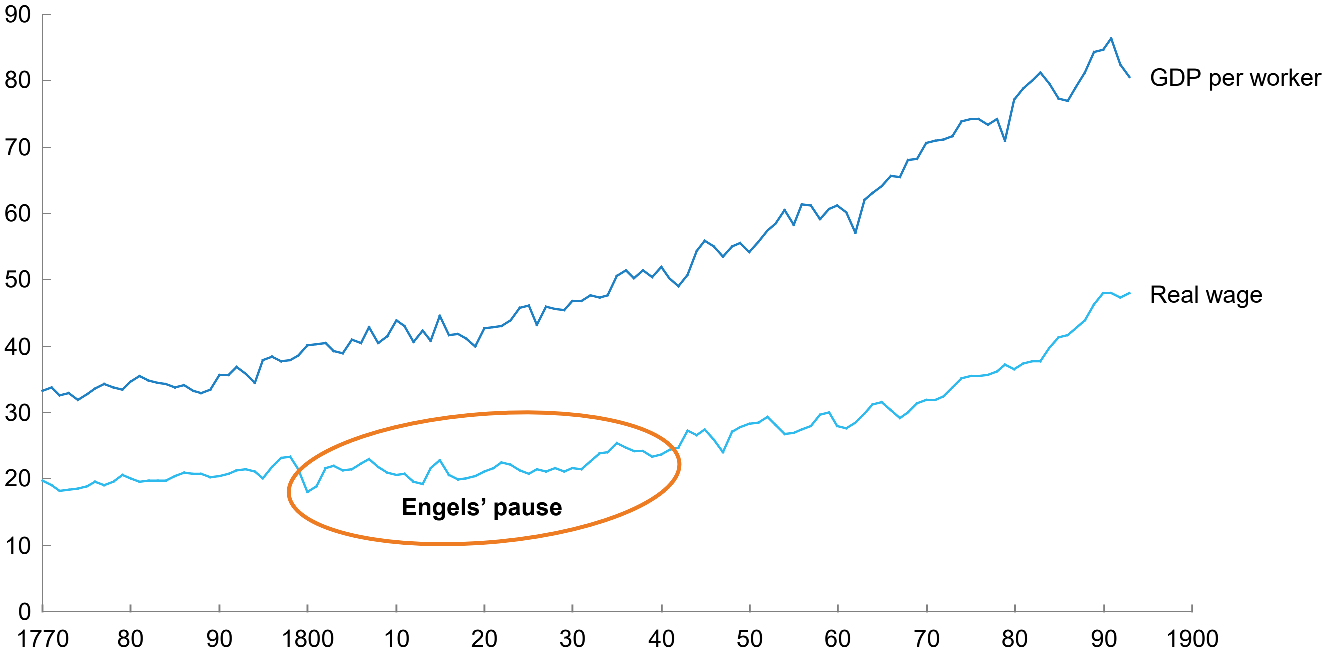
51 Dickens's novels painting a stark picture of everyday life in Victorian England include *Oliver Twist* (1838) and *Hard Times* (1854). The line about dark, satanic mills is in William Blake's poem "And did those feet in ancient time," from the preface to *Milton: A Poem, 1804*.

child labor, the introduction of public high schools, urban planning to improve public health, elimination of debtors' prison, and the extension of the right to vote to landless workers.[52]

Exhibit 13

Engels' pause shows that during the Industrial Revolution, UK wages stagnated despite accelerating productivity growth

UK historical real wage vs. GDP per worker, 1770–1893
1851 real £ per year



SOURCE: Robert C. Allen, "Engels' pause: Technical change, capital accumulation, and inequality in the British industrial revolution," *Explorations in Economic History*, volume 46, issue 4, October 2009; McKinsey Global Institute analysis

The growing mechanization led to a shift in the skills of the workforce and affected semi-skilled artisans negatively. Economic historians have documented the consequences for previously well-paid workers such as hand-loom weavers, whose income tumbled in the 1820s, leading to immiseration of many, even as the invention of automated looms lifted other, unskilled workers out of poverty.[53] At the same time, the share of unskilled labor in the British workforce increased, from 20 percent in the late 16th century to nearly 40 percent in the early 19th century.[54] This "deskilling" of the workforce occurred in agriculture and industry alike, prompted by land concentration that enabled mechanized agriculture and the shift from artisans' workshops to factory production in industry. During this period there was also some growth in the share of skilled workers such as machine erectors and operators, who were needed to facilitate the Industrial Revolution.

More recently, academic research shows that local labor markets, including in the United States, have taken years to adjust to trade shocks from competition from China, with wages and labor-force participation rates remaining depressed and unemployment rates remaining elevated for at least a full decade after the trade shock started.[55] Some research also

[52] Peter Mathias, *The first industrial nation: The economic history of Britain 1700–1914*, Routledge, 2001.

[53] Robert C. Allen, *The hand-loom weaver and the power loom: A Schumpeterian perspective*, University of Oxford, discussion papers in economic and social history, number 142, March 2016.

[54] Alexandra M. de Pleijt and Jacob L. Weisdorf, "Human capital formation from occupations: The 'deskilling hypothesis' revisited," *Cliometrica*, volume 11, number 1, January 2017.

[55] David H. Autor, David Dorn, and Gordon H. Hanson, *The China shock: Learning from labor-market adjustment to large changes in trade*, NBER working paper number 21906, January 2016.

suggests that increasing structural unemployment of non-college US whites of the past two decades—driven by automation and offshoring in manufacturing, among other things—may have contributed to rising morbidity rates.[56]

Whether the experience of technological disruption in the past is relevant for economies in the future can be debated. In Chapter 4 of this report, we present new analysis of the impact of automation today on the demand for different types of skills and discuss the potential impact on wages. Even if the particulars of the historical experience turn out to differ from conditions today, one lesson seems pertinent: although economies adjust to technological shocks, the transition period is measured in decades, not years, and the rising prosperity may not be shared by all.

AUTOMATION TODAY: COULD THIS TIME BE DIFFERENT?

Despite the reassuring lessons from history on the long-run impact of automation on employment, some technology experts argue that automation today will not behave like previous technology waves. They cite a number of reasons that the future may bring more disruption to workers than in the past, including the ability of machines to perform work activities requiring cognitive capabilities, the rate of progress in new innovations, and a potential future in which machines teach themselves to improve at particular tasks without much human intervention.[57] Many economists, however, tend to view automation as the next wave of technological advancement and point out that an equilibrium between the supply and demand of jobs in labor markets has always been reached historically, even if the transition period may be difficult.[58]

In part, the discord between the two points of view may be caused by the lack of a common language: what exactly could be different about automation compared with previous technologies? What time frame are we considering? In our research we looked at a range of arguments on both sides and examined the evidence for both the scope of automation's impact and its nature across multiple dimensions. This framework is useful for disentangling the different elements of technological disruption and assessing the ways in which today's technology may—or may not—have a different impact than in the past.

We conclude that in many respects, the impact of automation on employment today is not likely to be different than in the past, particularly if we look back centuries, to the First Industrial Revolution in the late 1700s. But we have identified two ways in which automation, robotics, and AI could diverge from earlier waves of technology disruption: the speed at which scientific advances are being made, if the accelerated rate of progress in machine learning and AI continues, and the potential to displace a higher share of the workforce in a relatively short period of time, particularly if the adoption of automation is rapid across multiple sectors of the economy.

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56 Anne Case and Angus Deaton, "Rising morbidity and mortality among white non-Hispanic Americans in the 21st century," *Proceedings of the National Academy of Sciences of the United States of America*, volume 112, number 49, December 2015.

57 See for example the 2017 public debate between Tesla CEO Elon Musk and Facebook CEO Mark Zuckerberg over artificial intelligence and the threat that it may or may not pose to mankind. Ian Bogost, "Why Zuckerberg and Musk are fighting about the robot future," *The Atlantic*, July 27, 2017. See also, Rafi Khatchadourian, "The Doomsday invention," *The New Yorker*, November 23, 2015.

58 Christopher Pissarides and Giovanna Vallanti, *Productivity growth and employment: Theory and panel estimates*, Center for Economic Performance, discussion paper number 663, December 2004; Jason Furman, "Is this time different? The opportunities and challenges of artificial intelligence," remarks at AI Now: The Social and Economic Implications of Artificial Intelligence Technologies in the Near Term conference in New York, July 7, 2016.

Rate of technological innovation

Could be faster than the past

In Chapter 1 we noted the rapidity of recent technological innovation as a result of the development of deep learning and reinforcement-learning techniques based on neural networks; the availability of exponentially increasing computing capacity that is accessible to users via the cloud; and the sheer volume and variety of data generated that can be used to train machine learning models. Advocates of the argument that automation today is fundamentally different in its scope point to this acceleration of innovation as evidence of a real break with the past.

Those who disagree, however, point to Moore's Law, named for Gordon Moore, a co-founder of Intel, who in 1965 noted that the number of transistors incorporated in a computer chip would approximately double every 24 months—which became the basic business model for the semiconductor industry for the following decades.[59] The shrinking of transistors in semiconductors improved computing speed and capacity and helped usher in the internet era, as well as the mobile phone revolution and the cloud. However, the rate of progress in shrinking transistors has slowed, and some scientists project that without a new computing model, future advances may run out. Moreover, AI veterans point to previous eras when what seemed to be fast-moving advances in AI gave way to frustrating lulls. AI dates back to the 1950s, when Alan Turing suggested that computers could communicate as well as humans and Princeton students including Marvin Minsky and Dean Edmonds built the first artificial neural network using 300 vacuum tubes and a war-surplus gyropilot. After the initial excitement, funding slumped in the 1970s as research backers—primarily the US government—tired of waiting for practical AI applications and cut appropriations for further work. Another lull followed in the 1990s.[60]

Our view is that the recent technical advances, enabling machines to read lips or X-rays more proficiently than human experts, are indeed remarkable and that if this pace of innovation continues rather than encountering a new AI "winter," the rate of automation innovation could indeed be faster than in the past. If so, the potential disruption of workforce models and displacement of labor could be greater than past technological revolutions.

Rate of technological adoption

Faster than 100 years ago, but no evidence of acceleration in recent decades

Even if technological innovations are occurring more rapidly, the impact on workers will be different only if the diffusion and adoption of new technologies also accelerates. Some researchers say this is the case, pointing to examples such as landline telephones, electrification, or the automobile. Indeed, while it took almost a century for landline phones to reach saturation, or the point at which new demand falls off, mobile phones in some markets reached that point in just 20 years and smartphones in even less time.[61] One commonly found reference is the speed with which certain online videos on YouTube or smartphone games such as Angry Birds or Pokemon Go reach a certain threshold of downloads—50 million, 100 million, or more.[62] Based on measures of gross numbers, for example, of people adopting a technology, you could say that adoption rates have accelerated. However, it is also worth considering adoption rates when measured using percentages.

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59 "Moore's law and Intel innovation," Intel, https://www.intel.com/content/www/us/en/history/museum-gordon-moore-law.html

60 Michael Negnevitsky, *Artificial intelligence: A guide to intelligent systems*, Addison-Wesley, 2002. See also, *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.

61 Michael De Gusta, "Are smart phones spreading faster than any technology in human history?" *MIT Technology Review*, May 9, 2012; Gisle Hannemayr, The Internet as hyperbole: A critical examination of adoption rates, https://hannemyr.com/en/diff.html.

62 Stanford University Infolab, Stanford University, infolab.stanford.edu.

Looking at only the last 60 years, our review of the historical rates of adoption of 25 previous technologies shows that the time from commercial availability to 80 percent adoption has tended to fall within a relatively constant range: between approximately eight and 28 years. For 50 percent adoption, the range is five to 16 years. The technologies reviewed date back to TVs in the 1950s, and include recent examples of cell phones, customer relationship management software, and lithium-ion cell batteries. This range of times for adoption was observed for both hardware-based technologies that are capital-intensive and require physical installation; and technologies that are available purely online. Technologies with the fastest adoption rates include stents, airbags, MRIs, TVs and online air booking, while slower adoption categories include dishwashers and pacemakers from the 1960s, and cellphones in the 2000s. Even highly popular and widely-used social media applications do not achieve a high level of adoption faster than technologies in previous eras. Facebook is one example: it was launched in 2004 and quickly achieved worldwide success. Yet even by mid-2016, when it had about 1.7 billion users globally, it was still far from full adoption, even outside China.[63] Moreover, it was not the first social network, and so the adoption period could be calculated as being even longer—since the advent of the first modern social network, Six Degrees, which launched in 1997, or Classmates.com, which launched in 1995.[64]

Our view is thus that there is no evidence that technological adoption has yet accelerated over the last 60 years, when measured in percentages, although, not surprisingly, diffusion is faster than it was for technologies introduced in the early 20th century.

Breadth of sectors in which work can be automated

Not different from the past

Some commentators say that today's automation is different from the past because it has the potential to transform work in multiple sectors simultaneously. They argue that the largest technological disruptions of the past have been the move out of agriculture or, more recently, from manufacturing into services. Advocates of the "this time things are different" argument point to the pervasiveness of automation technologies as being different, in that they will affect multiple sectors of the economy—from finance to retail to manufacturing to transportation—simultaneously.[65]

As points of comparison, one can consider the application of some technologies in the past, such as electricity or computers, which also transformed work across multiple sectors of the economy simultaneously. Electrification transformed household lighting, heating, and refrigeration; it enabled stores and factories to open for longer hours; and it gave birth to mass production. Similarly, computers transformed business services, finance, and retail and gave birth to the Internet and mobile computing. The steam engine drove the Industrial Revolution, upending numerous sectors from weaving to printing, for example. Between 1910 and 1950, successive waves of innovation also proved highly pervasive, from automobiles to assembly lines.

Our view is that little is new about the breadth of impact of automation technologies.

Share of jobs in the economy that be automated by 2030

Could be higher than past technologies if adoption is rapid

Even if past technological innovations transformed work in multiple sectors of the economy, today's automation could affect a larger share of work. Proponents of this view point out that some sector employment shifts have been extremely large—for example, the rapid transitioning out of agricultural employment in China, or the steep decline in US agriculture in

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[63] Internet World Statistics.

[64] Danah M. Boyd and Nicole B. Ellison, "Social network sites: Definition, history, and scholarship," *Journal of Computer-Mediated Communication*, volume 13, number 1, October 2007; Classmates.com.

[65] Rudina Seseri, "The AI disruption wave," *TechCrunch*, October 13, 2016.

the 20th century. The potential impact on demand for current work activities in some sectors as a result of automation today could likewise be very large. Viewed over a 15-year period, our automation model suggests that roughly half of the existing work in countries such as Germany, Japan, and the United States could be displaced by 2030 if automation adoption is at the most rapid end of our modeling. In the past, also looking at 15-year periods, our analysis shows that as much as 30 percent of jobs were displaced in historical episodes—in other words, lower than our most rapid automation scenario but not of a completely different order of magnitude.

Our view is thus that, if automation adoption is very rapid, it could potentially displace a greater percentage of work in some advanced economies in the next 15 years than we have seen in the past.

Types and complexity of tasks that can be automated

Every wave of automation affects more complex tasks

Alongside the scope of automation's impact, its very nature has sparked discussion about differences between technological change today and in the past. One frequently-cited argument concerns the type of tasks that AI in particular now can accomplish with prowess, from driving trucks to creating music and art to playing championship Go. The power of algorithms to take on activities requiring cognitive capabilities and creativity is held up as a fundamental break with previous technologies.[66]

Skeptics point out, however, that this is not the first time that machines have been able to carry out tasks requiring cognitive capabilities. Every new wave of automation seems remarkable at the time. From the 1980s, with the birth of computerized spreadsheets, machines have taken on ever more sophisticated tasks that previously required human brainpower, from manipulating large quantities of data and alphabetizing lists or doing complex calculations to anticipating the words your fingers are about to type on a smartphone. While the tasks themselves have changed, our view is that the ability of machines to acquire such capabilities is not in itself new. While significant progress has been made in specific "narrow" AI applications, formidable multi-decade-long technological challenges must still be overcome before machines can match human performance across the range of cognitive activities and approach "artificial general intelligence"—which would indeed be a break with historical precedent.

Skill bias of technical change

Today's automation could complement both high- and low-skill workers

Technological innovation has affected workers in different ways in the past. As already noted, the steam engine and other technologies introduced during the Industrial Revolution in Europe and the United States in the 19th century increased the productivity of unskilled or low-skill workers and enabled them to undertake work previously carried out by high-skill, and higher-paid, workers including artisans such as hand-loom weavers. In the academic literature, technological change was thus considered to be biased toward enabling low-skill workers at the expense of high-skill ones.

In our era, the opposite has happened: computers and factory-floor robots have tended to increase the productivity and complement the work of high-skill workers, while machines have substituted for the programmable and routine tasks that had been undertaken by low-skill workers, including those working on assembly lines or as switchboard operators.[67]

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[66] See, for example, the interview with Andrew Ng and Neil Jacobstein,"How artificial intelligence will change everything," *The Wall Street Journal*, March 6, 2017.

[67] David H. Autor, Frank Levy, and Richard J. Murnane, "The skill content of recent technological change: An empirical exploration," *The Quarterly Journal of Economics*, volume 18, number 4, November 2003; David Hounshell, *From the American system to mass production 1800-1932: The development of manufacturing technology in the United States*, JHU Press, 1985.

This is known as skill-biased technical change. Some economists view the effects of technological change and technology-enabled globalization in recent decades as a significant driver of inequality.[68]

We do not have firm evidence yet on whether automation today will tend to be more skill-biased or unskill-biased in its impact. Our analysis of how automation will affect skills, detailed in Chapter 4, suggests that workers of all skill and educational levels will be affected. Some technologies might enable lower-skill workers to replace higher-skill ones—such as nurses who can perform some of the more routine tasks of doctors with the aid of diagnostic tools. Other technologies will complement high-skill workers and enable them to command even greater power in the marketplace—for instance surgical robots or AI algorithms that can suggest new investment strategies.

Impact on high-wage vs. low-wage work

Both will be affected

A final dimension on which technological change could be different today is its impact on workers at different wage levels. One of the frequently-cited concerns about automation is that machines could replace activities of high-wage jobs previously considered "safe," including experts in financial services, some types of doctors, and lawyers.

While our analysis of automation's impact on wages, also in Chapter 4, suggests that a range of high-wage occupations could be affected, there is ample historical precedent for this, including the hand-loom weavers in 19th-century England who suffered a steep decline in their livelihoods after the arrival of mechanized looms, which allowed lower-wage and lower-skill workers to produce more cloth, faster, and less expensively.[69] We therefore conclude that today's automation is unlikely to be different from the past on this dimension.

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In 1930, at the height of the Great Depression, John Maynard Keynes wrote, "We are suffering, not from the rheumatics of old age, but from the growing-pains of over-rapid changes, from the painfulness of readjustment between one economic period and another." As many do today, he saw the speed of technological change as something formidable, an era of progress and invention incomparable to any that had come before—yet also as a time of painful transition for many. In the 1960s, a US national commission on technology, automation, and economic progress established by President Lyndon B. Johnson concluded that, "the basic fact is that technology eliminates jobs, not work. It is the continuous obligation of economic policy to match increases in productive potential with increases in purchasing power and demand. Otherwise, the potential created by technical progress runs to waste in idle capacity, unemployment, and deprivation."[70] The question for us today is whether, this time, the transitions will be larger and more painful than ever, and indeed how demand for human labor will evolve. In this chapter, we have described the historical evidence showing that employment remains strong even in periods of technological ferment. In the following chapters, we look at the trends that can create demand for tens of millions of new jobs in the global economy over the next decade and more, even as robotics and AI increasingly make their way into our daily work lives, and what the implications will be for sectors, occupations, skills, and wages.

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68 Laura Tyson and Michael Spence, "Exploring the effects of technology on income and wealth inequality," in *After Piketty: The agenda for economics and inequality*, Heather Boushey, J.Bradford DeLong, and Marshall Steinbaum, eds, Harvard University Press, May 2017.

69 Ibid. Robert C. Allen, *The hand-loom weaver and the power loom*, March 2016.

70 *Technology and the American economy: Report of the National Commission on Technology, Automation, and Economic Progress*, US Department of Health, Education, and Welfare, February 1966.

A surgeon examining MRI scans in Montreal, Canada

3. JOBS GAINED: SCENARIOS FOR EMPLOYMENT GROWTH

While automation will displace some workers and transform occupations, we also know that new and additional work will be created in the next decade and beyond. What is less clear is how job growth net of automation will vary by occupation, and under what conditions there will be enough new jobs to offset the work that is lost as robotics, artificial intelligence, and other technologies assume a greater role in the workplace. Predicting all the jobs that will exist in the future is an impossible task, yet even without a crystal ball, it is possible to identify some sources of future labor demand.

In this chapter, we discuss two different analyses that shed light on these questions. To understand some of the occupations and types of jobs likely to be in demand in 2030, we model seven specific global trends that we expect will be significant drivers of job creation. To inform the impact of automation on aggregate employment, we conduct a second analysis using the McKinsey Global Growth Model, which is a multi-country macroeconomic model. This exercise allows us to model the dynamic effects of automation on productivity, employment, and GDP growth in different scenarios. Automation has the potential to raise productivity growth and GDP growth, but our analysis reveals that a key factor in whether this will be achieved without large adverse effects on employment and wages is how quickly displaced workers are reemployed in other jobs.

Both analyses reach broadly similar conclusions: although some workers will be displaced by automation, other occupations will grow. While in the long-term the economy can adjust to provide enough work for everyone, automation will prove challenging for tens of millions of workers globally who will need to switch occupations. Depending on how societies manage this transition, unemployment could rise in the medium-term and wages could be eroded. Both the impact of automation and potential new sources of labor demand will play out differently from country to country.

SEVEN GLOBAL TRENDS THAT WILL HELP SHAPE THE FUTURE OF WORK

250M
number of new jobs net of automation that could be created to 2030 by rising incomes

In seeking to identify potential sources of labor demand to 2030, we started with a long list of trends and then prioritized seven for deeper analysis, based on high-level initial estimates of their potential for job creation (see Box 3, "Our analysis of seven trends that will contribute to future labor demand"). While there are many scenarios and sources of potential labor demand we have not included, the seven trends we focus on in this report have the potential to create demand for hundreds of millions of workers globally in the years to 2030, albeit with significant variations among countries.

For each trend, we model both the direct impact on employment and the indirect impact. By direct jobs, we mean employment created in a sector itself (for instance, increased spending on cars would create direct employment in the automobile manufacturing sector). Indirect refers to employment created in all the sectors that supply goods and services to the direct sector (for automobiles, indirect sectors would include spare parts, paint, leather, etc.). We do not include induced effects, since some are captured directly by our rising consumption trend.

Box 3. Our analysis of seven trends that will contribute to future labor demand

We examine potential labor demand created between 2016 and 2030 as a result of our seven trends, and compare that to the amount of work that could be displaced by automation. Sizing methodology varies by trend; however we capture direct and indirect jobs that could be created from each of our seven catalysts, take into account the decline in hours worked per person, and factor in globalization of work.[1]

For each occupation and sector, our incremental labor demand nets out automation and other productivity gains. We then compare that incremental labor demand with the reduction in labor demand due to automation against a projected 2030 baseline of employment. This uses the model we developed for our January 2017 report on automation, which also modeled ranges for the pace of technology development, and for automation adoption.[2]

As well as calculating direct and indirect labor demand from our select trends, we identified key occupations that will increase, and compare those with the occupations in which work could decline as a result of automation.

For three of the seven—investment in infrastructure, investment in buildings, and investment in renewable energy and energy efficiency—we examined two scenarios: a "trendline" scenario in which spending follows the observed trends across countries and a "step-up" scenario, in which labor demand increases as a result of societal and policy choices. For a fourth trend, the increasing shift to market of services that were long done without remuneration, we only examine a step-up scenario that assumes rising female participation in the workforce.

Our analysis offers a static view of the potential labor demand that could be created from the seven trends and does not factor in supply-demand dynamics and feedback from factors such as changes in wage levels. (For a more dynamic view, we used the McKinsey Global Growth Model, as we discuss later in this chapter). The labor demand that our seven trends could generate is potential, and whether this potential is captured will depend on the choices and investments made by businesses, policy-makers, and workers. The scenarios we construct do not take into account any sources of labor demand outside of our seven trends. We do not model entirely new industries, occupations, and activities that could be invented in the future, in part enabled by technology; one study suggests that on average, 0.5 percent of the workforce has been working in "new jobs" per year.[3] We do not take into account sectoral shifts in industries that are not directly related to automation or these seven trends, such as the rise of e-commerce in retail. We also do not model changes in work structure, such as the growth of the gig economy, or activities within an occupation that could change as a result of technological innovation. A more detailed discussion of our methodology can be found in the technical appendix.

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1 Our estimates of potential labor demand from each driver exclude growth in employment from population growth until 2030.

2 Ibid. *A future that works*, McKinsey Global Institute, January 2017. See also, *Shaping the future of work in Europe's digital front runners*, McKinsey & Company, October 2017.

3 Ibid. Jeffrey Lin, "Technological adaptation," May 2011.

Rising incomes in emerging economies will create large-scale new labor demand as spending increases on consumer goods, health care, and education

Rising GDP per capita generates higher spending on consumer goods and services, health care, and education, especially in emerging economies, and is the largest driver of labor demand we have identified (Exhibit 14). Prior MGI research has found that rising per capita consumption will generate about three-quarters of global consumption growth in the period from 2015 to 2030, with population growth accounting for the remaining 25 percent.[71] The expanding consuming classes in emerging economies will drive most of this increase. As incomes rise, consumers will spend disproportionally more on discretionary goods and services such as automobiles, leisure, and accommodation and food services, but they will also increase their non-discretionary spending on essentials such as food and clothing.[72] We estimate that this higher consumer expenditure could create between about 250 million and 280 million new full-time equivalent jobs, net of automation, across the 46 countries in our model. The growth due to rising incomes can mitigate automation's expected toll on workers in retail and accommodation and food services; retail salespeople, food preparation workers, and waiters see some of the largest boosts from higher consumer spending.

While this spending will create labor demand locally in sectors such as manufacturing, retail, accommodation and food services, as well as personal services, it will also create labor demand in other countries that export goods and services to these countries. We assume that a proportion of demand for tradable goods such as apparel and furnishing will continue to be served by countries rich in natural resources or with strong manufacturing or service sectors. For the purposes of simplifying our modeling, we assume current shares of global exports to remain constant; our model assumes that a country such as Germany will continue to serve its 2014 share of 18.5 percent of all automotive exports in 2030.[73]

Higher GDP per capita is also generally correlated with higher expenditures in health care and education. Access to health care, defined as the number of care providers (such as physicians) per capita, could increase, especially in fast-growing emerging economies such as India that currently have poor access to health care. We estimate that greater access to health-care providers alone at all levels, including physicians and medical assistants, could increase labor demand by 26 million to 43 million jobs (64 percent direct jobs in health-care provision and 36 percent indirect jobs in other sectors).[74] Demand for health-care providers could increase the most in developing countries such as India and China with the highest economic growth, although this may be contingent on the necessary provision of funding for health care by governments and consumers.

71 *Urban world: The global consumers to watch*, McKinsey Global Institute, April 2016.

72 We model scenarios around the potential developments of shares of expenditure on different product categories in line with observable cross-country trend lines. See the technical appendix.

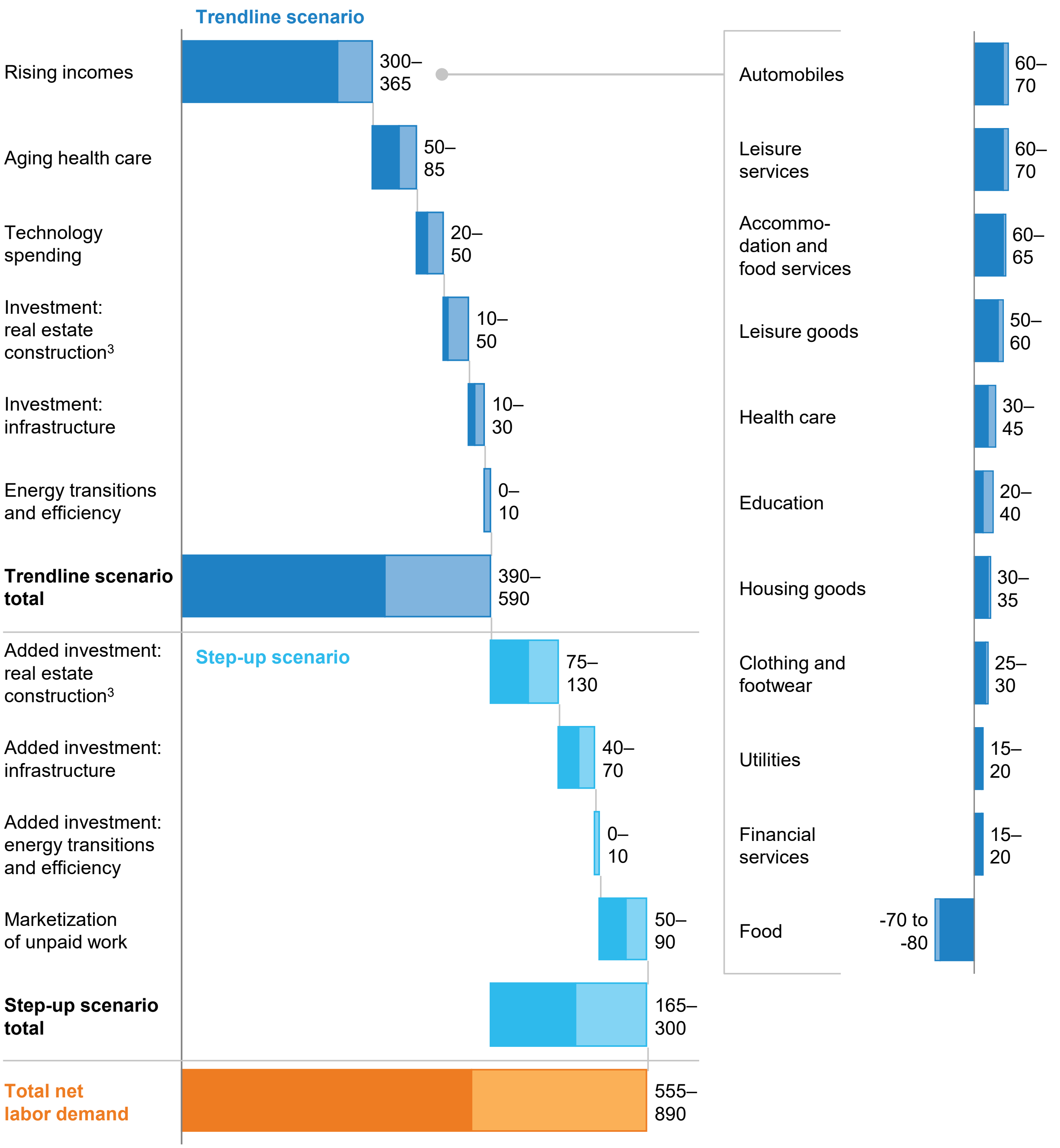
73 World Trade Organization, June 2017.

74 Similar to consumer expenditure, the numbers are modeled around observable trends between health-care employment and economic growth. It is important to note that the creation of these jobs will depend on funding from governments.

Exhibit 14

Rising consumer incomes are the largest source of job creation among our seven catalysts

Potential jobs created from seven catalysts of labor demand, 2016–30[1]
Million FTEs, ranged low–high[2]



1 Includes 46 countries; see technical appendix for full list. Assumes the midpoint adoption of automation scenario. Some occupational data projected into 2016 baseline from latest available 2014 data.
2 Low–high range reflects variance of underlying trends beneath modeled labor demand; additional details in technical appendix
3 Does not include land.

SOURCE: McKinsey Global Institute analysis

In education, as with health care, economic development typically raises expenditures, with a rise in gross enrollment rates, particularly at secondary and tertiary levels, and falling student-teacher ratios as quality improves. Our analysis suggests that these continuing improvements could create demand for up to 37 million jobs (78 percent direct jobs in the education sector and 22 percent indirect jobs in other sectors) globally by 2030, especially in fast-growing emerging economies. We compared gross enrollment rates and student-teacher ratios of students in primary education and conducted regression analyses against GDP per capita. Using demographic projections to estimate the number of students by country in 2030, we use our projections for gross enrollment rate and student-teacher ratio to infer the potential labor demand for teachers and support staff across each educational level.

Education as a creator of labor demand is most important for countries such as India, which has low enrollment rates, particularly at secondary and tertiary levels, high student-teacher ratios, and high GDP per capita growth. In other countries including China, where demographic trends are likely to have a smaller impact on labor demand in primary and tertiary education, increases in gross enrollment rates for secondary education and decreasing student-to-teacher ratios could imply an overall positive impact on labor demand in education on an aggregate level. In advanced economies with aging populations, such as Germany and Japan, there will be limited increase in labor demand from education as the relative share of students in the overall population declines. However, as with health care, the creation of these jobs would depend on the allocation of sufficient funding from public, private, and philanthropic sectors.

The global trend of aging populations will create new and additional labor demand for health care

The global population is continuing to rise and will likely reach 8.5 billion people by 2030.[75] At the same time, the population in many countries, both developed and developing, is aging: by 2030, there will be at least 300 million more people aged 65 and above than there were in 2014.[76] The aging trend is particularly acute in countries such as China, Germany, Italy, and Japan; by 2030, about 25 percent of their population will be over 65, if current fertility rates and immigration trends continue. This aging trend is less significant in developing countries with younger populations such as India and Nigeria, which are experiencing a demographic dividend, but it is also not restricted to advanced countries and China. Brazil, for example, also has an aging population.[77]

As people age, their needs and spending patterns change—in particular, spending on health care. For example, spending on hospital care for an 85-year-old American is more than five times higher than for those 19 to 44 years old.[78] We estimate that shifts in demographics could create incremental demand for 51 million to 83 million workers globally (55 percent direct and 45 percent indirect), especially for health care occupations that focus on taking care of the elderly, such as home health aides, personal care aides, nursing assistants, and so on.[79] (As with all the estimates of incremental labor demand in this chapter, this figure is net of automation, which will displace work including in health care, according to our model). In countries with aging populations such as Japan or China, our model suggests that aging and related health-care needs could drive the creation of between 10 and 15 percent of net new labor demand.

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75 *Population by age and sex*, United Nations, June 2017.

76 For details of the aging trend and its effect on the global economy, see *Global growth: Can productivity save the day in an aging world?* McKinsey Global Institute, January 2015.

77 Population estimates and projections, World Bank, April 2017. For a discussion of the limitations of this view and further information, see the technical appendix.

78 US Center for Medicare and Medicaid Services.

79 Our estimates include primary health-care occupations, as well as directly and indirectly created labor demand, e.g., in health-care device manufacturing.

6M
new tech jobs could be created in India under our scenarios

Technology development and deployment will create additional employment

As technology development continues apace, the technology sector is expected to keep growing rapidly, and this in turn will create incremental labor demand to develop and deploy technology. The scale of this employment will be modest, however. Today, an estimated 2.9 million people are employed in the US high tech sector, but this is only 1.9 percent of the workforce. In Germany, about 2.4 percent of the workforce is in a high-tech occupation.

Higher consumer spending on technology products and services, which typically rises as incomes increase, and larger outlays by businesses that adopt technology to improve productivity and improve output as they grow, are driving the increased spending on software, hardware, and services. We modeled consumer and enterprise technology spending per capita with rising GDP per capita across countries in 2014. Assuming that the correlation holds, we estimate that by 2030 technology spend could increase by $1.7 trillion to $2 trillion of which about 70 percent would be on information technology (IT) services. This includes hardware/software support, outsourcing, IT consulting, implementation, and internal IT services.[80] This increased spending on technology will create demand for 20 million to 46 million incremental workers (55 percent direct and 45 percent indirect) globally, net of automation. They will be a mix of high-skill workers such as software engineers and electrical engineers as well as medium-skill workers including web developers and electronic technicians. While IT services jobs such as computer support specialists will remain largely local, demand for technology hardware and especially software will likely be served by the global players, for example China, Germany, India, the Netherlands, and the United States. More than half of all global tech jobs could be created in these five countries. Of these, the largest demand will likely land in China and India, with up to 13 million and six million jobs respectively. Both large economies are expected to go through significant digitization in the next decade and beyond.

Investment in infrastructure and buildings can create new labor demand, particularly in our step-up scenario

Infrastructure and buildings are two areas of historic underspending that may create significant additional labor demand if action is taken to bridge infrastructure gaps and overcome housing shortages. We modeled two scenarios: one in which annual investment follows the observed trends across countries and one in which significant additional investment is made to fill gaps in infrastructure and real estate.

Global infrastructure systems have not kept up with demand and housing shortages persist in many countries. In critical areas of infrastructure such as transportation, water treatment, and power grids, years of neglect are catching up with countries around the world. MGI has found that, from 2016 to 2030, the world needs to invest about 3.8 percent of GDP in economic infrastructure, or an average of $3.3 trillion per year, just to support expected rates of growth, with emerging economies accounting for some 60 percent of that.[81] In real estate, as many as 330 million urban households in emerging and advanced economies live in substandard housing or are financially stretched by housing costs.[82]

80 IT services includes work outsourced to companies such as Accenture and Infosys, but does not include consumer services such as Google or Facebook.

81 *Bridging global infrastructure gaps*, McKinsey Global Institute, June 2016.

82 For an overview of the global housing shortage, see *A blueprint for addressing the global affordable housing challenge*, McKinsey Global Institute, October 2014.

Under our trendline scenario, in which investment in infrastructure and buildings continues to follow patterns we have observed across countries, we note that spending on both of these increases as countries develop economically. Thus, if countries were to increase their spending on the current trajectory as they develop, our model shows that up to 53 million gross new jobs could be created by continued spending on buildings, and up to 34 million on infrastructure. Yet considerably more could be done than matching the investment levels of other countries. Any additional efforts would consequently stimulate increased labor demand, especially for middle-wage jobs that will otherwise be particularly affected by automation in some advanced economies.

In our step-up scenario, we assume that the infrastructure gap has been closed, and that infrastructure and building spending in 2030 is subsequently higher to sustain this higher level of infrastructure stock and investment. We used infrastructure stock averages across countries and real estate stock averages in the United States as a proportion of GDP to estimate the infrastructure and housing investment needed in 2030 to keep pace with projected economic growth.

This increased spending could create demand for an incremental 76 million to 134 million workers from added investments in building structures and 38 million to 72 million incremental workers from added investments in infrastructure. As with health care and education, the creation of those jobs will depend on the allocation of necessary investments by the private and public sector. About 30 to 40 percent of this labor demand could come from India, which has currently under-invested in infrastructure, is going through a process of large-scale urbanization, and would need to invest a significant amount to keep pace with an ambitious target of 6.5 percent annual growth in GDP until 2030. The currently unproductive nature of the construction sector in some emerging economies such as Nigeria and Indonesia, coupled with low wage rates that may slow the adoption of automation technologies, contribute to the labor-intensity of this sector. China has already made significant investments in infrastructure over the past decade and our model shows that it may not need as much incremental investment in 2030. Developed economies including the United States and Germany could also invest in building new and repairing or re-building existing infrastructure, creating additional employment opportunities in the construction sector, particularly for middle-wage jobs.

Investment in renewable energy and energy efficiency

We similarly modeled two scenarios of labor demand for investment in new energy sources and improving energy efficiency, depending on whether spending follows current trends or is accelerated. The energy landscape is shifting rapidly as the cost of renewable energies, such as wind and solar, falls sharply. A range of new technologies, from smart electricity meters to Internet of Things sensors in oil rigs and advanced leaching techniques in mines, is transforming both the production and the consumption of resources.[83] The global policy environment for energy has been shifting: with the conclusion of the Paris Agreement in December 2016, countries around the world pledged to take measures that would keep the global temperature rise this century below two degrees Celsius above pre-industrial levels.[84] The International Energy Agency estimated in 2015 that to reach this goal could take up to $16.5 trillion of investment by 2030, including increasing the share of renewables and by making buildings, transportation, and technologies more energy efficient.

83 Ibid. *Beyond the supercycle*, McKinsey Global Institute, February 2017.

84 While the United States has announced it will withdraw from the Paris Agreement, many other signatory countries and even local governments in the United States have said they will continue to support it and meet the emission reduction targets that it established.

Governments including those in India and China are already spending more heavily on renewable energy and climate adaptation measures. India, for instance, has announced its intention to increase its share of renewable power to as much as 40 percent by 2030.[85] Overall, our modeling indicates that moving to renewable energy and raising energy efficiency at current trends could contribute up to seven million new jobs globally in 2030, under our trendline scenario, and an additional four million to seven million under our step-up scenario. (These jobs are incremental to the increase in employment in the power sector driven by GDP per capita growth, which is modeled in our rising incomes driver discussed above.)

In the transition to new energy sources, we model the potential job creation as countries shift their capacity mix for electricity generation. Making these transitions will require significant investments in manufacturing, construction, and operations and maintenance of solar panels, wind turbines, and other equipment. Shifts in capacity mix create jobs in two ways. First, large amounts of fixed investment are needed to increase the capacity for the growing new energy source, creating jobs in manufacturing, construction, and installation. Second, jobs may also be created in the decreasing energy sources through decommissioning of fossil fuel and other generation facilities, as some countries decide to shut down nuclear plants. Jobs associated with the ongoing operations and maintenance of electricity generation are largely variable with capacity, so job levels here will depend on relative labor intensity of operations and maintenance between energy types. Renewable manufacturing is enjoying a remarkable period of productivity growth—across three leading renewables manufacturers, employees declined by 65 percent on average per gigawatt shipped in 2010 to 2014. If these productivity gains continue at an aggressive rate, renewables manufacturing is likely to be a comparatively less labor-intensive part of the renewables value-chain.

To attain the international goal of avoiding a rise of more than two degrees Celsius, the UN's Intergovernmental Panel on Climate Change has calculated that CO_2 concentrations in the earth's atmosphere need to be stabilized at 450 parts per million. That will require targeted policy choices, including accelerated transitions to renewables and increased spending on energy efficiency measures, both in industry and in housing. This in turn could have a significant impact on job creation. In our step-up scenario, using data from McKinsey & Company's Energy Insights, we modeled a more ambitious shift into renewables and higher investment in energy efficiency, which would create an additional four million to seven million jobs globally.[86] High productivity and further automation potential in energy reduce the opportunity for energy to have a transformative impact on the jobs story in many countries; in the United States, less than 1 percent of all full-time equivalents in 2014 were in utilities and mining. But major investments in renewable energy will be crucial to meeting global climate change goals, which could create middle-wage jobs along the way.

"Marketization" of unpaid work could create new jobs

Today, much work done in households—from childcare to cooking and cleaning—is unpaid and disproportionately performed by women. At least some of this work could be shifted to paid employment through daycare or pre-kindergarten schooling programs and senior care programs. Rising female labor participation rates could be one way to prompt this shift, which economists call "marketization"; social decisions to expand government-supported programs could be another (and those programs in turn might enable higher female labor force participation). In recent years, we have seen the rise of digital "sharing economy" platforms that enable consumers to purchase many household and personal services more conveniently and cheaply, including meals ordered online and delivered by hand, thereby

[85] *Remap: Renewable energy prospects for India*, International Renewable Energy Agency, May 2017.

[86] This modeling does not include an estimate of other issues related to climate change that could cause potential for incremental labor demand, such as reconstruction and carbon capture and storage.

increasing demand. Academic research has found that such platforms result in an increase in employment in the industry, both for traditional workers providing those services and for the newly self-employed workers on the platform.[87] The marketization of previously unpaid housework is already prevalent in some advanced economies, especially in urban areas. For example, more than 90 percent of three-year-olds are enrolled in preschools in France and Sweden, most of which are funded by the government. In comparison, the rate is about 70 percent in the United States and less than 15 percent in India.[88]

Women account for half of the global working-age population but generate only **37%** of GDP

Shifting unpaid housework and childcare to paid employment could boost the number of women in the workforce globally, if governments decided to invest in these areas (such as by providing universal preschool and paid family leave). Women currently account for half of the world's working-age population but generate only 37 percent of global GDP, and in some regions of the world—including India, other parts of South Asia, the Middle East and North Africa—their contribution to regional output is considerably lower still. At the same time, about 75 percent of the world's total unpaid care is undertaken by women, including the vital tasks that keep households functioning, such as childcare, caring for the elderly, cooking, and cleaning. This unpaid work amounts to as much as $10 trillion of output per year, roughly equivalent to 13 percent of global GDP.[89] In our analysis, we observe the average amount of unpaid time currently spent on childcare, adult care, cooking, and cleaning using time use surveys. As these unpaid activity hours move to the marketplace, we expect labor demand to increase for them. While productivity gains will reduce the net number of hours worked, we estimate that between 51 million and 89 million incremental jobs globally could be created from this step-up scenario of shifting currently unpaid domestic work to paid employment.

JOBS OF THE FUTURE: IMPACT OF NEW LABOR DEMAND VS. AUTOMATION

The seven trends we selected for our analysis provide us with indications about types of occupations that will be in demand to 2030, even net of automation of activities within those occupations. At the same time, our automation modeling highlights occupations that could decline, if the current activities within those occupations that are automated are not replaced by other activities. The patterns differ among countries. One of the key differentiating factors is wage rates, since our model assumes that automation adoption will generally be more rapid in countries such as Germany and Japan, with relatively higher wages, than in India, China, or Mexico, where wages are lower. But there are also differences among emerging economies depending on whether populations are aging and the occupation mix across sectors, among other factors.

Exhibit 15 shows the top five occupations that will grow in the United States based on each of the seven trends described above before accounting for displacement due to automation. These are primarily direct additions, for example registered nurses related to aging, or construction laborers and carpenters from the building out of infrastructure. But the list also includes indirect additions, such as accountants, customer service representatives, and lawyers, who will see greater demand as support functions within the health-care industry feel a boost from increased spending due to aging.

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87 Thor Berger, Chinchih Chen, and Carl Benedikt Frey, *Drivers of disruption? Estimating the Uber effect*, University of Oxford, Oxford Martin School, working paper, January 23, 2017.

88 OECD, 2014; *World development indicators*, World Bank, 2014.

89 Ibid. *The power of parity*, McKinsey Global Institute, September 2015.

Exhibit 15

Each of our labor demand catalysts creates different types of jobs

US top five growing occupations by catalyst, trendline to step-up scenario, 2016–30[1]
Thousand

Catalyst	Occupation	Thousand
Rising incomes: consumer goods	Retail salespersons	1,269
	Cashiers	896
	Combined food preparation and serving workers, including fast food	547
	Waiters and waitresses	434
	First-line supervisors of retail sales workers	353
Rising incomes and aging: health care	Registered nurses	1,304
	Nursing assistants	701
	Personal care aides	476
	Home health aides	364
	Licensed practical and licensed vocational nurses	329
investment: real estate and infra-structure[2]	Construction laborers	232–760
	Carpenters	152–497
	Electricians	128–418
	First-line supervisors of construction trades and extraction workers	116–378
	Plumbers, pipefitters, and steamfitters	85–277
Business investment in technology	Software developers, applications	289
	Software developers, systems software	111
	Computer systems analysts	108
	Computer user support specialists	94
	Computer programmers	84
Rising incomes: education	Teacher assistants	368
	Elementary school teachers, except special education	113
	Education administrators, elementary and secondary school	83
	Secondary school teachers, except special and career/technical education	70
	Education administrators, postsecondary	46
Energy transitions and efficiency	Construction laborers	31–86
	Insulation workers, floor, ceiling, and wall	29–80
	Carpenters	28–80
	Construction managers	23–65
	First-line supervisors of construction trades and extraction workers	23–62
Profession-alizing previously unpaid work	Childcare workers	0–858
	Nursing assistants	0–638
	Preschool teachers, except special education	0–535
	Janitors and cleaners, except maids and housekeeping cleaners	0–518
	Home health aides	0–375

1 Some occupational data projected into 2016 baseline from latest available 2014 data.
2 Does not include land.

SOURCE: McKinsey Global Institute analysis

Advanced economies have a similar pattern of job growth and declines

In advanced economies, we identify six broad groups of occupations that will experience growth in labor demand from our trends, although the size of the increase will depend on country and on scenario. For example, in our step-up scenario, the demand for builders and construction workers rises considerably (Exhibit 16). Workers in occupations in the following groups spend considerable time on work activities that are among the least susceptible to automation based on our analysis, as they require human capabilities including social and emotional interaction, higher-level logical reasoning, creativity, and application of expertise that machines for now are less capable of accomplishing. The occupational groups that generally grow as a result of our drivers, even net of automation, are:

- **Care providers**: that is, doctors, nurses, home health aides and others in caring occupations who will be in greater demand as a result of rising health-care spending, both from increased prosperity and from aging. Given the disproportionate cost of health care for the elderly, aging is expected to be the predominant driver of increased health-care employment. Countries with aging populations such as Japan and China will see a sharp increase in occupations that work closely with seniors, for example nurses, nursing assistants, personal care aides, and home health aides.

- **Professionals**, defined as white-collar occupations that require academic training and expertise in a specific industry or functional area. These include accountants, engineers, and scientists. Most of these occupations cut across a wide range of sectors. While generally less automatable than other job types, certain supporting occupations such as paralegals and scientific technicians may face high automation.

- **Technology professionals.** Technology experts will be in continued demand everywhere as automation is increasingly adopted, although the total numbers remain quite small compared with other occupations. Occupations will include IT workers such as computer scientists and software developers, who typically have college educations, but also occupations such as web developers and electronics technicians, which only require a secondary education. That said, many of these latter occupations involve activities that are more automatable than technology workers with higher levels of education.

- **Builders.** In this category we have included architects, surveyors, and cartographers, as well as construction occupations and maintenance and repair workers, such as construction laborers, electricians, carpenters, and plumbers. Even though construction laborers primarily do physical work, their activities are mostly in unpredictable settings, and hence not as highly susceptible to automation by 2030.

- **Managers and executives** also cut across all sectors and cannot easily be replaced by machines, as much of their work involves interacting with and managing stakeholders. However some of their more routine activities will be automated, such as collecting information, analyzing data, or preparing reports.

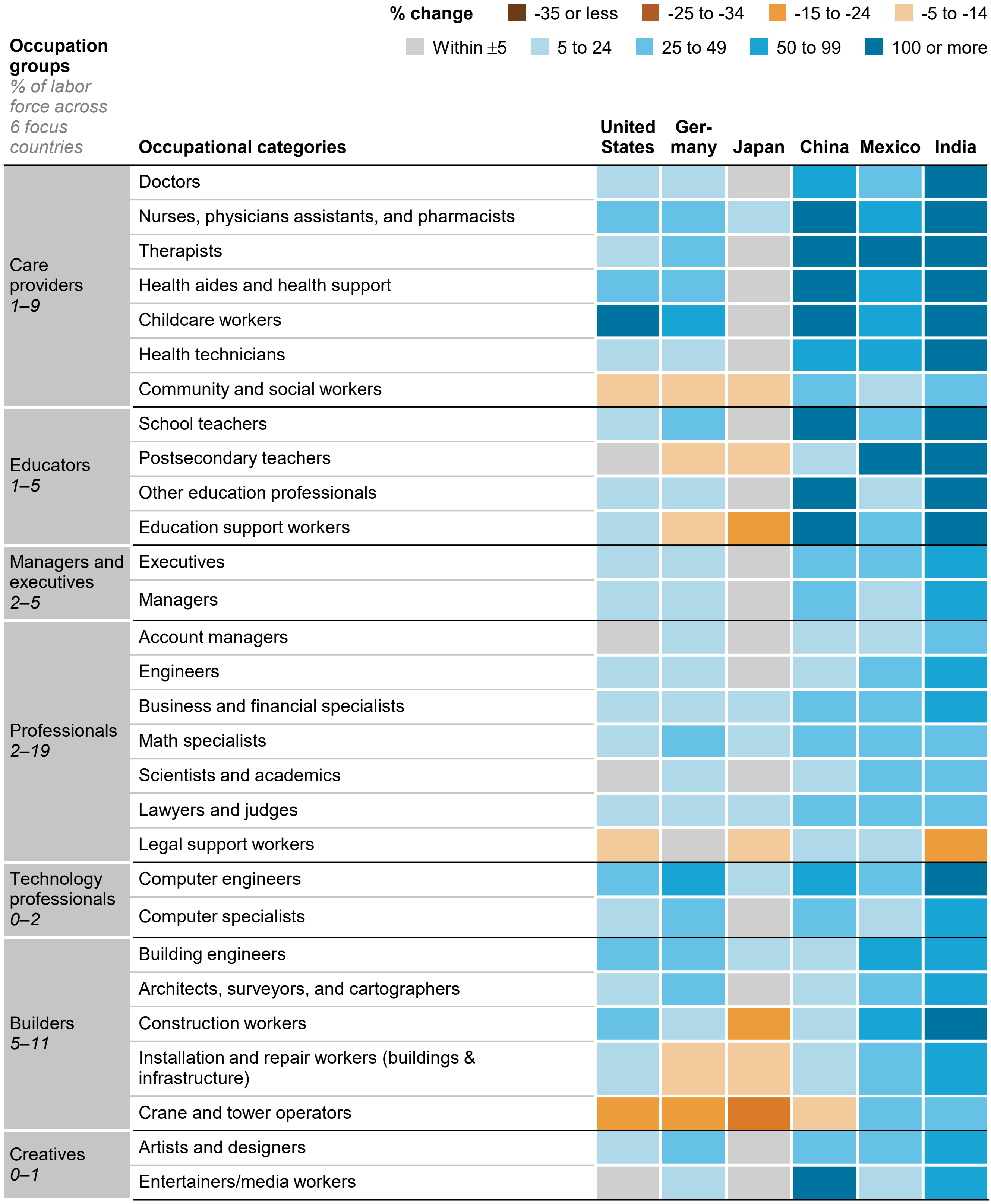
- **Educators.** School teachers and others will see a significant increase in demand, especially in emerging economies with young populations such as India. Childcare workers and early childhood educators will also grow under our step-up scenario in which more childcare is shifted to paid providers.

- **"Creatives"**: Rising incomes in emerging economies will create more demand for leisure and recreational activities. This in turn will create demand for artists, performers, and entertainers, although the total numbers will remain relatively small.

Exhibit 16

Jobs of the future: Employment growth and decline by occupation

Net impact of automation and seven catalysts of labor demand, 2016–30
% change (+/–), step-up labor demand, midpoint automation[1]



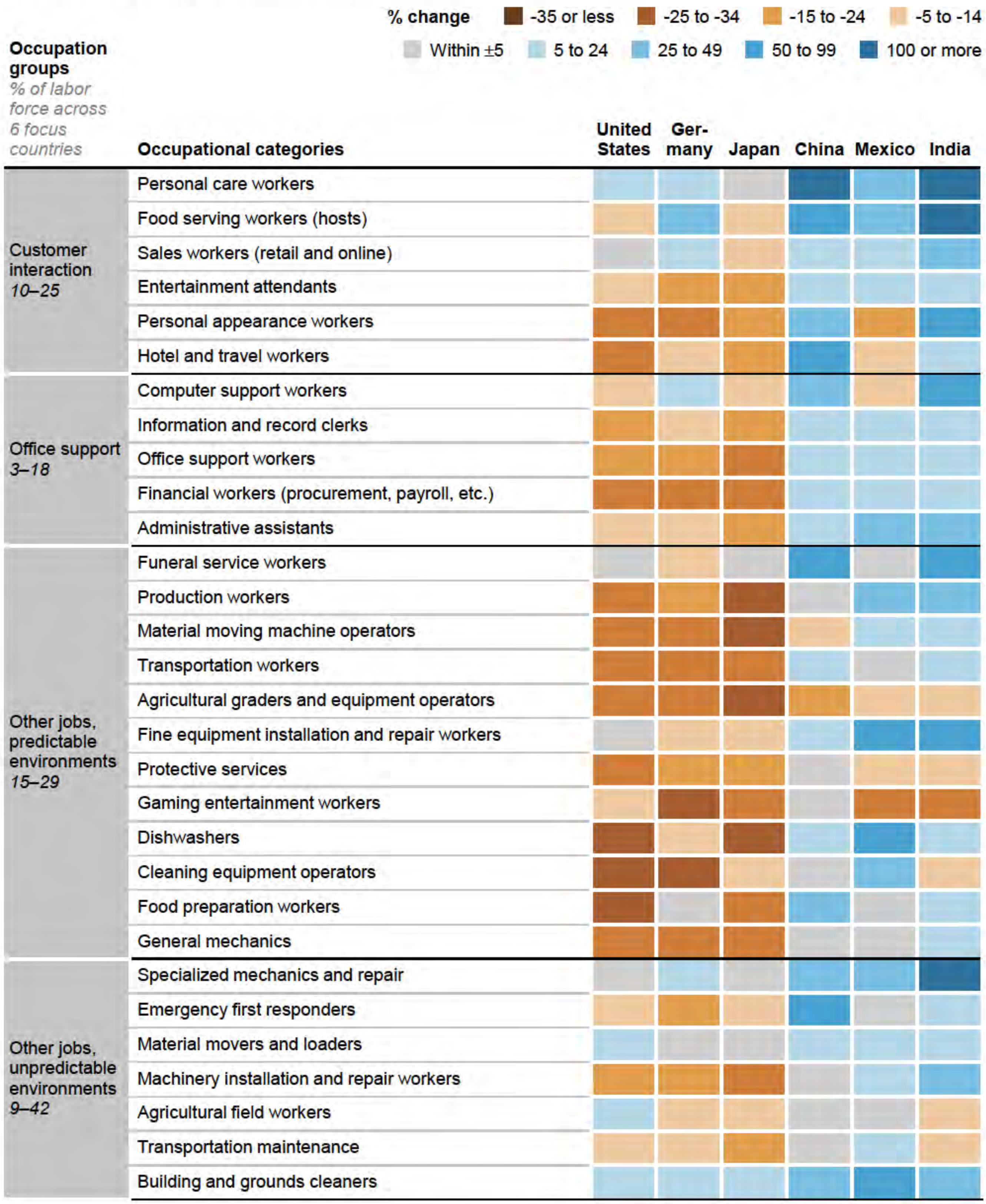
1 Midpoint of earliest and latest automation adoption in the "step-up" scenario (i.e., high job growth). Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

Exhibit 16

Jobs of the future: Employment growth and decline by occupation (continued)

Net impact of automation and seven catalysts of labor demand, 2016–30
% change (+/–), step-up labor demand, midpoint automation[1]



1 Midpoint of earliest and latest automation adoption in the "step-up" scenario (i.e., high job growth). Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

By contrast, our analysis suggests that, in advanced economies, other occupations will see a net decline by 2030, with more work automated than created by our seven trends, assuming they do not add non-automated activities. These include:

- **Some customer interaction jobs**, including hotel workers, travel agents, entertainment attendants, and cafeteria workers.

- **Office support jobs**, including information clerks, payroll processors, and administrative assistants.

- **Jobs carried out in predictable settings.** These are among the most susceptible to automation and include factory workers, material moving machine operators, transportation workers, and installation and repair workers.

It is important to note that even occupations that may have a net decline due to automation will not disappear: rather, their numbers could shrink from today's levels in the next 15 years. For instance, even though some of the current activities of food preparation and serving workers could be automated (for example, by ordering kiosks in fast food restaurants), and about one-fifth of their hours worked could be automated under our midpoint adoption scenario, there could still be demand in the United States for more than three million of them.

Developing countries see net job growth in nearly all occupational groups

The picture is rather different in rapidly growing and low-income countries such as India, where we see net job growth in nearly every occupational category. This is for two reasons: low wages mean delayed adoption of automation, and relatively high GDP growth creates jobs across the economy, including in predictable environments that are among the most affected in advanced economies. For example, production workers would rise 34 percent in India under our step-up scenario, compared with a 28 percent decline in the United States and a 56 percent drop in Japan.

34%
potential increase in production workers in India under our step-up scenario

Middle-income countries such as China and Mexico also have net job growth in a range of occupations under our scenarios that in advanced economies experience declines. This is the case with the category of workers who are primarily engaged in customer interaction, such as entertainment attendants, and food-service workers. These types of occupations will remain in high demand in emerging economies including China, as a result of rising consumption from an increasingly prosperous consuming class. However, in Mexico, the potential growth is not as large as in India, reflecting the lower GDP growth and higher wages.

WILL THERE BE ENOUGH WORK IN THE FUTURE?

The public debate in many countries over automation can quickly focus on the existential question of whether there will be enough jobs for workers in a future marked by automation. We can see from history that such fears have so far been unfounded: over time, labor markets have adjusted to changes in demand for workers from technological disruptions, although in some eras real wages have remained depressed for some time. We address this question of whether there will be enough work in the future through two different but complementary sets of analyses. The first is based on our model of new and additional labor demand and automation described above, using the select trends we have identified, and provides only a partial view. For the other analysis, we used a macroeconomic model of the economy that incorporates the dynamic interactions among various factors.

Both analyses point in the direction that, in most scenarios, there can be enough new job creation to offset the impact of automation. But a larger challenge will be ensuring that workers have the skills and support needed to transition to new jobs. Countries that fail to enable and smooth these transitions could see rising unemployment and depressed wages.

Outcomes will vary significantly by country, depending on four factors

We find a significant difference of likely outcomes among countries, with four factors largely influencing the extent to which enough new jobs will be created to offset those displaced by automation. The four factors are:

- **Wage levels.** Advanced economies will likely adopt automation in the workplace earlier and faster than emerging economies since their wages are relatively higher, making the business case for automation stronger. (Our model assumes that automation begins to be adopted only when its cost reaches parity with the cost of human labor). Advanced economies will therefore likely see the largest impact from automation in the next 15 years.

- **Demand growth.** Economic growth is essential for job creation. While it may sound obvious, economies that are stagnant or growing only slowly create few, if any, net new jobs. Countries with the most rapid GDP growth rate per capita will have higher growth rates of consumption and spending, thus stimulating greater proportional increases in labor demand. Slower-growing economies will create jobs at a slower rate. Advanced economies have much lower projected rates of GDP growth than developing countries, reflecting aging workforces and also less rapid productivity growth. Developing countries such as India and China are projected to have much higher GDP per capita growth rates, which will contribute to job creation. Furthermore, innovation and entrepreneurship often underlie the creation of new business models and work activities, another catalyst of job growth.

- **Demographics.** The outcome of automation and future labor demand will play out very differently in countries with a young and rapidly-growing population, such as India, compared with countries that have a shrinking population and workforce, such as Japan. Countries with a growing workforce have a potential "demographic dividend" that will lift growth. However, rapid growth of the population will bring millions more young people into the workforce, creating considerable pressure to expand formal employment opportunities. While the impact of automation will be less, given lower wage rates in these countries, automation will make this already considerable challenge more difficult. In Germany and Japan, by comparison, aging is reducing the working-age population, which reduces the need for economic growth and the potential impact of automation.

- **Mix of economic sectors.** The automation potential of national economies differs among countries depending on the structure of their economies and, within the economy as a whole, on the mix of sectors, occupations, and their constituent work activities. Japan, for example, has a higher automation potential than the United States because the weight of certain sectors that are highly automatable, such as manufacturing, is higher in Japan; 17 percent of jobs in Japan are in the manufacturing sector compared with 9 percent in the United States. And within the manufacturing sector itself, Japan is more susceptible to automation because a larger proportion of the jobs involve tasks that can be more easily automated, such as production.

These factors combine to create different outlooks for the future of work in each country. In general, countries with similar characteristics across these four factors could see broadly similar outcomes from automation adoption, albeit with nuances for cultural and other differences. Some clusters are apparent. For example, developed countries with aging populations and high wages that will accelerate automation adoption—such as Germany, Italy, and Japan—could follow a similar trajectory, as will developed countries with younger populations, such as Canada, France, Sweden, the United Kingdom, and the United States. Across the Middle East, countries such as Kuwait, Saudi Arabia, and the United Arab Emirates share similarities on demographics and automation adoption and, to a lesser extent, on GDP per capita. Developing countries with the youngest populations, including Egypt, Kenya, and Nigeria, will face similar challenges to grow aggregate demand, given their fast-growing workforce.

Our scenarios of new and additional labor demand, net of automation, while incomplete, suggest ample job creation to 2030

We compare the number of jobs created by the seven selected trends identified above with the number of jobs expected to be displaced by automation. We are conscious that this exercise paints an incomplete picture. While our seven trends model the major sources of new labor demand, they do not account for induced job demand creation nor the creation of novel work activities and occupations. One research study has found that, each year, roughly 0.5 percent of the US labor force is employed in an occupation that did not exist in the prior year—in other words, performing an entirely new set or combination of work activities. By 2030, this would imply that 9 percent of the US labor force could be employed in occupations that do not exist today.[90] Just as many occupations today, such as search engine optimization, app designers, and website designers, would have been impossible to imagine in the pre-Internet era, we cannot foresee the new occupations that will arise in the future.

In order to address the question, "Will there be enough work in the future?," we compare the net effects of jobs displaced by automation, jobs created by the seven trends, the creation of new work and other unsized labor demand, and demographic changes in labor force size. Even limiting our estimates of new and additional job creation to the select factors that we model, we find that our focus countries could generate enough labor demand to offset the impact of automation and take into account changes in the size of labor forces.[91] Nevertheless, our modeling from the seven trends indicates that the transition toward 2030 looks quite different depending on the country (see Exhibit 17).

For instance, Japan is rich but projected to grow slowly to 2030. It faces the combination of slower job creation coming from economic expansion and a large share of work that can be automated as a result of high wages and the structure of its economy. However, Japan will also see its workforce shrink by 2030 by four million people. In the step-up scenario, and considering the jobs in new occupations we cannot envision today, Japan's net change in jobs could be roughly in balance.

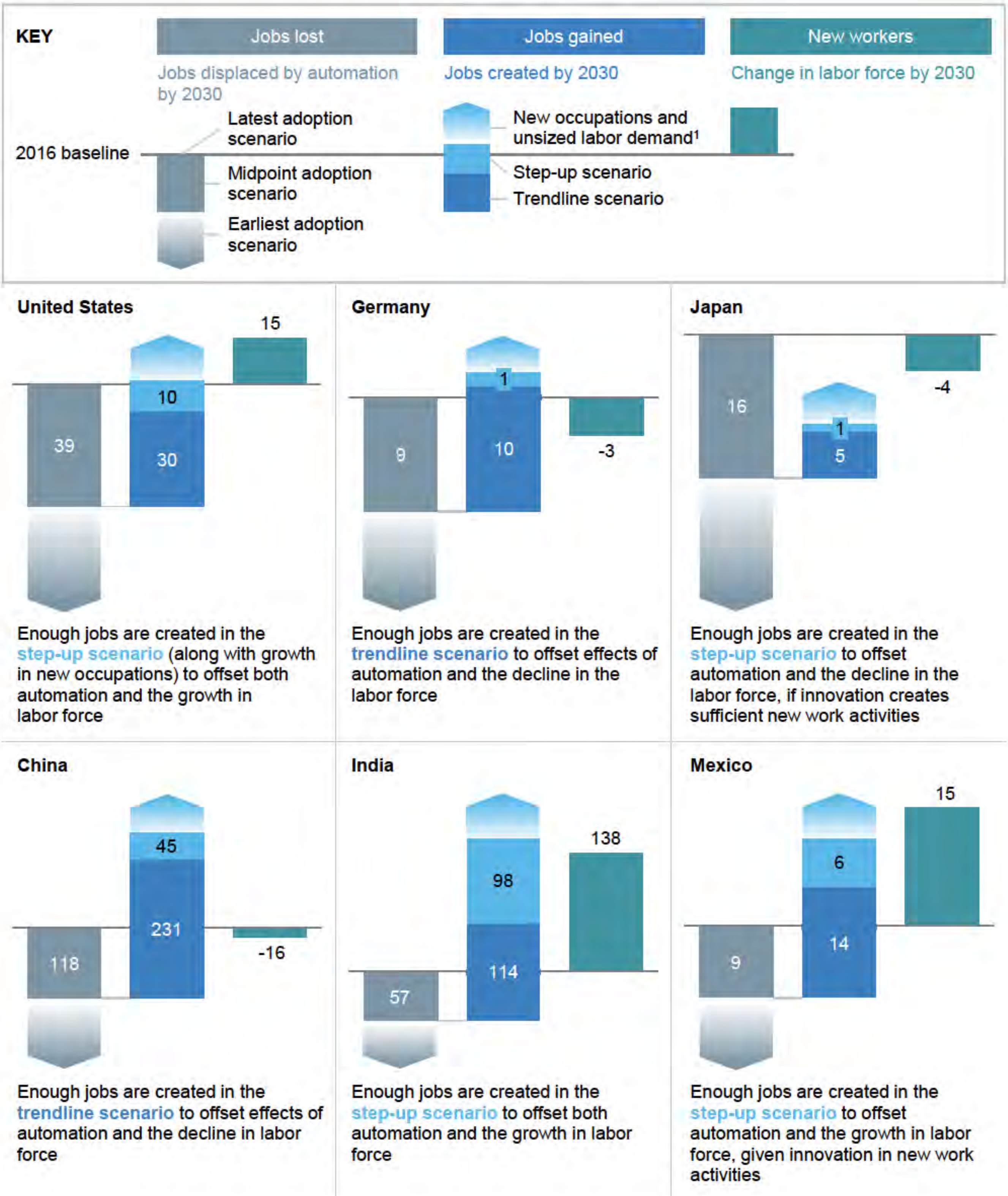
[90] Ibid. Jeffrey Lin, *Technological adaptation*, 2011.

[91] Our results are broadly in line with prior research by McKinsey & Company in nine northern European digital "front-runner" countries. This research suggests that technology diffusion contributed 0.4 to 0.6 percentage points, or around 30 percent, to GDP growth between 1990 and 2016 in the nine countries. Digital technology replaced jobs at a rate of about 120,000 jobs a year between 1999 and 2010, and boosted employment by around 200,000 jobs a year, creating positive net employment of 80,000 jobs per year. More than half of the new jobs were high-skill. *Shaping the future of work in Europe's digital front-runners*, McKinsey & Company, October 2017.

Exhibit 17

Jobs lost, jobs gained: Automation, new job creation, and change in labor supply, 2016–30

Range of automation scenarios and additional labor demand from seven catalysts



1 Historical analysis suggests that we could expect 8–9% of 2030 labor supply will be in "new jobs," which is additional to labor demand we have estimated.
NOTE: We identified seven catalysts of labor demand globally: rising incomes, health-care spending, investment in technology, buildings, infrastructure, and energy, and the marketization of unpaid work. We compared the number of jobs to be replaced by automation with the number of jobs created by our seven catalysts as well as change in labor force, between 2016 and 2030. Some occupational data projected into 2016 baseline from latest available 2014 data. Not to scale.

SOURCE: McKinsey Global Institute analysis

Like Japan, the United States and Germany also face significant workforce displacement from automation by 2030, but their projected future growth—and hence new job creation—is higher. However, the United States has a growing workforce. In the step-up scenario, and considering new occupations that may arise, it is roughly in balance. Germany's workforce will decline by three million by 2030, and it will have more than enough labor demand to employ all workers.

At the other extreme is India: a fast-growing developing country with relatively modest potential for automation over the next 15 years, reflecting low wage rates. Our analysis finds that most occupational categories are projected to grow in India, reflecting its strong economic expansion. However, India's labor force is expected to grow by 138 million people by 2030, or about 30 percent. Employing these new entrants in formal sector jobs will require job creation on a much larger scale than in the past. Automation will make this challenge more difficult; some fear "jobless growth" will make the challenge greater. However, our analysis suggests that India can create enough new jobs to offset automation and employ new entrants, for example by undertaking the investments in our step-up scenario.

China and Mexico have higher wages than India, and so are likely to see more automation. China still enjoys robust economic growth and will have a shrinking workforce; like Germany, China's problem could be a shortage of workers. Given net job creation as well as declining labor forces, China and Germany may need to explore different options such as accelerating automation adoption or immigration in order to fulfill the expected creation of growing future labor demand. Mexico's rate of future economic expansion is more modest than China's, and its workforce will grow by 15 million by 2030. Like the United States and Japan, our results suggest that Mexico may need the extra job creation from the step-up scenario plus innovation in new occupations to make full use of its workforce.

Our macroeconomic modeling highlights the critical importance of rapid reemployment of workers displaced by automation

The analysis of net job creation given expected automation rates and the seven trends is an informative but incomplete exercise, even after adjusting for labor supply changes and the creation of new occupations. This is because the analysis above does not take into account dynamic interaction among the trends, such as the impact of automation investment and automation-related unemployment on GDP growth rates or economy-wide average wage rates. Thus, to develop a perspective on the potential net impact of automation and job creation potential of the economy, we use a general equilibrium model in order to triangulate our results with the analysis from the seven trends (see Box 4, "Modeling the economic impact of automation").

The overall result of the general equilibrium model is the same as the result from the seven trends: it shows that labor markets will generally be flexible enough to absorb the workers displaced by automation. Furthermore, like the outcome of the analysis from the seven trends, differences arise between countries in the expected transition toward 2030. The general equilibrium model points toward a strong distinction in the expected transition between the advanced economies and the emerging economies we focus on in this report.

Box 4. Modeling the economic impact of automation

We used McKinsey & Company's Global Growth Model to model the dynamic impacts of automation on the economies of our six focus countries.[1] This is a supply-side general equilibrium macroeconomic model that covers more than 100 countries with data from 1960 through 2015.

In the model, we directly included three factors by which automation affects economic growth: labor displacement, resulting in workers losing their jobs; capital investment needed to implement the automation technologies; and an increase in productivity growth, as firms employ more capital per worker. These inputs to the Global Growth Model are derived from our automation research. To calculate the impact on productivity, we estimate the implied productivity growth that would be needed to maintain constant total output with fewer workers, under the rationale that firms would not adopt the new technology unless it produced at least the same level of output. In reality, this is likely to be an underestimate of the impact. Our experience working with firms and our prior automation research shows that automation often results in higher quality output and significantly higher level of output as well.

We also model how quickly displaced workers are employed in new jobs, or the reemployment rate. Not every displaced worker will enter unemployment; some will have the skills and the opportunity to transition quickly into a new role at the same company or with a new firm. Indeed, each year millions of US workers leave a job and find a new one. Between 2013 and 2015, 66 percent of displaced workers in the United States found a new job by the end of the period; 49 percent of workers displaced between 2007 and 2009, during the financial crisis, were reemployed by the beginning of 2010.

We model four reemployment rate scenarios—low, medium, high, and full reemployment. The reemployment rates modeled differ by country and are estimated from literature and adjusted for labor market flexibility factors.

[1] The structure of the model is anchored in the academic literature on economic growth models. For details see *Shifting tides: Global economic scenarios for 2015–25*, McKinsey & Company, September 2015.

In advanced economies, all scenarios result in full employment by 2030, but the transition may include a period of higher unemployment and wage adjustments

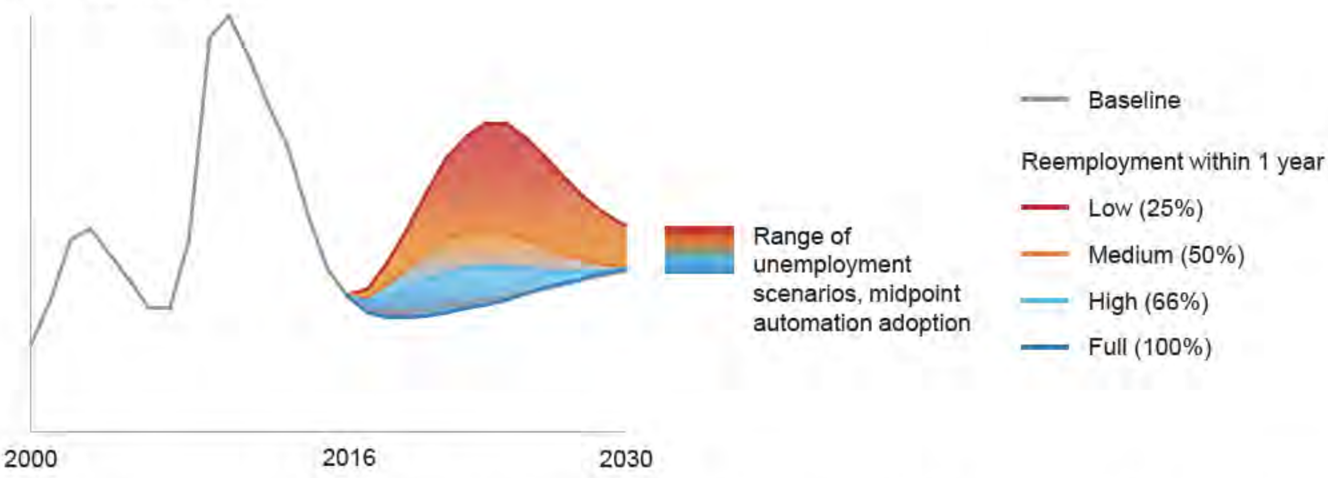
For the three advanced economies we focus on in this report—Germany, Japan, and the United States—economies are flexible enough to absorb most if not all the displaced workers by 2030 in all reemployment scenarios. The pace at which displaced workers are reemployed is critical: lower reemployment leads to higher medium-term unemployment, while in the highest reemployment scenario, the labor displaced by automation will be reemployed fast enough such that the unemployment rate does not rise (Exhibit 18).

Automation will also have a wage impact. Our modeling results in a temporary increase in wages in all reemployment scenarios because of increased productivity as a result of automation. But, as with the unemployment rate, wages will also depend on the pace of reemployment. In the lower reemployment scenarios, wages fall in the long-run in response to high medium-term unemployment. This leads to a lower labor share of income, as the gains of automation in this scenario primarily accrue to capital owners, not laborers. Conversely, in the highest reemployment scenario, wage growth is expected to persist, and thus the decades-long trend of declining labor share of income slows or even reverses by 2040.

Exhibit 18

Unless displaced workers are reemployed quickly, medium-term unemployment could rise

US unemployment rate



NOTE: These unemployment scenarios based on reemployment rates are hypothetical simulations derived from McKinsey & Company's Global Growth model.

SOURCE: McKinsey Global Institute analysis

In emerging economies, automation's impact on employment is smaller than in advanced economies

The impact of automation is lesser in China, India, and Mexico than in the advanced economies we focus on, according to our simulation. First, automation rates are expected to be lower, leading to smaller percentages of displaced workers, lower levels of capital investment, and smaller productivity increases. As such, unemployment is not expected to rise significantly, nor are modeled wages or GDP growth sensitive to the automation effect under any of the reemployment scenarios.

For more detailed analysis of each of our six focus countries, see the country impact section starting on page 91.

•••

Automation will displace jobs around the world by 2030, but in our analysis demand for certain types of labor—from care providers to builders—will also increase, spurred by the rising consumer class in emerging economies and the growing health-care needs of aging populations in nations from Germany and Italy to China and Japan, among other trends. Our dynamic modeling of the US and other economies suggests that enough new jobs will be created to return to full employment by 2030, but the transition could be difficult. Depending on the rate at which displaced workers are reemployed, the unemployment rate could rise in the short- to medium-term, and wages may fall thereafter. Moreover, our analysis highlights differences between the sorts of jobs that will be lost from automation, and those that will be gained from a range of trends. Even if there is enough work to go around in 2030, millions of individuals may need to find new jobs and possibly acquire new skills. We examine these trends in the next chapter.

Midcareer retraining will be a major challenge

4. IMPLICATIONS FOR SKILLS AND WAGES

The combination of labor displacement by automation and changing demand for occupations that we have outlined in the previous chapters will have enormous implications for individual workers. We estimate that 60 million to 375 million individuals around the world may need to transition to new occupational categories by 2030 , in the event of midpoint or early automation adoption (although that number would be negligible in 2030 in our edge-case slow automation adoption scenario). Nearly all jobs will involve a shifting mix of tasks and activities.

Within occupations, the mix of activities and the capabilities required will skew toward more personal interactions and more advanced levels of cognitive capabilities. Educational requirements will also change: net of automation, a greater share of jobs in the future will likely require higher levels of educational attainment. In advanced economies, that includes increasing demand for jobs that currently require a college degree (or other advanced training). At the same time, employers and workers may need to take a more fine-grained approach to identify skills that are the most important.

Our results also suggest that income polarization in advanced economies including the United States could be exacerbated.[92] We do not dynamically model how wages might change for individual occupations by 2030, but based on current wages, we find that in most advanced countries, middle-wage jobs may decline the most as a result of automation. Growing occupations in these countries will tend to be either those that are less remunerative, for example, retail salespeople or childcare workers, or quite the opposite: highly paid jobs, such as software engineers. In developing economies including China, however, we see the opposite trend. Here the strongest job growth will likely be for middle-wage occupations, including service and construction jobs.

THE MIX OF ACTIVITIES WITHIN OCCUPATIONS WILL CHANGE

Up to
375M
workers globally may need to transition to new occupational categories by 2030

For nearly all occupations, automation will change the mix of activities that humans perform, as some tasks are taken over by machines or software. Over time, occupational definitions may change, as the boundaries between different occupations become blurred. Already, physician assistants and registered nurses carry out many tasks that doctors used to do, such as handling routine cases or giving shots. For their part, doctors now write up memos and enter data rather than dictating to assistants.

With automation, such shifts may become more pronounced, although the specifics will vary by country. In Germany, workers of the future will likely spend more time on activities that require applying expertise (+2.9 billion full-time equivalent hours), interacting with stakeholders (+1.5 billion hours), and managing people (+1.4 billion hours), and less time on predictable physical activities (-2.6 billion hours), collecting data (-2.5 billion hours) and processing data (-2.1 billion hours), where machines already exceed human performance (Exhibit 19). In other words, many of the rote activities that have dominated the workplace in the post-industrial age will be taken over by machines. Work activity will shift to human interaction and working in unpredictable environments—and will also require increasing application of expertise. Similar shifts will occur in other high-wage, advanced economies.

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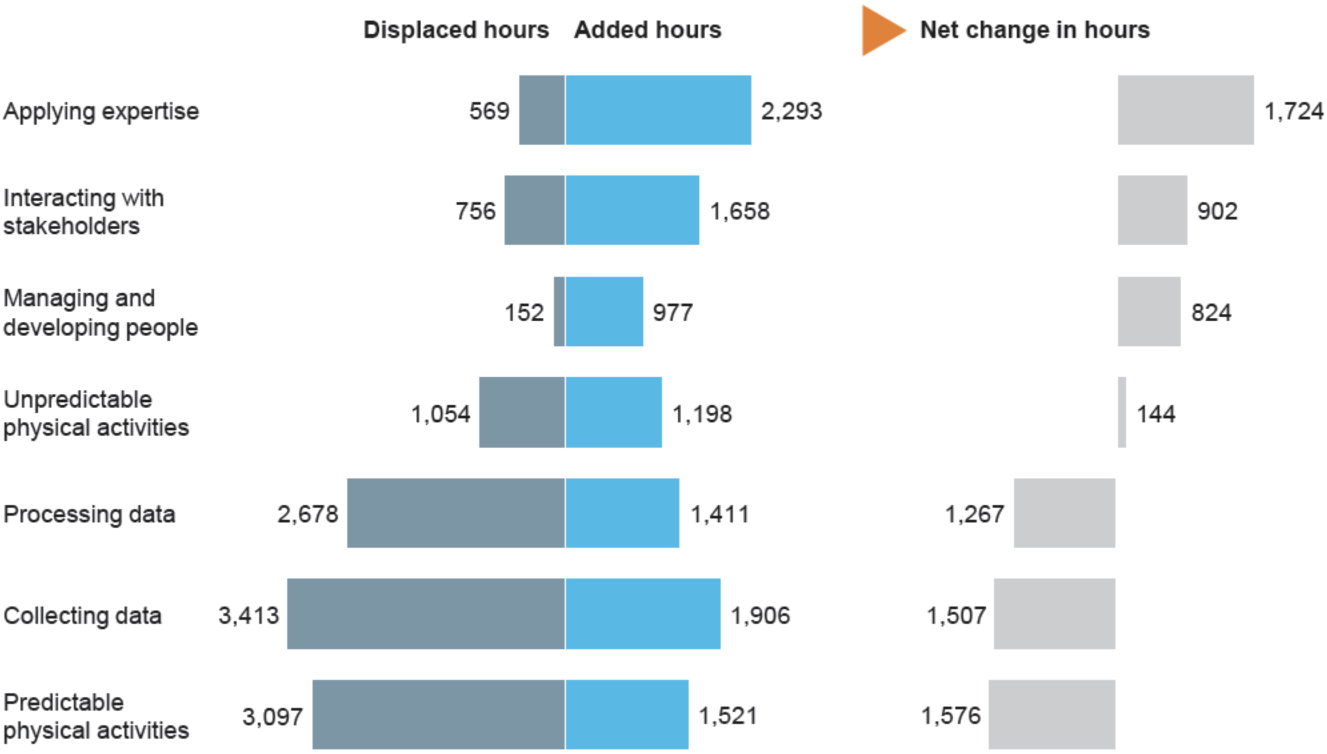
[92] See, for example, Daron Acemoglu and David H. Autor, "Skills, tasks, and technologies: Implications for employment and earnings," in *Handbook of Labor Economics*, Volume 4, Orley Ashenfelter and David E. Card, eds., 2011.

Exhibit 19

Activities within all occupations will shift: New work will involve more application of expertise, interaction, and management

Total hours by activity type, Germany example, 2016–30 (midpoint automation, step-up demand)
Million FTE hours



NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

In India, much of the projected growth in activity hours will be in physical activities, driven by demand for construction work, particularly in the step-up scenario. China, which has higher levels of existing infrastructure and building development, will still see some growth in physical activities. However, most of the growth will be in activities similar to its advanced-economy counterparts, such as interacting with stakeholders and applying professional expertise.

This shifting set of activities has implications for the capabilities that will be needed for future work. Exhibit 20 shows how US workers will need to upgrade their mastery of the 18 performance capabilities we used for our automation modeling.

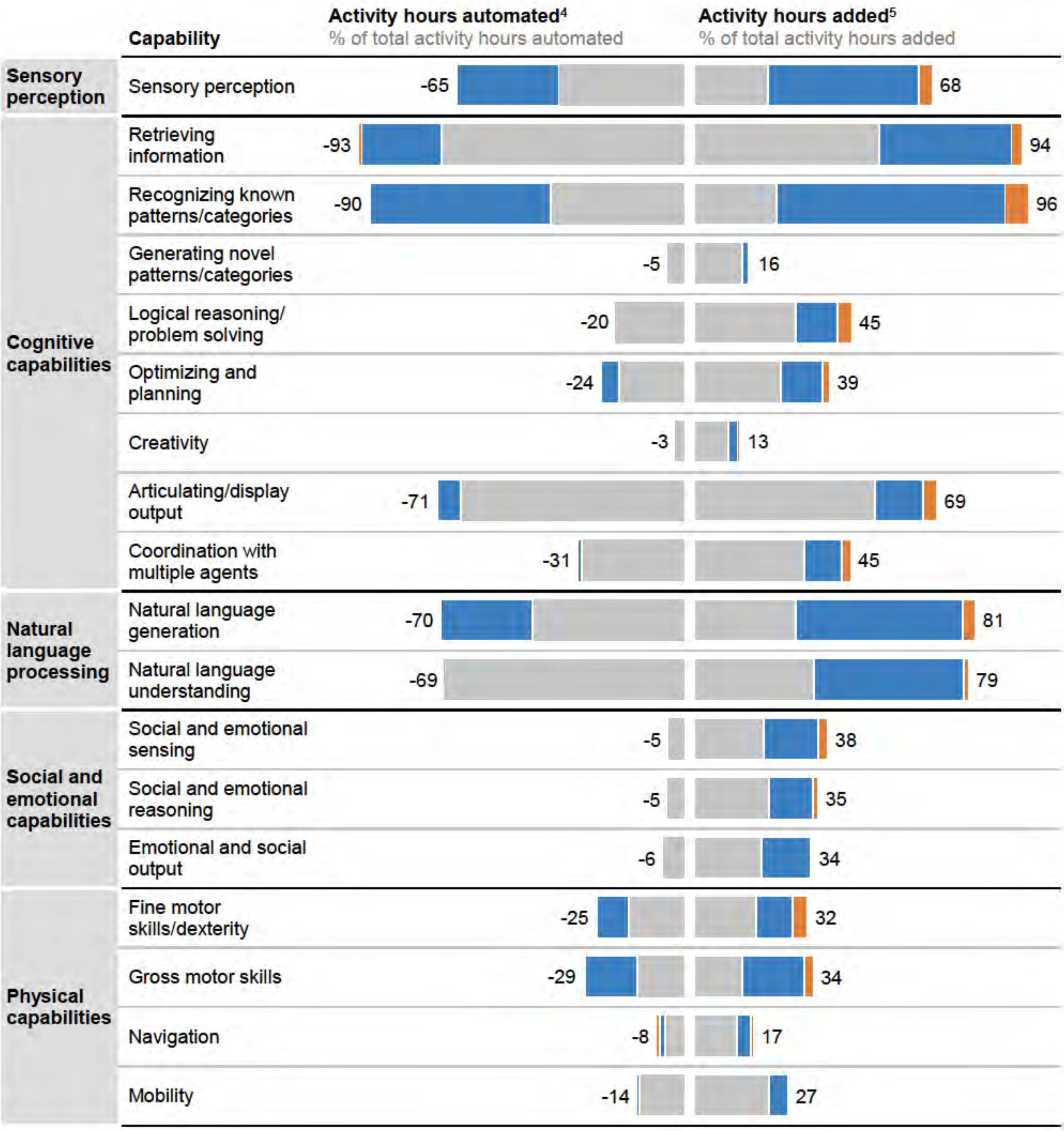
More work activities will require social and emotional skills and advanced cognitive capabilities, such as high-level logical reasoning—capabilities that are required today for only a relatively limited number of jobs. This will be a challenge for education, training, and skill assessment models, which for now do not always emphasize "soft skills" such as social and emotional reasoning and sensing.

Exhibit 20

Future work activities will require more social emotional, creative, and logical reasoning abilities—and more advanced capabilities across the board

Difference in share of work activity hours which require specified capability, by level of expertise, between new work and displaced work, 2016–30
US example, midpoint automation, step-up scenario

Basic[1]
Intermediate[2]
Advanced[3]



1 Below-median capability required.
2 Median human capability required.
3 At least 75th percentile capability required.
4 80.3 billion activity hours automated (38.6 million jobs).
5 66.3 billion activity hours added (31.9 million jobs).
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: U.S. Bureau of Labor Statistics; McKinsey Global Institute analysis

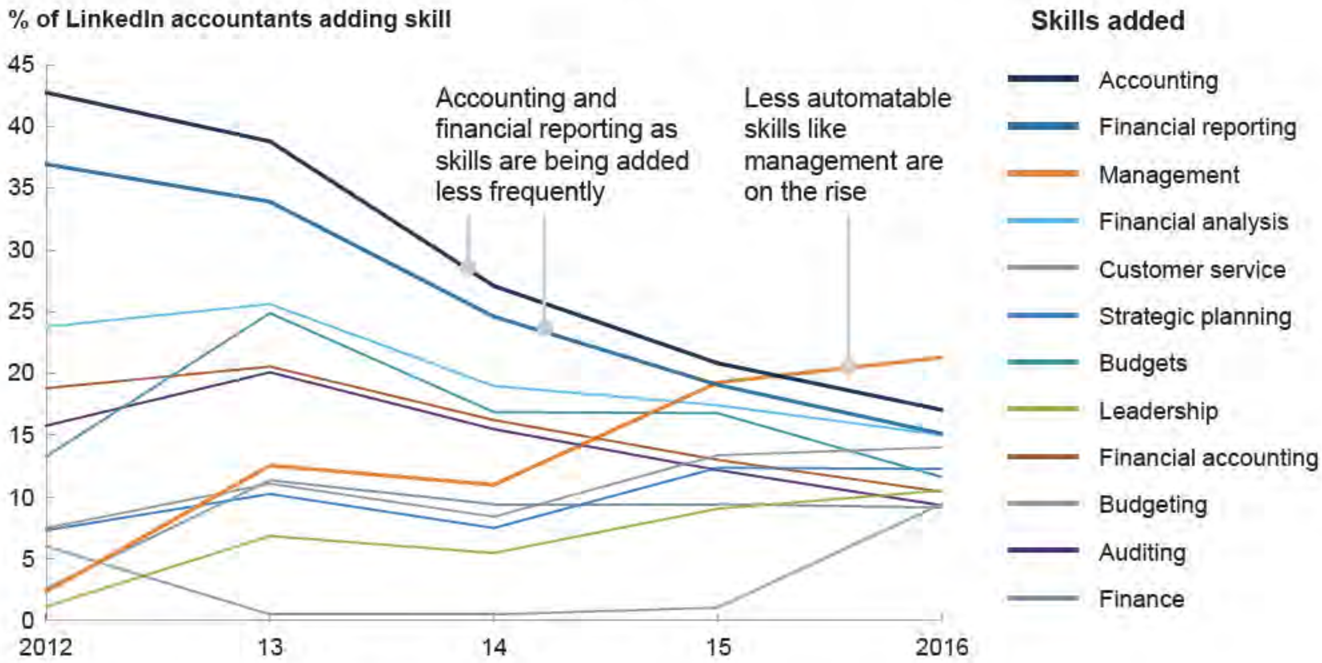
Additional jobs will often require a higher level of performance across many capabilities. For instance, machines will be able to perform work activities requiring basic levels of retrieving information and understanding natural language—but jobs requiring higher levels of these capabilities will grow. In advanced economies, physical capabilities will be less in demand as a percentage of the activity hours demanded in the economy. In developing economies such as India, given the increase in demand for physical activities, demand for physical capabilities will accordingly grow as a percentage of the new activity hours demanded. The shift in activities and underlying capabilities required will touch almost all jobs in the economy, to varying degrees—but especially in advanced economies. As one example, the work of retail salespeople in these economies could change significantly; about 20 percent of their current work activities could be automated in the midpoint scenario. The rote aspects of the job such as processing transactions and gathering product information may be automated. Retail workers instead may turn their attention to the more people-focused side of the job: greeting customers and answering questions, for example, or suggesting new products.

The capability shift is not limited to front-line jobs. Many workers in occupations with high educational requirements who spend much of their time collecting and processing data could experience a significant shift in their work activities. Financial managers, for example, could spend less time monitoring cashflow or approving expenditures, and instead have time to focus on more managerial functions such as supervising employees and advising others on business matters. Professionals of all stripes are quickly realizing the growing importance of "soft skills"—although understanding the implications of numerical calculations will continue to be important. On LinkedIn, the professional networking site, for example, professionals are increasingly developing and marketing themselves around these softer skills, which are less automatable (Exhibit 21).[93]

Exhibit 21

Some indications suggest individuals are highlighting skills that are less susceptible to automation

Accountants on LinkedIn have been prioritizing less automatable skills and deprioritizing more automatable skills
% of ~160,000+ accountants globally on LinkedIn adding specified skills



SOURCE: LinkedIn; McKinsey Global Institute analysis

[93] Data analysis from LinkedIn.

This changing nature of activities and capabilities has important implications for the requirements and aims of job training, which will be particularly relevant in times of transition. For example, as activities requiring basic levels of performance are automated in the United States, training efforts will need to focus on capabilities for which automation is more challenging, such as social and emotional capabilities. Increasingly across occupations, workers will be valued for strong interpersonal skills and advanced reasoning. As these skills are often developed through guided experience, workers will likely spend more time being coached in apprentice-like environments. The workers of the future will still need to apply expertise and judgment, so training to promote fluency with and understanding of information will remain important.

GROWING JOB CATEGORIES HAVE HIGHER EDUCATIONAL REQUIREMENTS THAN THE WORK DISPLACED BY AUTOMATION

Across our six focus countries, a greater share of jobs in the future—accounting for both the effects from automation and the additional labor demand from the seven trends—are likely to demand increased levels of education (Exhibit 22).[94]

Defining and measuring the skills required to perform well in any job is a difficult and imprecise task. In our modeling, we look at several different measures of workforce skills. First, we consider the formal educational requirements of each occupation: secondary school degree, Associate's, Bachelor's, and graduate degrees. Educational requirements by occupation are fairly well standardized globally and allow for cross-country comparisons. However, even within an occupation, there will be a range of degrees that existing workers have obtained; we focus on the educational levels that are typically required.[95] We also look at how activities within occupations will change, which gives some indication of the types of skills that will be more or less in demand, and we consider the capabilities required to perform those activities—such as cognitive skills, creativity, social and emotional skills. Other definitions of skills and credentials are equally valid and important, but are beyond the scope of this report. Many practitioners and researchers today focus on unbundling traditional degrees into well-defined credentials that can be obtained by demonstrating mastery of specific skills. This is particularly attractive for midcareer workers who cannot afford to spend years earning a traditional degree, or who have accumulated valuable experience on the job. Some credentials are for quite narrow skills: programming in a certain computer language, or mastering one specific type of mechanical expertise.[96]

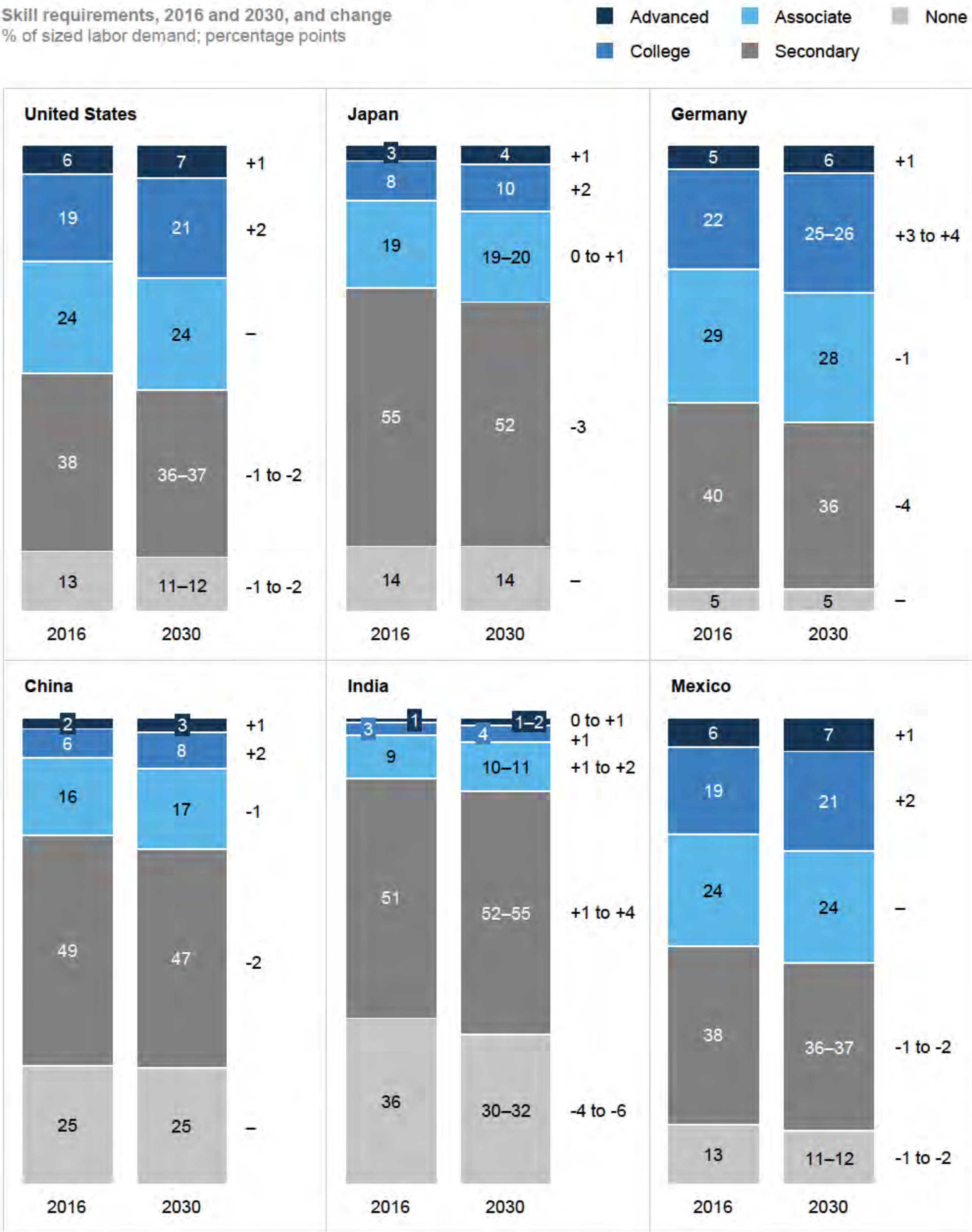
[94] We do not model changing skill requirements for occupations, and assume that educational requirements for an occupation in all countries are the same as in the United States. See technical appendix for details.

[95] Economists note the general trend of "degree inflation." For instance, in the United States, while 80 percent of job openings for executive assistants list a bachelor's degree as a requirement, fewer than half of existing EAs have that degree. See Peter Capelli, *Will college pay off? A guide to the most important financial decision you'll ever make*, PublicAffairs, 2015.

[96] For a discussion of skills and credentials, see *The narrow ladder: The value of industry certifications*, Burningglass Technologies, October 2007; David Deming et al, "The value of postsecondary credentials in the labor market: An experimental study," *American Economic Review*, 2016; Rajeev Darolia et al., "Do employers prefer workers who attend for-profit colleges? Evidence from a field experiment," *Journal of Policy Analysis and Management*, volume 34, issue 4, fall 2015.

Exhibit 22

Skill requirements for jobs are increasing globally; an increasing percentage of jobs will require college and advanced degrees



NOTE: All figures are projected using the midpoint automation scenario; only includes the sized labor demand (e.g., the creation of new occupations is not included). Some occupational data projected into 2016 baseline from latest available 2014 data. Numbers may not sum due to rounding.

SOURCE: US Bureau of Labor Statistics; McKinsey Global Institute analysis

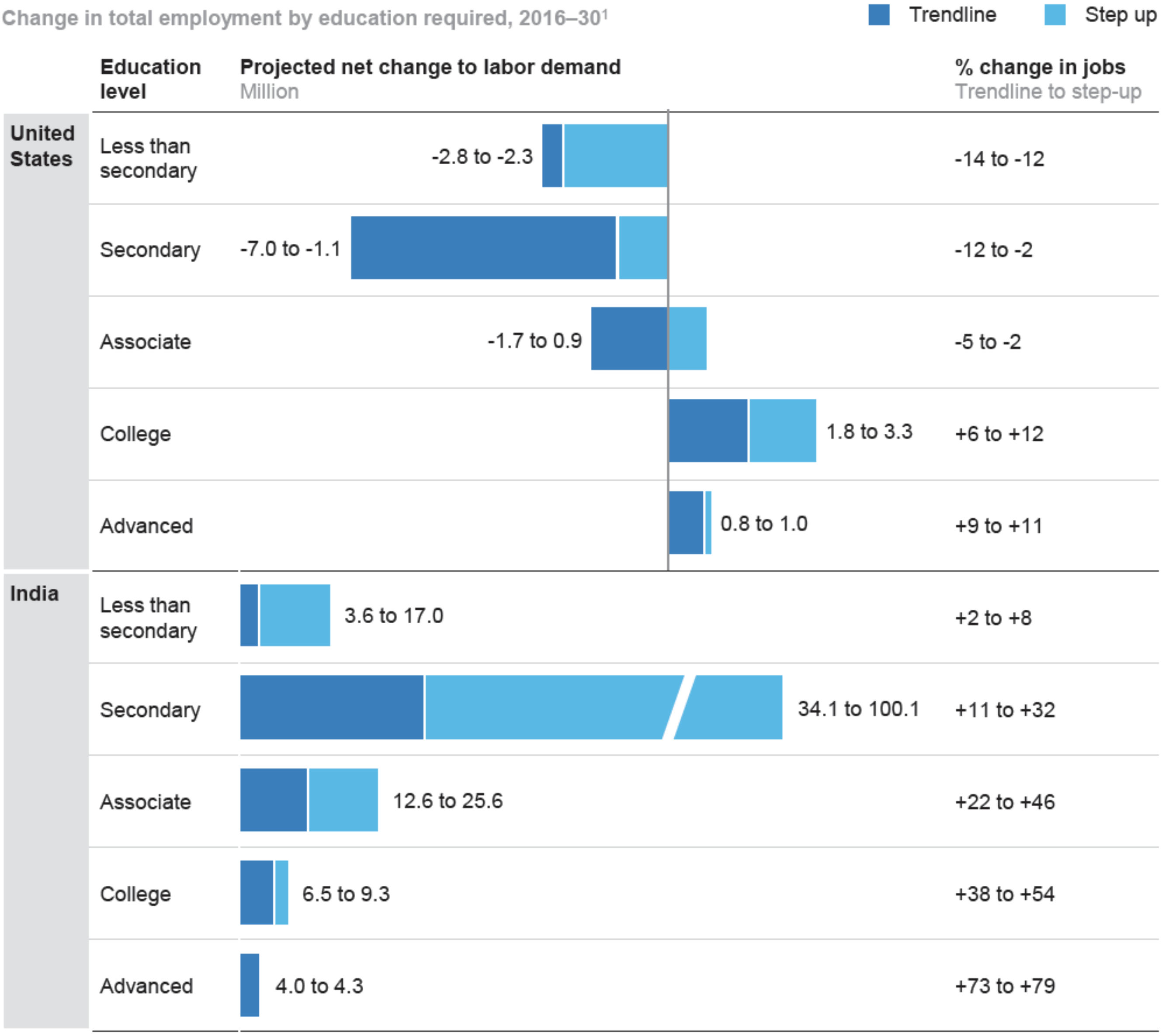
In advanced economies, demand for work currently requiring completion of secondary school or less will likely decline

In advanced economies, our model shows a common pattern of educational requirements. Occupations that currently require only completion of secondary school or less, including jobs such as office clerks, hand packers and packagers, and tellers, are most likely to be affected by automation and have a net reduction in labor demand, based on the factors we have modeled (Exhibit 23).

Exhibit 23

In the United States, occupations with lower educational requirements are declining, while in India, both trendline and step-up scenarios will see large increases in demand for secondary degrees

Change in total employment by education required, 2016–30[1]



1 Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: O*Net skill classification, US Bureau of Labor Statistics; McKinsey Global Institute analysis

Not all jobs in these categories will disappear, but in 2030, demand for the activities they currently perform will be lower in all of our modeled scenarios. In contrast, occupations requiring a college or graduate degree will see the most growth as a percentage of jobs in the economy. Occupations that require training on top of a traditional post-secondary degree (for example, career, technical, vocational training) or two-year associates' degree have a mixed outlook. As a share of jobs in the economies, countries such as Japan will see increased demand for associates' and equivalent degrees, primarily from middle-skill health-care occupations such as nurses and paramedics. Meanwhile, countries such as Germany will see decreased demand, primarily because of a greater share of automatable office support jobs such as clerks and secretaries.

The relative growth of jobs requiring higher educational attainment is not a new observation.[97] Nor is the increase of skill requirements necessarily a break from historical trend: the manufacturing revolution saw increased need for literacy training that spawned movements toward secondary education including the High School Movement in the United States, which we discuss in the next chapter.

However, many of the middle-income jobs of the past that required only a secondary education or less, and minimal training, will likely face significant displacement in an automated world. These jobs include heavy truck drivers and office clerks, both of which have high technical potential for automation over our modeled time horizon, and whose current middle-level wages raise the economic incentives to deploy automation. Many additional jobs requiring low and middle levels of educational attainment could be created, driven particularly by the caring economy, such as the rise of nurses and nursing assistants. However, for many jobs that require no or only secondary education, the additional future labor demand will not fully make up for the jobs displaced by automation. This would mean that many displaced workers would need to retrain and/or raise their educational levels to gain employment in one of the in-demand occupations.

The seven trends we modeled alone suggest that overall new demand for work currently requiring a college degree could be sufficient to balance the reduction in demand for work activities lost to automation in occupations requiring college completion, in the United States, as well as in Germany (where the net modeled demand for these occupations increases).

However, that does not obviate the need for college and advanced degree holders to retrain, as their activities will change. Some will switch to jobs that require a similar level of educational attainment, but very different skills. The coming wave of technology deployment, bolstered by advances in machine learning and artificial intelligence, has significant potential to automate work activities previously thought to be the exclusive domain of highly-trained humans. In the midpoint automation scenario, 13 percent of the current work activities performed in occupations that require college or advanced degrees in the United States could be displaced. Even within a given field, certain occupations will fare better than others. In the United States, for example, the high-skill job of application software developer has large net additional demand (we model nearly ten times as many jobs created as displaced). Meanwhile certain technology support jobs including computer systems administrators and support specialists may see a cooling of demand, because a substantial portion of their current activities have relatively high technical automation potential. Similarly, in US financial services, the varied skills required of management analysts could see high demand, while financial managers and securities sales agents could face substantial automation of their current work activities with limited sources of new demand.

[97] For example, MIT economist David Autor has credited the trend to productivity boosts from information technology that magnifies the productive power of cognitive functions, which is often central to higher-skill work. Ibid. David H. Autor, "Why are there still so many jobs?" summer 2015. In the United States, about two-thirds of jobs from Baby Boom retirement require more than a secondary school education. Jamie Merisotis, *America needs talent: Attracting, educating, and deploying the 21st century workforce*, Rosetta Books, 2015; see also, Anthony Carnevale et al., "Good jobs that pay without a BA," Georgetown University Center on Education and the Workforce, 2017.

Workers displaced by automation may need to invest time to acquire new skills, either through formal education or other training programs. Conversely, jobs themselves may need to be redesigned to accommodate an influx of new workers with less sector-specific training and overall education. The transitions could be varied and lead to friction in the labor market and potentially higher unemployment in the short-run. But other steps could be taken to make markets function better. For example, defining job requirements, as well as providing training and certification, based on specific skills, could improve the matching of labor supply and demand, as these skills can be much more fine-grained than traditional educational degrees, and can often be acquired in less time than finishing a multi-year degree program.

While some workers who are displaced by automation will be able to find a job in a similar function and with similar educational requirements (for example, a displaced cashier finding a new job as a retail salesperson), many will not, and will need to gain additional skills, which may or may not actually raise their educational level. This is discussed in a subsequent section of this chapter.

Additional job creation in our step-up scenario could help mitigate some of the impact of automation, with additional investment in infrastructure, buildings, and energy transitions potentially creating new work for workers with low and mid-level educational attainment. In all, in the United States, we estimate additional demand for mid-skill labor of up to 1 million jobs, net of automation, in the step-up scenario. Demand for occupations requiring post-secondary education also increases in the step-up scenario. Engineers and cost estimators will be brought in to develop infrastructure projects, for example, and various professionals, from accountants to research analysts, will also see increased demand.

In developing countries, the largest number of new jobs will be those requiring secondary education or technical skills

In emerging economies, the rate of job growth is highest for occupations that require a college degree or more, but the absolute amount of job growth is highest for occupations with a secondary education diploma.

In China, for instance, occupations currently requiring college and advanced degrees will see increased demand—in the case of those with college degrees, this could be as high as 22 million additional net jobs under our step-up scenario. However, the largest absolute number of jobs created—almost 60 million in the step-up scenario—currently require only a secondary school diploma, with significant increased demand for retail salespeople, nursing assistants, childcare workers and others according to our analysis. Despite the dual threat of automation (particularly for manufacturing, which makes up about 19 percent of employment in China) and other increasing productivity, significant demand will be created for lower-skill work, primarily due to rising prosperity. Also, jobs with low educational attainment requirements in these countries are generally lower wage, and are thus less economically attractive to automate.

India, meanwhile, will see the largest new demand net of automation for workers with a secondary education. According to our analysis, as many as 100 million new jobs could be created for Indians with secondary education—even after accounting for the effect of automation—as rising prosperity will create a surge of new labor demand for construction, retail, and health care and education jobs, among others. The largest countries in the developing world, in short, should not have a shortage of labor demand across any education level, but the significant increase in work requiring completion of secondary education indicates a need for India to upgrade its school system.[98]

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98 In 2011, only 40 percent of Indian adolescents attended secondary school (Grades 9-12), compared to more than 95 percent who attended primary school. The World Bank, *Education in India*, September 20, 2011.

TENS OF MILLIONS OF INDIVIDUALS GLOBALLY WILL NEED TO SWITCH OCCUPATIONAL CATEGORIES, AND MAY REQUIRE TRAINING TO DO SO

Our findings shed some light on the potential size of the worker transitions that will be necessary in the years to 2030—and the immense training efforts that will be necessary as the nature of some work changes. We estimate that up to 75 million workers may have to switch occupational categories and/or educational levels in the midpoint automation scenario (Exhibit 24).[99] If automation technologies are developed and adopted sooner, those numbers grow rapidly; in the earliest automation adoption scenarios that we analyze, as many as 375 million people may need to change occupational categories and/or educational levels. However, our step-up scenarios reduce our estimates of the number of people needing to make these types of transitions, with additional labor demand trends offsetting more job displacement from automation within occupational categories. Not shown on the exhibit, in the slowest automation scenario, the number of required transitions is significantly reduced (almost negligible in most countries).

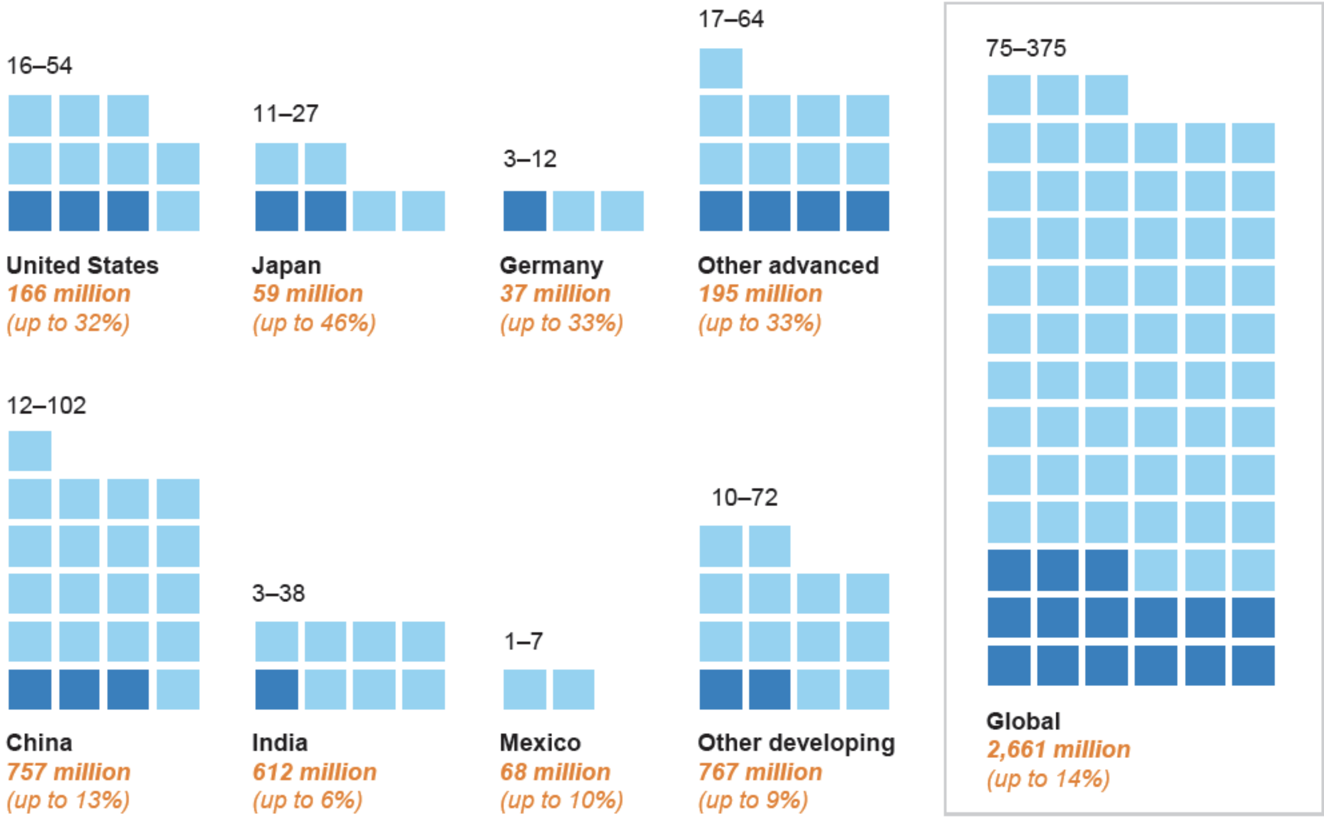
Exhibit 24

Globally, up to 375 million workers may need to switch occupational categories

Number of workers needing to move out of current occupational categories to find work, 2016–30 (trendline scenario)[1]
Million (1 block = ~5 million)

Additional from earliest adoption scenario
Midpoint automation scenario

2030 workforce (% transitioning)



1 Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: U.S. Bureau of Labor Statistics; McKinsey Global Institute analysis

[99] Analysis conducted by segmenting all US Bureau of Labor Statistics occupations into 58 occupational categories. See technical appendix for details.

Some of these people who are displaced will seek new education and many will need new skills. People will also need to learn new skills within their occupations as activities change, particularly where those activities are augmented by automation. As a point of calibration, in our rising incomes trend, we project that between 190 million and 205 million students will be in tertiary education in 2030.[100] In the fastest automation scenario that we model, the number of people that will need to transition between 2016 and 2030 is almost double that number.

These transitions could surface frictions in the labor market, for reasons ranging from lower wages to cultural and gender bias, but also present new opportunities for work and job growth. For example, men could find opportunities to retrain into jobs in which women have dominated in some countries, such as nursing in the United States, and vice versa.[101]

WAGE POLARIZATION MAY CONTINUE IN SOME ADVANCED ECONOMIES

Middle-wage jobs have felt the impact of automation in the past decades in the United States, creating a polarization phenomenon. Modeling the potential impact of automation, we find that this polarization could continue and become exacerbated in advanced economies—but not universally. Indeed, one of our findings is that the potential wage impact of automation and future labor demand could vary considerably among countries. We also find that any polarization of wages is not due solely to skill gaps; some of the additional demand for middle-skill jobs are in those that are currently paid low wages in countries such as the United States.

In advanced economies, high-wage occupations see the most growth net of automation

Academic literature examining the recent impact of technology on wages has found that a distinct pattern of "hollowing" or a decline in middle-skill and middle-wage jobs with growth in high- and low-wage occupations (see Box 5, "Our prior research on income and equality trends").[102]

Our analysis is based on current average wages for each occupation in each country. Modeling wages over time by occupation based on the dynamics of labor supply and demand is outside the scope of this study, beyond the top-down analysis of wage impact that we described in the previous chapter. Nonetheless, our examination of job growth at different current wage levels offers some indications of what the future may hold.

In the United States and Germany, in our trendline labor demand and midpoint automation scenarios, occupations in the top 30 percent of average current wages experience net job growth by 2030 (Exhibit 25). This holds for the United States even in the modeled step-up scenario; in the step-up scenario for Germany, rising need for jobs such as nursing assistants is expected to increase demand for middle-wage jobs. The largest declines are in jobs in the middle of the wage distribution. Occupations in the lowest 30 percent of wages decline, but this reflects the net impact of modest growth in low-wage occupations such as retail salespeople, and declining occupations such as hand packers/packagers and cafeteria cooks.

[100] Based on analysis conducted with World Bank tertiary education data.

[101] Our analysis suggests that future labor demand on an aggregate basis will not have a gender bias. Automation overall will affect jobs that are traditionally male-dominated, as in manufacturing, but also jobs that are traditionally female-dominated, such as food services or accommodation. New jobs with a traditional male bias such as construction work will be created, as will jobs such as nurses that have traditionally been dominated by women.

[102] Harry Holzer, *Job market polarization and U.S. worker skills*, April 2015; and Ibid. David H. Autor, "Why are there still so many jobs?" summer 2015.

Box 5. Our prior research on income and equality trends

The trends we identify in this report for both low- and middle-wage jobs and high-wage, high-skill jobs overlap with some of the structural shifts in the labor market in the past few decades that we have examined in prior reports. Among our findings:

"Superstar" effects and the hollowing of the middle. Digitization has already affected the occupational and skill mix of the US workforce. Since the 1980s, employment in both low-skill and high-skill jobs has increased, while middle-skill jobs have declined. With many routine production and assembly tasks being automated, most of the growth at the low-skill end of the spectrum has been in occupations such as restaurant workers, home health-care aides, security guards, maintenance workers, and other roles that provide in-person services that are less susceptible to automation. At the same time, idea-intensive sectors have been capturing a larger share of the overall corporate profit pool. There is now a premium on creative and cognitive tasks that improves overall productivity of highly skilled workers. The result is an increasingly two-tiered labor market.[1]

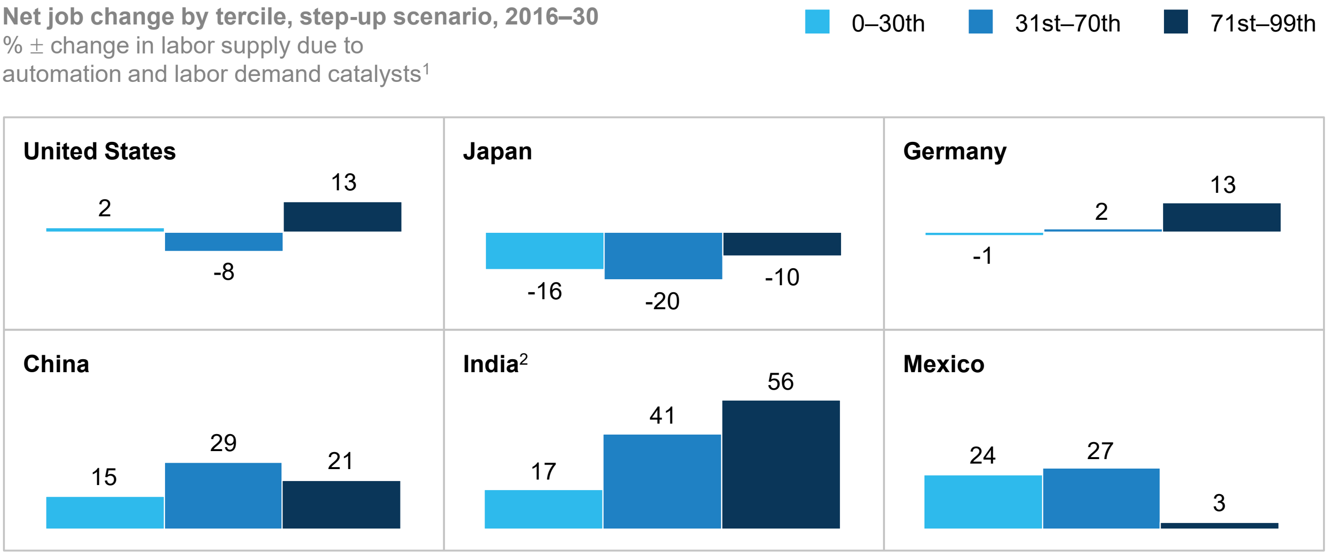
Flat and falling incomes in advanced economies. With only occasional exceptions, most income groups in advanced economies have experienced steady income advancement since World War II, but that changed abruptly in the past decade. Between 2005 and 2014, our research found that about two-thirds of income groups had either flat or falling market income (wages and capital), although in some countries including the United States government taxes and transfers cushioned the blow for disposable income. While economic recession and slow recovery after the global financial crisis were a primary cause, other long-run factors—including a decline in the wage share of GDP, aging, and shrinking household size—will continue to weigh on incomes in the future. The decline in wage share has taken place despite rising productivity, suggesting that productivity and incomes have become disconnected. The distribution of this wage share among different income segments has also been uneven: since 1993, households in the uppermost income segments in the countries we looked at received a growing share of the total wages, even as the share for low- and middle-income segments has either stagnated or fallen.[2]

1 Ibid. *Digital America*, McKinsey Global Institute, December 2015.
2 *Poorer than their parents? Flat or falling incomes in advanced economies*, McKinsey Global Institute, July 2016.

Exhibit 25

Generally, high-wage jobs show the most positive percentage change in advanced economies, while mid-wage jobs fare best in emerging economies

Net job change by tercile, step-up scenario, 2016–30
% ± change in labor supply due to automation and labor demand catalysts[1]



1 Midpoint of earliest and latest automation adoption.
2 Low-wage group for India includes all production occupations (~45% of total population).
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: ONET skill classification, US Bureau of Labor Statistics; McKinsey Global Institute analysis

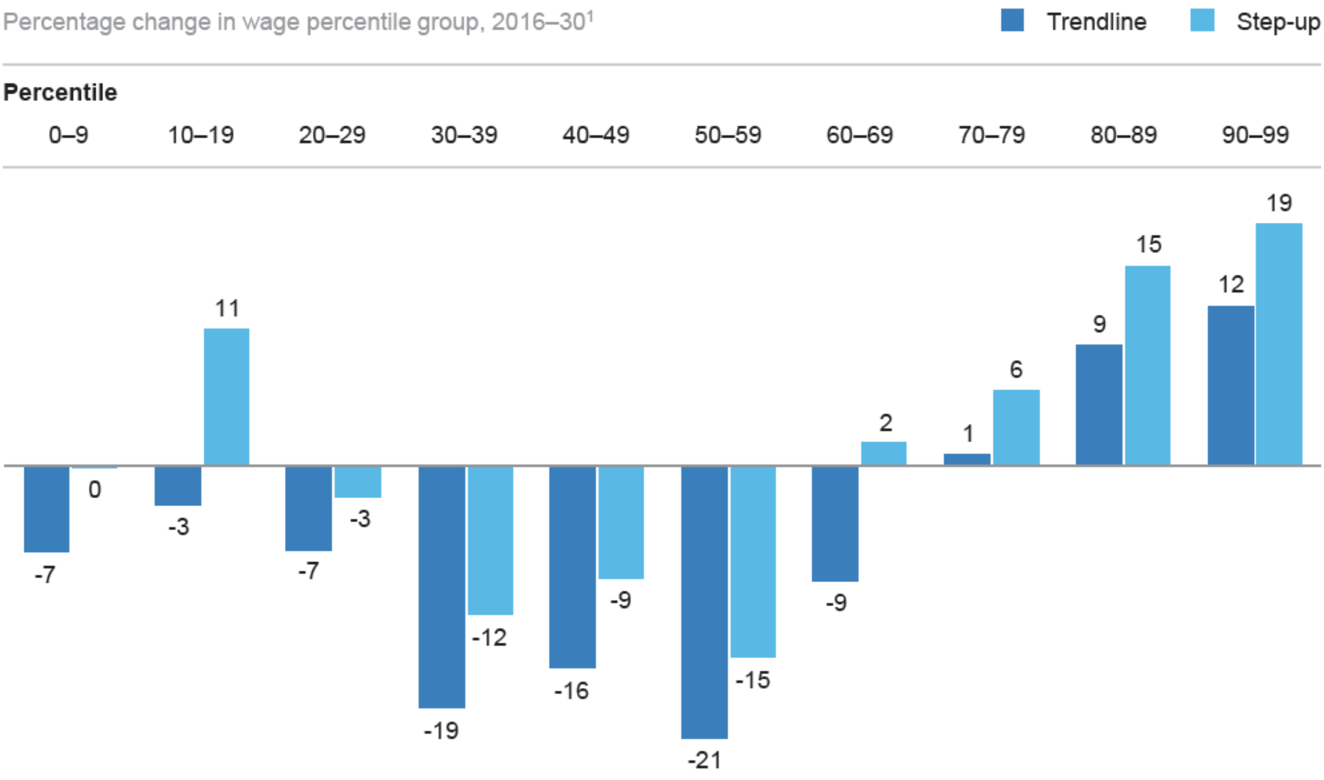
In the United States, the pattern of polarization is clearer if we look at the net job growth by wage decile (Exhibit 26). The top two deciles experience significant new demand for labor net of automation, primarily driven by an increase in demand for high-skill professionals, including technology and medical professionals. The effects of aging and, in the step-up scenario, professionalization of unpaid work also create growth at the lower end of the wage spectrum, around the 20th percentile. This is driven by growth in nursing assistants, teaching assistants, and personal care aides, among others.

In our model, the step-up scenario involving increased spending on such areas as infrastructure, real estate, and energy transitions can help create more growth in middle-wage (as well as low-wage) jobs. For example, in the United States, increased infrastructure and real estate spending can create additional demand for labor in construction, skilled craftspeople, and technical production jobs, which are middle-wage jobs. The increased professionalization of unpaid services would also add jobs for middle-wage work in countries like Germany through increased demand for nursing assistants and childcare workers. These types of jobs could help produce some of the additional labor demand to offset activities that could be automated, in particular, providing demand for middle-wage jobs in advanced economies.

Exhibit 26

In the United States, high wage jobs see the most growth and middle wage jobs decline the most

Percentage change in wage percentile group, 2016–30[1]



	0–9	10–19	20–29	30–39	40–49	50–59	60–69	70–79	80–89	90–99
% of total FTE, 2016	11	9	10	10	11	9	10	10	10	10
Average wage, 2016 ($)	20,414	23,969	26,755	30,092	33,902	39,354	47,389	56,104	67,963	105,511

1 Numerator: net change; denominator: 2030 scaled FTE in the given wage percentile bucket. Some occupational data projected into 2016 baseline from latest available 2014 data.

SOURCE: McKinsey Global Institute analysis

In developing countries, middle-wage occupations could experience strong growth

The potential wage trend picture is quite different in emerging economies. In India, occupations at all wage levels are boosted by demand from rising prosperity, while the economy will largely be shielded from automation because of lower wages. In China, our scenarios show that middle-wage jobs will rise similarly. Across both countries, the main occupations that are driving this growth in middle-wage jobs involve customer interaction. Job growth is particularly pronounced for cashiers and retail salespeople, which are middle-wage jobs in these markets. While in the developed world many of these jobs may be automated, in India and China, wages are low enough that automation rates will likely be constrained in the 2030 timeframe (modeled at under 10 percent). The story is a positive one for wage advancement and the development of the middle class: in India, for example, if farmworkers (with annual salary of $1,752) find themselves out of a job because of productivity improvements, many new and more highly-paid services jobs will sprout up in hosting (average wage of $2,204), and for retail salespeople ($4,101).

In these developing countries, the challenge will be to continue to create more high-wage work opportunities for high-skill workers, and move a greater proportion of workers into higher wage jobs. While India will have high demand for high-wage work, this type of work in China is more susceptible to automation compared with other developing countries, according to our model, primarily because of higher wage rates. Computer support specialists and law clerks, two high-wage occupations, have an automation potential in the midpoint adoption scenario of 34 percent and 35 percent, respectively. Overall, then, while developing countries may have less to worry about when it comes to creating labor demand to offset the effects of automation in the near term, policy makers and business leaders may want to focus on the creation of more gainful and desirable employment.[103]

•••

Work will change in the next decade and beyond, with significant implications both for skill requirements and wages. While our research suggests that these trends will play out differently among countries, some commonalities are apparent. One is that educational requirements and performance capabilities, including for soft skills such as social and emotional reasoning, will become ever more important. In advanced economies including the United States, middle-wage workers could continue to see a shrinking pool of opportunities as automation outpaces new job creation. As many as 375 million individuals around the world will need to switch occupational categories. Providing retraining opportunities at scale will be imperative. What should the policy priorities be in this changing workplace? In the following chapter, we look at how the transitions brought about by automation can best be managed.

[103] Ibid. *India's labor market*, McKinsey Global Institute, June 2017.

THE FUTURE OF WORK BY COUNTRY

In the following section, we highlight scenarios for the future of work in our six focus countries: China, Germany, India, Japan, Mexico, and the United States. The charts show a range of possible outcomes for jobs displaced by automation adoption to 2030 and scenarios for future jobs that could be created by seven catalysts of labor demand, as well as by new occupations that could arise. For the automation of work, we consider scenarios based on the speed of adoption of automation technologies. For potential labor demand, we model a trendline scenario based mainly on past experience, and a step-up scenario that considers, among other things, increased investment in infrastructure, buildings, and energy efficiency that countries may choose to make. Based on the net impact of automation versus future labor demand growth by occupation, we estimate the number of workers who may need to change occupational categories, and the possible implications for educational attainment and wages.

These charts should not be taken as forecasts or predictions. Rather, they illustrate a range of possible outcomes. The scenarios we assess in this report may overstate or understate the actual impact of automation on work and future labor demand. For example, if automation adoption is more rapid than even our earliest adoption scenario, this could mean that more work would be automated than we estimate. On the other hand, automation might boost productivity growth more than we have modeled, and this could lead to stronger aggregate demand growth and more job creation across the economy than we have modeled. Box E2 on page 21 discusses the many factors that could change our results for any individual country.

China

China's shift out of agriculture into manufacturing and services is likely to continue and, as incomes continue rising, consumption will increase. With its aging and shrinking workforce, China will benefit from embracing automation to increase productivity and meet projected 2030 labor needs.

Economics and demographic context

Demographics
9% over 65 years of age in today's population, and growing to 17% by 2030

Economic development
5.5% GDP per capita growth, annualized 2016–30

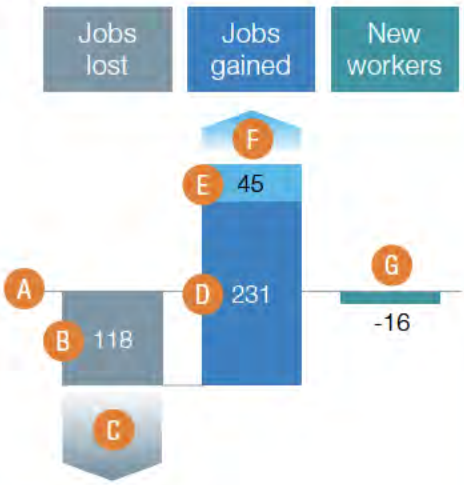
Wages
$10,500 average annual wage

Automation potential
16% of current work activity hours automated by 2030 in the midpoint scenario, and up to 31% in the rapid scenario

Jobs lost, jobs gained

Net change in jobs by 2030 (Million)

Enough jobs are created in the trendline scenario to offset effects of automation and the decline in labor force



- A 2016 baseline
- B Jobs displaced by automation by 2030 in the midpoint scenario
- C Jobs displaced by automation by 2030 in the rapid scenario
- D Jobs created by 2030 in the trendline scenario
- E Jobs created by 2030 in the step-up scenario
- F New occupations and unsized labor demand[1]
- G Change in labor force by 2030

Growth/decline of occupation types by 2030

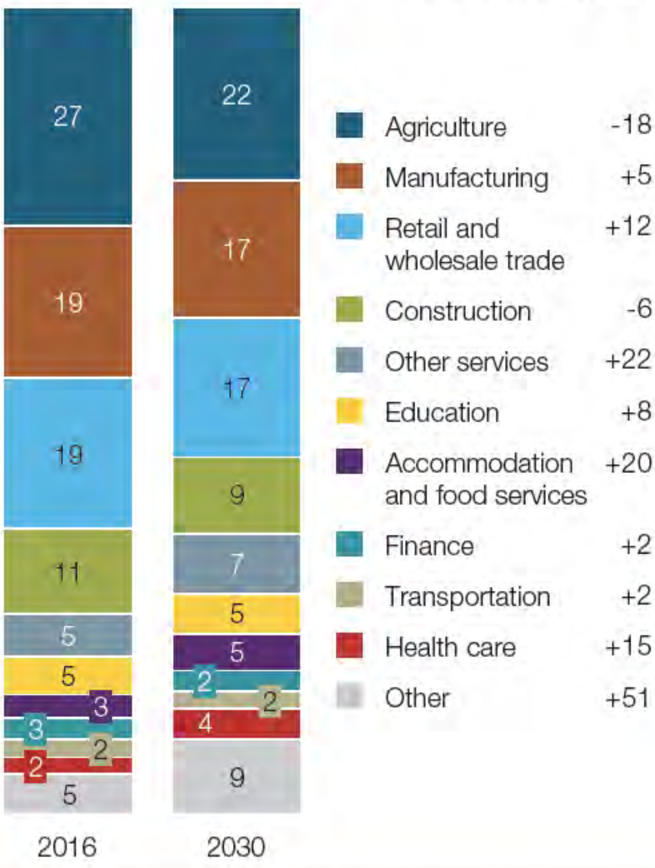
Occupation type *Examples*	Net change in jobs (midpoint automation, step-up scenario)[2] Million	% of jobs 2016	% of jobs 2030
Customer interaction *Retail sales, bartenders*	57.4	21	23
Care providers *Surgeons, nurses*	26.8	3	5
Other jobs, unpredictable environments *Farmworkers, firefighters*	22.4	24	22
Educators *Teachers, librarians*	19.0	2	4
Office support *Payroll clerks, data entry*	10.7	10	9
Professionals *Lawyers, business specialists*	8.8	4	5
Builders *Construction workers, electricians*	7.2	11	10
Managers and executives *CEOs, sales managers*	4.8	2	2
Creatives *Authors, designers*	3.8	1	1
Technology professionals *Web developers, IT*	3.0	1	1
Other jobs, predictable environments *Machinists, cooks*	-3.6	23	19

1 Historical analysis suggests that we could expect 8-9% of 2030 labor supply will be in "new jobs" relative to today, which is additional to what we have estimated.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

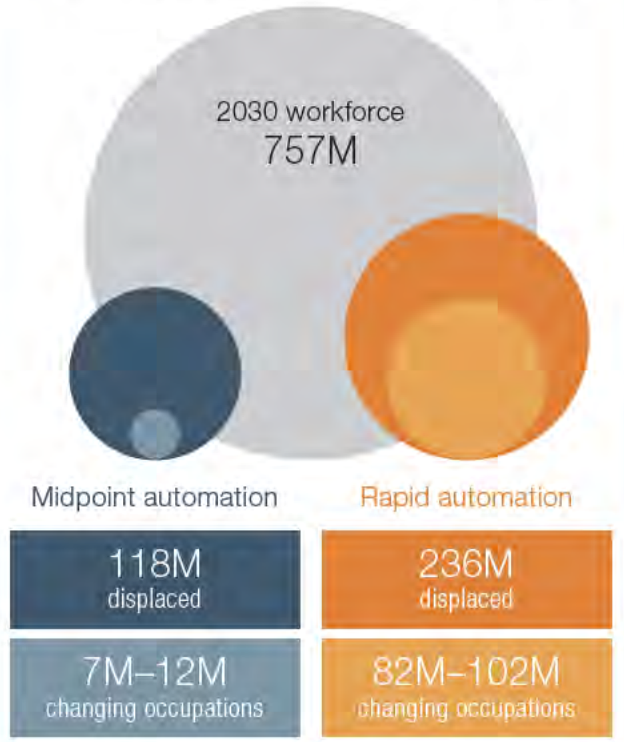
Sector and occupation shifts

With automation and the labor demand catalysts, workers may need to switch occupations

Sector share of labor force (%)[1] / Additions, net of automation (Million)



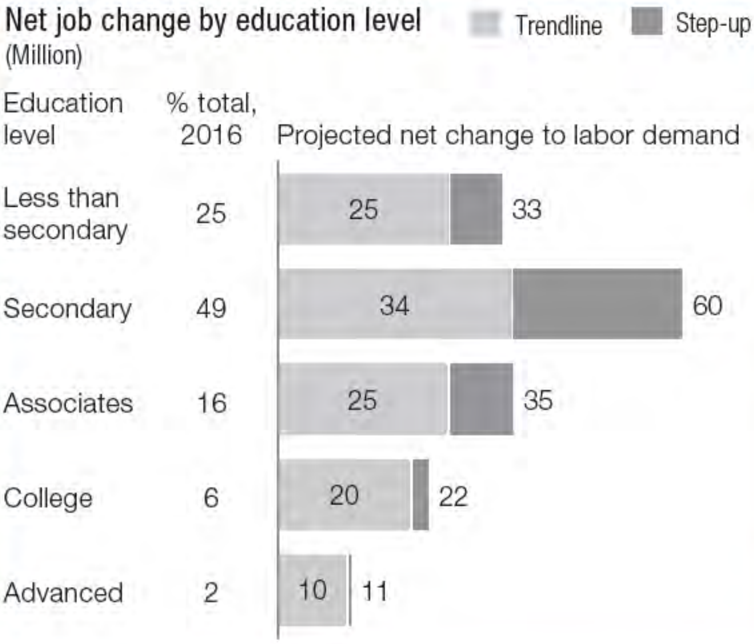
Number of workers displaced by automation, and those needing to change occupational categories[2]



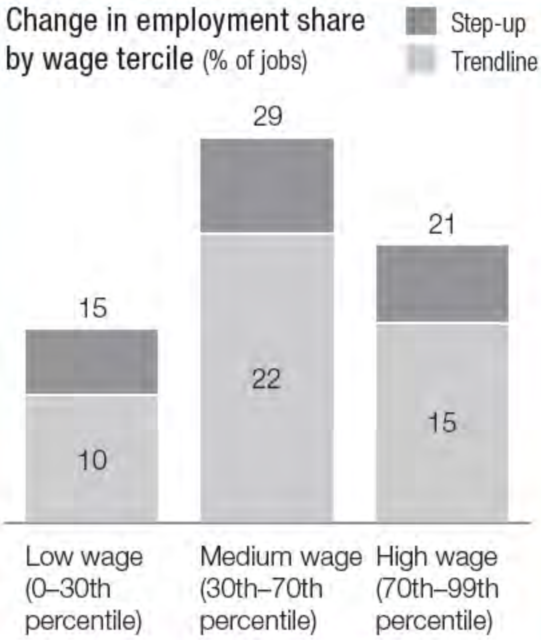
Up to 13% of the 2030 workforce may need to switch occupational groups

Job change by education and wage level, 2016–30[3] (midpoint automation)

Net job change by education level (Million)



Change in employment share by wage tercile (% of jobs)



1 Step-up scenario, midpoint automation, not all sectors modeled in labor demand catalysts (e.g., government).
2 "Transition" = switch occupation groups or gain new skills. Numbers given are trendline – step-up scenario.
3 Educational analysis based on current educational requirements. Employment analysis based on current wages.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

Germany

Germany has an aging population and a declining working-age population. Relatively high wages make a stronger case for early automation adoption, while medium GDP growth creates sufficient labor demand in most scenarios. Health-care needs from aging and increased consumer spending will drive most job creation.

Economics and demographic context

Demographics
21% over 65 years of age in today's population, and growing to 28% by 2030

Economic development
1.6% GDP per capita growth, annualized 2016–30

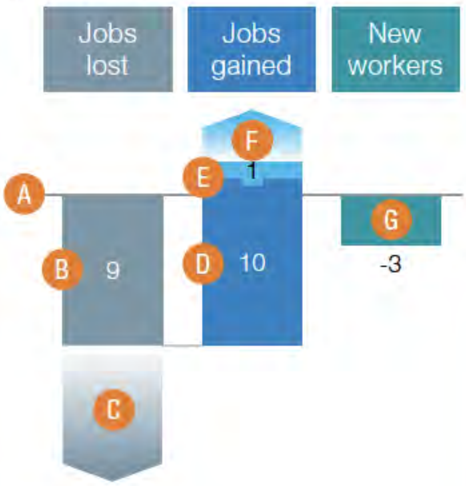
Wages
$38,600 average annual wage

Automation potential
24% of current work activity hours automated by 2030 in the midpoint scenario, and up to 47% in the rapid scenario

Jobs lost, jobs gained

Net change in jobs by 2030 (Million)

Enough jobs are created in the trendline scenario to offset effects of automation and the decline in the labor force



- A 2016 baseline
- B Jobs displaced by automation by 2030 in the midpoint scenario
- C Jobs displaced by automation by 2030 in the rapid scenario
- D Jobs created by 2030 in the trendline scenario
- E Jobs created by 2030 in the step-up scenario
- F New occupations and unsized labor demand[1]
- G Change in labor force by 2030

Growth/decline of occupation types by 2030

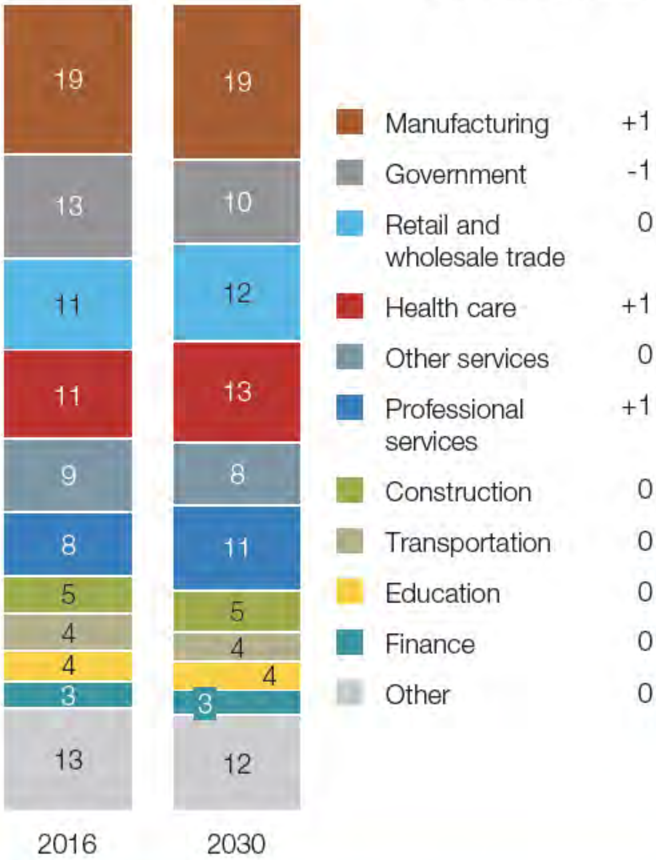
Occupation type *Examples*	Net change in jobs (midpoint automation, step-up scenario)[2] Million	% of jobs 2016	% of jobs 2030
Professionals *Lawyers, business specialists*	1.4	17	19
Care providers *Surgeons, nurses*	1.1	11	13
Technology professionals *Web developers, IT*	0.6	2	4
Customer interaction *Retail sales, bartenders*	0.4	10	11
Builders *Construction workers, electricians*	0.4	7	8
Managers and executives *CEOs, sales managers*	0.4	4	5
Educators *Teachers, librarians*	0.2	3	3
Creatives *Authors, designers*	0.1	1	1
Other jobs, unpredictable environments *Farmworkers, firefighters*	-0.2	9	8
Office support *Payroll clerks, data entry*	-1.1	18	15
Other jobs, predictable environments *Machinists, cooks*	-1.4	18	14

1 Historical analysis suggests that we could expect 8-9% of 2030 labor supply will be in "new jobs" relative to today, which is additional to what we have estimated.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

Sector and occupation shifts

With automation and the labor demand catalysts, workers may need to switch occupations

Sector share of labor force (%)[1] / Additions, net of automation (Million)



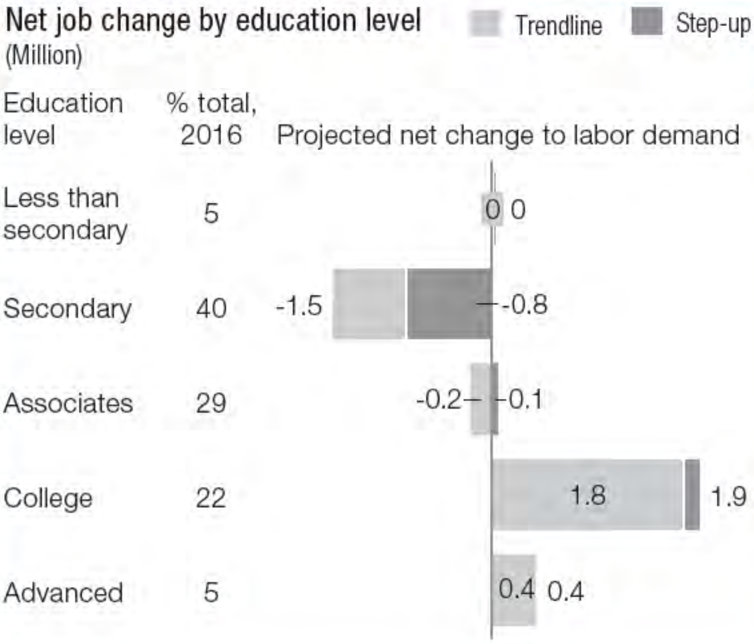
Number of workers displaced by automation, and those needing to change occupational categories[2]

Midpoint automation	Rapid automation
9M displaced	17M displaced
3M changing occupations	12M changing occupations

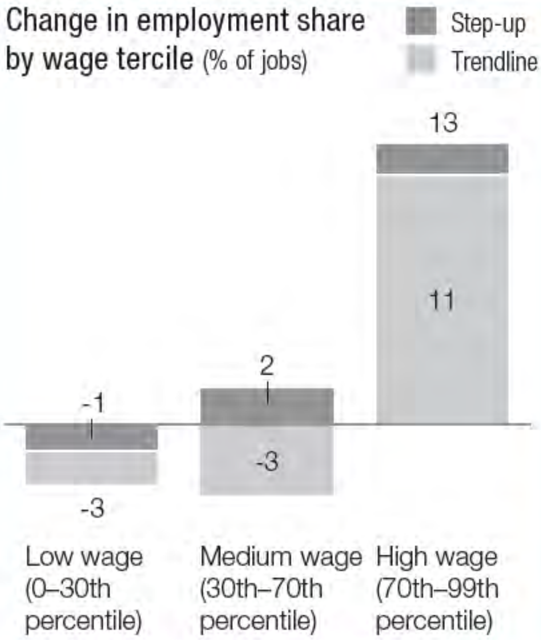
Up to 32% of the 2030 workforce may need to switch occupational groups

Job change by education and wage level, 2016–30[3] (midpoint automation)

Net job change by education level (Million)



Change in employment share by wage tercile (% of jobs)



1 Step-up scenario, midpoint automation, not all sectors modeled in labor demand catalysts (e.g., government).
2 "Transition" = switch occupation groups or gain new skills. Numbers given are trendline – step-up scenario.
3 Educational analysis based on current educational requirements. Employment analysis based on current wages.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

India

India is expected to continue industrializing as its economy shifts away from agriculture. As GDP per capita continues to expand amid rapid growth of the labor force, many of India's jobs of the future will be driven by construction and the consumption habits of the expanding middle class.

Economics and demographic context

Demographics
5% over 65 years of age in today's population, and growing to 8% by 2030

Economic development
5.4% GDP per capita growth, annualized 2016–30

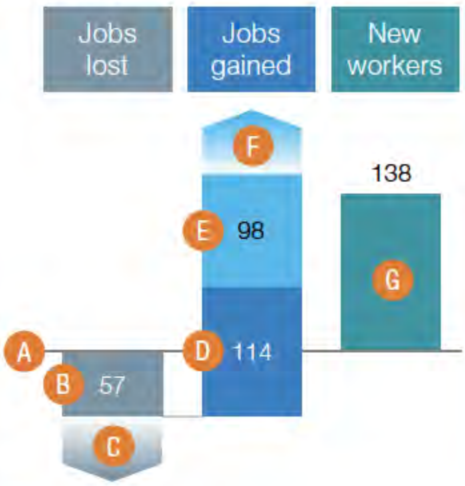
Wages
$4,800 average annual wage

Automation potential
9% of current work activity hours automated by 2030 in the midpoint scenario, and up to 19% in the rapid scenario

Jobs lost, jobs gained

Net change in jobs by 2030 (Million)

Enough jobs are created in the step-up scenario to offset both automation and the growth in labor force



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- C Jobs displaced by automation by 2030 in the rapid scenario
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- E Jobs created by 2030 in the step-up scenario
- F New occupations and unsized labor demand[1]
- G Change in labor force by 2030

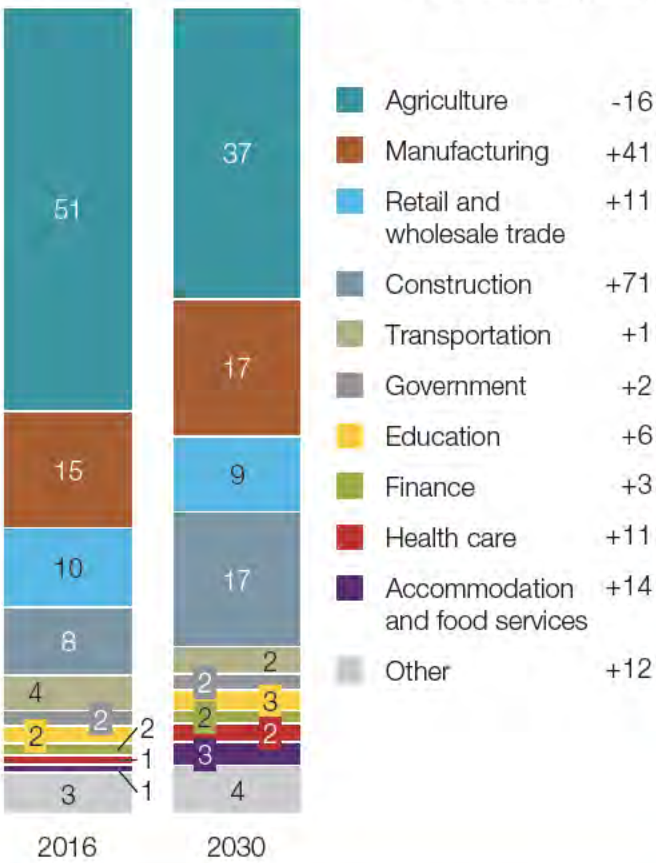
Growth/decline of occupation types by 2030

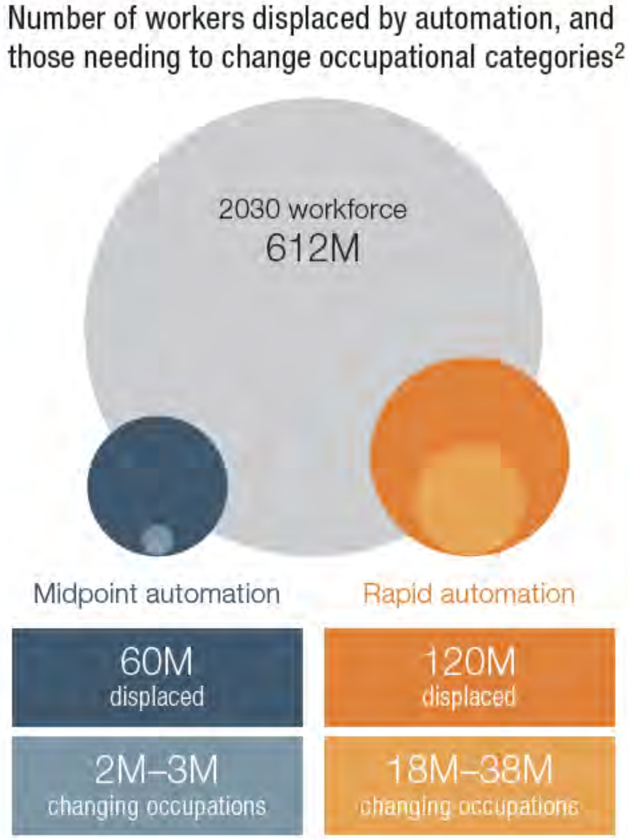
Occupation type *Examples*	Net change in jobs (midpoint automation, step-up scenario)[2] Million	% of jobs 2016	% of jobs 2030
Builders *Construction workers, electricians*	60.0	11	18
Other jobs, predictable environments *Machinists, cooks*	28.3	30	27
Customer interaction *Retail sales, bartenders*	22.7	10	11
Care providers *Surgeons, nurses*	12.8	1	3
Other jobs, unpredictable environments *Farmworkers, firefighters*	10.8	40	32
Educators *Teachers, librarians*	8.0	1	2
Managers and executives *CEOs, sales managers*	5.9	2	2
Office support *Payroll clerks, data entry*	3.0	3	3
Professionals *Lawyers, business specialists*	2.8	1	1
Technology professionals *Web developers, IT*	1.2	0	0
Creatives *Authors, designers*	0.6	0	0

1 Historical analysis suggests that we could expect 8-9% of 2030 labor supply will be in "new jobs" relative to today, which is additional to what we have estimated.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

Sector and occupation shifts

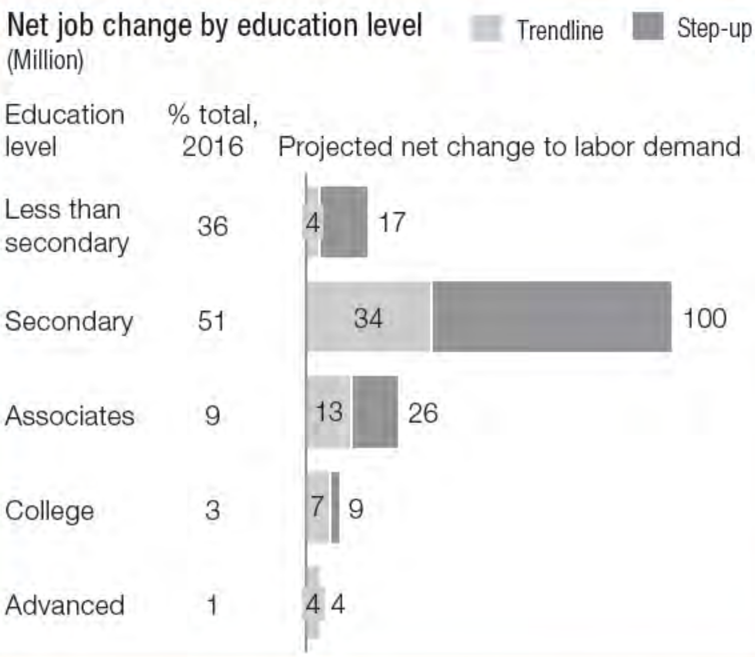
With automation and the labor demand catalysts, workers may need to switch occupations

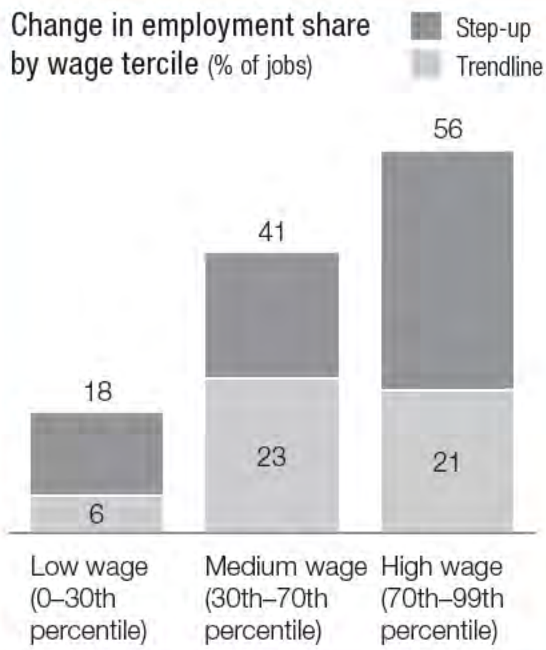




Up to 6% of the 2030 workforce may need to switch occupational groups

Job change by education and wage level, 2016–30[3] (midpoint automation)





1 Step-up scenario, midpoint automation, not all sectors modeled in labor demand catalysts (e.g., government).
2 "Transition" = switch occupation groups or gain new skills. Numbers given are trendline – step-up scenario.
3 Educational analysis based on current educational requirements. Employment analysis based on current wages.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

Japan

Japan's sector mix and relatively high wages will speed automation adoption, while relatively slow GDP per capita growth could dampen labor demand. The decline in the working-age population will act as a countervailing force, but a step-up scenario of job creation will be needed to sustain future employment.

Economics and demographic context

Demographics
26% over 65 years of age in today's population, and growing to 30% by 2030

Economic development
1.0% GDP per capita growth, annualized 2016–30

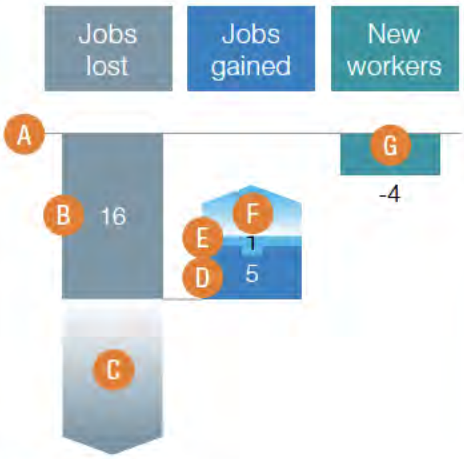
Wages
$31,300 average annual wage

Automation potential
26% of current work activity hours automated by 2030 in the midpoint scenario, and up to 52% in the rapid scenario

Jobs lost, jobs gained

Net change in jobs by 2030 (Million)

Enough jobs are created in the step-up scenario to offset automation and the decline in the labor force, if innovation creates sufficient new work activities



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- D Jobs created by 2030 in the trendline scenario
- E Jobs created by 2030 in the step-up scenario
- F New occupations and unsized labor demand[1]
- G Change in labor force by 2030

Growth/decline of occupation types by 2030

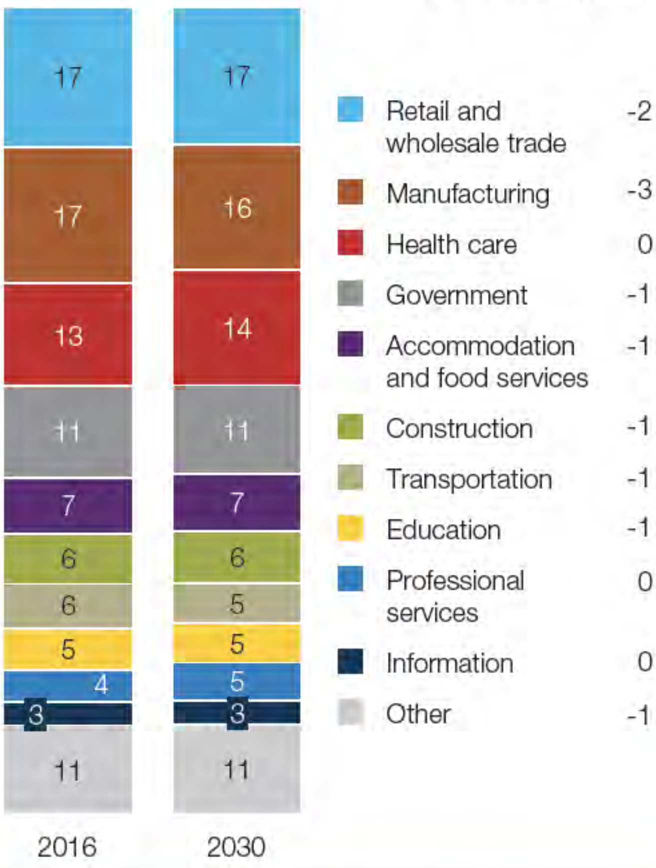
Occupation type *Examples*	Net change in jobs (midpoint automation, step-up scenario)[2] Million	% of jobs 2016	% of jobs 2030
Professionals *Lawyers, business specialists*	0.1	3	4
Technology professionals *Web developers, IT*	0.1	1	1
Managers and executives *CEOs, sales managers*	0	3	3
Creatives *Authors, designers*	0	1	1
Care providers *Surgeons, nurses*	-0.1	10	12
Educators *Teachers, librarians*	-0.1	3	3
Other jobs, unpredictable environments *Farmworkers, firefighters*	-0.2	9	10
Builders *Construction workers, electricians*	-0.5	5	5
Customer interaction *Retail sales, bartenders*	-2.0	25	26
Office support *Payroll clerks, data entry*	-2.7	18	17
Other jobs, predictable environments *Machinists, cooks*	-4.5	23	19

1 Historical analysis suggests that we could expect 8-9% of 2030 labor supply will be in "new jobs" relative to today, which is additional to what we have estimated.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

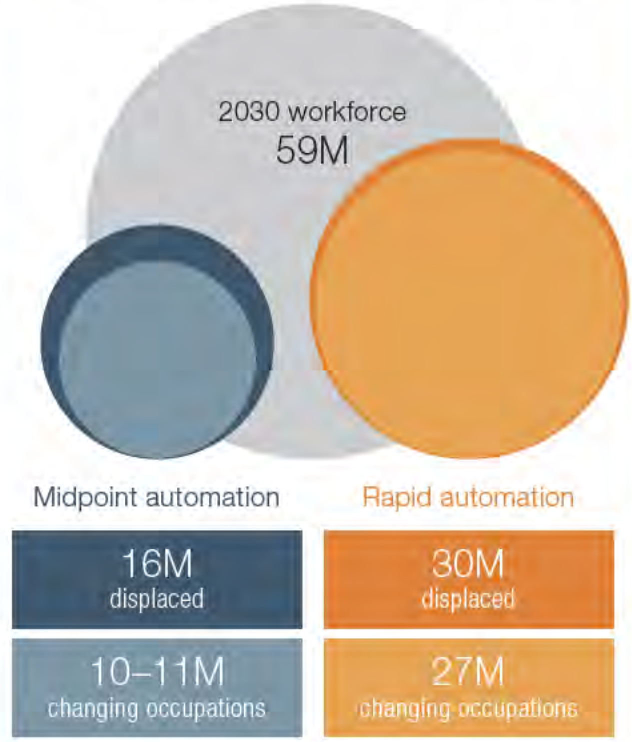
Sector and occupation shifts

With automation and the labor demand catalysts, workers may need to switch occupations

Sector share of labor force (%)[1] / Additions, net of automation (Million)



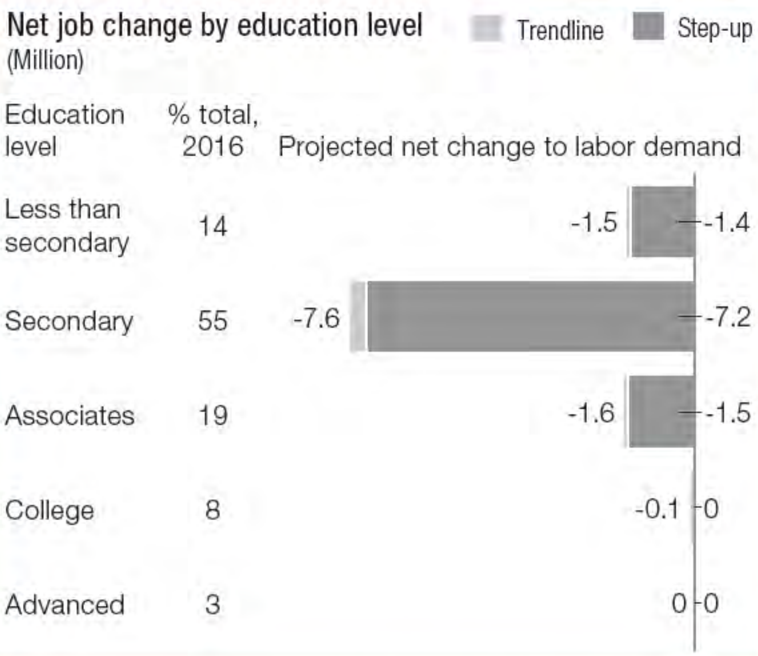
Number of workers displaced by automation, and those needing to change occupational categories[2]



Up to 46% of the 2030 workforce may need to switch occupational groups

Job change by education and wage level, 2016–30[3] (midpoint automation)

Net job change by education level (Million)



Change in employment share by wage tercile (% of jobs)

1 Step-up scenario, midpoint automation, not all sectors modeled in labor demand catalysts (e.g., government).
2 "Transition" = switch occupation groups or gain new skills. Numbers given are trendline – step-up scenario.
3 Educational analysis based on current educational requirements. Employment analysis based on current wages.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

Mexico

Mexico has a young population and a growing workforce. Mid- to low-wage levels may slow automation adoption, while comparatively low GDP growth may temper growth in labor demand. The step-up scenario will create enough labor demand to offset the effects of both automation and demographics.

Economics and demographic context

Demographics
6% over 65 years of age in today's population, and growing to 10% by 2030

Economic development
1.3% GDP per capita growth, annualized 2016–30

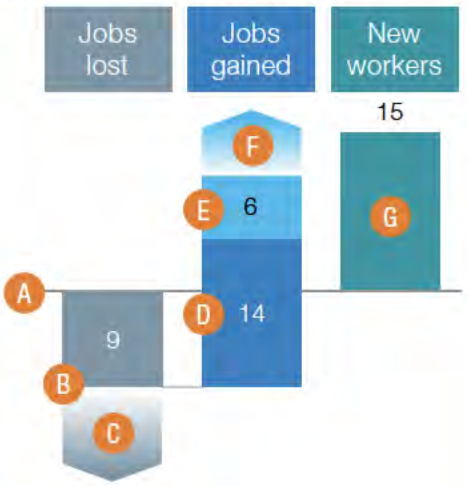
Wages
$9,000 average annual wage

Automation potential
13% of current work activity hours automated by 2030
in the midpoint scenario, and up to 26% in the rapid scenario

Jobs lost, jobs gained

Net change in jobs by 2030 (Million)

Enough jobs are created in the **step-up scenario** to offset automation and the growth in labor force, given innovation in new work activities



- A 2016 baseline
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- D Jobs created by 2030 in the trendline scenario
- E Jobs created by 2030 in the step-up scenario
- F New occupations and unsized labor demand[1]
- G Change in labor force by 2030

Growth/decline of occupation types by 2030

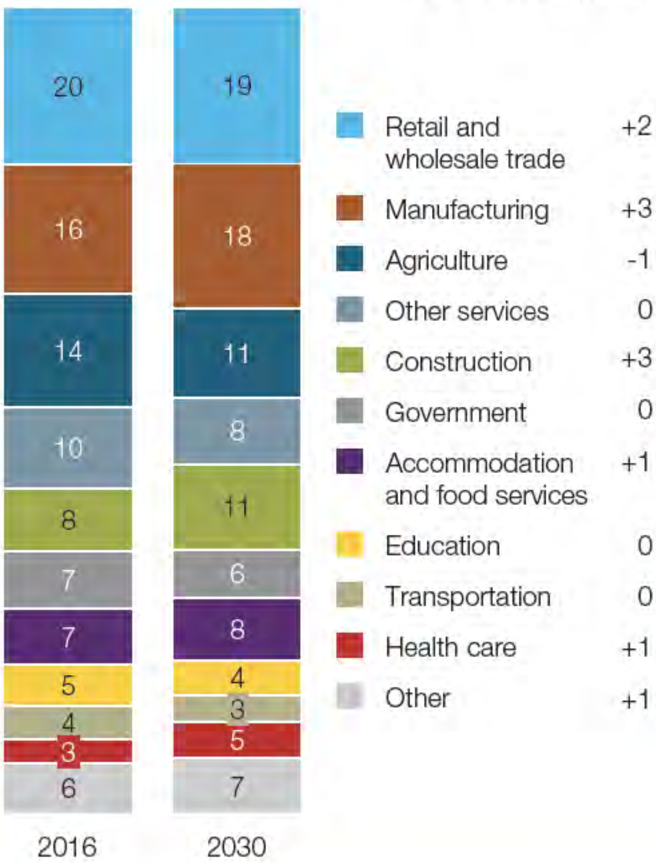
Occupation type *Examples*	Net change in jobs (midpoint automation, step-up scenario)[2] Million	% of jobs 2016	% of jobs 2030
Customer interaction *Retail sales, bartenders*	2.7	35	34
Builders *Construction workers, electricians*	1.7	7	8
Other jobs, predictable environments *Machinists, cooks*	1.7	25	24
Care providers *Surgeons, nurses*	1.6	4	5
Other jobs, unpredictable environments *Farmworkers, firefighters*	0.8	16	15
Office support *Payroll clerks, data entry*	0.7	6	6
Professionals *Lawyers, business specialists*	0.4	3	3
Managers and executives *CEOs, sales managers*	0.4	3	3
Educators *Teachers, librarians*	0.2	1	1
Technology professionals *Web developers, IT*	0.1	1	1
Creatives *Authors, designers*	0.1	0	0

1 Historical analysis suggests that we could expect 8-9% of 2030 labor supply will be in "new jobs" relative to today, which is additional to what we have estimated.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

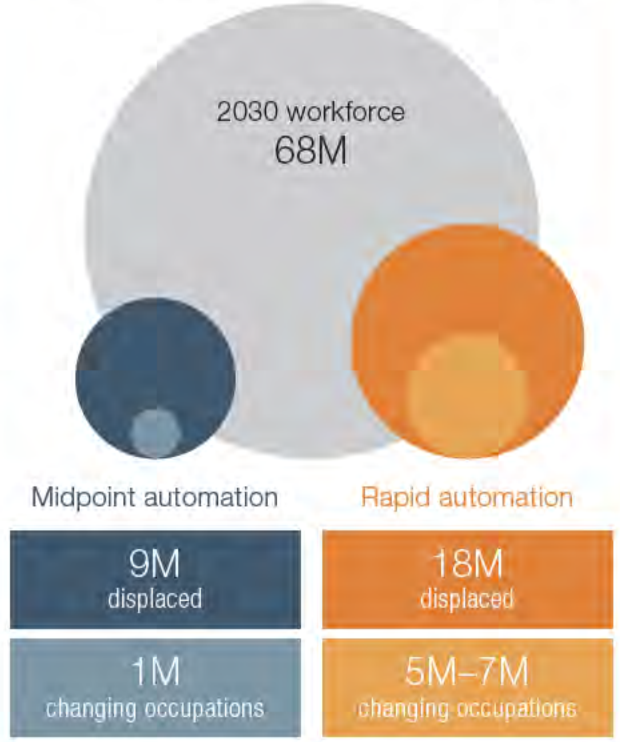
Sector and occupation shifts

With automation and the labor demand catalysts, workers may need to switch occupations

Sector share of labor force (%)[1] — Additions, net of automation (Million)



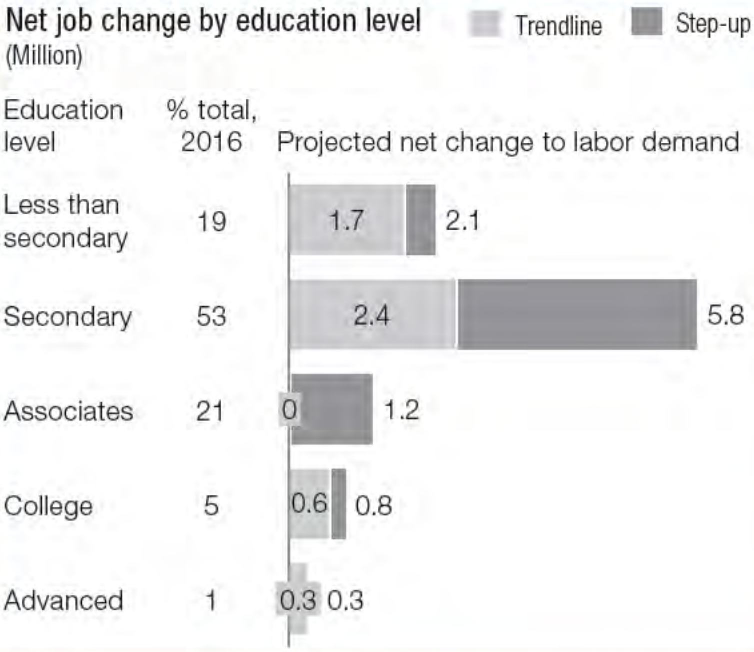
Number of workers displaced by automation, and those needing to change occupational categories[2]



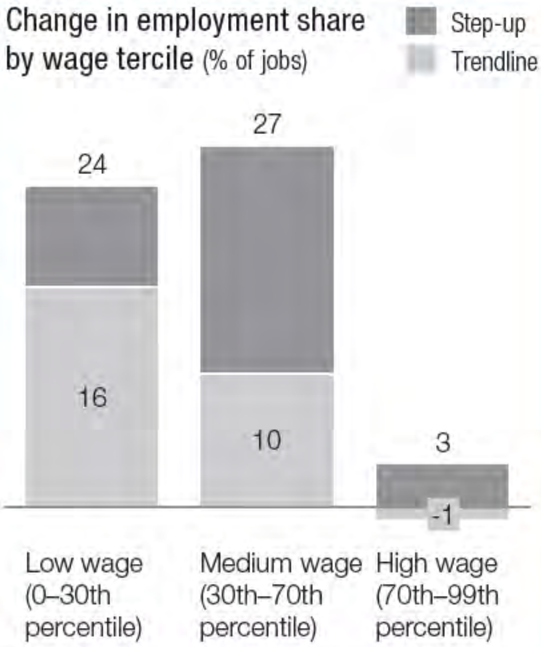
Up to 10% of the 2030 workforce may need to switch occupational groups

Job change by education and wage level, 2016–30[3] (midpoint automation)

Net job change by education level (Million)



Change in employment share by wage tercile (% of jobs)



1 Step-up scenario, midpoint automation, not all sectors modeled in labor demand catalysts (e.g., government).
2 "Transition" = switch occupation groups or gain new skills. Numbers given are trendline – step-up scenario.
3 Educational analysis based on current educational requirements. Employment analysis based on current wages.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

United States

Automation adoption will likely be significant in the United States, even as steady projected GDP per capita growth drives new labor demand. While labor demand will enable employment of displaced workers in the step-up scenario, up to one-third of the workforce may need to change occupational categories.

Economics and demographic context

Demographics
14% over 65 years of age in today's population, and growing to 21% by 2030

Economic development
1.3% GDP per capita growth, annualized 2016–30

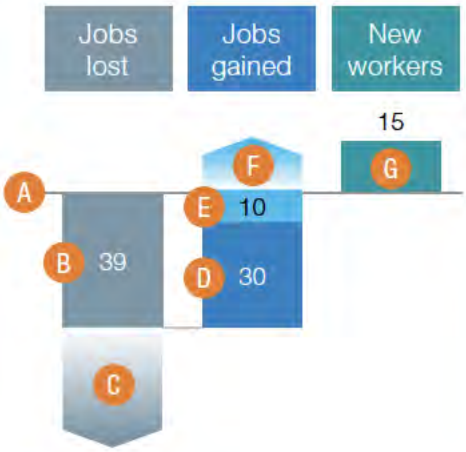
Wages
$44,700 average annual wage

Automation potential
23% of current work activity hours automated by 2030 in the midpoint scenario, and up to 44% in the rapid scenario

Jobs lost, jobs gained

Net change in jobs by 2030 (Million)

Enough jobs are created in the **step-up scenario** (along with growth in new occupations) to offset both automation and the growth in labor force



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- F New occupations and unsized labor demand[1]
- G Change in labor force by 2030

Growth/decline of occupation types by 2030

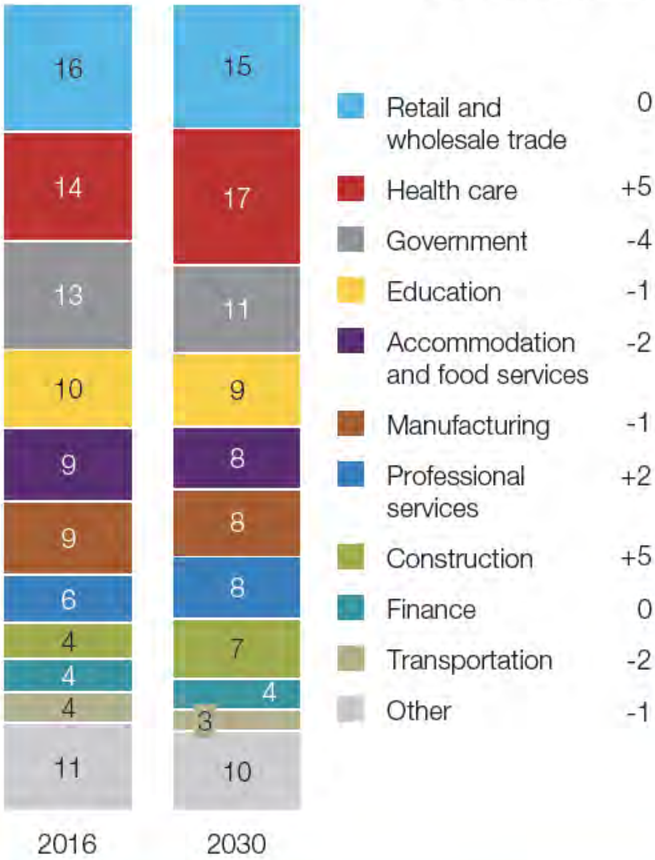
Occupation type *Examples*	Net change in jobs (midpoint automation, step-up scenario)[2] Million	% of jobs 2016	% of jobs 2030
Care providers *Surgeons, nurses*	4.9	11	14
Builders *Construction workers, electricians*	2.7	5	7
Professionals *Lawyers, business specialists*	1.7	11	12
Managers and executives *CEOs, sales managers*	1.1	5	6
Other jobs, unpredictable environments *Farmworkers, firefighters*	1.0	10	11
Technology professionals *Web developers, IT*	1.0	2	3
Educators *Teachers, librarians*	0.8	6	7
Creatives *Authors, designers*	0.2	1	1
Customer interaction *Retail sales, bartenders*	-0.4	18	18
Office support *Payroll clerks, data entry*	-4.6	15	12
Other jobs, predictable environments *Machinists, cooks*	-6.6	15	10

1 Historical analysis suggests that we could expect 8-9% of 2030 labor supply will be in "new jobs" relative to today, which is additional to what we have estimated.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

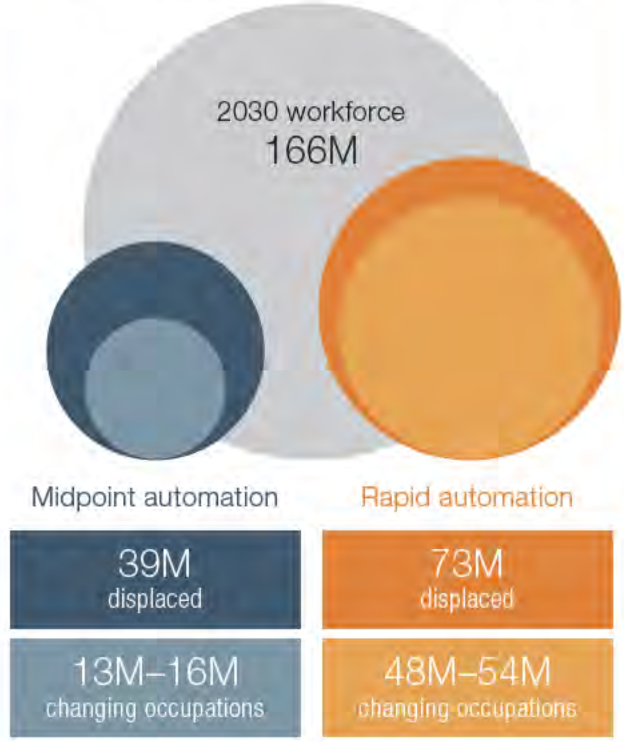
Sector and occupation shifts

With automation and the labor demand catalysts, workers may need to switch occupations

Sector share of labor force (%)[1] / Additions, net of automation (Million)



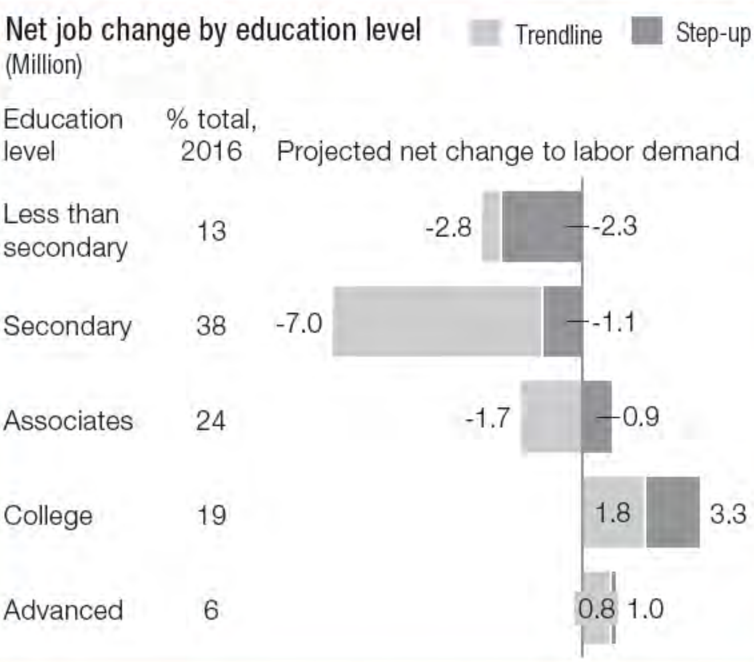
Number of workers displaced by automation, and those needing to change occupational categories[2]



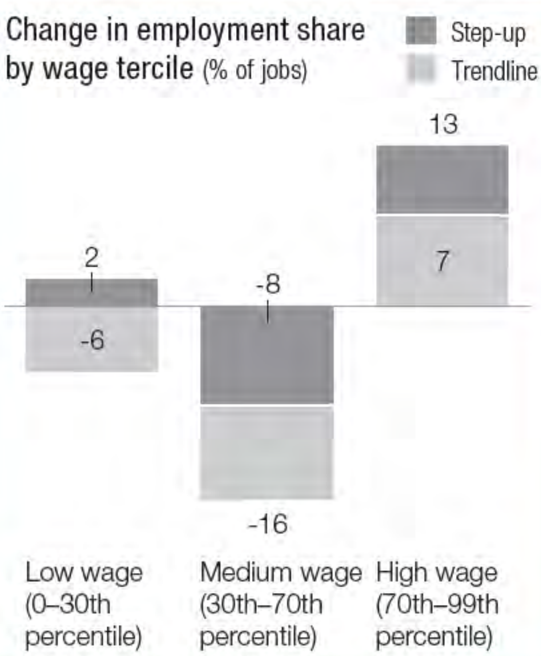
Up to 33% of the 2030 workforce may need to switch occupational groups

Job change by education and wage level, 2016–30[3] (midpoint automation)

Net job change by education level (Million)



Change in employment share by wage tercile (% of jobs)



1 Step-up scenario, midpoint automation, not all sectors modeled in labor demand catalysts (e.g., government).
2 "Transition" = switch occupation groups or gain new skills. Numbers given are trendline – step-up scenario.
3 Educational analysis based on current educational requirements. Employment analysis based on current wages.
NOTE: Some occupational data projected into 2016 baseline from latest available 2014 data.
SOURCE: McKinsey Global Institute analysis

Office workers in the state of Washington, United States
© Thomas Barwick/ DigitalVision/Getty Images

5. MANAGING THE WORKFORCE TRANSITIONS

Brace yourself. All countries will face large-scale workforce transitions over the next 15 years as automation displaces some workers and labor demand shifts. Enabling and smoothing these transitions will be a significant challenge for policy makers and business leaders. Some policy choices could substantially improve the employment outcomes, including speeding reemployment. Indeed, it may take a Marshall Plan-scale initiative of sustained investment by the public and private sectors in new training models and workforce transition programs to address all the social, political, and economic issues that automation will raise.

In this chapter, we discuss four priorities that could make a critical difference: maintaining robust economic growth to support job creation; scaling up workforce retraining and skill development programs, particularly for midcareer workers; improving labor market dynamism; and providing income and transition support to displaced workers. We explore some of the choices that could be considered and cite examples of successful interventions. These ideas should not be taken as exhaustive or prescriptive, but rather as prompts to spur discussion and new ideas. Specific choices will vary based on country circumstances and societal choices.

MAINTAINING ROBUST ECONOMIC GROWTH AND INNOVATION TO SUPPORT JOB CREATION

The starting point is an economic one: sustaining robust aggregate demand growth is essential for enabling employment growth. Economies that are not expanding do not create new jobs. Indeed, the experience of the past decade has underscored the lingering negative employment effects of insufficient demand.

Appropriate fiscal and monetary policies can be deployed to ensure that demand growth is vibrant, and it goes beyond the scope of this report to catalog the appropriate macroeconomic policies. Nonetheless, the importance of sustaining demand growth cannot be overemphasized. Much has also been written about potential ways to encourage innovation and entrepreneurship, from investments in research and development and human capital, to investment capital, and lowered barriers to entry for innovative businesses.[104] Supporting innovation and technological diffusion is critical, including the adoption of automation technologies themselves, as these advances are the fundamental source of long-run productivity, growth, and prosperity, as well as the creation of new business models, occupations, and work activities. To do so will require an effective and balanced system for encouraging the development and deployment of intellectual property, a high-skill scientific and engineering workforce, and public or private funding for basic research and its commercialization. New business creation, start-up communities, and dynamic firm entry and exit are also essential.[105] For small cities that lack a diversified economy and where the principal employer leaves, more holistic economic revival plans are needed.[106]

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[104] See, for instance, Brad Feld, *Startup communities: Building an entrepreneurial ecosystem in your city*, Wiley, October 2012 and Enrico Moretti, *The new geography of jobs*, Mariner Books, March 2013.

[105] See *Making it in America*, McKinsey Global Institute, June 2017.

[106] See Amy Goldstein, *Janesville: An American story*, Simon & Schuster, 2017.

Actions can be taken not only at the national level, but also locally. MGI studies of cities around the world, along with a growing body of academic research, illustrate the vast differences in economic growth and prosperity that arise among cities and regions of the same country.[107] The last 20 years of globalization and technological change have resulted in many communities in the United States and Europe suffering large-scale job losses—but some of these communities have also shown that reviving growth through knowledge-based economies is possible. A common pattern emerges: harnessing intellectual capital, often found in universities, with private sector R&D and local governments willing to ensure workforce training to meet the new demand.[108]

Many policymakers, in both advanced and developing countries such as India, worry about "jobless growth."[109] Since the 2008 global financial crisis, it has become clear that not all sources of GDP growth have an equal impact on employment creation. Growth in industries that are heavily capital-intensive or those that are highly automated will not have the same impact on job creation. To support broad-based job creation, some countries may provide incentives to labor-intensive service sectors, such as health care, education, and construction. Targeted initiatives may also be used. Catalyzing public and private investment for infrastructure, including the housing and commercial buildings needed in urbanizing countries in the developing world, not only supports long-term economic growth but also has the potential to create large-scale employment in the near-term. Supporting measures to shift energy to renewable sources, manage and mitigate climate change, and boost energy efficiency through increased digitization of the sector likewise have global economic benefits while boosting near-term employment. The step-up scenario we outline in Chapter 3 reflects the potential impact of these types of "no-regret" initiatives; we estimate that roughly 150 million to 300 million jobs could be created incrementally on top of the trendline scenario jobs as a result. Importantly, these initiatives create many middle-skill jobs, such as those for electricians, carpenters, crane operators, and other trades.

In prior research, we examined the critical role of migration and gender parity, both of which amount to low-cost ways to boost aggregate demand in the short- and medium-term. For example, as much as 70 percent of population growth in urban areas going forward could come from migration—with key challenges on how migrants can be integrated effectively.[110]

SCALING UP JOB RETRAINING AND WORKFORCE SKILL DEVELOPMENT

Providing job retraining and enabling individuals to learn marketable new skills throughout their lifetimes will be a central challenge for some countries over the next decade and beyond. As we have shown in this report, hundreds of millions of people will likely need to find new jobs as automation advances, and even more will need to learn new skills, including how to work seamlessly with machines.

In recent years, some countries have experienced significant challenges in trying to create the conditions in which workers displaced by globalization and technology quickly find new high-quality employment. The result for many individuals has been a series of lower-wage jobs with limited opportunities for advancement and lower rates of labor market

107 *Urban world: Mapping the economic power of cities*, McKinsey Global Institute, March 2011; Ibid. Enrico Moretti, *The new geography of jobs*, March 2013.

108 Antoine van Agtmael and Fred Bakker, *The smartest places on Earth: Why rustbelts are the emerging hotspots of global innovation*, PublicAffairs, March 2016.

109 *Asian experience on growth, employment and poverty: An overview with special reference to the findings of some recent case studies*, UNDP and International Labour Organization, January 2007.

110 Ibid. *The power of parity*, McKinsey Global Institute, September 2015, and *People on the move: Global migration's impact and opportunity*, McKinsey Global Institute, December 2016.

participation.[111] The social consequences can be dire.[112] The challenge for the next decades will be to create effective workforce retraining programs at scale. This could require actions by policy makers, business leaders, and educators, as well as individuals.

History offers examples of large-scale programs to improve the skills of workers

At a time when millions of individuals will need new skills, public funding for job training programs is falling in many countries (Exhibit 27).[113] Between 1993 and 2015, spending on workforce training programs as a percent of GDP fell from 0.08 percent to 0.03 percent in the United States, while Japanese spending dropped from 0.03 percent to 0.01 percent. In Germany—still one of the larger spenders—outlays for training fell from 0.57 percent of GDP to 0.2 percent.

Nonetheless, we can find examples of societies, past and present, which have chosen to invest in education and workforce training, with impressive results. The United States provides examples of two at-scale investments in the past century: the US High School Movement (1910 to 1940), which made attending secondary school the norm for all children, and the 1944 GI Bill, which enabled millions of returning war veterans to obtain a tertiary education (see Box 6, "The US High School Movement and the GI Bill dramatically raised educational attainment of American workers"). Academic researchers have found that the sizable human capital increases enabled by these programs account for a measurable share of the rise in incomes over those decades, creating a large and increasingly affluent American middle class.[114]

120K
Number of workers in Singapore who have used a government initiative to upgrade skills

More recently, Singapore implemented an innovative form of support aimed at upgrading skills as part of its efforts to promote growth and competitiveness in 23 industries.[115] Through the "SkillsFuture Initiative," introduced by the Ministry of Education in January 2016, the government provides all Singaporeans aged 25 and above credit of about $400, to pay for approved work-skills related courses. More than 18,000 such courses are available, and as of December 2016, more than 120,000 people—some 4 percent of the resident population aged 25 and above—had used the initiative to take courses, more than 60 percent of them over 40.[116]

Businesses can play a significant role in training and retraining workers

Companies also have a significant role to play in training and retraining workers. This goes beyond a purely social role or sense of civic responsibility: business leaders will be on the front lines of automation and will have the earliest and most detailed knowledge about what types of skills they will need as they move to adopt the technologies. In the United States, some companies are working directly with education providers to give employees an opportunity to raise their educational and skill levels (see Box 7, "Some US companies are working with educational providers, even as spending on corporate training declines").

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[111] See, for instance, David H. Autor, David Dorn, and Gordon H. Hanson, "The China shock: Learning from labor-market adjustment to large changes in trade," *Annual Review of Economics*, volume 8, October 2016.

[112] In the United States, for example, some studies show declining life expectancy for white US citizens under age 50, reflecting a surge in death from suicide, drug addiction, and alcoholism. Anne Case and Angus Deaton, "Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century," *Proceedings of the National Academy of Sciences of the United States of America*, volume 112, number 49, December 2015.

[113] *Public spending on labor markets*, OECD Data, 2017.

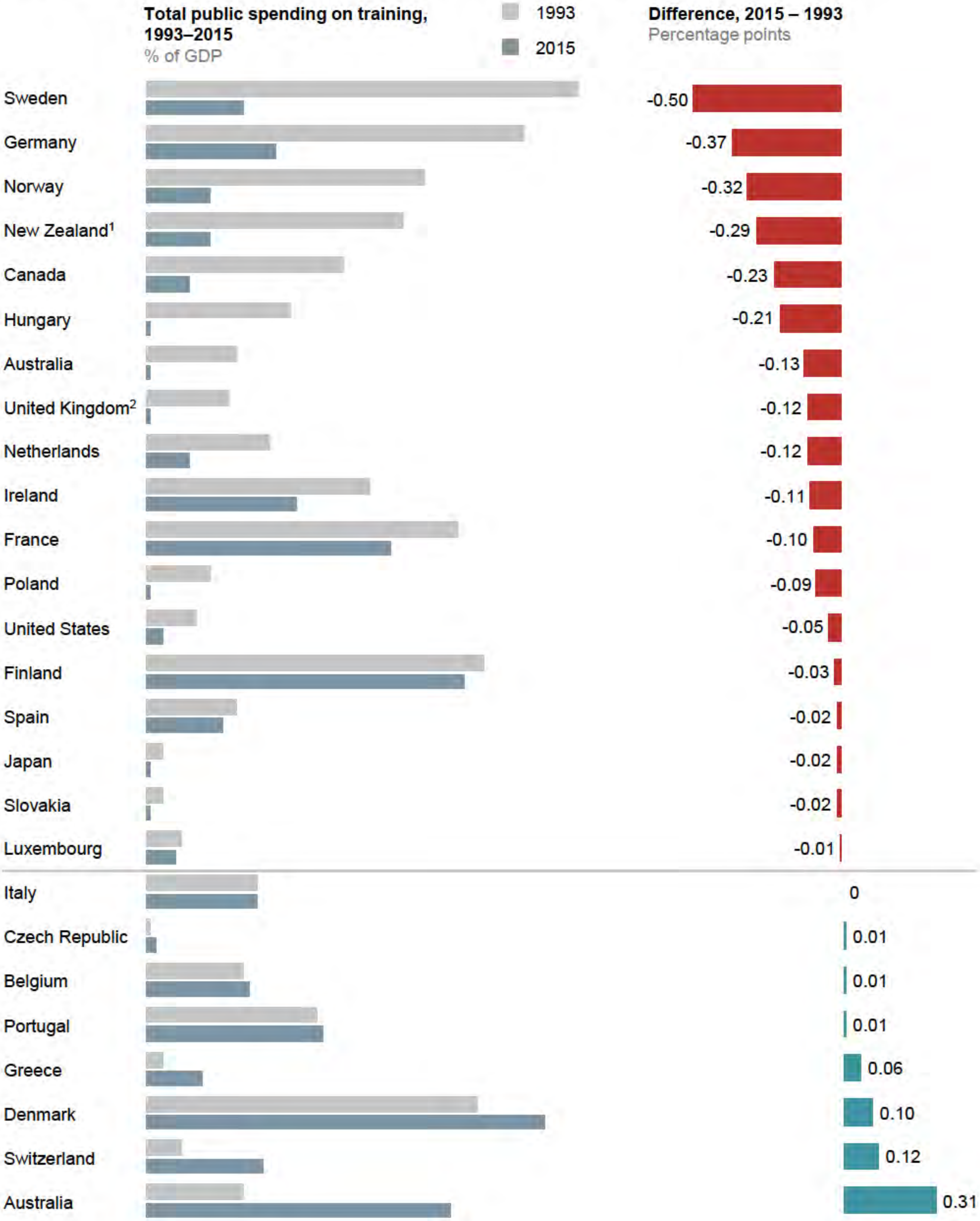
[114] Suzanne Mettler, *Soldiers to citizens: The GI Bill and the making of the greatest generation*, Oxford University Press, 2005.

[115] The overall program is known as Industry Transformation Maps, and skills upgrades are an integral part of it. See www.skillsfuture.sg.

[116] *Steady progress in implementation of SkillsFuture credit*, SkillsFuture factsheet, January 8, 2017.

Exhibit 27

Most OECD countries have been spending less on worker training over the past 20+ years



1 2014 data used for New Zealand.
2 2011 data used for United Kingdom.
NOTE: Countries where 1993 data was not available omitted Not to scale.

SOURCE: OECD; McKinsey Global Institute analysis

Box 6. The US High School Movement and the GI Bill dramatically raised educational attainment of American workers

The US High School Movement (1910 to 1940) propelled a sharp increase in high school enrollment and graduation rates, making a high school qualification the norm.[1]

In 1910, most students left education after primary school to work in agriculture or other low-skill jobs. Those who attended high school did so primarily to gain entrance to college. However, the economy had begun producing large numbers of jobs in cities that demanded a formal education beyond primary school. This demand led to a grassroots movement: more high schools were built and the curriculum shifted from teaching skills "for college" to skills "for life." Vocational (including commercial), technical or manual, and industrial courses were rapidly incorporated into most high school curricula.

Secondary school enrollment increased spectacularly, from 18 percent in 1910 to 73 percent in 1940. Graduation rates for 17-year-olds rose from 9 percent to 51 percent in the same period (Exhibit 28).

Higher educational attainment had an impact on incomes. On an aggregate level, national incomes per worker grew annually at a 1.48 percent average from 1929 to 1982. One study attributes 28 percent of the economic growth to human capital accumulation and technological progress, with changes at the secondary school level being quantitatively the most significant driver to the increased educational stock of Americans in the first three-quarters of the 20th century.[2]

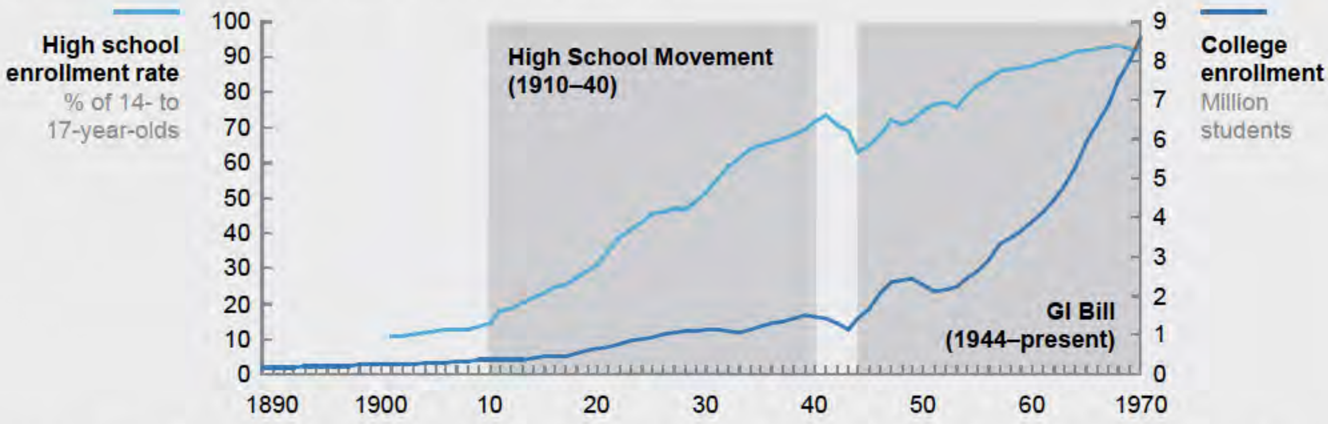
The GI Bill of 1944, created to help integrate World War II veterans back into civilian life, was instrumental in making a college education mainstream.[3] Studies estimate that 1.4 million people-years of undergraduate training had been lost because of the war.[4] The bill provided all veterans dedicated payments of tuition and living expenses to attend high school, college, or vocational or technical school. By 1956, just under eight million veterans had used the GI Bill educational benefits, with 2.2 million attending colleges or universities and an additional 5.6 million engaging in some kind of training program.[5] In all, just over half of all veterans tapped the education benefits in some form, greatly exceeding the government's projections.[6] Veterans accounted for as many as 49 percent of all enrolled students at colleges and universities—and created demand for growth of a world-class university system.[7]

The GI Bill also changed perceptions about college attendance, making it accessible to the average person and not simply reserved for an elite.

Exhibit 28

The High School Movement and GI Bill significantly raised education and skill levels in the United States

Evolution of high school and college enrollment, 1890–1970



SOURCE: Claudia Goldin, "America's graduation from high school: The evolution and spread of secondary schooling in the twentieth century," *Journal of Economic History*, volume 58, number 2, June 1998; National Center for Education Statistics; McKinsey Global Institute analysis

1 Ibid. Claudia Goldin, "America's graduation from high school," June 1998.
2 Ibid.
3 Michael J. Bennett, *When dreams came true: The GI Bill and the making of modern America*, Brassey's Publishing Co., 1996.
4 Roger M. Shaw, "The GI challenge to the colleges," *Journal of Higher Education*, volume 18, 1947.
5 Ibid. Milton Greenberg, "How the GI Bill Changed Higher Education," June 18, 2004.
6 Keith W. Olson, "The G. I. Bill and Higher Education: Success and Surprise," *American Quarterly*, volume 25, number 5, December 1973.
7 Ibid. Milton Greenberg, "How the GI Bill Changed Higher Education," June 18, 2004.

Box 7. Some US companies are working with educational providers, even as spending on corporate training declines

Spending on corporate training in the United States has been declining for decades, along with public spending on workforce training (Exhibit 29).[1]

Against that background, some employers have begun offering educational assistance and programs to their workforces to fill current gaps in skills needed or in response to a looming number of retirees. For example, AT&T has partnered with Georgia Tech to provide opportunities for all employees to enroll in the university's online computer science program, which AT&T helped set up. AT&T's move was aimed at bridging a skills gap: internal projections suggested that 95 percent of the 135,000 employees in its technology and services unit would need training in STEM subjects—science, technology, engineering, and mathematics—whereas only 50 percent had such training in 2013.[2] AT&T offers scholarships to all employees to attend classes, pays tuition, and enables employees who did not go to a brick-and-mortar university to improve their technical skills. In 2014, about 18 percent of the 1,268 students enrolled in Georgia Tech's computer science master's program were AT&T employees.[3]

Walmart, the world's largest private-sector employer with a global workforce of nearly 2.5 million, is conducting training and retraining of its US employees in-house, through its Walmart Academy. This is one of the largest employer training programs in the United States. The company expects to train more than 225,000 associates by the end of 2017, using both experiential, on-the-floor training and traditional classroom instruction.[4]

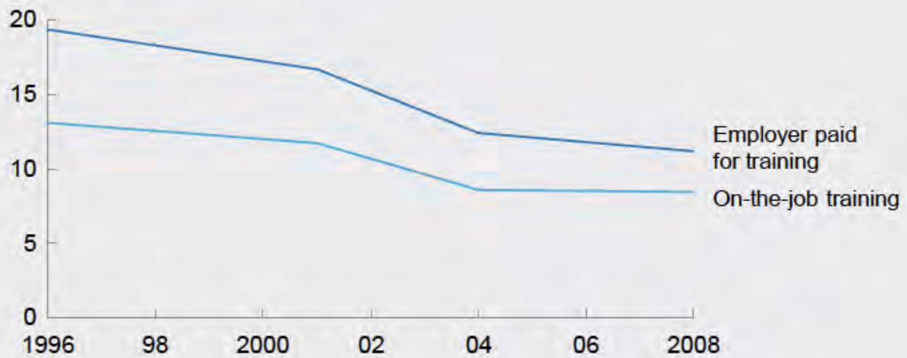
Other companies offer broader educational assistance for employees to attain any degree, whether it is linked to the company or not. For instance, Starbucks has entered a partnership with Arizona State University that provides an opportunity for all eligible employees to earn their bachelor's degree with full tuition coverage all the way to graduation through ASU's online degree program.[5] Amazon, through its Career Choice program, reimburses 95 percent of tuition, fees, and materials of its hourly associates with as little as one continuous year of tenure for a wide array of accredited degree programs.[6]

Some employers are working together with educators to train young workers for jobs in high-growth areas including technology, health care, and customer service.[7]

Exhibit 29

US workers receiving employer-sponsored or on-the-job training

Share of US workers receiving employer-sponsored or on-the-job training, 1996–2008
Fraction of workers ages 18–65 receiving training of any duration in the last year
%



SOURCE: 2015 Economic Report of the President; US Council of Economic Advisors; Census Bureau; Survey of Income and Program Participation (Employment and Training Topical Module); CEA calculations; McKinsey Global Institute analysis

1 This trend is not true in Europe, for example. See *Economic Report of the President* prepared by the US Council of Economic Advisers, February 2015, and Jean-François Mignot, "Continuing training for employees in Europe: The differences between countries continue to narrow" Céreq Training & Employment, July-August 2013.

2 Aaron Pressman, "Can AT&T retrain 100,000 people?" *Fortune*, March 13, 2017.

3 Natalie Kitroeff, "Why AT&T is investing in virtual school," *Bloomberg*, October 24, 2014.

4 Jacqui Canney, "The future of work is already here," LinkedIn, May 2, 2017; Michael Corkery, "At Walmart academy, training better managers. But with a better future?" *The New York Times*, August 8, 2017; Diane Stafford, "Inside Wal-Mart's new training sessions: Trying to adapt to retail landscape changes," *Chicago Tribune*, May 16, 2017.

5 "Starbucks offers full tuition reimbursement for employees to complete a bachelor's degree," Starbucks Newsroom, June 15, 2014, https://news.starbucks.com/news/starbucks-offers-full-tuition-reimbursement-for-employees-to-complete-a-bac

6 "Career choice," Amazon, https://www.amazon.com/p/feature/fsp92a2bhozr3wj

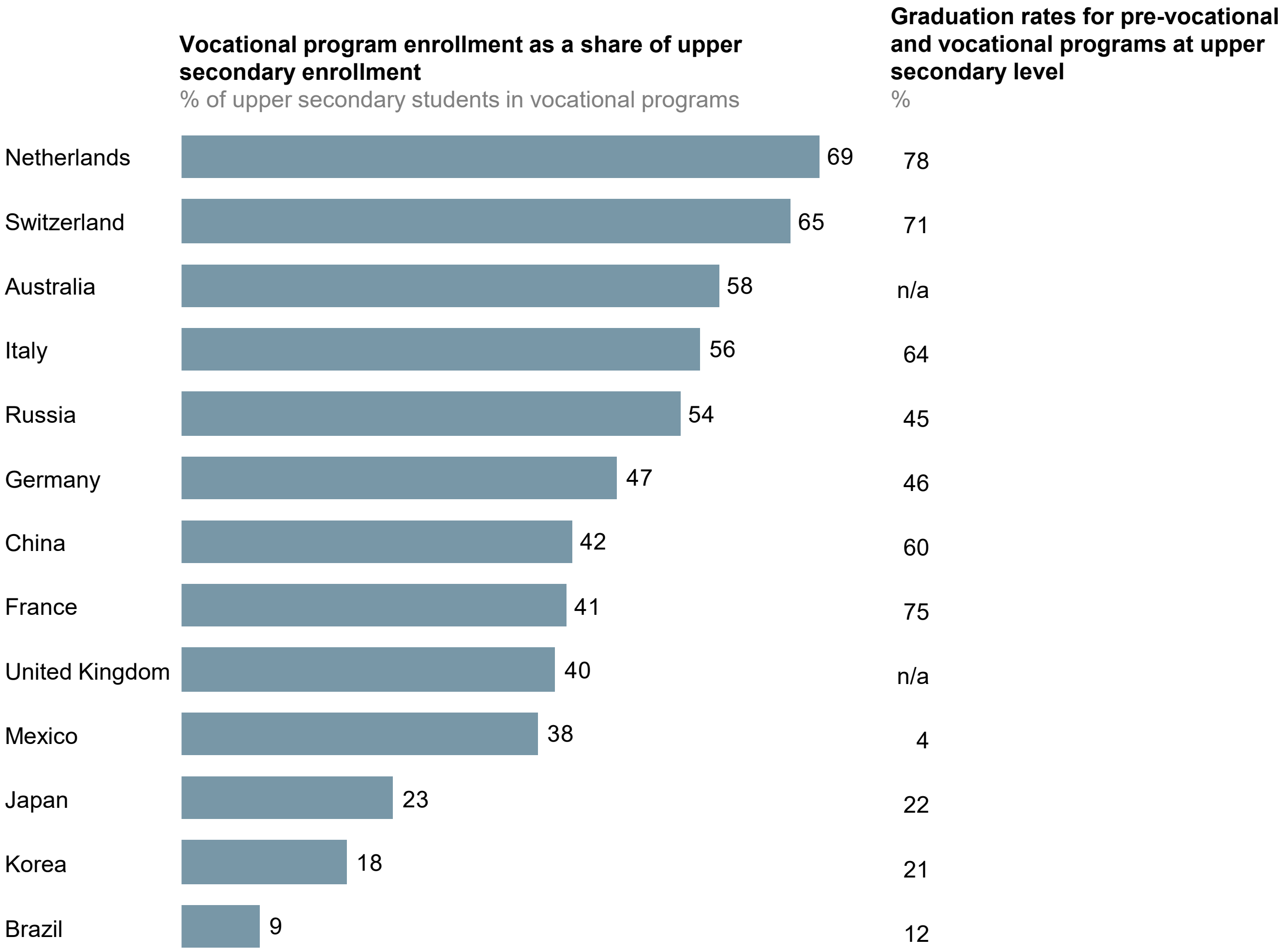
7 More than 10,000 youths have graduated globally from one such program, "Generation," founded by the McKinsey Social Initiative, a non-profit organization founded by McKinsey & Company, and supported by local and global funders including Walmart, USAID, and the European Commission. See Rana Foroohar, "US workforce: paying young Americans to learn the right skills," *Financial Times*, June 15, 2017.

Traditionally, educational degrees—especially in the fields of science, technology, engineering, and mathematics (STEM)—have acted as a signal of talent for job hiring. Lacking other markers of skills, many employees focused on whether candidates have multi-year, expensive degrees. As the workplace evolves, however, more granular and varied definitions of skills are emerging as critically important markers, more so even than a college education in some cases. This focus on an individual's skills rather than educational credentials is gaining momentum with companies, state governments, and nonprofit organizations. Markle Foundation, for example, has begun an initiative in Colorado to foster skills-oriented hiring, training, and education. Among companies supporting it, Microsoft has announced a grant of more than $25 million to support the program, known as Skillful.[117]

One intensive approach to corporate training programs merges on-the-job training with formal education through apprenticeships. These programs exist in many countries, although participation and graduation rates vary (Exhibit 30).

Exhibit 30

Vocational enrollment rates vary greatly by country, though the highest rates are found in developed countries



NOTE: Exact US vocational enrollment rates are not available from OECD; per the US National Center for Educational Statistics, ~1 million students are in vocational programs, with ~15 million total high school students. Data used is latest available, for 2012, except for Australia (2011).

SOURCE: OECD; McKinsey Global Institute analysis

[117] Steve Lohr, "A new kind of tech job emphasizes skills, not a college degree," *New York Times*, June 28, 2017.

Apprenticeships primarily benefit youth newly entering the workforce. Germany's "dual-system" apprenticeship program combining work- and school-based learning is the best known, and prepares students for a successful transition to full-time employment. Beginning in secondary school, students choose a vocational or a college-preparation track. Traditionally, this allocation was done through student test scores, but today there is more flexibility. Vocational students spend part of their time attending high school, learning the basic curriculum, and part of their time working and earning at an employer. The system offers qualifications in a broad spectrum of professions and adapts to the changing needs of the labor market.

A major strength of the dual system is the high degree of engagement and ownership on the part of employers, although a web of checks and balances at the national and local levels ensures that the short-term needs of employers do not distort broader educational and economic goals.[118] The system has produced impressive results: about one-third of German students are educated in the apprenticeship system, which is a widely respected career path.

Like Germany, Switzerland also has a robust apprenticeship pipeline—indeed, nearly 70 percent of Swiss high-school students choose vocational training. In this track, students rotate between school and workplace settings, and receive a salary throughout their training.[119] Some studies show that students in Switzerland who opt into vocational training over general education on average attain higher lifetime earnings.[120]

Germany's apprenticeship system is being emulated by other countries. For instance, German auto manufacturers in the United States now offer apprenticeships (although the program remains small). South Korea has adopted the apprenticeship model at scale (see Box 8, "South Korea's Meister schools apprenticeship system").

[118] *Vocational education and training in Germany: Strengths, challenges, and recommendations*, OECD, 2010.

[119] *Gold standard: The Swiss vocational education and training system*, Center on International Education Benchmarking, March 2015.

[120] Eric A. Hanushek, Ludger Woessmann, and Lei Zhang, *General education, vocational education, and labor-market outcomes over the life-cycle*, CESifo working paper, number. 3614, October 2011.

Box 8. South Korea's Meister schools apprenticeship system

South Korea has one of the highest university enrollment rates in the world, but unemployment rates for graduates have been high, even as small- and medium-sized businesses cannot fill openings for manual and other jobs. The government studied the German and Swiss apprenticeship systems and transformed a subset of existing vocational schools into "Meister" ones. (*Meister* is German for a skilled craftsman.) Students graduate with the equivalent of two years' work and/or community college experience. To provide incentives, the Korean government pays the students' tuition, room, and board.

The program is still relatively young, but already bearing fruit: Meister schools have produced significantly higher employment rates among their graduates, more than 90 percent, compared with less than 65 percent for college graduates. College enrollment rates have fallen in favor of vocational qualifications as a result.[1]

[1] Ministry of Education, South Korea.

Educators have a role to play in adjusting school curricula for the automation age

While automation will be a major challenge to workers already in jobs, it also will have implications for how future generations of workers are trained, involving adjustments to school curricula and education systems more broadly. Curricula will need to adapt to provide students with the skills necessary for a dynamic, technology- and increasingly service-oriented labor market, particularly in countries and industries where automation technologies are likely to be adopted most quickly. Several changes will be required.

First, demand will increase for workers to develop and deploy technology, or interpret and act on the data analytics that these technologies can produce, yet there may not be enough workers with the skills to meet this demand, for instance, for data scientists.[121] STEM subjects will be crucial for the workforce. Early education in subjects such as statistics, to help students understand an increasingly data-driven world, where experiments are a key source of insight, will be vital. Some countries including Estonia and the United Kingdom have introduced computer coding into primary and secondary education. Coding classes in these countries start as early as age five or seven, with an introduction to necessary fundamental concepts (such as gaining an understanding of algorithms) and coding skills such as logic and the creation and debugging of simple computer programs.[122] However, a strong liberal arts education to go alongside the high tech workplace skills could also be required for the "new collar" jobs of the future.[123]

Our analysis has shown that an increasing percentage of activities that workers will do in the future will be in categories such as managing and leading other people and interacting with others, which require skills such as social and emotional sensing and reasoning, and applying creativity and collaborative problem-solving. These skills are often not part of the formal curriculum in traditional school programs. Another finding from our research is that automation and other factors, including globalization, independent work, and companies crossing sector boundaries, will require all workers to change what they do over time. This puts a premium on a set of meta-skills, around agility, flexibility, grit, and learning how to learn. Teaching such qualities is a challenge for all educational systems.

39%
Percentage of employers who say that a skills shortage is a cause of entry-level vacancies

Third, educational institutions will need to adapt to the evolving demands of the labor market to ensure that critical job skills are being taught. Unless they become more responsive to labor market demands, educators risk creating an ever-larger disconnect between education and employment. This disconnect is already visible in some surveys. In a McKinsey survey in 2012, only 50 percent of youths said they believed their post-secondary studies improved their employment opportunities, and only 43 percent of employers reported being able to find enough skilled workers. Moreover, 39 percent of employers said a skills shortage was a leading reason for entry-level vacancies. However, a big majority of education providers (72 percent) said they believed new graduates were ready to work.[124]

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121 *The age of analytics: Competing in a data-driven world*, McKinsey Global Institute, December 2016.

122 Parmy Olson, "Why Estonia has started teaching its first-graders to code," *Forbes*, September 6, 2012; Richard Wilson, "Computer programming will soon reach all Estonian schoolchildren," *Ubuntu Life*, May 4, 2014; *Computing programmes of study. Key stages 1 and 2*, UK Department of Education, September 2013. It is also important to note that the aims of introducing coding into early education are not to teach specific computer languages, which change constantly in their popularity, but rather computational thinking.

123 George Anders, *You can do anything: The surprising power of a "useless" liberal arts education*, Little, Brown & Company, August 2017.

124 *Education to employment: Designing a system that works*, McKinsey & Company, January 2013.

Several measures can reduce or correct disconnects among education providers, employers, and students. Providing actionable data is one. Students need to know that curricula will provide them with relevant knowledge and work skills, and be able to select the best courses and institutions to achieve their desired educational outcome. In one survey, less than 50 percent of students said they had a solid understanding of which disciplines lead to professions with good job openings and wage levels.[125]

Finally, the digital age itself has brought a multitude of possibilities for new ways of learning, both within the educational system and outside. Digital learning resources are more flexible in terms of their timing and content than traditional classroom training, and programs can adjust content for individual students to optimize their learning outcomes. For individuals, online degrees can be more advantageous from a cost perspective than degrees from traditional colleges and universities, particularly in the United States where tuition costs are rising faster than overall inflation. Some massive open online courses (MOOCs) are free and have helped expand access to educational content for those outside traditional educational institutions. At Coursera, for example, half of students are from developing countries, and about 60 to 70 percent of users are employed but preparing for better jobs, while 15 percent are unemployed. Most are between ages 22 and 45.[126] MOOCs present a promising channel for at-scale distribution of educational content at low cost and have potential to help ease future workforce transitions. However, their educational impact at scale remains to be seen.[127]

IMPROVING LABOR MARKET DYNAMISM

Workers in countries with more fluid labor markets find work more quickly and obtain jobs that are a better fit; this will blunt potential increases in unemployment as automation is adopted. For now, there are significant information asymmetries in the workforce, with poor job matching: companies struggle to find the people they need, and people cannot find the opportunities for which they are best qualified. Both policy changes and new digital tools can help address this challenge.

Labor market fluidity has been declining within advanced economies

In advanced economies, there is evidence that labor markets are becoming less dynamic, with fewer people switching jobs.[128] One striking example is the United States, which has experienced a decline in job reallocation rates since the early 1980s (Exhibit 31).[129] The root causes of this decline are not fully understood, but include an aging workforce that is less likely to change jobs, declining rates of new business formation, lower geographic mobility (see next section), and increasing regulations, licensing, and more intense training requirements that have made it harder to join some professions.[130] Removing overly burdensome occupational licensing and restrictions, ensuring that benefits are not lost in moving from one employer to another, and easing the process and financing for entrepreneurs to start new firms and for existing firms to innovate are all part of the solution.

[125] Ibid.

[126] Coursera.

[127] For example, edX has reported that between 2012 and 2016, only 5.5 percent of enrollees completed certifications. Isaac Chuang and Andrew Dean Ho, *HarvardX and MITx: Four years of open online courses—fall 2012–summer 2016*, SSRN, December 23, 2016.

[128] See Steven J. Davis and John Haltiwanger, *Labor market fluidity and economic performance*, NBER working paper 20479, September 2014; Raven Molloy et al., *Understanding declining fluidity in the US labor market*, Brookings Papers on Economic Activity, spring 2016.

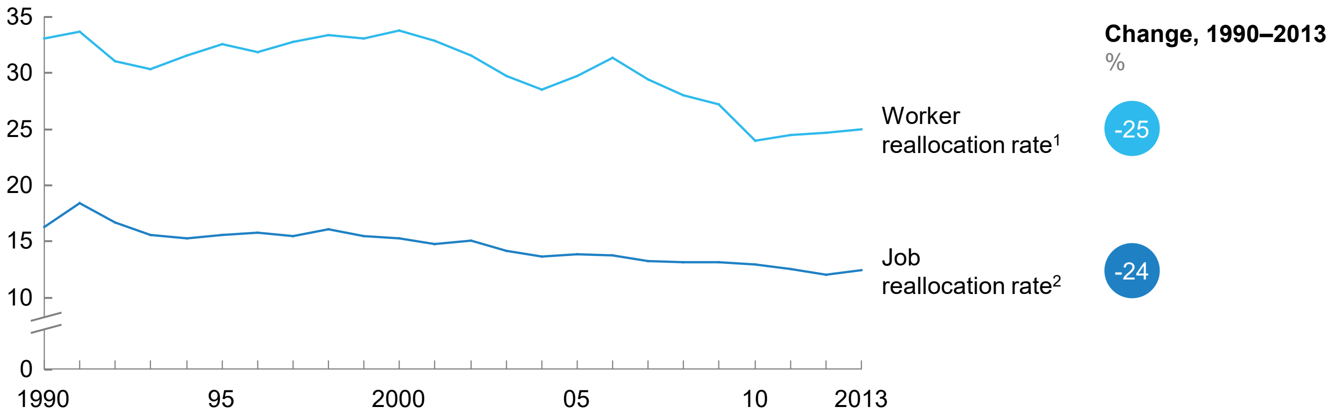
[129] Ibid. Steven J. Davis and John Haltiwanger, *Labor market fluidity*, September 2014.

[130] *Dynamism in retreat: Consequences for regions, markets and workers*, Economic Innovation Group, February 2017.

Exhibit 31

Measures of labor market dynamism have been declining in the United States

Quarterly rates of common measures of labor market dynamism for the United States, 1990–2013
% of total employment



1 Worker reallocation rate: sum of hires and separations, inclusive of retires and other separations, expressed as percentage of total employment.
2 Job reallocation rate: sum of job creation and destruction rates.

SOURCE: Steven J. Davis and John Haltiwanger, *Labour market fluidity and economic performance*, NBER working paper number 20479, September 2014; McKinsey Global Institute analysis

Improving geographic mobility can enhance labor market fluidity

While our analysis does not look at the intra-country geography of job loss and job growth, it is clear that increasing the geographic mobility of the workforce will aid the transition. Yet labor mobility has declined steadily in many advanced economies.[131] In the United States, geographic mobility has declined since the 1980s (both within and between states), reversing the increased mobility that was a characteristic of the US labor market earlier in the 20th century.[132] Whereas about 3 percent of workers relocated across state lines each year prior to 1990, that figure has steadily fallen to closer to 1.5 percent today, suggesting that geographic labor mobility halved within less than 30 years. In Europe, despite the ambition of creating free movement of people, mobility across borders is still complicated, especially for services, in which regulating the cross-border posting of workers remains subject to political disagreements and different labor market regulations. In the European Union, overall, about 17 million people, or 3 percent of the population, have taken advantage of the free movement possibilities to live in a different EU country, although the annual flow is one tenth of that, about 0.3 percent of the population.[133]

Improving geographic mobility may require regulatory change as well as incentives. One major obstacle to internal mobility is the cost and availability of housing. Academic literature has shown that residential mobility is positively correlated with worker reallocation rates and the efficiency of job matching.[134] Lack of information on job opportunities in other areas, family ties, and different job licensing requirements are also deterrents, as are legal hurdles such as land-use laws, different eligibility standards for public benefits, state and local tax regimes, and even basic property law rules.[135]

[131] Developing countries are experiencing massive migration of workers from rural areas to urban areas as they urbanize and industrialize.

[132] Raven Molloy, Christopher L. Smith, and Abigail Wozniak, *Declining migration within the US: The role of the labor market*, Federal Reserve Board, Finance and Economics Discussion Series, number 27, April 2014.

[133] Mikkel Barslund and Matthias Busse, *Labour mobility in the EU: Addressing challenges and ensuring "fair mobility,"* CEPS special report number 139, July 2016.

[134] *Economic policy reforms 2011: Going for growth*, OECD, April 2011.

[135] David Schleicher, "Stuck! The law and economics of residential stagnation," *The Yale Law Journal*, volume 127, number 1, October 2017.

International mobility is a controversial topic in some political arenas, but the skill mismatches we have identified as a consequence of automation and new labor demand will not stop at national borders. Our research on global migration has found that the world's 247 million cross-border migrants contributed 9.4 percent of global GDP, or roughly $6.7 trillion worldwide in 2015—more than $3 trillion above their contribution had they remained in their home countries.[136] More than 90 percent of these cross-border migrants moved voluntarily, usually for economic reasons, while refugees and asylum seekers who tend to attract the most public attention make up the remainder.

Digital platforms can make labor markets more transparent and improve job matching

Digital platforms offer an efficient way to improve the information available to individuals about job opportunities, and to companies about job candidates. By improving information signals, job platforms such as LinkedIn, Indeed.com, and Monster.com can speed and improve the process of matching individuals to jobs, thereby fostering fluidity. These platforms allow individuals to post their entire resume and showcase their work, displaying a rich set of credentials and skills other than simply their educational record. But transparency cuts both ways: other platforms, such as Glassdoor.com, enable prospective employees to find out more about their potential employers, including salary information and anonymous reviews by current employees. MGI has estimated that up to 540 million individuals could potentially benefit from online talent platforms, with as many as 230 million shortening search times between jobs, reducing the duration of unemployment. Up to 60 million people could find work that more closely suits their skills or preferences, and an additional 50 million could shift from informal to formal employment.[137]

Companies can benefit from using digital technologies to transform recruiting, training, and managing talent as well. Companies that adopt these tools are discovering that better-informed decisions about human capital produce better business results. On average, our analysis finds that companies could see a 275 basis point increase in their profit margins.[138] In addition, talent platforms could improve signaling about the skills that are actually in demand. As this information shapes decisions about education and training, the supply of skills in the economy could adjust more quickly and accurately over time.

Creating more flexible work options may enhance reemployment of displaced workers

The workplace is changing, with the rise of more flexible forms of independent work, including independent contractors, freelancers, self-employed individuals, and people working in the "gig" or "sharing" economy. MGI finds that 20 to 30 percent of the working age population in Europe and the United States already earn income through independent work—and that 70 percent of those say they do so out of preference, not because they cannot find a traditional job. Moreover, the number of people choosing to work outside traditional jobs may rise.[139] Digital platforms such as Upwork, Freelancer.com, HourlyNerd, Uber, Lyft, TaskRabbit, eBay, and Airbnb offer vast new markets and lower the barriers to entry, thereby removing some of the risk for those who want to be their own boss.

Independent work may offer solutions as well as new challenges. Among the benefits, it can enable many people currently not employed to work in flexible ways that suit their needs. It is particularly attractive for care-givers, retirees, students, and others who need flexible schedules. For the unemployed, independent work may provide a critical bridge to keep earning income while seeking employment. But as independent work grows, questions

[136] Ibid. *People on the move*, McKinsey Global Institute, December 2016.
[137] Ibid. *A labor market that works*, McKinsey Global Institute, June 2015.
[138] Ibid.
[139] Ibid. *Independent work*, McKinsey Global Institute, October 2016

surrounding benefits, income security measures and other worker protections become more prominent and need to be addressed. Key policy recommendations of the United Kingdom's Taylor Review in July 2017, for instance, included recommendations to expand the definition of "worker," extend minimum wage standards, and ensure that benefits such as holiday and sick pay cover independent workers.[140]

PROVIDING TRANSITION AND INCOME SUPPORT TO WORKERS

Germany's labor market reforms in the 1990s helped raise its share of the working-age population in employment by **10** percentage points

Job losses cause economic stress, as well as physical, emotional, and psychological distress. A wide body of academic research has found correlations between extended unemployment and declines in physical and mental health. Studies have even shown poorer academic outcomes among the children of the long-term unemployed.[141] Other research has documented the stagnation in market incomes, and increasing wage polarization, in many developed markets.[142] Both policy makers and business leaders have a role to play in supporting workers as they transition between jobs to avoid long-term negative consequences and to ensure that they receive adequate incomes.

Actively supporting workers in job transitions

A range of measures can speed the transition of workers between jobs, beyond improving labor market dynamism, job matching, and retraining and skill development. Most countries have labor agencies focused on providing assistance to the unemployed. In many, the focus is mainly on doling out benefits and reducing fraud. Germany provides an example of a nation that overhauled its labor force system—and reduced high unemployment as a result. In 2003, when the country was still struggling with the legacy of reunification, it adopted the "Hartz reforms," based on recommendations of a labor market commission. The lower-wage segment of the labor market was liberalized, and a new category of jobs was created with employers paying a low flat rate for employees, who work a limited number of hours per week, exempt from social security and tax contributions.

The move created millions of "mini-jobs," whose wages were then supplemented by welfare payments. In addition, the local labor market agencies were restructured. Case workers are assigned to every unemployed individual, with strong incentives to successfully place their clients into jobs. Skills assessments are performed, and training is provided if needed. These reforms helped reduce the unemployment rate from 10 percent in 2003 to below 4 percent today and, at the same time, increased Germany's share of the working-age population in employment by 10 percentage points. While these reforms have returned more individuals to work, there is controversy over the impact on the post-unemployment earnings of workers.[143]

To ensure that workers develop the skills needed for the working world of the future, the German labor agency is now planning to put a greater emphasis on counseling. It is currently piloting innovative online and offline counseling services directed at students, the unemployed, but also employees in jobs which are massively impacted by digitization. The hope is that better individual orientation about job market trends and future opportunities will smooth the transition to a digital economy, without a large net loss of jobs and corresponding increase in unemployment.

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[140] Matthew Taylor, *Good work: The Taylor review of modern working practices*, Report for the UK government, July 2017.

[141] Many of these studies are summarized in Austin Nichols, Josh Mitchell, and Stephan Lindner, *Consequences of long-term unemployment*, Urban Institute, July 2013; and in Edward Alden, *Failure to adjust: How Americans got left behind in the global economy*, Rowman and Littlefield, October 2016.

[142] Ibid. *Poorer than their parents?* McKinsey Global Institute, July 2016; David Autor, David Dorn, and Gordon H. Hanson, *The China shock*, January 2016.

[143] Niklas Engbom, Enrica Detragiache, and Faezeh Raei, *The German labor market reforms and post-unemployment earnings*, IMF Working Paper number 15/162, July 2015.

In Denmark, employers and governments work with unions to maintain the country's "flexicurity system," which combines active labor market policies with flexible rules for hiring and firing and high levels of benefits for unemployed individuals (up to 90 percent for the lowest paid workers). They also offer active job counseling, including career guidance, training or education to all unemployed individuals, and offer all workers access to numerous vocational training programs. This creates a labor market environment of flexible employment and job security. Notably, firms and unions get together to identify skills needs, agree on wages and enshrine rights to paid leave for training. Some studies suggest that similar collaborative efforts between employers and unions can play an important role in raising skill levels, including in the United States, and are already doing so in some cases.[144]

Neighboring Sweden has a system for retraining midcareer workers through private sector "job-security councils." Employers pay into these councils, which provide financial support and job counseling to laid-off workers, with the aim of helping them get back to work as soon as possible. Personal counselors help workers with their resumes and steer them into classes in their fields or other fields.[145]

Supporting worker incomes may also be necessary

Our research indicates that millions of individuals will likely need to transition to new occupations—and identifies the risk that wages may become stagnant or even decline for middle and lower-skill occupations that have a large supply of potential workers but might have reduced demand, particularly in developed economies. Supporting incomes in both cases may have an economic rationale. Consider that in 1914, Henry Ford announced that he would begin paying his employees $5 per day, more than twice the average wage for automakers, and reduce the work day from nine hours to eight, at a time when the 60-hour work week was the standard in American manufacturing. He explained that "unless an industry can so manage itself as to keep wages high and prices low, it destroys itself, for otherwise it limits the number of its customers. One's own employees ought to be one's own best customers."[146]

Two forms of income support need consideration in the age of automation. First are payments such as unemployment insurance to provide income to workers during training or transitioning between jobs. Yet unfortunately, the amount of public resources devoted to supporting worker transitions—including on unemployment benefits—has been declining in most countries (Exhibit 32). Given the large workforce transitions we see in the decades ahead, re-evaluating this trend could be necessary.

144 For example, Kaiser Permanente offers programs in nursing, health-technician training, and basic language, math, and communications skills. Thomas A. Kochan, David Finegold, and Paul Osterman, "Who can fix the 'middle-skills' gap?" *Harvard Business Review*, December 2012.

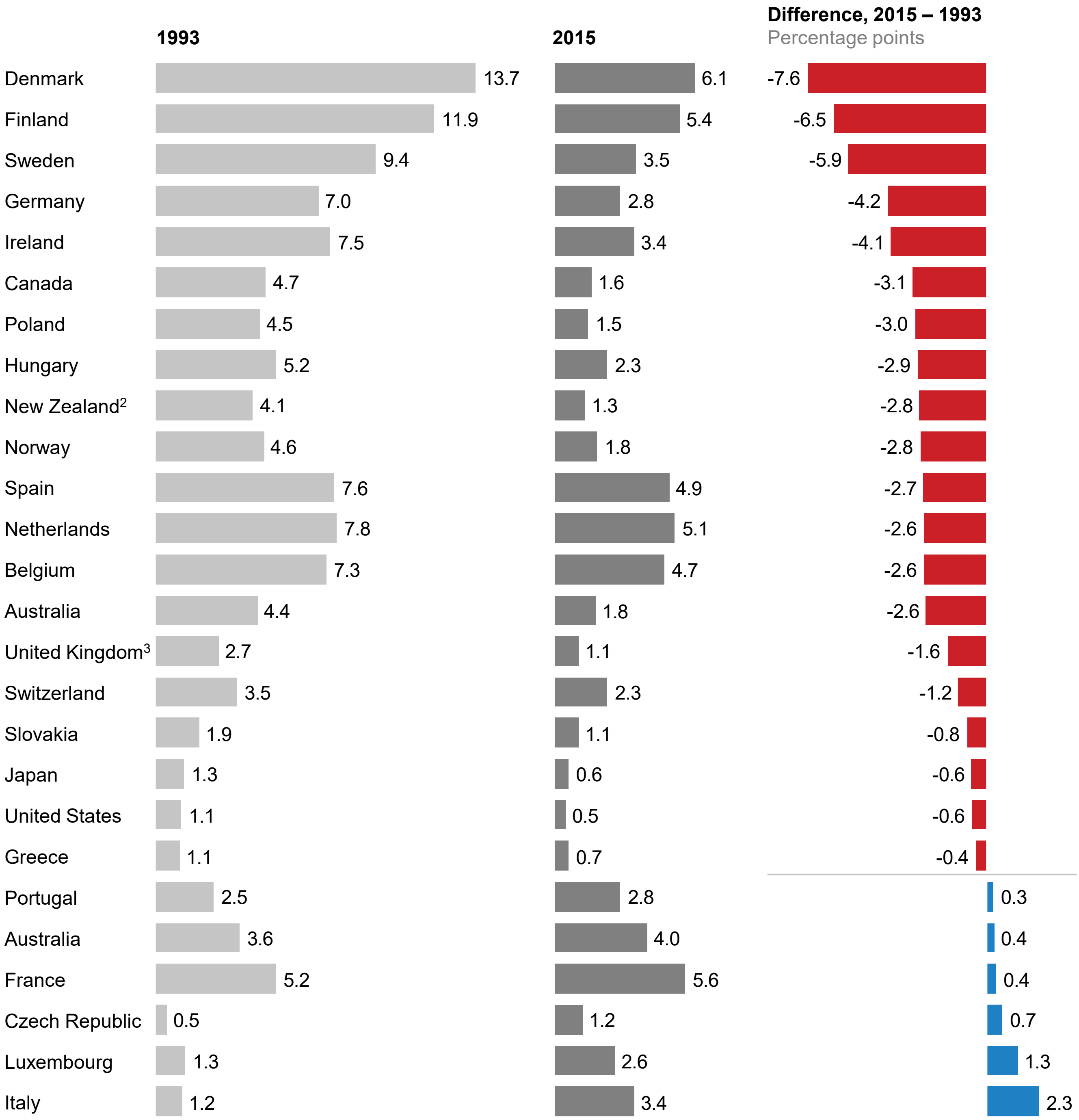
145 Alana Semuels, "What if getting laid off wasn't something to be afraid of?" *The Atlantic*, October 25, 2017.

146 Henry Ford, *Today and tomorrow*, 1926.

Exhibit 32

Most OECD countries have been spending less in labor markets over the past 20+ years

Total public spending on labor markets, 1993–2015[1]
% of GDP



1 Public spending on employment incentives; startup incentives; direct job creation; out-of-work income maintenance and support; early retirement; public employment services and administration; and sheltered and supported employment and rehabilitation (excluding worker training).
2 2014 data used for New Zealand.
3 2011 data used for United Kingdom.

SOURCE: OECD; McKinsey Global Institute analysis

In addition, however, wages may be under pressure in a wide range of jobs as economies transition to new forms of work. A range of options exists for addressing these income effects. Some employers can choose to pay higher wages and better benefits, recognizing the value that their workers are producing. In addition to societal responsibility, these companies may be motivated by competition for talent and an interest in reducing employee turnover. In the United States some companies have unilaterally raised minimum wages they pay.[147] In Europe, companies have traditionally paid more attention to stakeholders such as workers, in part because of unionization and regulatory choices; in Germany, for example, worker representatives sit on corporate boards under 1976 "codetermination" legislation and play an important role in shaping wage and benefit policies, as well as overall corporate strategy. There are also policy options for providing income support to workers to ensure that they remain active consumers. Minimum wages are widely deployed throughout the world, and there are moves to raise them, including in US cities such as Seattle.[148] While some studies have shown that increasing minimum wages can raise employment, the issue is actively debated. Other forms of income support, such as "earned income tax credits" and wage subsidies, provide incentives for people to work. These measures attempt to provide income support without discouraging people from working. Pilot projects are underway in a number of countries to test the idea of paying a universal basic income (see Box 9, "Experimenting with universal basic income").

In recent decades, the long-standing correlation between rising productivity and wage growth has broken down in some countries, such as the United States. The cause of this shift is unclear. But policy makers are considering new ways to ensure that wages are linked to rising productivity, so that prosperity is shared with all. Some have suggested that minimum wages should be indexed to measures of productivity. In another specific example, Singapore has a program that supports corporate investments in productivity on condition companies share the gains from productivity improvements with low-wage workers.[149] Between 2010, when the program was launched, and 2013, more than 800 projects were launched, most of them by small and medium-sized enterprises, which will benefit 53,000 workers once completed. Their wage increases are more than 10 percentage points above the national average.

•••

In the new era of automation, governments and businesses will need to undertake a balancing act between embracing the technology, which will boost productivity and economic growth, and at the same time addressing the complex transitions it will create. Ensuring robust demand growth and economic dynamism is a priority: history shows that economies that are not expanding do not generate job growth. Upgrading workforce skills and creating opportunities for midcareer job retraining will also be essential, at a time when spending on these has been declining in most countries, and labor markets will need to become more dynamic and adaptable to changing work needs and patterns of worker redeployment. A final priority is reassessing and strengthening transition and income support for workers caught in the cross-currents of automation. Each of these priorities on its own presents a challenge, and all together may require a Marshall Plan-like initiative, involving clear focus and investment. In the concluding chapter, we examine the implications for policy makers, business leaders, and individual workers.

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147 Becky Yerak, "Allstate raises minimum pay to $15 an hour," *Chicago Tribune*, May 16, 2016; Tim Worstall, "Walmart to speed worker pay rises—another sign of a tight labor market in US," *Forbes*, January 29, 2017; Danielle Paquette, "'Look, I can quit': Why Target is giving workers a big raise," *The Washington Post Wonkblog*, September 26, 2017.

148 Noam Scheiber, "How a rising minimum wage affects jobs in Seattle," *The New York Times*, June 26, 2017.

149 Singapore NTUC e2i (National Trades Union Congress' Employment and Employability Institute).

Box 9. Experimenting with universal basic income

Universal basic income (UBI) consists of giving a periodic cash payment to all individuals without a means test or work requirement, to cover basic living costs. Some see it as a policy to address the challenges of a jobless future in which automation has resulted in mass unemployment.

Advocates say the assurance of a minimum standard of well-being encourages people to switch jobs and take more entrepreneurial risks, and supports consumption for those in low-paying work. Others point to the high costs and difficulties in giving cash transfers, particularly in developing countries. The potential costs are high, particularly in developed markets. An OECD study found that large tax revenue increases would be needed in most countries to finance a basic income at meaningful levels.[1] Opponents say that there is no assurance that these payments would lead to increases in innovation and that UBI could undermine productivity by discouraging work. Other arguments question the assumption of planning for mass unemployment rather than attempting to enable the mass redeployment of labor.

A number of pilots of UBI have been conducted or are now underway around the world that may shed light on the impact that this program has on incentives, work, and welfare (Exhibit 33) in developing and developed countries.

Exhibit 33

Experiments with universal basic income are being conducted in several countries

● Trial completed ● Trial in progress ● Trial in plan

Manitoba, Canada (1970s)
- No significant reduction in hours worked for primary earners
- Increased quality of life—increased parental leave, healthcare

Finland (2017–18)
- 2-year trial for 2,000 unemployed Finns across country; guaranteed monthly sum of €560 ($624)
- Aims to focus on labor market impact, including potential efficiency improvements of benefits system and social security levers

United States (planned, late 2017)
- 3-year experiment for 1,000 individuals, with household incomes below the median in their area; monthly sum of $1,000
- Aims to understand and measure impact (e.g., labor market participation, risk-taking, training and education, and health)

Busibi, Uganda (2017–18)
- 2-year experiment involving all residents in one village of 56 adults and 88 children
- Each adult receives monthly sum of $18.25, approximately 30% of average income of lower-income families in Uganda; children receive half of adult amount
- Aims to study 4 main dimensions: entrepreneurship and economic development; girls' educational achievement; participation in democratic institutions; access to health care

Kenya (full experiment: 2017–29; pilot launched 2016)
- 2- to 12-year controlled experiments comparing 4 groups (total of 26,000 recipients across 200 villages); full experiment projected to produce some of the most comprehensive basic income data yet
- Aims to study economic status, time use, risk-taking, gender relations, aspirations and outlook on life
- Initial evidence of economic empowerment (i.e., cash used to purchase livestock, fishing nets, motorbikes)

Madhya Pradesh, India (2011–13)
- 2-year pilot experiment of ~1,100 households, across 8 villages, totaling > 6,000 adults and children; each received the equivalent of 20%–30% of an average household's income
- No impact on reducing work hours, while entrepreneurialism, education, and female empowerment increased

1 Netherlands authorized testing monthly payments in 6 municipalities (Utrecht, Amsterdam pending) but not true tests of basic income. Among other basic-income defying caveats, participants are required to seek work or face removal from experiment.

SOURCE: UNICEF; GiveDirectly; Y-Combinator; KELA; McKinsey Global Institute analysis

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1 *Basic income as a policy option: Can it add up?* OECD, May 2017.

Apprentices at a car plant, Ulsan, South Korea
© Yonhap News/YNA/Newscom

6. PRIORITIES FOR GOVERNMENT, BUSINESS, AND INDIVIDUALS

Automation will be a powerful motor of future economic growth, but the challenges it presents for workforce transitions are sure to be very substantial. Policy makers, business leaders, and individual workers will need to be flexible, creative, and even visionary as they look to harness these rapidly-emerging technologies and ensure that the time of automation is a productive and prosperous one. A range of outcomes is possible, from one in which economic growth and productivity grow strongly, creating myriad new jobs, as automation is adopted rapidly, to one marked by slow automation adoption, weak economic growth and low net job growth.

Faced with the scale of worker transitions we have described, one reaction could be to try to slow the pace and scope of adoption in an attempt to preserve as much of the status quo as possible. But this would be a mistake. Although slower adoption might limit the scale of workforce transitions, it would curtail the contributions that these technologies make to business dynamism and economic growth. Automation technologies and in particular artificial intelligence are the key to finding solutions for many important societal challenges in fields ranging from climate science to health care. We should embrace these technologies, but also address the workforce transitions and challenges they bring. To do this, there are a number of imperatives and priorities for governments, business, and individuals. In this concluding chapter, we highlight a number of them.

GOVERNMENTS MUST MAKE WORKFORCE TRANSITIONS AND JOB CREATION A MORE URGENT PRIORITY

Managing the coming workforce transitions with foresight is not just a question of smart policy. Automation's power to lift the productivity of national economies has the potential to accelerate productivity and economic growth and improve lives. Governments can support the development and deployment of these technologies, for example through investments in basic and applied research, as well as through building out digital infrastructure. Ensuring positive employment outcomes will require a laser focus on retooling the workforce, stepping up support for workers in transition, and improving how local and national labor markets function. Societies can choose to transform the coming labor market disruptions into an opportunity rather than a pitfall.

As daunting as the task may seem, history shows us that governments, across the globe, when faced with monumental challenges, can rise to the occasion for the well-being of their citizens. As we have seen, the US High School Movement and GI Bill were instrumental in raising the education of the US workforce and countries such as Germany have shown that revamping labor market agencies and support for workers in transition is not only possible but can also dramatically reduce unemployment. Such examples highlight the importance of executing targeted policy decisions swiftly and clearly.

Yet in the last few decades, investments and policies to support the workforce have eroded, not been enhanced. Public spending on labor force training and support has fallen in most countries. Educational models have not fundamentally changed in 100 years; we still use systems designed for an industrial society to prepare students for a more dynamic, rapidly-changing knowledge economy. Unions are on the decline. Government data collection on the growing independent workforce and new ways of working is fragmented. It is now critical to reverse these trends. A new "Marshall Plan" for the workforce is needed. Priorities include the four areas for action discussed at length in Chapter 5, but also the following:

- **Radically scale midcareer training opportunities to make lifelong learning a reality.** Lifelong learning has long been talked about reverentially in policy circles, but the new age of automation will be the time when large-scale application of it will be needed more than ever. Flexibility and adaptability will be the new workforce mantras, as machines both replace some human activities and—probably more frequently—fundamentally change them. Recent examples of effective large-scale retraining of midcareer workers are few and far apart. For the future, more short-term and targeted training for people will be needed, especially for those in midcareer who will be looking to develop new skills even if they keep their jobs.

- **Modernize educational systems for the 21st century.** Our analysis of the performance capabilities most in demand in the new age of automation shows the critical importance of technology skills, but also of teamwork, creativity, communication, and social and emotional skills. Schools in many countries continue to adhere to a culture of education that remains rooted in 19th century notions of teaching and learning. Governments and educators can use digital technologies to change that, for example creating more individual learning paths for students. Several countries including Germany and Switzerland continue to show that apprenticeships can be a powerful and successful approach to teaching technical skills. While university education has grown in popularity and lost its elitist reputation in many countries, many tertiary educational institutions have not focused sufficiently on the needs of the labor market or of the graduates entering it. Publishing job placement of graduates and similar data could help both employers looking for recruits and potential students trying to decide on their course of study. Singapore has shown through its SkillsFuture Initiative that individuals can be supported and motivated to continuously acquire new skills. Finally, governments could encourage, identify, and co-finance innovative pilot programs that address known skills gaps among workers, post-secondary students, and youth—and then scale the ones that work.

- **Expand transition support measures for workers.** Denmark, Germany, and Sweden, among others, have shown the importance of focusing labor agencies on reemployment and the acquisition of new skills, rather than simply on handing out unemployment benefits or controlling for fraud. Best practice requires a cultural shift of sorts, one that nudges workers to take a more active role in their own retraining and provides tools for them to be successful. Mobility can be an important part of that transition process, and in the United States, at least, it was long prized. However, mobility within borders has slowed in advanced countries including the United States, and mobility across borders faces new hurdles globally as countries revisit immigration policies and practices. Reducing the barriers to mobility—which include legal ones alongside prohibitive housing costs—will need to be a policy priority. And governments should not lose sight of the cardinal importance of increasing economic mobility and opportunity for all citizens. That means universal access to quality education, good neighborhoods, and basic healthcare.

- **Create income support measures consistent with the new wage realities.** Since 1970, market wages and productivity growth have diverged in some advanced economies including the United States, and income inequality has grown. With the advent of the new automation age, it is important to begin national discussions on whether we can assume that everyone who works can support a decent standard of living. A healthy consumer class is essential for both economic growth and social stability. Income supplementation programs already exist in certain countries, such as the earned income tax credit in the United States, and some countries are testing universal basic income programs or raising minimum wages; more could follow suit, to provide fact-based findings that can inform the debate.

- **Make job creation and worker re-deployment a national priority.** A broad range of incentives exists for businesses to invest in capital and research and development. Something similar is needed to encourage investment in human capital. In addition, governments could assess the impact on job creation of their policies and investments, much as they currently assess the impact of policies on the environment. Companies could be encouraged to invest in worker training and redeployment through tax and other incentives, just as they often are for their research and development investments; in some countries, that will mean reconsidering tax codes that provide subsidies (through interest) for investments in capital while taxing labor. The step-up scenario in this report showed the value in job-creation terms of raising public—and, with it, private—investment in infrastructure, affordable housing, and energy efficiency and climate change. Such investment will need to go hand-in-hand with other backing for job creation, including supporting entrepreneurship and small business creation by streamlining regulations and revisiting personal bankruptcy laws that discourage risk-taking, for example.

- **Modernize data collection on the labor market.** Government surveys of households and employers are the gold standard of national economic data. But these are time-consuming. In today's dynamically changing world, governments need to supplement these surveys with real-time data on the adoption of automation technologies, job openings, labor market dynamism, skills in demand, and how individuals are coping with job transitions.[150] The need for better data amounts to an opportunity for government statistics agencies to collaborate with online sources of data, including job boards, professional sites such as LinkedIn, and private tech companies, to obtain a more detailed and accurate picture of jobs, skills, wages, and individual mobility and career moves.

BUSINESS LEADERS SHOULD EMBRACE AUTOMATION AND AI WHILE CAREFULLY MANAGING WORKFORCE TRANSITIONS

20%
Proportion of AI-aware C-suite executives in our survey who say their companies use AI-related technology as a core part of their business

Business leaders also have much to gain by early adoption of automation technologies, enabling performance benefits such as quality and speed, as well as greater efficiency and productive use of all factors of production. But businesses will also be on the front lines of the workplace as it changes. Successful adoption of automation will require companies to re-imagine their entire business processes to take advantage of automation's benefits, rather than mechanically attempting to automate individual activities using current processes. As part of that review, they will need to reevaluate their talent strategies and workforce needs, considering how workers can be redeployed to other jobs, and where new talent may be required. Many companies are finding that it is in their self-interest—as well as important for societal responsibility—to train and prepare workers for a new world of work. Some companies are already working with external education providers or conducting in-house training—but many more could follow suit.

- **Accelerate deployment of automation and AI.** For CEOs in all industries and countries, developing an automation and AI strategy should be a priority. So far, few firms have deployed at scale. In an MGI survey of 3,000 AI-aware C-level executives, across 10 countries and 14 sectors, only 20 percent said they use any AI related technology in a core part of their businesses. Many firms say they are uncertain of the business case or return on investment. A review of more than 160 use cases shows that AI was deployed commercially in only 12 percent of cases.[151] But companies that ignore these technologies do so at their peril: the gap in performance between early adopters

[150] Tom Mitchell and Erik Brynjolfsson, "Track how technology is transforming work," *Nature*, April 13, 2017; National Academies of Sciences, Engineering, and Medicine, *Information technology and the US workforce: Where are we and where do we go from here?* National Academies Press, 2017.

[151] *Artificial intelligence: The next digital frontier*, McKinsey Global Institute, June 2017.

of digital technologies in general and AI in particular is widening. In the MGI survey, early AI adopters have higher profit margins. Our case studies in retail, electric utilities, manufacturing, health care, and education highlight automation and AI's potential to improve forecasting and sourcing, optimize and automate operations, develop targeted marketing and pricing, and enhance the customer experience.

- **Redesign businesses processes to unlock productivity gains.** Since the IT revolution began in the 1990s it has been clear that capturing the value from new technologies requires reimagining how the business operates, rather than mechanically applying automation to the current mix of activities and processes. Capturing the full opportunities offered by automation will require companies to conduct a thorough review of business processes and workflows and assess where automation could improve performance the most. That in turn requires companies to develop or acquire the talent, discipline, and know-how to implement the sort of changes that will be needed to harness the full potential of automation.

- **Rethink organizational design.** Automation adoption is a process that will not happen overnight, and the workplace norm for years to come will be people working alongside machines. This has profound implications for the way companies and their workforce are structured and organized. Until recently, for example, powerful manufacturing robots that can lift or weld have been kept well away from humans, often in cages, because of the risk of accidents. But today's robots can work intelligently and safely alongside humans. Such machine-human and machine-machine environments will become more pervasive, and that in turn will require workflows to change. Successfully rethinking organizational design will ensure that work is not only more productive and takes advantage of the new technical possibilities available, but that it will become more meaningful and rewarding for people, as the rote aspects of their jobs are taken over by machines, freeing them to use more innate human qualities including social and emotional reasoning and personal interaction.

- **Build core digital and analytics capabilities.** Companies that successfully adopt the latest automation and AI technologies typically already have strong digital capabilities. Indeed, our analysis shows that companies that are early adopters of AI are also digital leaders. There is no shortcut to creating a strong digital base. Companies will need to build the supporting digital assets, big data and analytics capabilities to make automation and AI a success. This includes building the data ecosystem and adopting the right advanced analytic techniques and tools.[152]

- **Adapt talent strategy and manage workforce transitions.** Business leaders will need to ensure that the talent their companies require to transition to more automated operations is in place. This will involve a combination of recruiting automation-savvy professionals, as well as retraining workers to play new roles. Determining the right mix of current talent, redeployed talent, and new talent from outside the company will require careful consideration. In the new era, STEM talent and data scientists will be increasingly important—and could provide a lasting competitive advantage. But filling new technical positions is expensive and time-consuming because we have not been turning out enough skilled professionals to keep up with the demand. In the United States, for instance, data scientist shortages are already appearing.[153]

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[152] See *The age of analytics*, McKinsey Global Institute, December 2016.
[153] Ibid.

- **Consider partnerships for talent development.** Some companies are turning to partnerships to develop the skills needed in their workforce and help smooth transitions. As we noted in Chapter 5, some companies have begun to establish partnerships with universities and other educational institutions to provide training and skill development in their workforces. This enables large-scale retraining, without creating the staff and overhead to manage it internally. Such partnerships may become more common as companies adopt automation at scale. In the future, as technical talent shortages increase, corporate partnership with universities and colleges may become more frequent as companies seek to develop a reliable pipeline of scarce technical talent. In other sectors, such as health care and manufacturing, there are many examples of companies partnering with local community colleges to shape and create the curricula for specific degree programs. Similar collaborations might increase the availability of data scientists and other technology-related professionals.

INDIVIDUALS MUST PREPARE FOR LIFELONG LEARNING AND EVOLVING CAREERS

Individuals will need to be prepared for a rapidly evolving future of work. Acquiring new skills that are in demand and resetting intuition about the world of work will be critical for well-being. Workers everywhere will need to reexamine traditional notions of where they work, how they work, and what talents and capabilities they bring to that work.

- **Embrace a "startup of you" mentality.** In the rapidly changing future of work, individuals will be in charge of their own destiny more than ever. The days of planning to have one employer for life are long gone. All individuals will need to adopt a more entrepreneurial approach to navigating through the world of work and managing their careers. Reid Hoffman, a co-founder of LinkedIn, calls it the "startup of you" approach.[154] Individuals will become more proficient and comfortable with navigating a more digital job search and managing their personal profiles.

- **Acquire the skills that will be in demand and embark on a journey of lifelong learning.** As machines perform a wider range and variety of tasks, individuals will need to put more focus on developing the skills that humans excel at. As we have described in this report, the activities in nearly all occupations will change, with more time spent on those activities that require social and emotional skills, team work and collaboration, creativity, and higher levels of communication and logical reasoning. Both governments and businesses have a role to play in providing individuals with better information on the skills and jobs in demand. Educators play a part as well. Secondary school students in most countries receive inadequate instruction and guidance on how to plan a career in today's workplace, and even less so for a workplace that is rapidly evolving. Ultimately it will be up to individuals themselves to think carefully about what skills will be needed and how they can demonstrate those skills to employers.

- **Prepare for a world of digital job search.** Digital platforms for matching people with jobs and assessing skills are rapidly becoming the norm for hiring.[155] Individuals will need to use these technologies if they are to be competitive in the job market. In the short term, this means putting time and care into building a personal online presence. To stand out, they will need to showcase their experience, establish expertise by joining groups or posting content, and build their professional networks. Workers could also benefit from understanding and participating in the innovations around skills-based training and credentials that could accelerate their career trajectories. Individuals without formal education credentials may be able to differentiate themselves through their online reputation via recommendations from former customers or employers.

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[154] Reid Hoffman and Ben Casnocha, *The start-up of you*, Random House, 2013.
[155] Ibid. *A labor market that works*, McKinsey Global Institute, June 2015.

- **Consider new ways of working.** Not only do most people now cycle through multiple employers throughout their careers, but many are moving beyond the traditional full-time (or part-time) job altogether. As many as 30 percent of workers in the United States and Europe earn part or most of their income through independent work—that is, freelance activities, self-employment, or through rapidly expanding digital gig or sharing platforms.[156] More than 70 percent of those individuals say that they prefer independent work and they report higher satisfaction with many aspects of their work-life than people with traditional jobs, including not only flexibility, but also opportunities for advancement, creativity and variety in their work, and even more security in their income. Roughly half of independent workers supplement their income from traditional jobs (or pensions) with these activities. In a world where wages are depressed for people without the skills in demand, independent work offers an opportunity to enhance incomes and branch out into new areas.

Ultimately, automation may force us all to reassess basic notions of work. In capitalist economies, individuals earn most of their income through applying their labor; except for the disabled, all of us are born with an endowment of labor from which to earn income, but only a privileged few are born with capital. In many decades hence, the value of this labor may be diminished if we reach a state in which machines can do a large share of the work. For workers around the world, policy makers, and business leaders—and not just social scientists who specialize in socio-economic paradigms—that should give pause for thought, and be a spur for action.

•••

Automation represents both hope and challenge. The global economy needs the boost to productivity and growth that it will bring, especially at a time when aging populations are acting as a drag on GDP growth. For companies, the technologies can lift productivity and profits to new heights. For society as a whole, machines can take on work that is routine, dangerous, or dirty, and may allow us all to use our intrinsically human talents more fully and enjoy more leisure. Yet even as we benefit, our societies will need to prepare for complex transitions ahead, as machines replace workers in many areas. Our research suggests that it may be time to refocus the current anxious debate about automation toward issues of demand growth, and how to manage the inevitable transitions created by automation. The task at hand is to prepare for a more automated future by emphasizing the skills that will be needed and ensuring dynamic job creation. The technology is advancing rapidly; the policy choices should not tarry.

[156] Ibid. *Independent work*, McKinsey Global Institute, October 2016.

Construction workers, Mumbai, India
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TECHNICAL APPENDIX

This appendix provides details on the methodology employed in our research in the following sections:

1. Work hours that could be automated
2. Labor demand drivers
3. Macroeconomic analysis
4. Skills and wages analysis
5. Glossary of automation technologies and techniques

1. WORK HOURS THAT COULD BE AUTOMATED

This report continues and adapts the methodology and findings of the January 2017 McKinsey Global Institute report, *A future that works: Automation, employment and productivity*. A full methodology of that work is detailed in its technical appendix; we will provide only a brief summary here and how it is applied in this report.

In that report, the technical potential for automation of the global economy and projected adoption rates are determined by an analysis of the underlying work activities for each occupation, covering 46 countries. It uses databases published by institutions including the World Bank and the US Bureau of Labor Statistics 2014 O*Net database to break down about 800 occupations into more than 2,000 activities, and determines the performance capabilities needed for each activity based on the way humans currently perform them. The report further breaks down activity into 18 capabilities and assesses their technical automation potential. This framework is informed by academic research, internal expertise, and industry experts. Our report focuses on 2016–30, and thus takes the automation adoption percentage through 2030. Much of the occupational data, at the time of original analysis, was harmonized through 2014. We adopted the simplification of referring to 2016 as the starting point of the analysis, and projecting in 2014 data (such as occupational mix) into 2016 baseline (for example, automation adoption percentages).

In this report, we use these findings to size the number of jobs that could be automated by 2030. We make an assumption that each hour of work that could be automated will result in proportional job loss, for example if 10 percent of current work activity hours in an occupation will be automated, then 10 percent of jobs in that occupation will be displaced. A priori, it is unclear if this assumption is conservative or aggressive. Based on what we have seen historically, we expect in many cases that the result of activities being automated will be a redistribution of efforts on other existing or new activities. However, it is also possible that with automation, existing work processes could be radically overhauled and reduced in complexity, reducing labor demand even further beyond automation potential of current activities. We have not modeled these countervailing effects.

$$\textit{Jobs lost} = (1 - \textit{weighted automation potential}) \times \textit{2030 labor force}$$

To calculate the work hours automated in 2030, we multiply the automation adoption percentage by the size of the labor force in 2030. By doing this, we assume that the occupation mix of the economy and the underlying work activities in each occupation in 2030 are the same as today. This is a conservative assumption, because in reality, we would expect that jobs will not be added back at the same occupation mix and that new jobs will be added in less automatable sectors.

To estimate the size of the 2030 labor force, we use population projections from the United Nations, labor force participation projections from the International Labour Organization, and the natural unemployment rate for OECD countries. For countries outside the OECD, we use the maximum unemployment rate of either 2007 or 2012 to adjust for the effects of the 2008 global financial crisis on unemployment.

2. LABOR DEMAND DRIVERS

Our work examines the labor demand created by seven catalysts. We selected these seven from a shortlist of 20 after conducting high-level sizing calculations to estimate their potential to create labor demand by 2030.

For catalysts that include a per capita metric, such as spend on automobiles or number of health-care professionals, we include population growth through 2030 based on projection from the United Nations.

We capture direct and indirect jobs that could be created from each catalyst, take into account the decline in hours worked per person, and factor in globalization of work. Our model offers a static view of the potential labor demand that could be created from the seven drivers and does not factor in supply-demand dynamics and feedback from factors such as changes in wage levels. It estimates potential labor demand; whether this potential is captured will depend on the choices and investments made by businesses, policy-makers, and workers. The scenarios we construct do not take into account any sources of labor demand outside of our seven drivers that could play an important role in determining the future of work. We do not model entirely new industries and occupations that could exist in the future, in part enabled by technology; studies have shown that on average, 0.5 percent of the workforce has been working in “new jobs” per year in the past couple of decades.[157] We do not take into account sectoral shifts in industries that are not directly related to automation, such as the rise of e-commerce in retail. We also do not model changes in work structure, such as the growth of the “gig” economy, or activities within an occupation that could change as a result of technological innovation.

157 Ibid. Jeffrey Lin, “Technological adaptation,” May 2011.

Gross Domestic Product projections

Increased prosperity is the underlying driver of many (but not all) of the labor demand sizings. Given the static modular modeling approach that we have taken, we have taken GDP per capita growth as an input to our driver models.

We use the McKinsey Global Growth Model (GGM) projections. The GGM is a global macroeconomic model that tracks long term economic trends and generates projections under a range of scenarios. For the inputs to our labor demand modeling, we use the GGM's baseline scenario where available. For countries that the GGM does not model and for Japan and Mexico, we use projections from Oxford Economics. See Exhibit A1 for the GDP/capita projections in use.

Exhibit A1

GDP growth assumptions

		United States	Germany	Japan	China	India	Mexico
GDP per capita	**2014** ($)	50,969	44,942	46,663	6,010	1,695	9,392
	2030 ($)	62,470	57,670	54,806	14,235	3,944	11,468
	Compound annual growth rate (%)	1.3	1.6	1.0	5.5	5.4	1.3

SOURCE: Global Growth Model; Oxford Economics; McKinsey Global Institute analysis

Job multipliers

For drivers of labor demand in which we are modelling an increase in spend, we use job multipliers from input-output tables to calculate the number of jobs created through each additional dollar of spend. In many drivers based on linear regression analysis (for example, rising consumer spending), the general sizing approach for the number of jobs created incremental to 2014 levels is captured in the following formula:

$$\textit{Net new jobs} =$$

$$(2030 \textit{ spend per capita} \times 2030 \textit{ population} \times 2030 \; I - O \textit{ multiplier})$$

$$-(2014 \textit{ spend per capita} \times 2014 \textit{ projected population} \times 2014 \; I - O \textit{ multiplier})$$

To take into account projected increases in productivity between 2014 and 2030, we adjust 2014 job multipliers for projected productivity gains (from factors other than automation) to create a 2030 job multiplier.

For all labor drivers, we calculate indirect jobs using indirect job multipliers from McKinsey input-output tables based on source data from the World Input-Output Database, making adjustments as necessary informed by expert input.

To avoid double-counting, we remove particular indirect multipliers if they may overlap with our drivers. For example, we exclude all indirect effects in healthcare, education and construction, since we have sized these drivers independently. This may undercount job creation in these areas.

Globalization of trade

For drivers that include tradable goods and services, we use data from the International Trade Organization and IHS Global Insight to model level of imports and exports in our 46 country set. In drivers with global trade, we model both locally- and globally-driven labor demand. We keep this model of global trade constant between today and 2030, as shifts in globalization are beyond the scope of our analysis. This approach would result in an underestimation of job creation in countries whose global export shares in 2030 would be greater than today's shares, and similarly overestimation of job creation in countries whose share of global exports in 2030 would be lower than today's.

Trendline and step-up scenarios

For three of our seven drivers—infrastructure, residential and commercial buildings, energy transitions and efficiency—we model two scenarios. These are a trendline scenario, based on the observed patterns across countries that vary by factors such as GDP per capita, and a step-up scenario, which is based on further changes that could boost labor demand above the trendline scenario. For our seventh driver, the marketization of previously unpaid work, we have only modeled a step-up scenario. We describe the assumptions for these scenarios in the relevant sections below.

Catalyst 1: Rising incomes

Our rising incomes driver represents increase in consumer spending as well as overall spending on health care and education that results from increased prosperity (that is, rising GDP per capita) in countries. We have taken GDP per capita projections as an exogenous input to our modeling for all drivers related to change in spend.

For consumer spending, we use univariate regression analysis to identify spending trends by category using 2014 GDP per capita and 2014 consumption per capita data for the 46 countries in our model. While GDP per capita changes from 2014 to 2030 as the independent variable, we model change in spend by category for accommodation and food services, automobiles, clothing, financial services, food, household goods, leisure goods, leisure services, and utilities. (We exclude some categories of consumer spending to avoid double counting, such as public transport, which could overlap with our infrastructure driver). An adjustment is made across categories to cap overall consumption, to ensure that our regression analyses do not imply a major shift in consumption per capita. To do this, we scale overall consumption to a low and high scenario, based on consumption per capita projections from the GGM. We then multiply the 2014 and 2030 spend by 2014 and 2030 job multipliers, respectively. The productivity-adjusted 2030 job multiplier accounts for an increase in productivity, which drives some consumption categories to have negative job growth in countries where productivity growth outstrips demand growth, such as the agriculture sector in India. Additionally, we use indirect job multipliers to capture the demand created in other sectors that supply to these sectors.

Goods and services modeled under rising incomes are determined to be tradable or non-tradable, and the labor demand for those which are tradable is distributed according to 2014 levels of global trade.

Given the discrepancies between countries in funding models for education and health care, these drivers have been sized separately from the rest of consumer spending, despite some proportion of education and health care spending being funded directly by consumers. For both these sectors, we model the full sector, which would include that funded by consumers as well as public and private sector funding.

We see a trend towards increased numbers of jobs in education as GDP per capita rises. We model this relationship through univariate regressions on student-teacher ratios and gross enrollment rates across primary, secondary, and tertiary levels using 2014 data for all 46 countries in our model. We also capture the effect of aging populations; if there is low population growth and the population is aging, this decreases education jobs, and vice versa. The general formula we use is:

$$\left(\frac{2030\ student\ age\ population}{2030\ STR} \times 2030\ GER\right) - \left(\frac{2014\ student\ age\ population}{2014\ STR} \times 2014\ GER\right)$$

We use this to model projected education jobs in 2030, then subtract the number of jobs in 2014 to size the incremental labor demand in education. We then use indirect job multipliers to capture jobs created in other sectors that are suppliers to the education sector.

Catalyst 2: Health care: Rising incomes and aging

In addition to rising incomes increasing demand for jobs in health care, aging populations in many countries will likewise raise health-care demand. We model these effects of rising incomes and aging together to avoid double-counting the increase in healthcare jobs.

The change in the number of health-care jobs is modeled through bivariate linear regression with 2014 GDP per capita and aging (share of population over 65 in 2014) as independent variables and health-care professionals per 1000 people in 2014 as the dependent variable for all 46 countries in our model. We use this trendline to model the increase in health-care professionals as GDP per capita increases and population ages from 2014 to 2030 levels. We include all parts of the health-care delivery sector including hospital care, home care, nursing homes, and other support roles. We then use indirect job multipliers to capture jobs created in other sectors that are suppliers to the health-care sector.

Catalyst 3: Development and deployment of new technology

We identify trends between rising GDP per capita and spend on information technology. For enterprise IT spend, we find that a country's GDP is correlated with the amount spent on hardware, software, and IT services. For consumer technology spend, we consider only the hardware and software components of spend, and find that the richer the population (i.e. the higher GDP per capita) the higher spend on technology goods. We use univariate linear regression analyses to find a relationship between 2014 GDP per capita as the independent variable and each category of IT spend per capita in 2014 (including consumer and enterprise spending) as the dependent variable across all 46 countries. These categories of IT spend are then multiplied by productivity-adjusted job multipliers for 2014 and 2030 to calculate net new jobs. All data is based on historical baselines from Gartner's *Market Databook* published in the first quarter of 2017.[158] Finally, we use indirect multipliers to capture jobs created in sectors supplying to the IT sector.

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[158] *Market Databook, 1Q17 Update*, Gartner, March 2017.

As the consumer technology element of rising incomes is captured within this driver, we omit it from the rising incomes driver. Likewise, since telecommunications and electric utilities are captured in the infrastructure driver, we did not consider increase in technology infrastructure spend as part of our technology definition in order to avoid double-counting. Finally, this driver assumes technology spend growth according to current trends and thus does not consider the scenarios of extraordinary technology spend that are possible in more rapid automation scenarios.

Catalyst 4: Infrastructure investment

In our trendline scenarios for infrastructure investment, we conduct univariate regression analyses with GDP per capita as the independent variable and infrastructure spend per capita as the dependent variable on 2014 cross-country data. From this, we estimate infrastructure spend in 2014 and in 2030, using GDP per capita projections. These 2014 and 2030 infrastructure spend numbers are then multiplied by 2014 and 2030 job multipliers for the construction sector, respectively, to estimate jobs in each year. 2030 job multipliers, as with other catalysts, are calculated using productivity growth as discussed below. The difference is the incremental addition of new infrastructure jobs between 2014 and 2030.

In our step-up scenario, we model a step-up in which countries have increased their infrastructure stock to a global benchmark of 70.5 percent of total GDP. This results in higher run-rate infrastructure spending in order to attain and maintain the infrastructure 70.5 percent benchmark, accounting for both GDP growth (accelerated in our step-up scenario) and depreciation. In all, this amounts to between \$4 trillion and \$4.5 trillion annual spending for economic infrastructure (transport, water, and power) compared with \$2.1 trillion to \$3 trillion in the trendline scenario. We assume annual non-automation productivity increases ranging from 1.5 percent to 4.8 percent in some emerging market countries based on historical trends (1.5 percent in China, 4.8 percent in Kenya, Nigeria, and the Philippines, and no productivity increases elsewhere). By the same method as the trendline scenario, we multiply 2014 and 2030 spend by job multipliers for the construction sector to estimate gross new jobs. Included in the ranges of our step-up scenario estimate are additional annual non-automation productivity increases in the remaining emerging market countries of 2.5 percent. This productivity adjustment would better indicate the range of possible outcomes in emerging market countries; in advanced economies, given low historical growth in productivity, we do not assume non-automation productivity will increase even in the low range of the step-up scenario. Finally, we use indirect job multipliers to capture jobs created in sectors that supply the construction sector.

Catalyst 5: Residential and commercial buildings

As with infrastructure, we have modeled two scenarios for residential and commercial buildings. For the trendline scenario, we again conduct univariate regression analyses, just as we did for infrastructure. For the step-up scenario, we model an increase of stock in structures to a US benchmark of 2.3 times that of total GDP, in line with data from the Bureau of Economic Analysis, and adjust downward for double-counting with infrastructure, inclusion of industrial structures, and spending on equipment outside of the construction sector. This amounted to \$8.2 trillion to \$9.8 trillion annual spending for buildings and structures (including residential, commercial and industrial structures) compared with \$3.8 trillion to \$5.5 trillion in the trendline scenario. As with the infrastructure catalyst, we also apply 1.5 to 4.8 percent productivity growth assumptions in select countries in the trendline scenario, and 2.5 percent annual non-automation productivity increase to remaining emerging market countries in the low range of the step-up scenario.

Catalyst 6: Energy transitions and efficiency

The energy transitions driver captures the potential job creation due to the shift in mix of electricity generation. The potential increase in jobs in electric power generation due to increase in demand for power is captured in the utilities category of consumer spending driven by rising incomes. We avoid double counting by isolating the mix shift effect in this driver. Using McKinsey modeled scenarios for gigawatt (GW) capacity in 2030, we multiply projected GW capacity by a jobs per GW multiplier across manufacturing, decommissioning, fuels, construction/installation, operations and maintenance by energy type (such as solar, coal, gas). Given the rapid and hard-to-predict changes in productivity across the renewables value chain, we model a minimum scenario in which rapid productivity growth continues, and a maximum scenario in which productivity gains plateau. To model a step-up scenario, we increase the GW capacity shift more heavily towards renewables targets that could help slow global temperature increases to two degrees Celsius above pre-industrial levels. This increased shift results in greater numbers of jobs created to change the energy generation mix by country.

We model potential spend on energy efficiency using estimates from the International Energy Agency's 2014 World energy investment outlook report. We use two scenarios that the IEA models: a "New Policies Scenario" and a "450 Scenario." In the New Policies Scenario, which is grouped with our other trendline drivers, "energy demand and supply projections reflect energy policies and measures that have been adopted as of early 2014, as well as other commitments that have been announced, but not implemented, taking a cautious view of the extent to which these may be realized."[159] For our step-up analysis, we use the IEA's 450 Scenario which "plots an emissions-reduction path for the energy sector consistent with the international goal to limit the rise to long-term average temperatures to two degrees Celsius."[160] In both scenarios, we use job multipliers to estimate the number of incremental jobs associated with the increase in spend that the IEA projects between 2014 and 2030, and use indirect multipliers to capture jobs created in other supplying sectors.

Catalyst 7: Marketization of currently unpaid work

We model the marketization of currently unpaid work solely as a step-up labor demand driver. We use local time-use surveys to understand the amount of time spent in various countries on unpaid domestic work including cooking, cleaning, childcare and elder care. We decrease the time spent on these activities in each country using a linear coefficient between the minimum and maximum values across countries. We then make assumptions around productivity gains in each activity through professionalization to estimate the potential for new labor demand creation.

3. MACROECONOMIC ANALYSIS

We used McKinsey's Global Growth Model to dynamically model the US economy. Given both the unemployment and productivity effects of automation, we use the model to determine the GDP growth needed to return the economy to full employment by 2030.

Of the automation effects modeled, we directly included four channels by which automation affects the economy: unemployment displacement, capital investment, total factor productivity growth, and reemployment rate. Three of the four channels are outputs from the MGI automation model. We take the unemployment displacement as the midpoint displacement directly from the automation model; capital investment as the solution cost given in the automation model; and total factor productivity as the implied productivity growth from automation that would at the minimum result in constant total output.

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[159] World energy investment outlook, International Energy Agency, 2014.

[160] Ibid.

Besides the outputs from the automation model, we also included a fourth channel, the reemployment rate, which describes how displacement actually translates into unemployment. Not every displaced worker will enter unemployment; some will have the skills and the opportunity to quickly transition into a new role. We define the reemployment rate as the percentage of displaced workers expected to return to work within the year; the remaining displaced workers enter unemployment.

On top of the four channels, we modeled four different labor market scenarios. Each of the four scenarios used a different reemployment rate—low, medium, high, or full reemployment—to describe conditions such as labor market flexibility, labor market slack, skills and geographic mismatch, etc. that could influence the rate at which displaced workers return to work. For the United States, we used a 25 percent reemployment rate in the low scenario, 49 percent reemployment rate in the medium scenario (the reemployment rate of displaced workers in January 2010), 66 percent in the high scenario (the reemployment rate of displaced workers in January 2016), and 100 percent reemployment in the full reemployment scenario. The modeled unemployment displacement and capital investment by country were held constant in all scenarios. For example, in the United States, the modeled unemployment displacement was 23 percent by 2030, and expected automation capital investment $145 billion by 2030. The reemployment rates for each of the labor market scenarios differed by country and were estimated from literature and adjusted for labor market flexibility factors.

The GGM first forecasts a baseline future without taking into account the effects of automation. It then uses the inputted unemployment displacement, capital investment, total factor productivity growth, and reemployment rate, and dynamically propagates these effects of automation throughout the modeled economy. The forecasted unemployment rate, GDP growth rate, and average wage rates from the GGM are to be interpreted by their deviation from the baseline state as a directional range of scenarios for several possible future states.

4. SKILLS AND WAGES ANALYSES

In this analysis, we look at the net impact of (i) automation and (ii) labor demand creation at an occupation level, to understand which occupations could see high levels of demand vs. decline by 2030.

Baseline for skills and wages analyses

The baseline for our skills and wages analyses is the 2014 employment levels by occupation, adjusted for the effects of automation and our labor demand drivers. Elements of the economy in which we have not sized growth (such as defense) remain at 2014 levels of employment; new occupations that do not currently exist do not show in this baseline.

Mapping new labor demand and automation to jobs

Our automation modeling is mapped to each of the 820 occupation codes used by the US Bureau of Labor Statistics for all of the 46 countries in our model. We multiply the percentage automation adoption rate in 2030 for each occupation by the size of each occupation in 2030 (which is assumed to be the same percentage of labor force as in 2014). This provides us with a projection of how the employment levels in jobs will be affected by automation in 2030.

To model the countervailing effect on labor demand creation, we map our drivers of demand according to a list of associated occupations on a driver-by-driver basis. Most drivers map to a specific sector, in which case we allocate incremental new jobs according to today's mix of jobs within a specified sector. In drivers that affect a narrower range of jobs, we create more customized mappings to reflect reality. For example, for energy transitions and efficiency, we map potential labor demand increase to the US Bureau of Labor Statistics' categorizations of "green jobs" and to the relevant jobs in fuels. Based on the sector of each direct job added, additional indirect jobs are created based on the specified job multipliers for a country. Indirect jobs are created according to the mix of their sector.

Combining these two calculations, we compare the total jobs displaced by automation based on our 2030 baseline (today's occupation mix, scaled in proportion with the growth of labor force) to the jobs added by our drivers to 2030. To calculate a percentage growth or decline, we divide this net change by today's employment level for the occupation.

Skills and educational categorizations

Our analyses take training requirements for jobs as a proxy for skill requirements. The five educational categories used in our analyses are: less than secondary, secondary, associate degree, bachelor's degree and advanced degree. These classifications map to the five job-zones defined by the US Bureau of Labor Statistics' O*Net and take into account educational degrees, amount of training required, and years of experience necessary in order to qualify for a given job. Associate degrees are more common in the United States than in the rest of the world and usually require two years of study.

To optimize for consistency across our modeling and data quality, we use these educational requirements from the O*Net classification across all 46 countries. This simplifying assumption is limiting in cases in which there are discrepancies among countries, but we find that requirements are broadly similar: the educational requirement to be a doctor is typically an advanced degree in most countries.

Wage assumptions

In our analyses on the effects of automation and new labor demand on wages, we keep wages constant at 2014 levels; chemical engineers, economists and lawyers were in the highest decile of wage earners in 2014 in the United States, where they remain for our analyses in 2030.

In reality, we would expect wages to adjust to shifts in response to automation and new labor demand. There could also be additional economic effects on wages, such as Baumol's cost disease, or policy effects such as minimum wage legislation. Modeling these effects on wages is beyond the scope of our analysis, so we exclude them in favor of keeping wages constant at 2014 levels. While we thus cannot say anything definitive about wage shifts and are limited in any commentary on inequality, our approach allows us to identify relative shifts between high-wage and low-wage occupations.

Exhibit A2

Glossary of automation technologies and techniques

OCTOBER 2017

This list is not comprehensive but is meant to illustrate some of the technologies and techniques that are being developed to enable automation of different work activities

Technologies and techniques		Description/examples
Artificial intelligence		Field of computer science specializing in developing systems that exhibit "intelligence." Often abbreviated as AI, the term was coined by John McCarthy at the Dartmouth Conference in 1956, the first conference devoted to this topic
	Machine learning	Subfield of artificial intelligence developing systems that "learn," i.e., practitioners "train" these systems rather than "programming" them
	Supervised learning	Machine learning techniques that train a system to respond appropriately to stimuli by providing a training set of sample input and desired output pairs. Supervised learning has been used for email spam detection by training systems on a large number of emails, each of which has been manually labeled as either being spam or not
	Transfer learning	Subfield of machine learning developing systems that store knowledge gained while solving one problem and applying it to a different but related problem. Often used when the training set for one problem is small, but the training data for a related problem is plentiful, e.g., repurposing a deep learning system trained on a large non-medical image data set to recognize tumors in radiology scans
	Reinforce-ment learning	Subfield of machine learning developing systems that are trained by receiving virtual "rewards" or "punishments" for behaviors rather than supervised learning on correct input-output pairs. In February 2015, DeepMind described a reinforcement learning system that learned how to play a variety of Atari computer games. In March 2016, DeepMind's AlphaGo system defeated the world champion in the game of Go
	Cognitive computing	Synonym for artificial intelligence
Neural networks	**Artificial neural network**	AI systems based on simulating connected "neural units," loosely modeling the way that neurons interact in the brain. Computational models inspired by neural connections have been studied since the 1940s
	Deep learning	Use of neural networks that have many layers ("deep") of a large number (millions) of artificial neurons. Prior to deep learning, artificial neural networks often only had three layers and dozens of neurons; deep learning networks often have seven to ten or more layers. The term was first used in 2000
	Convolution-al neural network	Artificial neural networks in which the connections between neural layers are inspired by the organization of the animal visual cortex, the portion of the brain that processes images, well suited for perceptual tasks. In 2012, the only entry using a convolutional neural network achieved an 84% correct score in the ImageNet visual recognition contest, vs. a winning score of 75% the year prior. Since then, convolutional neural networks have won all subsequent ImageNet contests, exceeding human performance in 2015, above 90%
	Recurrent neural network	Artificial neural networks whose connections between neurons include loops, well-suited for processing sequences of inputs. In November 2016, Oxford University researchers reported that a system based on recurrent neural networks (and convolutional neural networks) had achieved 95% accuracy in reading lips, outperforming experienced human lip readers, who tested at 52% accuracy.

SOURCE: John McCarthy et al., "A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955," *AI Magazine*, volume 27, number 4, 2016; Hayit Greenspan, Bram van Ginneken, and Ronald M. Summers, "Deep learning in medical imaging: Overview and future promise of an exciting new technique," *IEEE Transactions on Medical Imaging*, volume 35, number 5, May 2016; Volodymyr Mnih, "Human-level control through deep reinforcement learning," *Nature*, February 25, 2015; Igor Aizenberg, Naum N. Aizenberg, and Joos P.L. Vandewalle, *Multi-valued and universal binary neurons: Theory, learning and applications*, Springer Science & Business Media, 2000; www.image-net.org; Yannis M. Assael et al., "LipNet: End-to-end sentence-level lipreading," University of Oxford (forthcoming); McKinsey Global Institute analysis

Exhibit A2

Glossary of automation technologies and techniques (continued)

OCTOBER 2017

This list is not comprehensive but is meant to illustrate some of the technologies and techniques that are being developed to enable automation of different work activities

Technologies and techniques		Description/examples
Robotics	**Soft robotics**	Non-rigid robots constructed with soft and deformable materials that can manipulate items of varying size, shape and weight with a single device. Soft Robotics Inc. grippers can adaptively pick up soft foods (e.g., baked goods, tomatoes) without damaging them.
	Swarm robotics	Coordinated multi-robot systems, often involving large numbers of mostly physical robots
	Tactile/touch robotics	Robotic body parts (often biologically inspired hands) with capability to sense, touch, exhibit dexterity, and perform variety of tasks
	Serpentine robots	Serpentine looking robots with many internal degrees of freedom to thread through tightly packed spaces
	Humanoid robots	Robots physically similar to human beings (often bi-pedal) that integrate variety of AI and robotics technologies and are capable of performing variety of human tasks (including movement across terrains, object recognition, speech, emotion sensing, etc.). Aldebaran Robotics and Softbank's humanoid Pepper robot is being used to provide customer service in more than 140 Softbank Mobile stores in Japan
Automation product categories	**Autonomous cars and trucks**	Wheeled vehicles capable of operating without a human driver. In July 2016, Tesla reported that its cars had driven over 130 million miles while on "Autopilot." In December 2016, Rio Tinto had a fleet of 73 driverless trucks hauling iron ore 24 hours/day in mines in Western Australia
	Unmanned aerial vehicles	Flying vehicles capable of operating without a human pilot. The unarmed General Atomics Predator XP UAV, with roughly half the wingspan of a Boeing 737, can fly autonomously for up to 35 hours from take-off to landing
	Chatbots	AI systems designed to simulate conversation with human users, particularly those integrated into messaging apps. In December 2015, the General Services Administration of the US government described how it uses a chatbot named Mrs. Landingham (a character from the television show *The West Wing*) to help onboard new employees
	Robotic process automation	Class of software "robots" that replicates the actions of a human being interacting with the user interfaces of other software systems. Enables the automation of many "back-office" (e.g., finance, human resources) workflows without requiring expensive IT integration. For example, many workflows simply require data to be transferred from one system to another

SOURCE: www.ald.softbankrobotics.com; *A tragic loss*, Tesla blog, June 30, 2016; *Resource revolution: Transformations beyond the supercycle*, McKinsey Global Institute, forthcoming in 2017; www.ga-asi.com/predator-xp; Jessie Young, *How a bot named Dolores Landingham transformed 18Fs onboarding*, www.18f.gsa.gov, December 15, 2015; McKinsey Global Institute analysis

Nurse with elderly patient, Japan

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DEPARTMENT OF DEFENSE

ARTIFICIAL INTELLIGENCE, BIG DATA AND CLOUD TAXONOMY

Foreword by

Hon. Robert O. Work, 32nd Deputy Secretary of Defense

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GOVINI CLIENT MARKET VIEWS

Artificial Intelligence - Computer Vision

Artificial Intelligence - Data Mining

Artificial Intelligence - Deep Learning

Artificial Intelligence - Machine Learning

Artificial Intelligence - Modeling & Simulation

Artificial Intelligence - Natural Language Processing

Artificial Intelligence - Neuromorphic Engineering

Artificial Intelligence - Quantum Computing

Artificial Intelligence - Supercomputing

Artificial Intelligence - Virtual Agents

Artificial Intelligence - Virtual Reality

Big Data - Business Analytics

Big Data - Data Analytics

Big Data - Data Architecture & Modeling

Big Data - Data Collection

Big Data - Data Hygiene

Big Data - Data Hygiene Software

Big Data - Data Visualization Software

Big Data - Data Warehouse

Big Data - Distributed Processing Software

Big Data - ETL & Data Processing

Big Data - Intelligence Exploitation

Cloud - IaaS

Cloud - PaaS

Cloud - SaaS

DEPARTMENT OF DEFENSE

ARTIFICIAL INTELLIGENCE, BIG DATA AND CLOUD STANDARD MARKET TAXONOMY

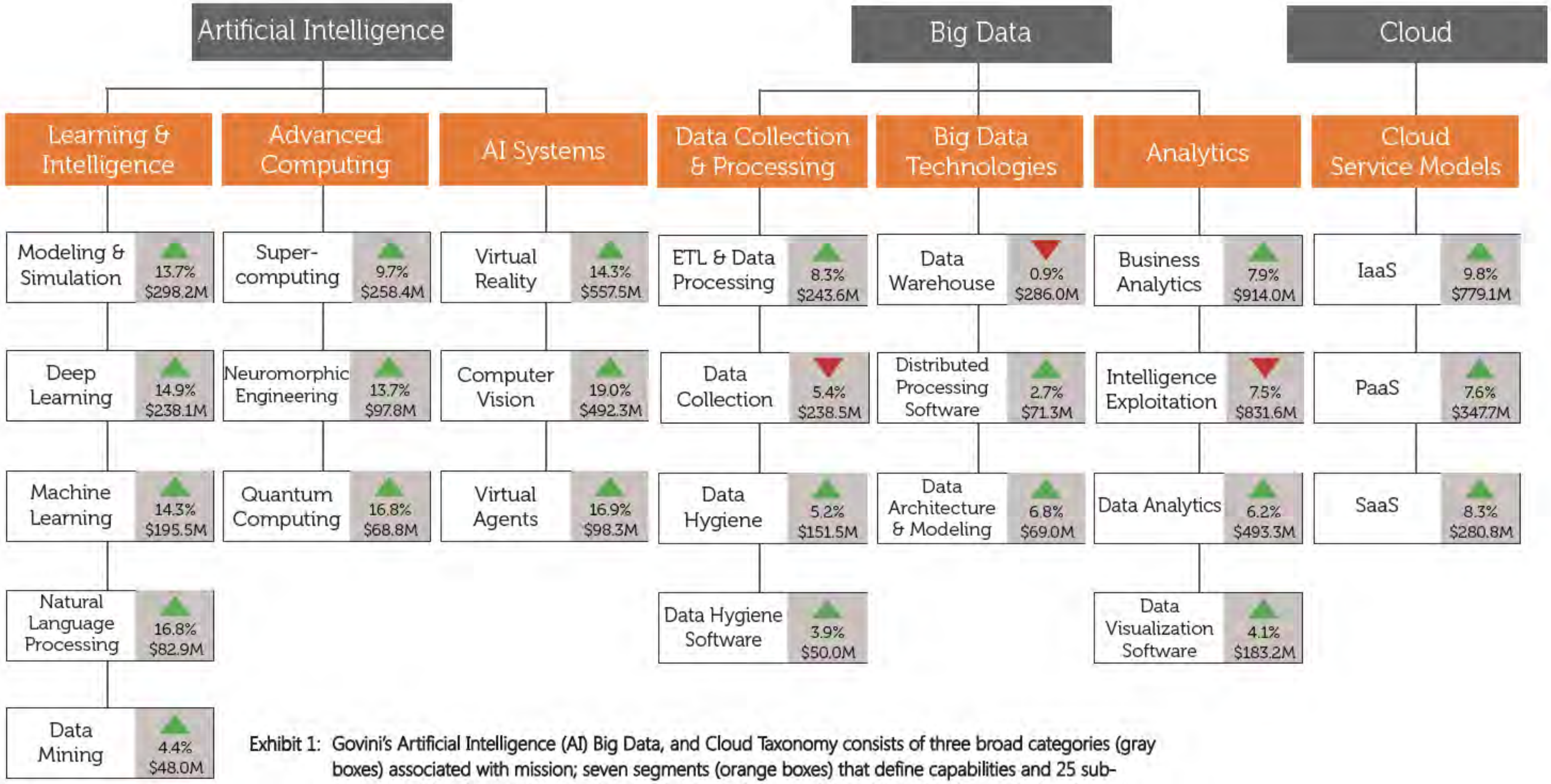

Exhibit 1: Govini's Artificial Intelligence (AI) Big Data, and Cloud Taxonomy consists of three broad categories (gray boxes) associated with mission; seven segments (orange boxes) that define capabilities and 25 sub-segments (white boxes) that constitute technological approach. The hierarchical organizational structure is designed to deliver insight ranging from high-level spending trends to granular details on specific programs and technical solutions. Current year spending and the five-year compound annual growth rate (CAGR) from FY2012 through FY2017 are noted for each sub-segment. Final FY2017 values are estimated based on public spending data that were available through October 2017.

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ARTIFICIAL INTELLIGENCE, AUTONOMOUS SYSTEMS AND THE THIRD OFFSET

Hon. Robert O. Work, 32nd Deputy Secretary of Defense

Autonomy results from delegation of decision to an authorized entity to take action within specific boundaries. An important distinction is that systems governed by prescriptive rules that permit no deviations are automated, but are not autonomous. To be autonomous, a system must have the capability to independently compose and select among different courses of action to accomplish assigned goals based on its knowledge and understanding of the world, itself and the situation.[1]

Rapid advances in Artificial Intelligence (AI)—and the vastly improved autonomous systems and operations they will enable—are pointing towards new and more novel warfighting applications involving human-machine collaboration and combat teaming. These new applications will be the primary drivers of an emerging military-technical revolution. Military revolutions "are periods of discontinuous change that render obsolete or subordinate existing means for conducting war."[2] The U.S. military can either lead the coming revolution, or fall victim to it.

This stark choice will be determined by the degree to which the Department of Defense (DoD) recognizes the revolutionary military potential of AI and advanced autonomous systems; ramps up research and development in their associated technologies, such as advanced computing, artificial neural networks, computer vision, natural language processing, big data, machine learning, and unmanned systems and robotics; and aggressively develops the new systems, operational concepts and organizational constructs that exploit them in warfare.

The "Third Offset Strategy," first articulated by Secretary of Defense Chuck Hagel in November, 2014, announced DoD's intentions to lead the coming AI/autonomy driven military-technical revolution. By exploiting advances in AI and autonomous systems to improve the warfighting potential and performance of the U.S. military, the Strategy aims to restore the Joint Force's eroding conventional overmatch versus any potential adversary, thereby strengthening conventional deterrence.

As its name suggests, the Third Offset Strategy follows two previous competitive strategies with similar ends. DoD adopted the Second Offset Strategy in the mid to late-1970s to overcome the Warsaw Pact's large numerical advantage in conventional forces along the Central European front. Up until then, the U.S. had offset superior Warsaw Pact numbers with a smaller force armed with battlefield atomic weapons. However, this First Offset Strategy was blunted once the Soviets achieved strategic nuclear parity with the U.S., which called into question NATO's threat to employ tactical nuclear weapons in its defense. A new strategy was needed to strengthen conventional deterrence. Rather than try to match the communist military machine soldier-for-soldier, tank-for-tank, or plane-for-plane, U.S. planners once again opted to offset Soviet strength—this time by developing an ability to "look deep and shoot deep" and destroy follow-on Warsaw Pact forces before they reached NATO front lines. Looking deep and shooting deep required the development of a new and far more capable theater-wide battle network able to target and attack advancing Warsaw Pact forces still far away from the "forward edge of the battle area." Battle networks were nothing new. They first appeared at the start of World War II in the form of the British homeland air defense system, with the four interconnected grids that defined all subsequent battle networks:

- A sensor grid capable of wide area surveillance as well as narrower battlefield reconnaissance and targeting;
- A C4I grid (Command, Control, Communications, Computer and Intelligence Grid), able to make sense of what was happening in the area of operations, facilitate decisions to seek combat advantage, and transmit orders to the...
- ...effects grid, consisting of a wide array of kinetic and non-kinetic combat forces and effectors designed to achieve specific battlefield outcomes; and
- A sustainment and regeneration grid designed to sustain combat operations and regenerate combat losses.

What made the new NATO Follow on Forces Attack (FOFA) network so powerful was the marriage of long-range sensors and a new generation of guided munitions and submunitions, linked by digitally enabled, real-time battle management capabilities. Take for example the TR-1 aircraft, a modification of the iconic U-2 spy plane. Carrying side-looking radar at high altitudes, it could image Warsaw Pact armored forces operating over 100 miles from the NATO front lines. It would then downlink its data directly to ground processing centers which then quickly sent accurate firing data to the Army Tactical Missile System (ATACMS), a ballistic missile armed with guided submunitions. Similarly, the Joint Surveillance and Target Attack Radar System (JSTARS), with its ground moving target indicator mode and onboard battle management capabilities, could vector NATO tactical fighter-bombers armed with a variety of guided munitions towards deep Warsaw Pact armor formations. At the theater level, the Air Force created what is now known as the Combined Air Operations Center, or CAOC, which would issue coordinated air tasking orders to all NATO air forces.

Happily, NATO and Warsaw Pact forces never came to blows. However, the guided munitions-battle network revolution spurred by the Second Offset Strategy was on display for all to see during Operation Desert Storm—the 1990-91 U.S.-led campaign to eject Iraqi forces from Kuwait. Although it was quite short, this campaign clearly demonstrated that the combination of theater-wide sensor grids, digital C4I grids designed for real-time battle management, and effects grids that emphasize guided weapon attacks rendered subordinate combined arms warfare characterized by massed formations employing unguided weapons fire.[3]

Because the U.S. military was the aggressive first mover in guided munitions-battle network warfare, it enjoyed a dominant conventional overmatch versus any regional competitor in the immediate post-Cold War period. Now, however, newly emerging great power competitors like Russia and China are rapidly achieving parity in guided munitions-battle network warfare, and Second Offset technologies are proliferating worldwide. As a result, the conventional overmatch enjoyed by the Joint Force over the past two-and-a-half decades is now eroding—and at an accelerating rate. This circumstance is challenging traditional means of U.S. power projection and undermining conventional deterrence, thereby raising the future risk of conventional interstate warfare.

Hence the need for a Third Offset Strategy, which seeks to exploit advances in AI and autonomous systems to improve the performance of Joint Force guided munitions-battle networks in five different ways:

- Deep learning machines, powered by artificial neural networks and trained with big data sets, and inserted in every battle network grid;
- New ways of human-machine collaboration, which rely on AI-enabled learning machines to help humans make more timely and relevant combat decisions;
- New ways to facilitate assisted human operations, whereby smart AI devices will allow operators of all types can plug into and call upon the power of the entire Joint Force battle network to accomplish assigned missions and tasks;
- New types of human-machine combat teaming that see seamless coordinated operations between manned and unmanned systems, including those that are increasingly autonomous in their operations; and
- Cyber and electronic warfare-hardened network-enabled, autonomous and high-speed weapons capable of collaborative attacks.

By gradually reconfiguring Joint Force battle networks in these ways, and by adopting new operational concepts and organizational constructs to exploit them, Joint Force battle networks will be able to sense and perceive battlefield patterns more readily and rapidly, facilitate more timely and relevant combat decisions, and apply more rapid, discreet and accurate effects with less loss of life. If all these things happen, the Joint Force will operate at a higher, more effective tempo than its adversaries, and thereby gain an important, if not decisive, advantage in both campaign and tactical level operations.

Importantly, however, the Third Offset Strategy recognizes that much of the research and development of AI and autonomous systems is being conducted in the commercial sector, meaning its fruits are available to all competitors. This means the competition to derive advantage from them will be very intense. For example, China, has similar ambitions with respect to these important technologies. It is betting on AI to drive its future military and economic strengths—so much so that its AI strategy calls for China to become the world leader in the field by 2030. Only a similarly focused effort will keep the U.S. Joint Force from falling behind, and being on the wrong end of a new generation of human-machine warfare.

The Third Offset Strategy's desirable ends are well within reach if tied to an urgent and concerted DoD initiative to pursue them. This initiative must consist of two complementary efforts. The first is a robust, focused, and prioritized research and development (R&D) program designed to explore and field the technologies necessary to implement the strategy's vision. This is the realm of the Office of the Secretary of Defense (OSD), specifically the new Undersecretary of Defense for Research and Engineering. The second is the development of new operational concepts and organizational constructs to exploit these new technologies. This effort will fall primarily to the military services and combatant commands to implement.

The purpose of the following report, prepared by Matt Hummer and the staff at Govini, is to support the OSD effort. Govini's powerful data gathering and analytic tools can track Federal contract spending down to the penny. Using these tools, this report displays and analyzes actual DoD spending on Third Offset technologies from FY2012 through FY2017. By so doing, it shows whether or not the Department of Defense is "putting its money where its mouth is" on the Third Offset Strategy.

When reading the report, please keep in mind three things:

- First, this report is not an argument about the pros and cons of autonomous systems. It is a summation of the DoD spending on the technologies that support their development, fielding and operations. It is aimed primarily at DoD and national level decision makers who must decide if the amount and focus of that spending is appropriate.

- Second, the following data reflects spending only on unclassified contracts. One can expect there to be additional Third Offset spending on classified contracts, so this report tells only part of the story. Nevertheless, spending on unclassified contracts provides a clear indicator for the overall seriousness of DoD Third Offset efforts.

- Third, the Govini Strategic Intelligence Platform allows for the natural aggregation of spending data into "market taxonomies." As will soon be apparent, the initial market taxonomy separates current DoD Third Offset spending into three broad technology categories: artificial intelligence; big data technologies needed for machine learning; and the cloud services needed to store big data sets. While this taxonomy is illuminating, the new Under Secretary of Defense for Research and Engineering may find a different taxonomy more useful, and Govini's Strategic Intelligence Platform allows for the flexible aggregation and display of data in ways most helpful to the user. For the time being, however, this first report provides a good baseline from which the new Under Secretary can build a prioritized AI/Autonomy R&D portfolio in support of the Third Offset Strategy.

[1] L.G. Shattuck, Transitioning to Autonomy: A Human Systems Integration Perspective, as cited in the Report of the Defense Science Board Summer Study on Autonomy, June 2016, p.4.

[2] Michael G. Vickers and Robert C. Martinage, The Revolution in War (Washington, D.C.: Center for Strategic and Budgetary Assessments, December 2004), pp. 2-3.

[3] Those who study military-technical revolutions or revolutions in military affairs consider Desert Storm the "defining battle" of the guided munitions-battle network revolution. A defining battle occurs when one of the forces involved demonstrates the dominance of a new way of war. Ibid., p. 3.

AI, BIG DATA AND CLOUD: CORNERSTONES OF THE THIRD OFFSET STRATEGY IN HIGHLY CONTESTED DOMAINS

DoD is investing in a wide array of technologies to enhance its military edge over large state competitors such as China and Russia. Of these, none are more important than Artificial Intelligence (AI) and Autonomous Systems, which are the technological cornerstones of the Department's Third Offset Strategy. As explained by Bob Work, by exploiting advances in AI and Autonomous Systems to improve the warfighting potential and performance of the U.S. military, the Strategy aims to restore the Joint Force's eroding conventional overmatch versus any potential adversary, thereby strengthening conventional deterrence.

This analytic report leverages data science to present Govini's AI, Big Data and Cloud Taxonomy, a roadmap for tracking major drivers of the these emerging technologies. The Taxonomy consists of three broad categories of spending: Artificial Intelligence, Big Data, and Cloud. Each of these categories are further divided into segments that define associated capabilities and sub-segments that constitute a technological approach. The hierarchical organizational structure is designed to deliver insight ranging from high-level spending trends to granular details on specific programs and technical solutions over the last six fiscal years as means for predicting budget priorities in FY2019 and beyond.

The Taxonomy shows sub-segments within the the Artificial Intelligence category having the most growth since FY2012. All together, AI spending grew by a CAGR of 14.5 percent. Cloud spending also increased by a CAGR of 8.9 percent and Big Data spending increased by 0.7 percent.

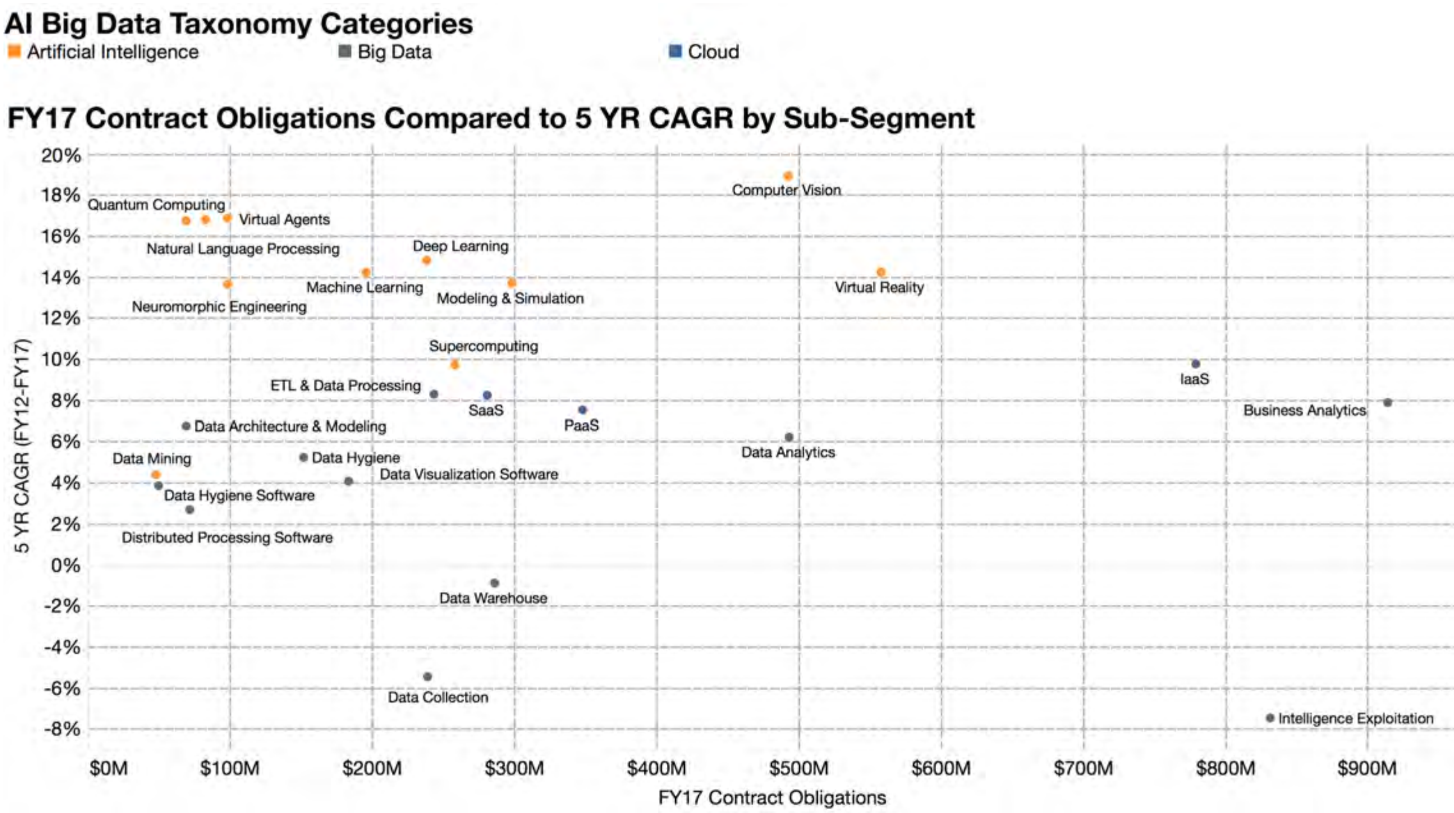


Exhibit 2: AI sub-segments (orange) had the most grow from FY2012 through FY2017. Spending on Computer Vision grew the most by 19 percent to $492.3 million in FY2017. Virtual Agents, another AI sub-segment grew by a CAGR of 16.9 percent, followed by Quantum Computing, Natural Language Processing, Deep Learning, Machine Learning, Modeling & Simulation and Neuromorphic Engineering.

Key Findings

- DoD spending on AI, Big Data and Cloud reached $7.4 billion in FY2017, which is 32.4 percent higher than the $5.6 billion spent in FY2012. In FY2017, AI accounted for 33 percent of the spending total, while Big Data accounted for 47.9 percent and Cloud accounted for 19.1 percent.

- While AI accounted for only 33 percent of the FY2017 total, it contributed significantly to the overall growth in spending from FY2012. DoD spending in the three AI segments—Learning & Intelligence, Advanced Computing and AI Systems—grew the most from FY2012 through FY2017 by CAGRs of 13.7 percent, 11.6 percent and 16.4 percent, respectively.

- Within the Learning & Intelligence segment, Natural Language Processing spending grew the most by 16.8 percent to $82.9 million in FY2017. Deep Learning spending increased the second most by 14.9 percent to $238.1 million in FY2017 and Machine Learning followed with an increase of 14.3 percent to $195.5 million in FY2017.

- Within the Advanced Computing segment, Quantum Computing spending increased the most by a CAGR of 16.8 percent to reach $68.8 million in FY2017. Neuromorphic Engineering followed with an increase of 13.7 percent, reaching $97.8 million in FY2017. Supercomputing, the largest and most mature sub-segment, had CAGR of 9.7 percent with spending reaching $258.4 million in FY2017.

- Within the AI Systems segment, Computer Vision spending grew the most by a CAGR of 19 percent from FY2012 through FY2017. Virtual Agents, the smallest AI Systems sub-segment, grew by 16.9 percent to $98.3 million in FY2017. Spending in the largest sub-segment, Virtual Reality grew by 14.3 percent to $557.5 million in FY2017.

- Most Computer Vision investment is related to Intelligence, Surveillance and Reconnaissance (ISR), specifically advancing image definition, widening field-of-view and micro chips for processing imagery data. Virtual Reality spending is primarily for battle simulation and training. The least mature AI System, Virtual Agents, is focused on large-scale language processing and translation and is being funded primarily through Defense Advanced Research Programs Agency (DARPA) programs.

- While advancing AI has been a priority of DoD, other investments in foundational categories such as Big Data and Cloud must be made in order for AI to reach its full potential. This is especially true of Big Data, which is central to “teaching” learning machines. When rolling up aggregate spending, Big Data—consisting of technologies and services for collecting, processing and analyzing data—represents the largest category, accounting for 54.4 percent of total spending from FY2012 through FY2017.

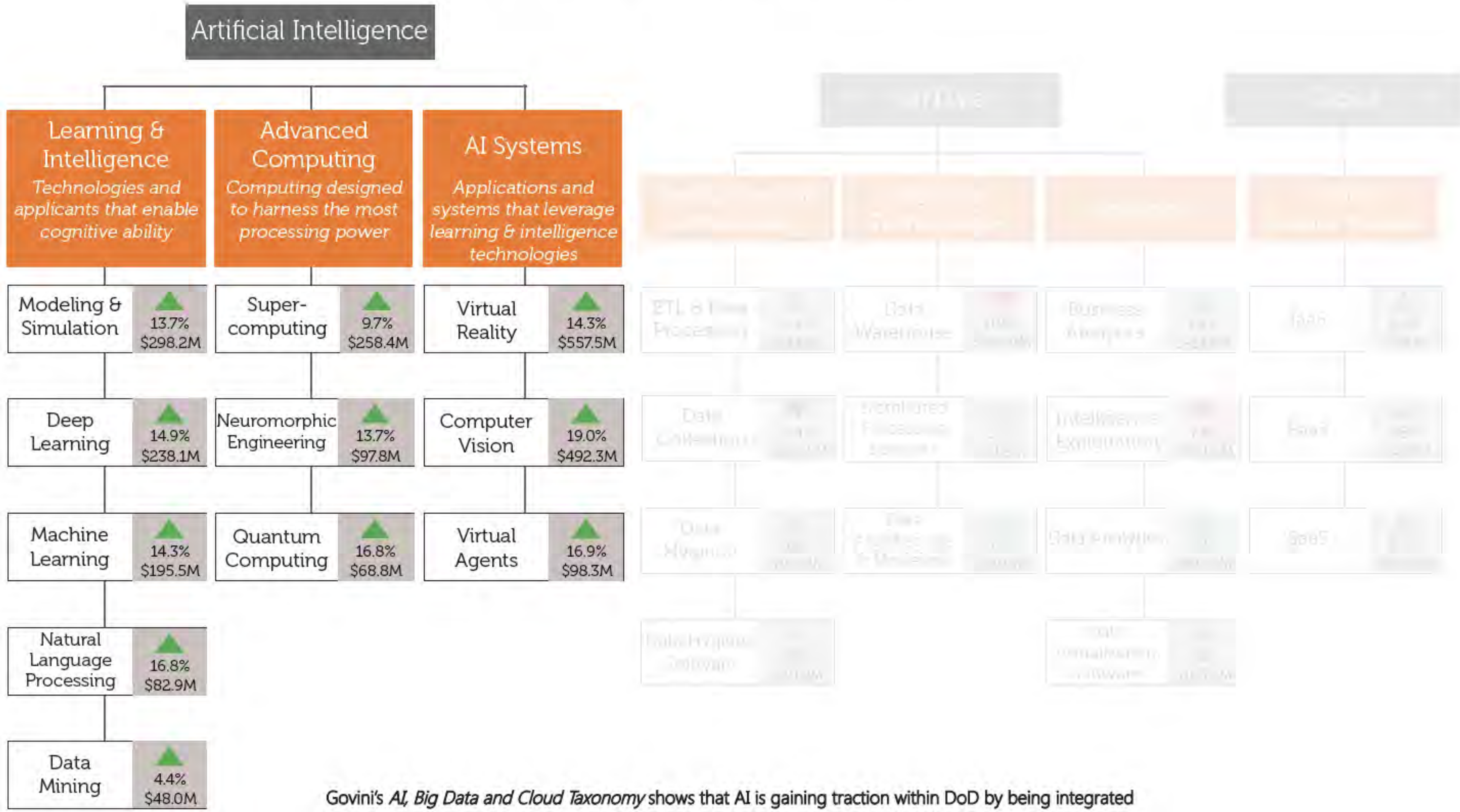
- Big Data segments had modest spending growth compared to segments in other categories. Spending on Analytics, the largest Taxonomy segment by contract obligations, grew by a CAGR of 0.5 percent. Big Data Technologies spending grew by 0.7 percent and Data Collection & Processing spending grew by a CAGR of 1.4 percent.

- The most efficient way to facilitate access to Big Data is to store it in the Cloud. Cloud is currently the smallest of the three spending categories; it grew by a CAGR of 8.9 percent reaching a high of $1.4 million in FY2017. However, with the recent announcement that DoD is accelerating a shift to the Cloud, this number is likely to rise.

DEPARTMENT OF DEFENSE

ARTIFICIAL INTELLIGENCE

STANDARD MARKET TAXONOMY



Govini's *AI, Big Data and Cloud Taxonomy* shows that AI is gaining traction within DoD by being integrated with operating concepts of mission systems. AI Systems was not only one of the largest Taxonomy segments by obligations, but also had the most spending growth. It accounted for 14.9 percent of overall Taxonomy spending since FY2012 and had a CAGR of 16.4 percent. The other AI-related segments also had strong spending growth. Learning & Intelligence spending grew by a CAGR of 13.7 percent and Advanced Computing grew by a CAGR of 11.6 percent.

DoD is Investing Heavily to Advance AI Learning & Intelligence Capabilities and Tools

Learning & Intelligence spending by DoD increased by a CAGR of 13.7 percent, the second most of all the *AI, Big Data and Cloud Taxonomy* segments. The overall growth in spending should not come as a surprise, but the prioritization of spending across sub-segments should.

Natural Language Processing (NLP) spending grew the most with a CAGR of 16.8 percent. DARPA fueled the spending growth accounting for 60.5 percent of the six-year total, through marquee programs such as Broad Operational Language Translation (BOLT) and Low Resources Languages for Emergency Incidents (LORELEI).

Other Learning & Intelligence sub-segments also had strong spending growth. Deep Learning spending grew by a CAGR of 14.9 percent and Machine Learning spending grew by 14.3 percent.

Govini has categorized Learning & Intelligence into the following five sub-segments:

- Modeling & Simulation - facilitating understanding of system behavior without testing
- Deep Learning - mimicking cognitive functions such as learning or problem solving
- Machine Learning - the ability for computers to learn without being explicitly programmed
- Natural Language Processing - programming to process large natural language corpa
- Data Mining - discovering patterns in large data sets and transforming the data into understandable structures for further analysis

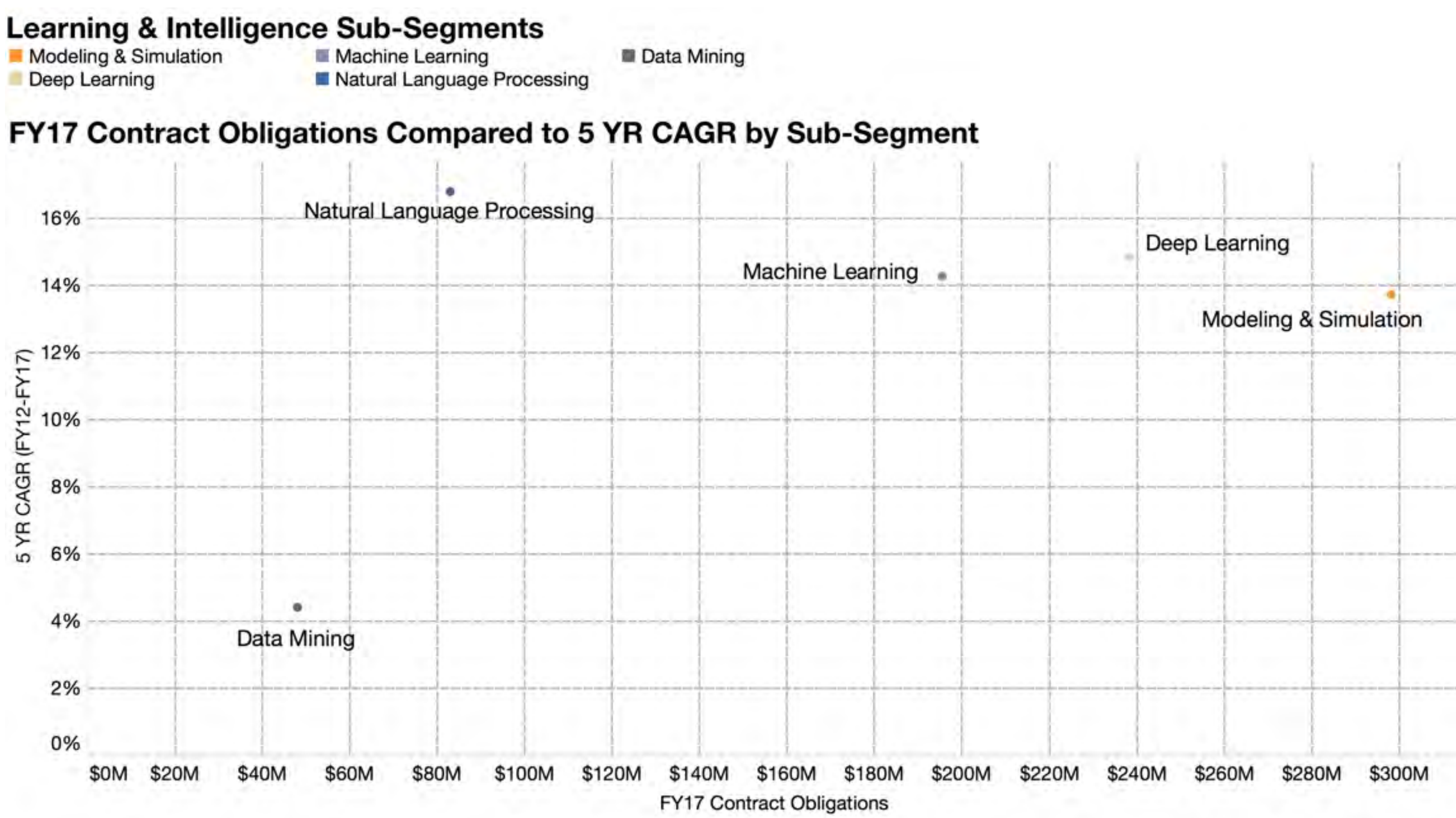


Exhibit 3: Annual spending increased significantly in most sub-segments with the exception of Data Mining. Natural Language Processing spending increased the most by 16.8 percent, followed by Deep Learning with a 14.9 percent spending increase and Machine Learning with a 14.3 percent spending increase. DARPA funded 60.5 percent of NLP programs and 28.9 percent of Deep Learning programs.

System Integrators are Seeking to Acquire Advanced Learning & Intelligence Capabilities

FY2016 marked a rapid rise in Learning & Intelligence spending. Modeling & Simulation, Deep Learning, and Data Mining spending increased the most by dollar value. Whereas FY2017 proved to have slightly different priorities such as Machine Learning and Natural Language Processing.

The fact remains that all fields of Learning & Intelligence theories are important to advancing DoD AI capabilities. They are also broadly deployed across programs funded by several DoD agencies including Army, Air Force Life Cycle Management Center (AFLCMC) and Missile Defense Agency (MDA).

Spending in the largest sub-segment, Modeling & Simulation is spread across the services with Navy and Army taking the lead through their warfare analyses and sensor simulation programs. Leidos, SAIC, AECOM and Orbital ATK led capture of Navy program spending and SAIC, CACI, Torch Technologies and Millennium Engineering led capture of Army spending. Northrop Grumman captured the most spending by MDA through its ballistic missile defense system threat software modeling work. Raytheon followed capturing 19.5 percent of MDA spending.

Each of these integrators are seeking advanced capabilities in Learning & Intelligence that will help differentiate their competitive offering. Northrop Grumman, Raytheon, Lockheed Martin and SAIC are all well represented across the other four sub-segments, but less so in the Deep Learning sub-segment. Most of the market leaders are not well established integrators rather little-known companies such as Aptima, Intelligence Automation, Soar Technology and Decibel Research. Machine Learning is similar, with Intelligent Software Solutions as the market leader through its WebTAS platform that integrates and visualizes data from multi-source data.

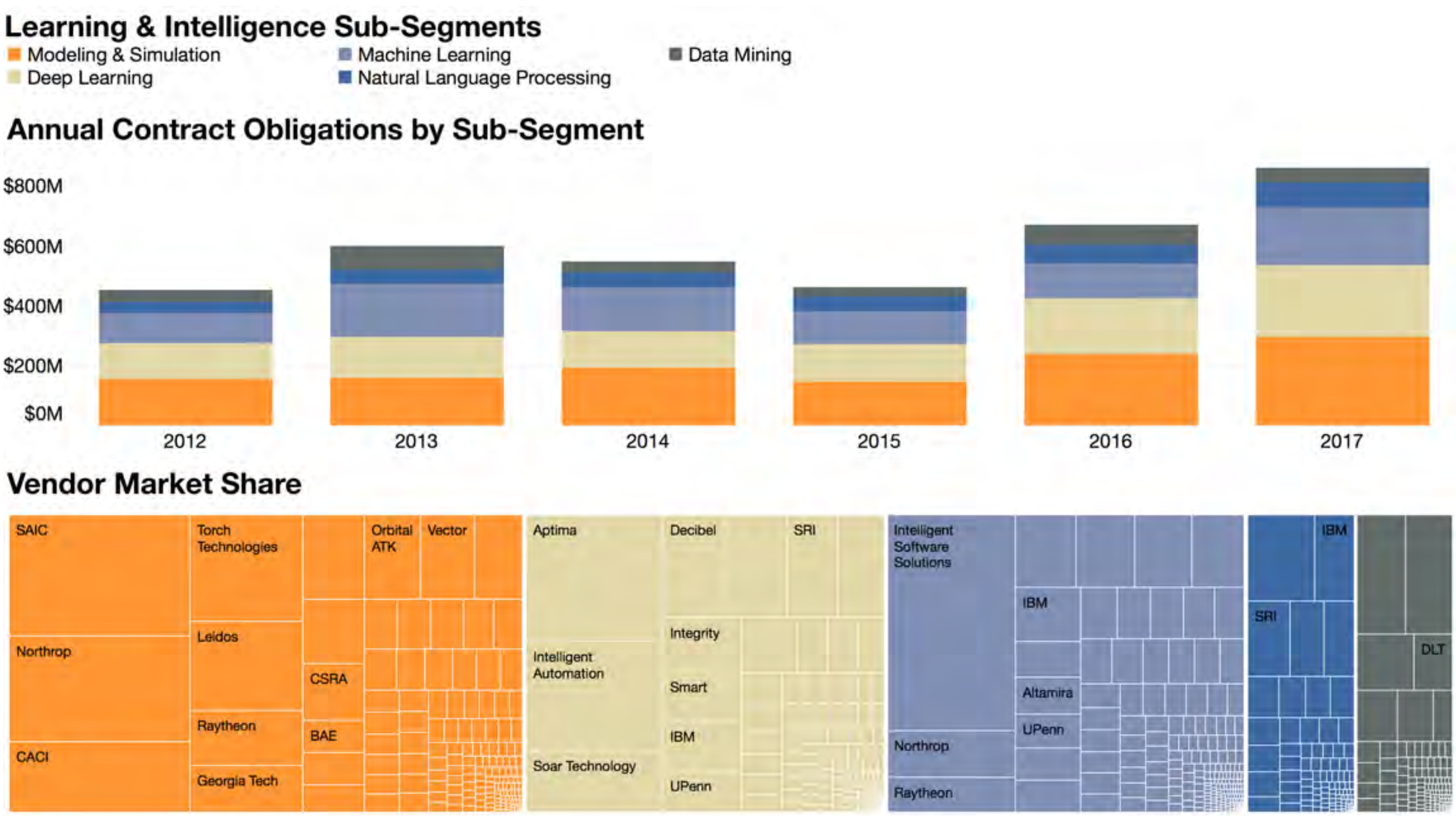


Exhibit 4: Three sub-segments, Modeling & Simulation, Deep Learning and Machine Learning accounted for 82.6 percent of total segment spending since FY2012. However, spending in smaller sub-segments like Natural Language Processing grew the most by 16.8 percent since FY2012.

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Advanced Computing Allows AI to Expand Beyond Narrow System Applications

Advanced computing power is the real enabler of AI. It allows machines to figure out how to perform tasks after being exposed to learning algorithms and training data.

DoD continues to invest in advancing computing capabilities, especially in the most recent fiscal year. Overall segment spending increased by 85.9 percent to $424.9 million in FY2017 from $228.5 million in FY2016. DARPA accounted for 37.3 percent of spending since FY2012, the most of all DoD funding offices. Naval Sea Systems Command, Army Program Office for Simulation, Training and Instrumentation (PEO STRI) and Warner Robins Air Logistics Center are also among the largest spenders on Advanced Computing.

Govini has categorized Advanced Computing into the following three sub-segments:

- Supercomputing - compute performance measured in floating-point operations per second (FLOPS)
- Neuromorphic Engineering - use of very-large-scale integration (VLSI) systems containing electronic analog circuits to mimic neuro-biological architectures
- Quantum Computing - use of quantum bits (qbits), which can be in superpositions of states instead of binary bits, which is always in one or two definite states (0 or 1)

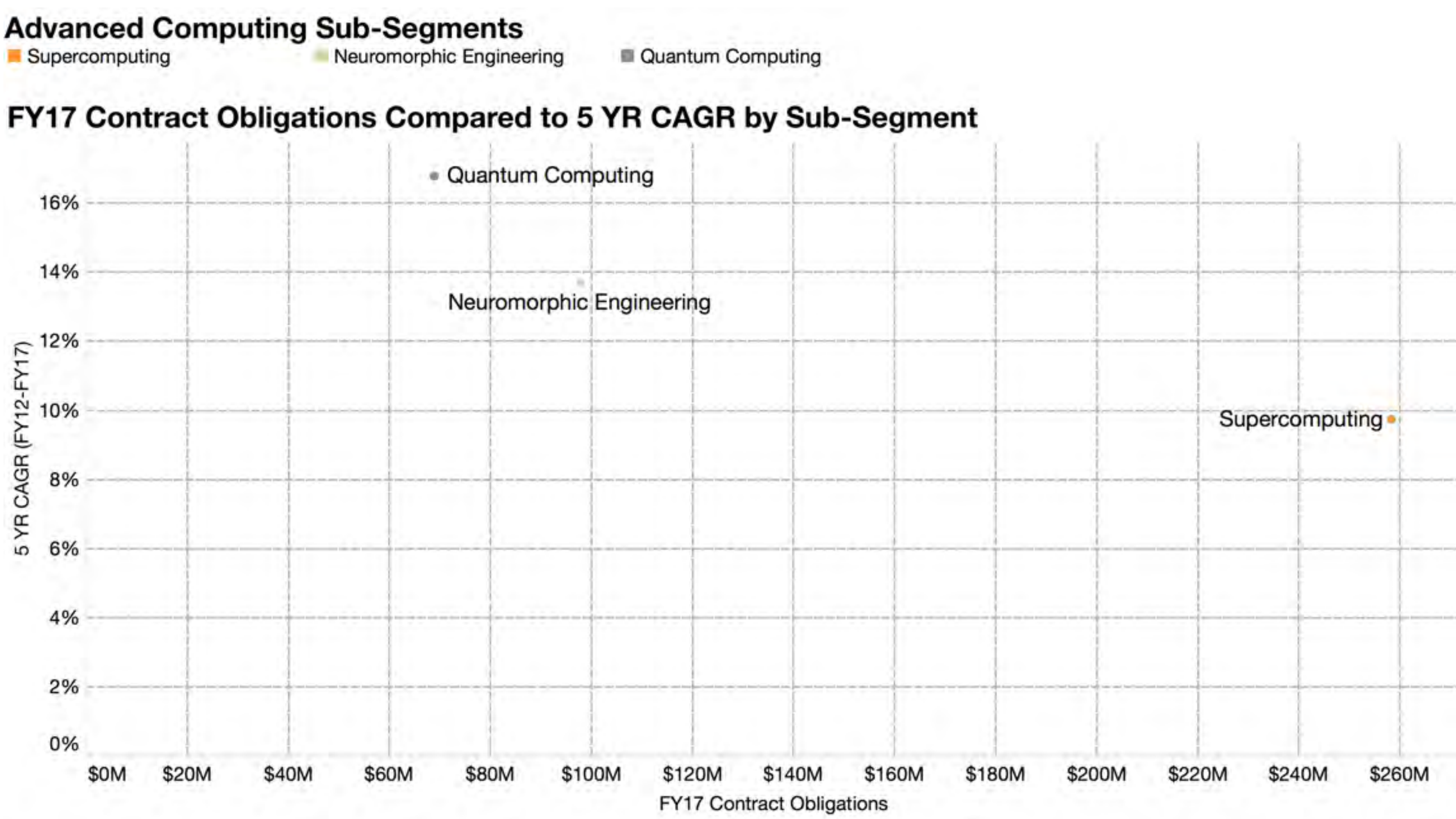


Exhibit 5: The largest Advanced Computing sub-segment, Supercomputing grew by a CAGR of 9.7 percent to $258.4 million in FY2017. The smaller sub-segments, Quantum Computing and Neuromorphic Engineering had stronger growth of 16.8 percent and 13.7 percent respectively. Spending on Neuromorphic Engineering reached $97.8 million in FY2017 and Quantum Computing spending reached $68.8 million. DARPA accounted for 37.3 percent of overall segment spending followed by Air Force Life Cycle Management Center and Office of Naval Research (ONR).

Advanced Computing Spending Increased Sharply in FY2017 and Will Continue to Grow

Ten years ago, spending on advanced computing was rationalized mostly by scientific leadership. Today, there are more practical reasons for spending; advanced computers underpin Deep Learning and Autonomy. All of which have cross-cutting applications within DoD operational concepts.

Such is the purpose of the Third Offset Strategy and AI and Advanced Computing are linchpins to successful implementation of the Strategy. Supercomputing, the largest and most mature sub-segment, is dominated by Cray, which accounted for 25.1 percent of direct capture. Cray's computers are also used by several other contractors as part of their technical solutions. IBM is also a big player in the defense market along with several others including Nvidia, Asetek, Aspen Systems, Gidel and Atipa.

The other sub-segments, Neuromorphic Engineering and Quantum Computing are less mature than Supercomputing as evident by type of organizations performing and funding contracts. DARPA accounts for 53.8 percent of spending on Neuromorphic Engineering of which large portions were obligated to Regents of University of California, IBM, University of Southern California (USC), Massachusetts Institute of Technology (MIT) and HRL Laboratories. Some of the same organizations are performing Quantum Computing contracts, notably HRL Laboratories and USC. Much like Neuromorphic Engineering, DARPA is funding most of the Quantum Computing work, accounting for 68.2 percent of sub-segment spending since FY2012.

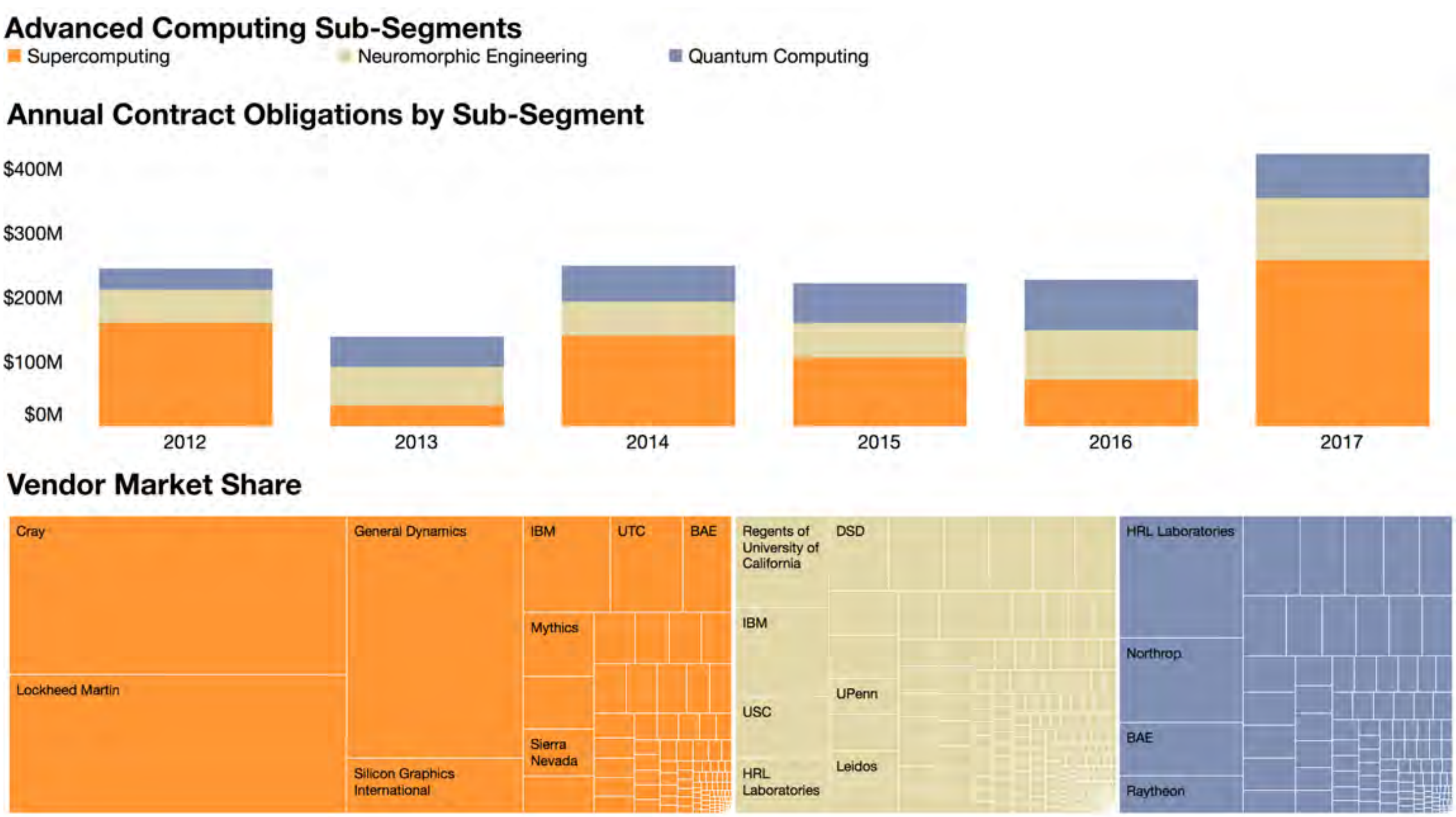


Exhibit 6: Supercomputing, the largest sub-segment, accounted for 51.3 percent of overall Advanced Computing spending since FY2012. The sub-segment's dominance can be explained by a spike in FY2017 spending. Neuromorphic Engineering spending also increased significantly in FY2017 by 26.3 percent. Army led spending on Supercomputing, while DARPA led spending in the other sub-segments.

AI Systems Segment Spending Grows Most of All AI Taxonomy Segments Since FY2012

DoD has already begun to integrate AI with mission systems and operating concepts. While the applications are narrowly defined, several years of spending increases provide indication that AI has gained traction moving beyond test and development phase.

Virtual Reality (VR), the largest sub-segment by contract obligations, is the most mature given the sustained high levels of investment. As the sustained funding suggests, VR is redefining planning, simulation, and training across battle domains.

Computer Vision, another mature AI Systems sub-segment is also gaining traction. Sub-segment spending increased by 19 percent, the most of any Taxonomy sub-segment. Each service is spending to advance the capability. Army is investing in high resolution 3D geospatial information and Air Force is spending on several capabilities including advanced synthetic airborne radar sensors, while Navy sees promise for Computer Vision in multi-spectral targeting.

Virtual Agents, although the smallest sub-segment by contract obligations, is attracting investment. Spending grew by 16.9 percent between FY2012 and FY2017 with a large portion being allocated by DARPA.

Govini has defined AI Systems in the following three sub-segments:

- Virtual Reality - environments which provide a virtual presence and artificial affects
- Computer Vision - systems that automate human vision tasks, including acquiring, processing and analyzing digital images and high-dimensional data
- Virtual Agents - abstract functional systems that respond to a wide array of questions

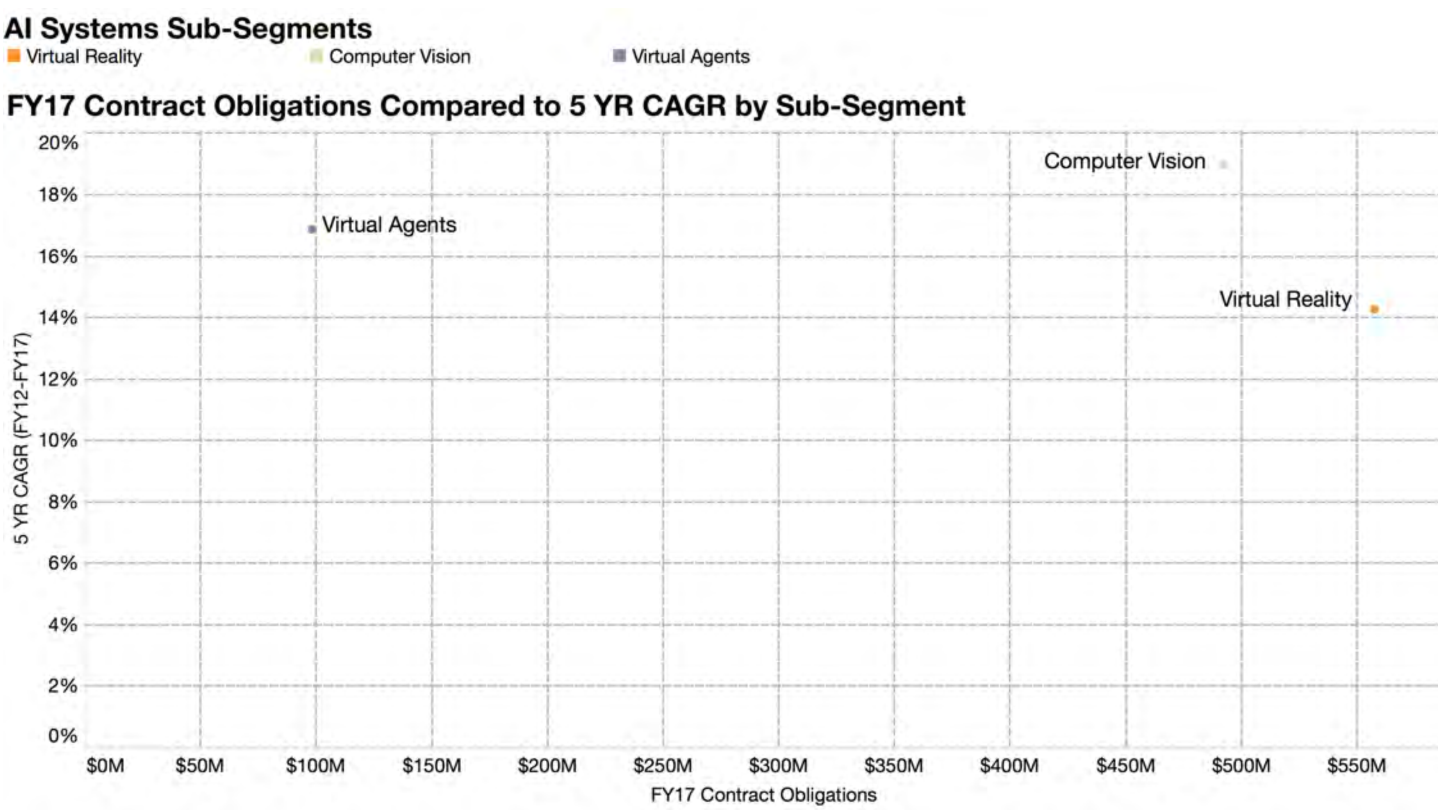


Exhibit 7: Computer Vision, the second largest sub-segment by contract obligations had the most spending growth of 19 percent from FY2012 through FY2017. Virtual Agents grew by 16.9 percent and Virtual Reality grew by 14.3 percent.

AI Has Moved Beyond R&D and is Beginning to Play Strong Role in Mission Systems

AI has great potential for creating asymmetric advantages in warfare. Its speed and accuracy in reacting, adapting and predicting scenarios makes it the cornerstone of DoD's Third Offset Strategy. While there are several challenges to widespread adoption of AI, DoD has begun to invest in applications where AI can match human cognition for specific purposes.

Virtual Reality for battle simulation and training is an example of one of these applications. AI has proven in several situations to match and even outperform the very best human cognition. As a result, DoD has embraced this particular application of AI as a solution. So much so that leading providers of virtualized simulation and training including Raytheon, Lockheed Martin, SRI International and JF Taylor are seeking to integrate AI with their solutions if they have not already.

Computer Vision, the second largest AI System sub-segment, is being applied in many missions critical to warfighting. The most obvious is Intelligence Surveillance and Reconnaissance (ISR) where Leidos supports Army's Geospatial Center's High Resolution 3-D Geospatial Information Program and Raytheon delivers multi-spectral targeting systems among other Computer Vision-related technologies. Research and development areas include high-resolution, wide-field-of-view gigapixel cameras and neuromorphic microchips for processing imagery data. Still other applications of Computer Vision are being funded including detection of defects to aircraft and undersea terrain mapping.

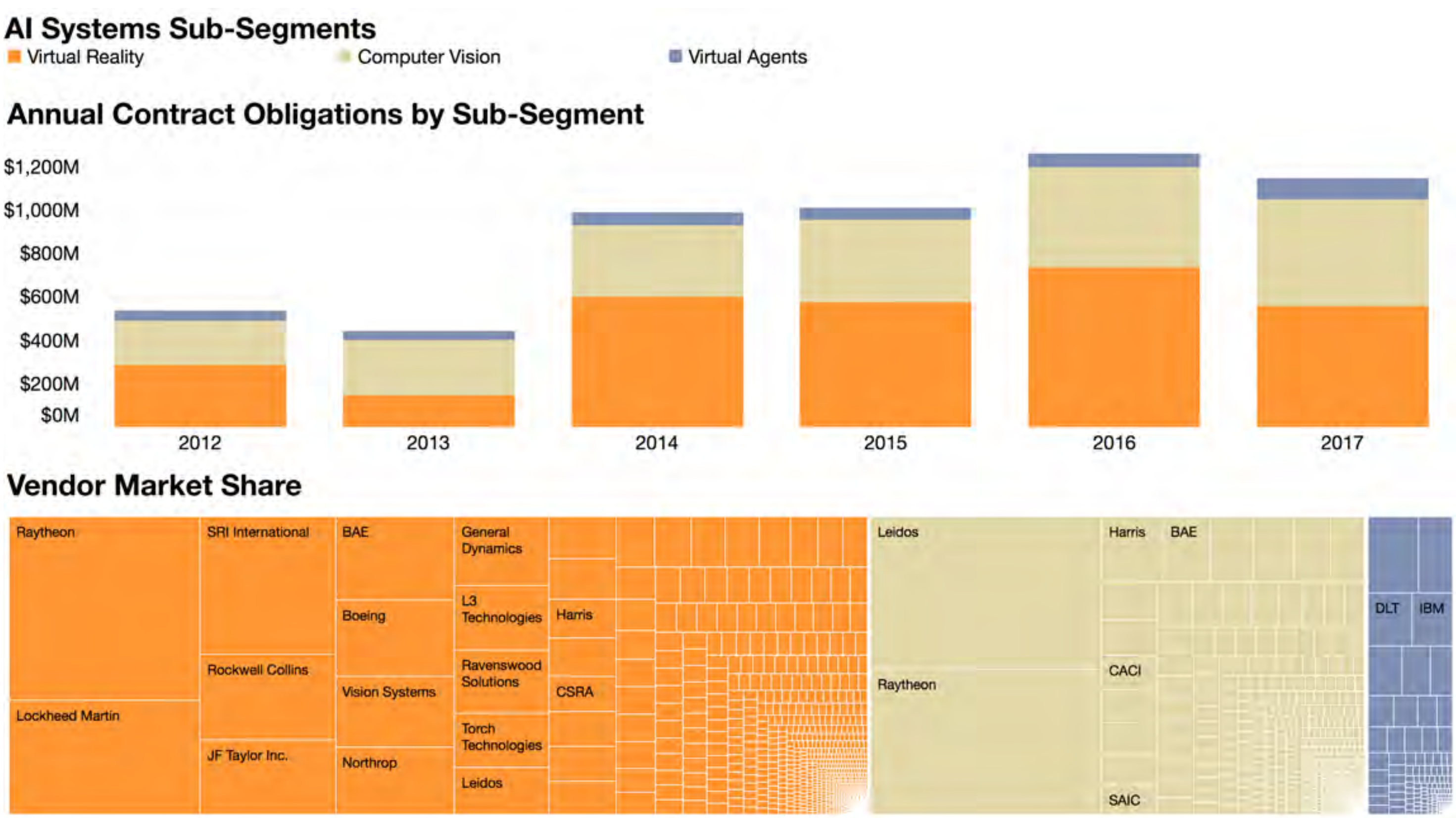
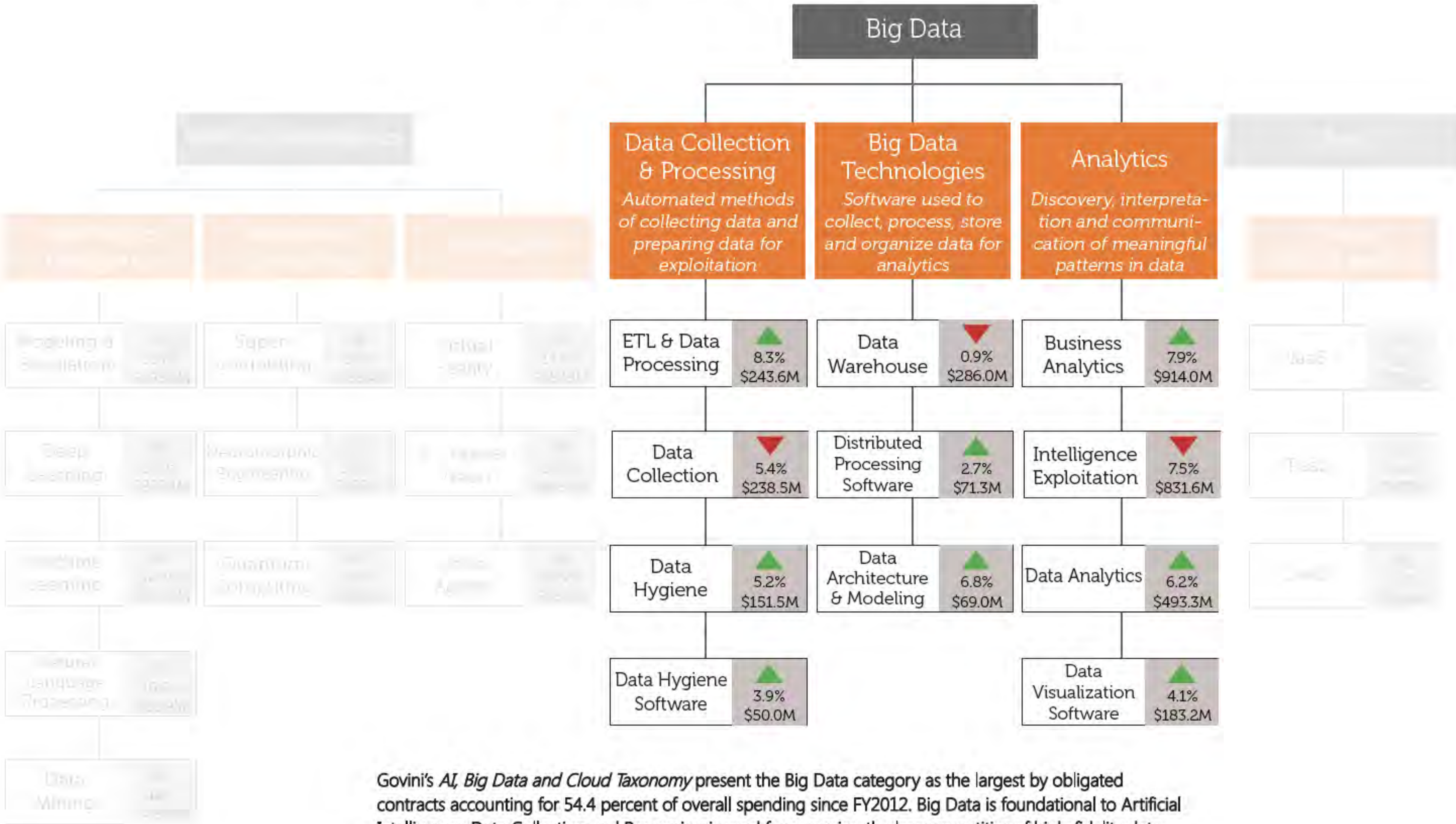


Exhibit 8: Virtual Reality and Computer Vision are the most mature and largest sub-segments. The two accounted for 93.3 percent of AI Systems segment spending since FY2012. Investment in the smallest sub-segment, Virtual Agents comes primarily from DARPA and Navy Research Labs.

DEPARTMENT OF DEFENSE
BIG DATA
STANDARD MARKET TAXONOMY



Govini's *AI, Big Data and Cloud Taxonomy* present the Big Data category as the largest by obligated contracts accounting for 54.4 percent of overall spending since FY2012. Big Data is foundational to Artificial Intelligence. Data Collection and Processing is used for amassing the large quantities of high-fidelity data required to train machines. Big Data Technologies such as Data Warehouse, Distributed Processing Software and Data Architecture & Modeling are used to manipulate data for real-time processing and pattern recognition. Analytics is used to surface insight critical to human-machine teaming.

DoD has Prioritized Data Processing and Data Hygiene Over Data Collection

AI can only be as smart as the data ingested, which is one reason why DoD spending on Data Processing and Hygiene grew the most of all Data Collection & Processing sub-segments.

Data quality is an often overlooked challenge in most Big Data projects. It has the potential to compromise results and lead to misinformed decision making. Effectively querying heterogeneous data sources, then extracting, transforming and loading data towards one or more data models also greatly impacts overall data quality.

Nonetheless, collecting data is not enough. AI simply will not work without data that is properly standardized, normalized, de-duplicated, verified and enriched, with verifying and enriching among the most critical steps for making data useful. Without AI, the Third Offset Strategy will fall well short of its intended objective of widening the military capability gap between the U.S. and potential adversaries and strengthening conventional deterrence.

Govini has categorized Data Collection & Processing into the following four sub-segments:

- Data Collection - the process of gathering information in a systematic fashion
- Extraction Transformation & Loading (ETL) & Data Processing - three functions used to pull data out of staging databases and place them into production databases
- Data Hygiene - the process to ensure that data is free from error and in a usable format
- Data Hygiene Software - software that detects and corrects corrupt or inaccurate records

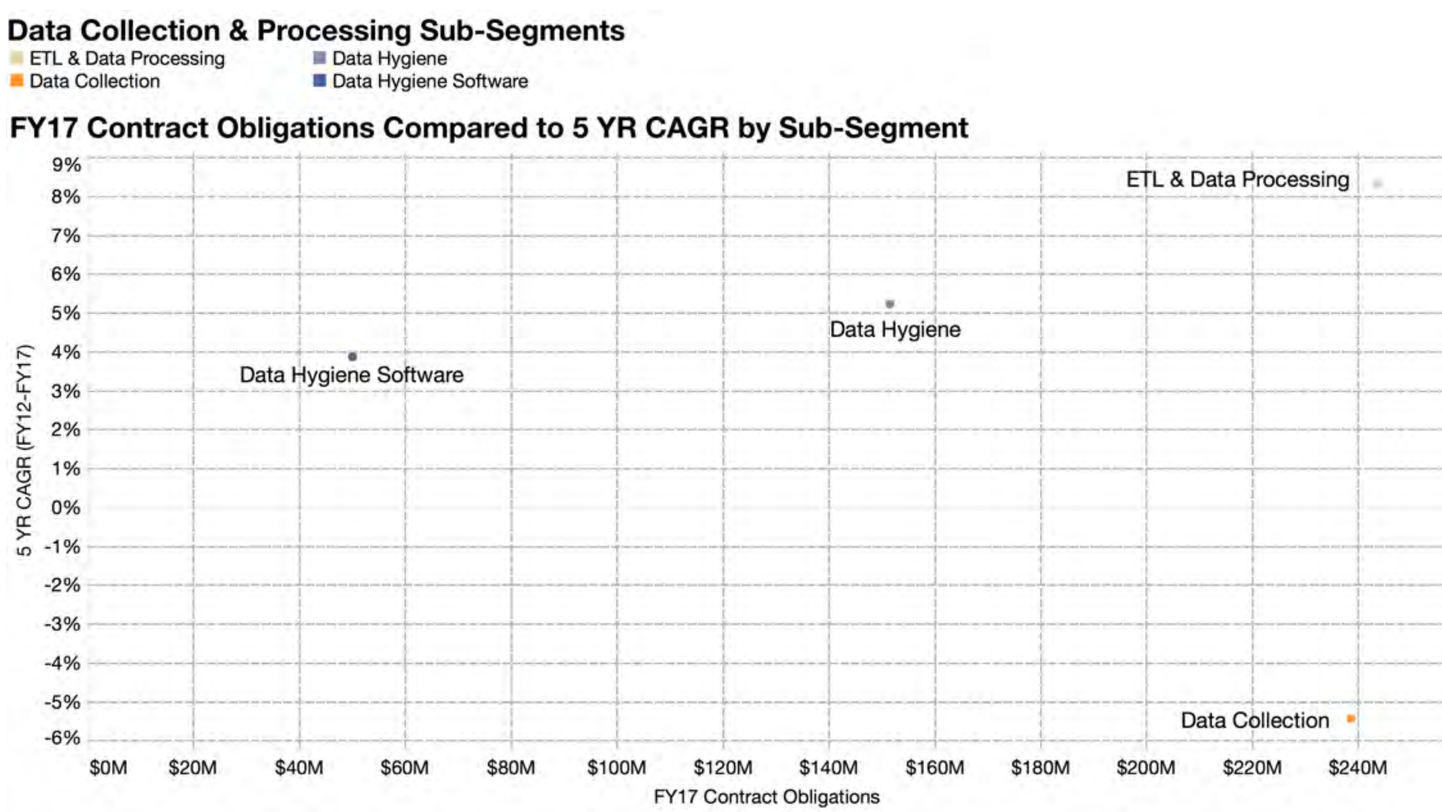


Exhibit 9: ETL & Data Processing became the largest sub-segment by FY2017 obligations accounting for 35.6 percent of total segment spending. Its emergence was fueled by a high annual spending growth rate of 8.3 percent. Other sub-segments related to data quality and usability, Data Hygiene and Data Hygiene Software, also had significant spending growth of 5.2 percent and 3.9 percent respectively.

Integrators Hold the Keys to Unlocking Potential Analytic Value of AI and Big Data

The digital universe is growing faster than ever. The world is expected to produce 44 zettabytes by 2020 and 163 zettabytes of data by 2025; only 4.4 zettabytes were produced in 2013. Video and images makes up a large portion of the digital data and this is especially true for DoD as it works to implement the Third Offset Strategy.

Despite the deluge of data, only a fraction of it has been explored for analytic value. By 2020, it is estimated that only 33 percent of the digital universe will contain information that has analytic value. In a world overwhelmed by information, Data Processing and Data Hygiene are critical to determining the value of data and unlocking the potential of AI and Big Data.

In the most recent fiscal year, DoD prioritized ETL & Data Processing, with spending increasing by 87.2 percent to $243.6 million. A large portion of the increased FY2017 spending was captured by systems integrators including General Dynamics, Raytheon, EHR Total Solutions, Booz Allen Hamilton, GeoNorth Information Systems and Johns Hopkins Applied Physics Lab.

Data Hygiene spending also increased significantly in FY2017 by 53.6 percent to $151.5 million. Lockheed Martin and Leidos led the market accounting for a combined 32.5 percent of total revenue captured. Northrop Grumman and Raytheon followed accounting for 6.5 percent and 4.8 percent of FY2017 spending respectively.

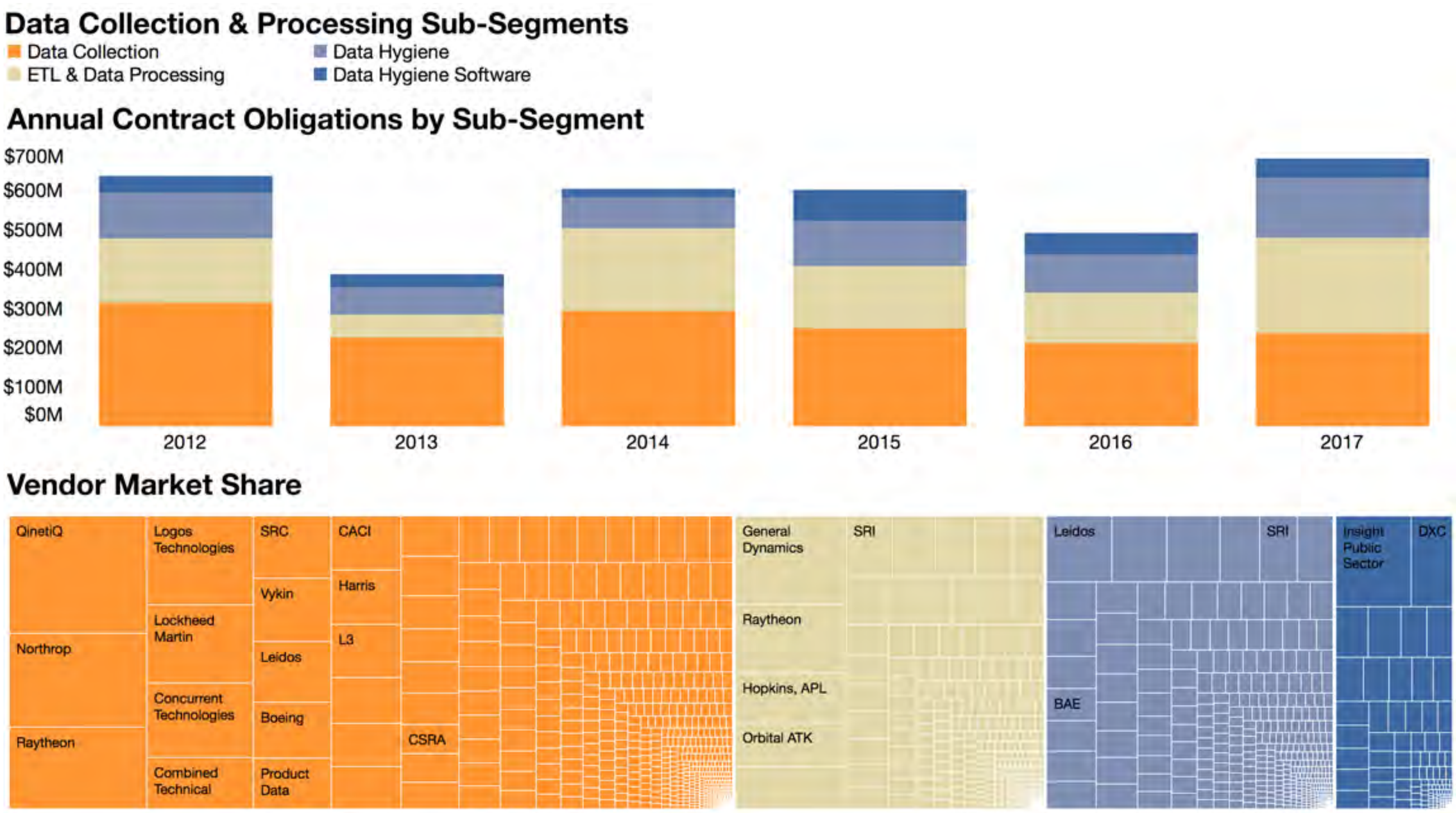


Exhibit 10: Systems integrators and technical service providers lead a Data Collection and Processing market more focused on data processing and cleansing than collection. Raytheon leads overall segment market share with 5.2 percent, mostly from its presence in ETL & Data Processing and Data Collection. Leidos, General Dynamics, Northrop Grumman, Lockheed Martin, DXC Technology, QinetiQ and CACI also rank among the top ten providers of Data Collection & Processing. Contractors that have a presence across Data Collection & Processing sub-segments have a competitive advantage.

The Convergence of Big Data and AI Set to Create Immense Value for DoD

Although many AI technologies have been in existence for several decades, only now are they able to take advantage of datasets of sufficient size to provide meaningful learning and results. Much of the credit goes to Big Data Technologies; without them easy access to large volumes of data and the ability scale ingestion would not be possible.

Advancement in Big Data technologies has certainly been helpful to AI and more broadly the Third Offset Strategy. But in the future, it may be AI that helps Big Data technologies to progress further, leading to the automation of decision making along logic trees made possible by Big Data and AI working together.

Govini has categorized Big Data Technologies into the following three sub-segments:

- Data Warehouse - repository of integrated data from one or more disparate sources, which are routinely manipulated and processed
- Distributed Processing Software - software used to manage shared resources in data processing, standardization and normalization
- Data Architecture & Modeling - collection of policies, models, rules and standards that govern which data is collected and how it is stored, arranged, integrated and put into data architectures and systems

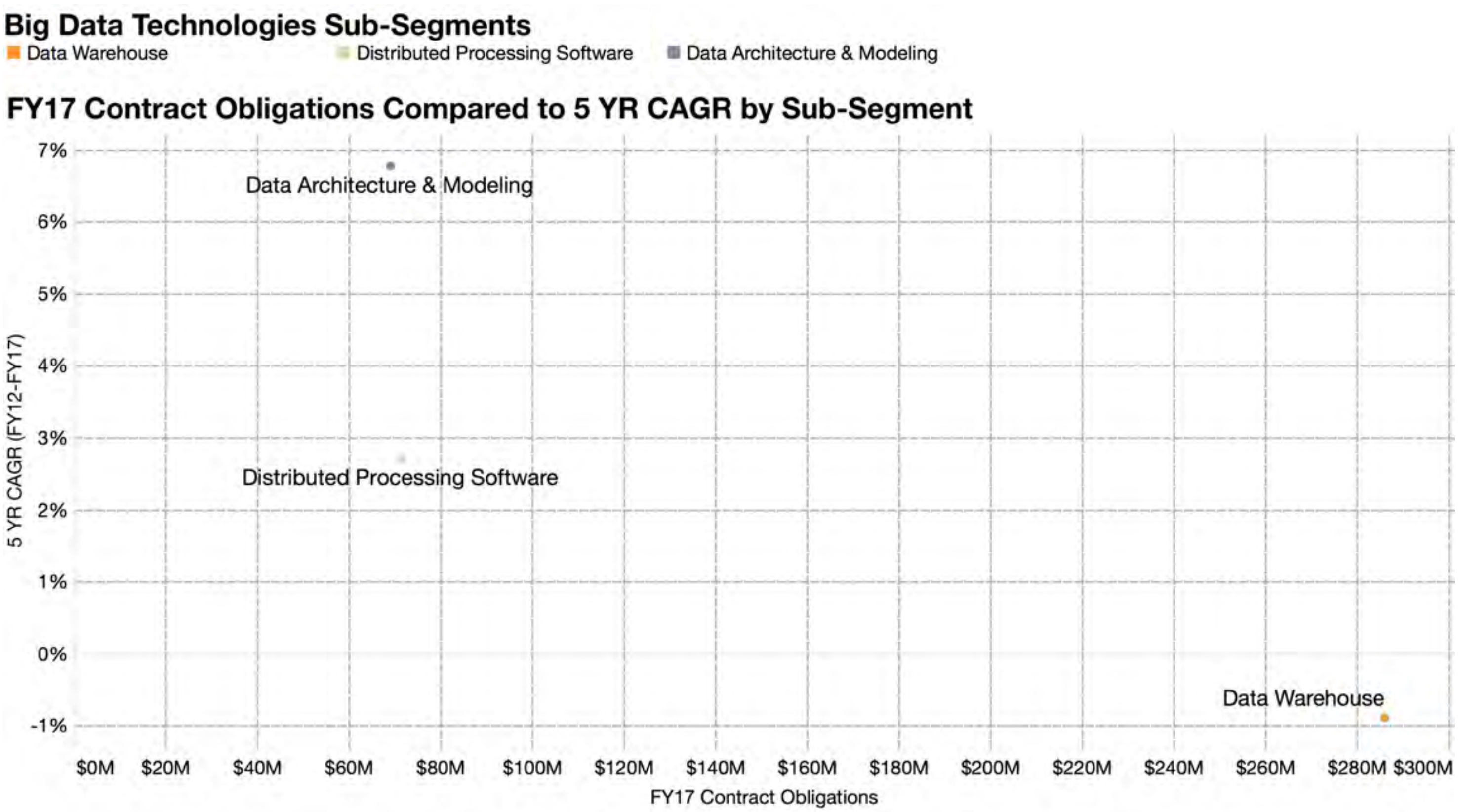


Exhibit 11: DoD is prioritizing investment in Data Architecture & Modeling and Distributed Processing Software over Data Warehouse. Annual spending on Data Architecture & Modeling grew by a CAGR of 6.8 percent to $69 million in FY2017. Spending on Distributed Processing Software grew by a CAGR of 2.7 percent to $71.3 million. Annual spending on the largest sub-segment, Data Warehouse, decreased by 0.9 percent to $286 million in FY2017.

DoD Investment in Data Quality Helps Pave Way for Convergence of Big Data and AI

DoD is placing greater emphasis on data quality than it did in the past. A primary reason is that the Department is finding that data quality is oftentimes more important that data quantity. FY2015 marked a turning point when DoD began prioritizing data quality over data collection.

Annual spending on the two smallest sub-segments related to data quality, Data Architecture & Modeling and Distributed Processing Software increased the most over the last five years by 6.8 percent and 2.7 percent respectively.

System Integrators such as Northrop Grumman, Raytheon, Deloitte, Leidos and Booz Allen Hamilton benefited the most from DoD's increased spending on Data Architecture & Modeling. Northrop and Raytheon generated most of its business from Missile Defense Agency, while Deloitte performed work for Defense Health Agency (DHA). Leidos' largest customer was AFLCMC and Booz Allen Hamilton performed work mostly for Navy. For now, these companies are well positioned to drive the Third Offset Strategy forward by integrating big data technologies with decision making operating concepts.

One of those Big Data technologies is Distributed Processing Software. Insight Public Sector, the market leader, sells its products mostly to AFLCMC, Army, Navy and NETCOM. Integrators also sell Distributing Processing Software to DoD. Lockheed Martin, Booz Allen Hamilton and Northrop Grumman rank among the top ten sellers of Distributed Processing Software.

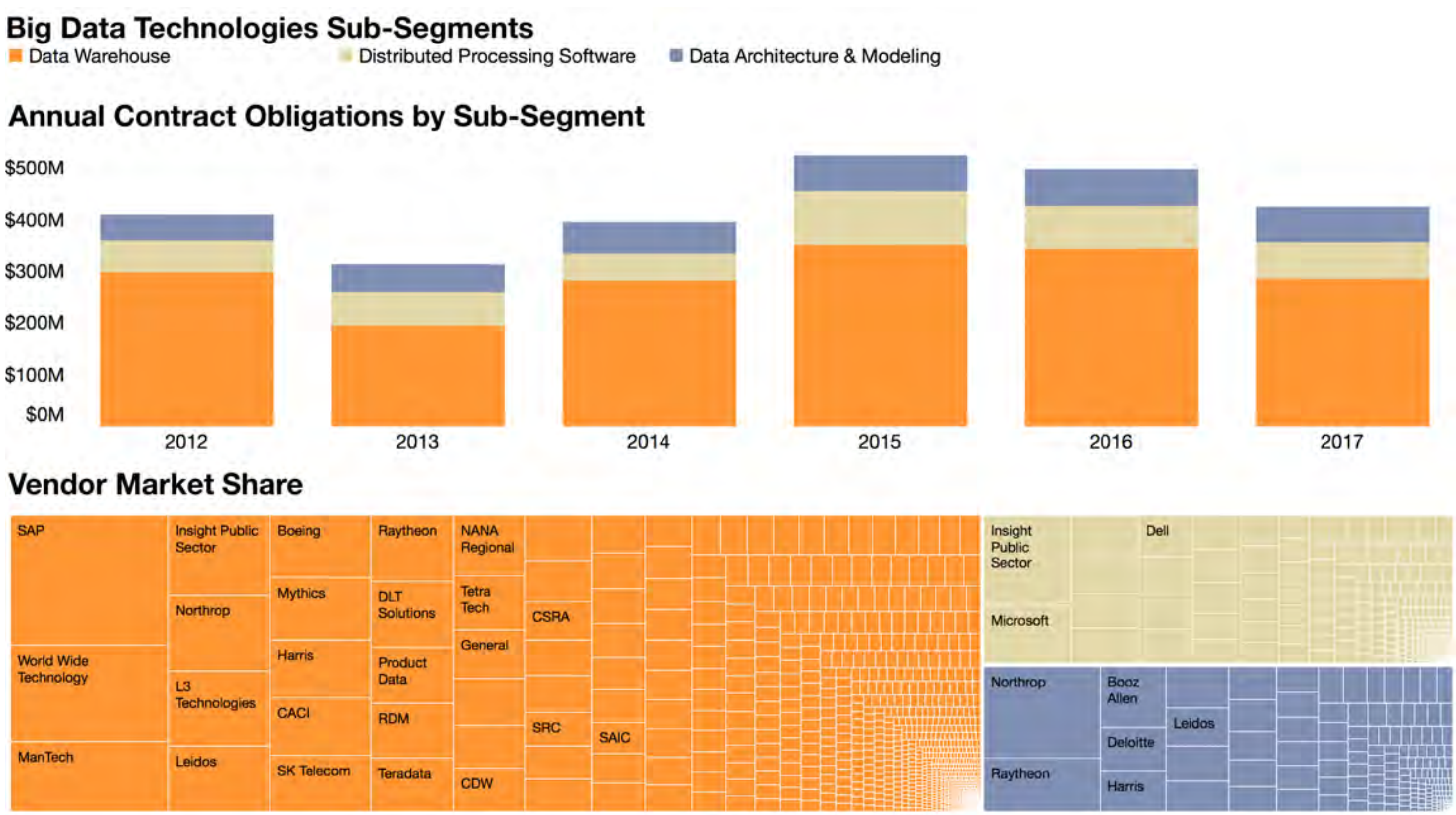


Exhibit 12: DoD prioritized data quality in recent years. Two closely related sub-segments, Data Architecture & Modeling and Distributed Processing Software had the largest spending increases since FY2012. Systems Integrators benefited the most from the spending increases, strengthening their positions for helping to integrate Big Data technologies and AI with agency operating concepts.

Analytics is the Largest Taxonomy Segment and Spending is Growing Modestly

With analytics it is possible to get answers from your data almost immediately -- an important facet of human and machine teaming. But what makes analytics different from traditional methods of analysis is the speed and efficiency it provides; AI is poised to augment the capability.

The convergence of AI and Big Data brings that speed and efficiency to entirely new levels, which is expected to completely alter existing methods of Business Analytics, Intelligence Exploitation and Data Analytics and related software. Until that happens, humans will team with machines to leverage advanced data science tools to squeeze the most out of Big Data and rely on analytics to surface the findings for decisive action.

DoD spending data trends shed light on this reality. Traditional methods of Intelligence Exploitation and Business Analytics are the largest sub-segments accounting for 72.7 percent of total segment spending since FY2012. One of those sub-segments, Business Analytics had the most spending growth of 7.9 percent over the last five years.

Govini has categorized Analytics into the following four sub-segments:

- Intelligence Exploitation - data methods such as translating, evaluating and transforming raw intelligence data and information into useful forms
- Business Analytics - data skills, technologies and practices used to gain insight
- Data Analytics - examining large data sets in order to draw conclusions, increasingly with the aid of specialized systems and software
- Data Visualization Software - software that abstracts data in schematic form and organizes for visual representation

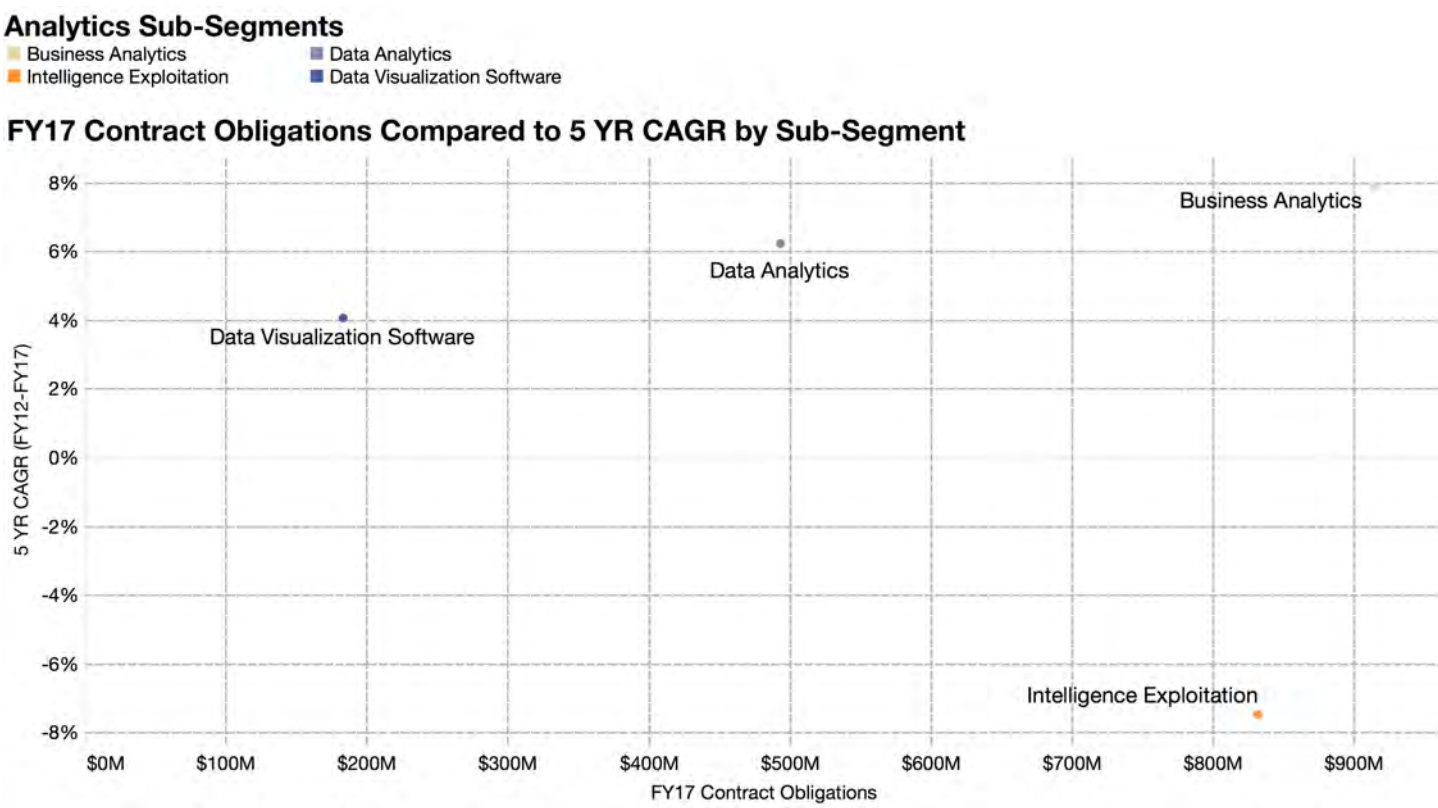


Exhibit 13: Annual spending on Business Analytics surpassed spending on Intelligence Exploitation in FY2017 from its strong average annual growth of 7.9 percent. Spending on Data Analytics and Data Visualization Software also had significant growth of 6.2 percent and 4.1 percent respectively.

Technical Engineering Contractors to Play Key Role in Integrating AI Big Data

DoD spending on Analytics has been relatively stable from year-to-year compared to other Taxonomy segments. While top-line spending dipped slightly from sequestration in FY2013, it recovered quickly to reach its highest level yet of $2.4 billion in FY2017.

Service firms that have the ability to deliver technical data solutions have benefited from the stable spending, particularly those providing Intelligence Exploitation and Business Analytics. The Third Offset Strategy, however, calls for much of the mission work to be automated under the direction of a human operator.

AASKI Technology captured 15.6 percent of Intelligence Exploitation spending, the largest share of all contractors through its support of Army. BAE Systems follows as the close second capturing 13.4 percent of the market mostly from support of its Digital Electronic Warfare System (DEWS). While Processing, Exploitation and Dissemination (PED) services are likely to play a critical role in operating concepts for the foreseeable future, those firms that leverage cutting-edge technologies that induce automation rather than prop-up manual human analysis stand the most to gain. This human-machine teaming process will not only end-up delivering more effective solutions, it will also reveal where AI could be easily implemented.

Business Analytics is not much different than Intelligence Exploitation in that professional service firms that can gain access to broader swaths of data and organize them for real-time analytics and high-fidelity analysis will gain share in a market in transition. Leidos led capture of Business Analytics spending with 7.5 percent mostly from its work on Geospatial Research, Integration, Development, Support (GRIDS II) Program.

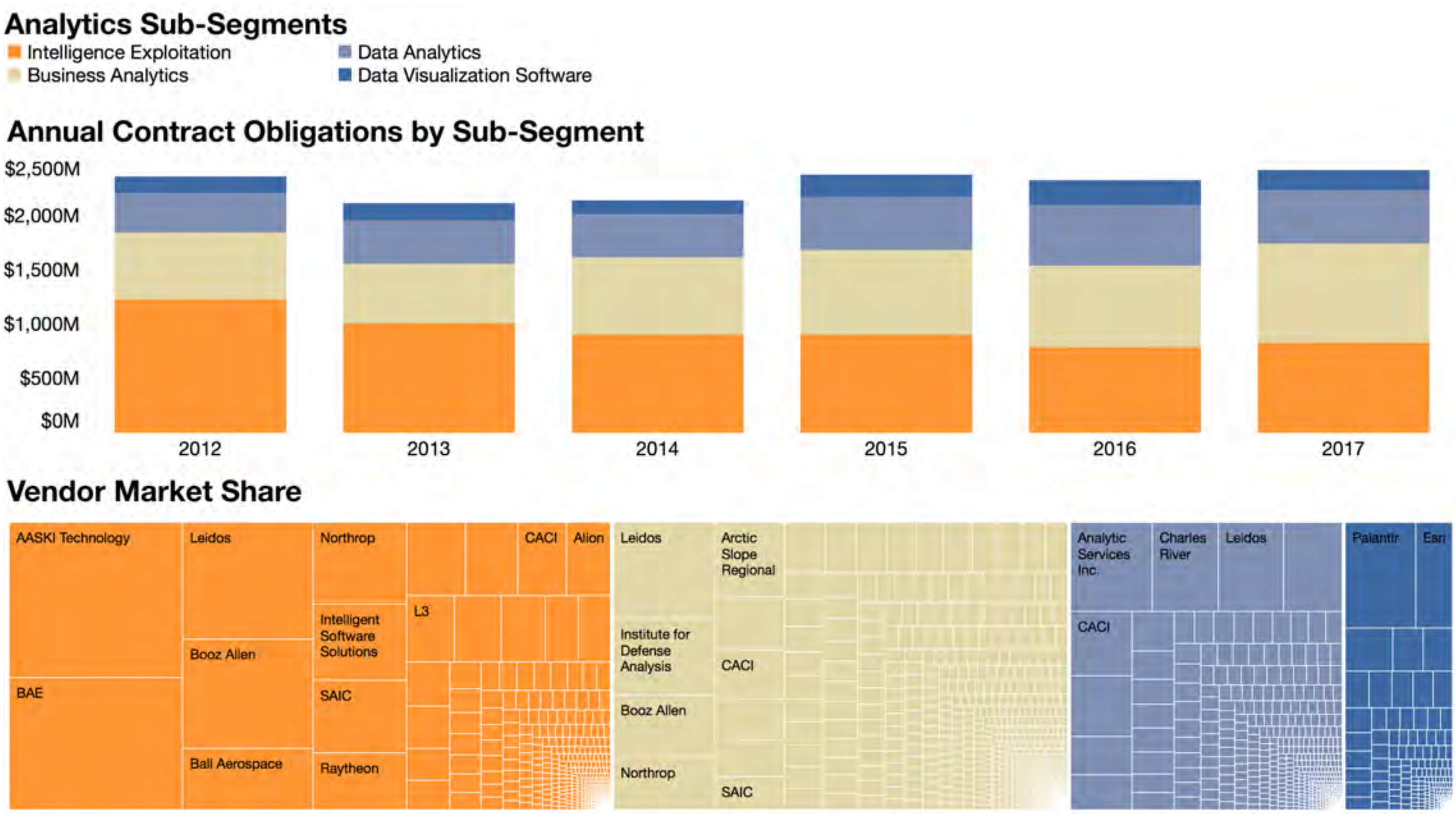
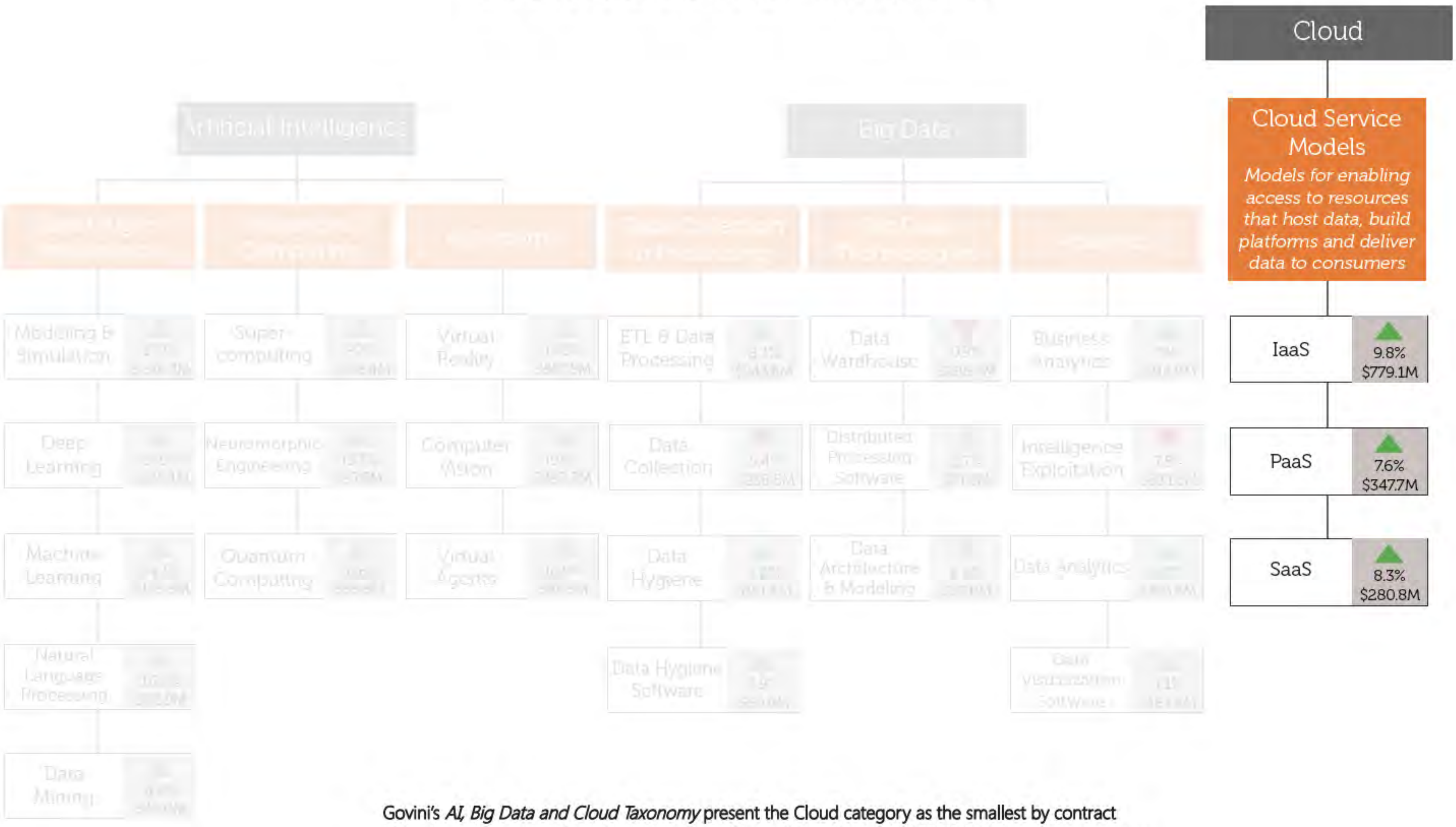


Exhibit 14: Intelligence Exploitation and Business Analytics accounted for 72.7 percent of spending since FY2012. The two sub-segments have the most to gain from advancement in AI and Big Data.

DEPARTMENT OF DEFENSE
CLOUD
STANDARD MARKET TAXONOMY



Govini's *AI, Big Data and Cloud Taxonomy* present the Cloud category as the smallest by contract obligations accounting for only 16.7 percent of overall spending since FY2012. The category, however, is poised for rapid growth driven by the recent directive signed by Deputy Secretary of Defense Patrick Shanahan to accelerate enterprise Cloud adoption. Cloud and other forms of digital operating models are critical to storing, processing, managing and delivering the massive amount of data required for AI.

DOD Embarks on Transition to Cloud with Spending Up Across All Service Models

DoD has been slow to embrace Cloud technologies as a solution to their data challenges, but that is beginning to change. FY2016 marked a turning point for DoD Cloud, with Service Model spending having its sharpest rise on record by 31.2 percent to $1.3 billion.

AI is among several factors prompting DoD to embark on its transition to Cloud. One use case showing great promise is the adoption of computer vision and machine learning technologies for concept search. The technologies allow users to search through troves of photos, images and other documents using visual components and concepts, instead of by file name or tag.

However, before AI can be applied at scale, DoD must transition to the Cloud and this is beginning to occur. Spending on the single largest Cloud Service Model, Infrastructure-as-a-Service (IaaS), increased the most since FY2012 by 9.8 percent to $779.1 million in FY2017. Software-as-a-Service (SaaS) spending increased the second most by 8.3 percent to $280.8 million and Platform-as-a-Service (PaaS) increased by 7.6 percent to $347.7 million.

Govini has categorized Cloud Service Models into the following three sub-segments:

- Infrastructure-as-Service - hosted infrastructure components traditionally present in on-premise data centers, including servers, storage and virtualization layer
- Platform-as-a-Service - resilient and optimized environment on which users can install applications and data sets
- Software-as-a-Service - hosted applications made available over the internet

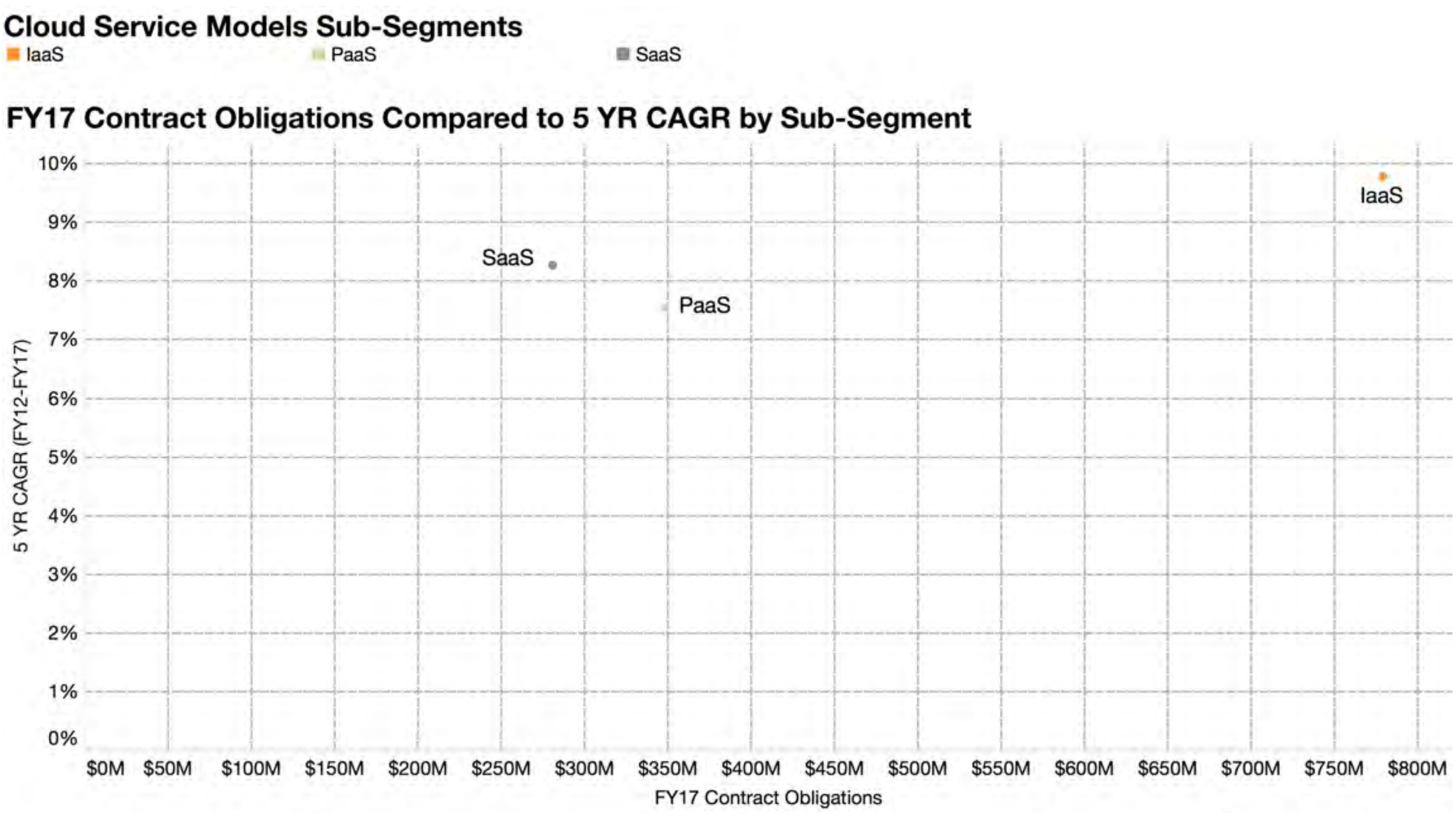


Exhibit 15: IaaS, the largest Cloud Service Model sub-segment, had the most spending growth of 9.8 percent since FY2012. Spending on PaaS, the second largest sub-segment, increased by 7.6 percent and SaaS spending increased by 8.3 percent.

Cloud Spending Sees Sharp Rise in FY2016 and is Set to Continue its Strong Growth

DoD spending on Cloud is set to surge and government and industry are positioning for the investment funds to flow. Increased budget for Cloud and IT Modernization is one indication and a recently issued directive from the Deputy Secretary of Defense to accelerate enterprise Cloud adoption is another reason.

What makes Cloud providers uniquely positioned in the market is how they will leverage Learning & Intelligence technologies to make optimal use of data in an open environment while keeping the data secure.

This fact has prompted industry to make big bets in the form of mergers and acquisitions. DXC Technology, CSRA, Leidos and Booz Allen Hamilton have doubled down on their market position while others like Lockheed Martin and Harris strategically chose to put their chips elsewhere. Still others like General Dynamics, Northrop Grumman and CACI have yet to make moves that help them keep up with the evolving competitive landscape of combining forces.

Thus far, DXC Technology is the Cloud Service Model market leader, mostly from its position in IaaS. IBM, Leidos, Booz Allen Hamilton, General Dynamics CACI and SAIC rank among the top ten Cloud Service Model providers by revenue captured.

Commercial Cloud solutions sold through Value-Added Resellers (VARs) DLT Solutions, Carahsoft, Inforeliance and World Wide Technology present viable alternatives to on-premise private cloud networks managed by integrators.

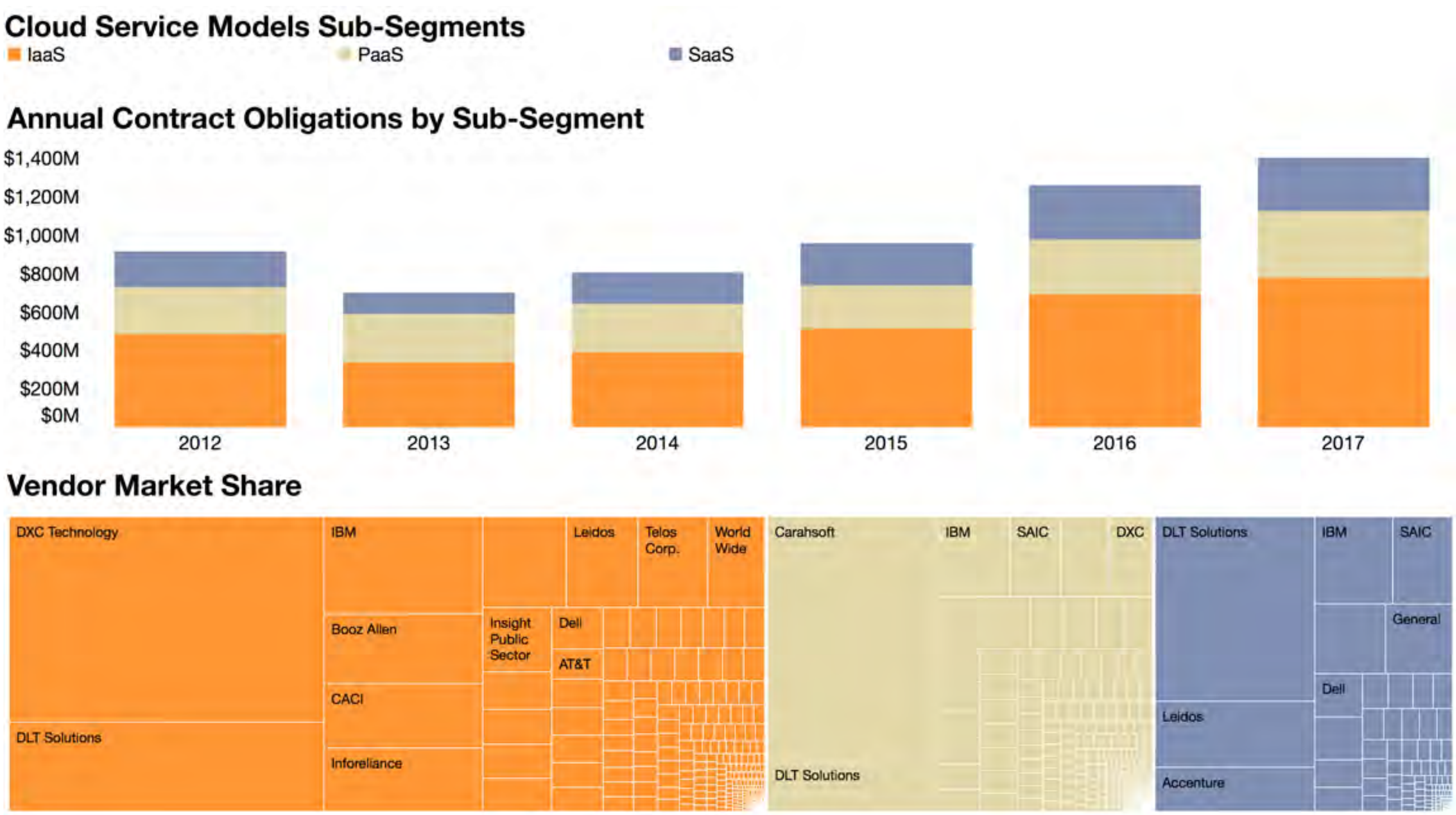


Exhibit 16: IaaS accounted for 53 percent of total Cloud Service Model spending since FY2012 and PaaS accounted for 26.4 percent. Spending in the two sub-segment also grew steadily over the six years by 9.8 percent and 7.6 percent respectively.

Conclusion

The Third Offset Strategy aims to improve Joint Force battle network performance and restore a comfortable U.S. conventional overmatch against potential adversaries, thereby strengthening conventional deterrence. Toward this end, the Strategy outlines DoD's intent to pursue rapid advancements in the field of Artificial Intelligence and Autonomous Systems, in order to pave the way towards major advances in human-machine collaboration and combat teaming, if not a new military-technical revolution.

DoD investments in AI and autonomous systems have been steadily rising since FY2013, and they saw a boost in FY2016 and FY2017 after the formal announcement of the Third Offset Strategy in November 2014. By FY2017, Department spending on the three biggest associated technological categories—Artificial Intelligence, Big Data and Cloud—reached $7.4 billion, which is 32.4 percent higher than the $5.6 billion spent in FY2012. The strong growth reflects both new DoD technological applications as well as a number of successful technological applications available from the U.S. private sector in AI technologies. Exploiting AI-related research and development in the vibrant American commercial sector is a key aspect of the Third Offset Strategy and so is leveraging the national network of Federally Funded Research and Development Centers (FFRDCs) and University Affiliated Research Centers (UARCs).

In the Artificial Intelligence category, spending on AI Systems has gained traction within DoD, especially with regard to Virtual Reality for training and simulation and Computer Vision for ISR. Spending on Virtual Agents is also increasing. More advanced military AI Systems will rely heavily on research and spending in the Learning & Intelligence segment being conducted and funded primarily by Defense Research Agencies and Laboratories, notably DARPA. DARPA accounted for 28.5 percent of spending on the three most critical Learning & Intelligence sub-segments—Deep Learning, Machine Learning and Natural Language Processing.

Spending in these three sub-segments has demonstrated great promise in narrowly defined military AI Systems. However, there are constraints to moving towards more advanced applications. For example, more capable AI systems are almost entirely dependent on Advanced Computing, an area that China is vying for leadership with the U.S. Despite the increased DoD spending in Advanced Computing since FY2013, it seems evident DoD will have to increase its investments in Supercomputing, Neuromorphic Engineering and Quantum Computing just to stay ahead, much less lead, in this area.

The same goes for Big Data and Cloud, the other two big Third Offset categories. DoD must continue to make foundational investments in Big Data and Cloud to facilitate advances in machine learning, the key to realizing the full revolutionary potential of autonomous systems. DoD must continue its transition to Cloud and do better at leveraging Big Data technologies for collecting and processing data as well as make better use of data science for analytics. The recent directive signed by Deputy Secretary of Defense Patrick Shanahan to hasten DoD's transition to Cloud is thus a welcome development.

Unfortunately, DoD will not derive much benefit from its move to the Cloud without demanding much better data hygiene that results in stored data that has been processed, standardized and normalized for use. A concerted commitment to good data hygiene is the primary reason why the U.S. private sector has achieved success in deploying AI applications. Leading AI companies like Google, Amazon, Facebook among others have access to endless data of the highest fidelity. In contrast, DoD struggles with data quality, data processing and data sharing. The Department's closed data architecture limits data sharing almost by design, which ultimately determines whether and how data can be cleansed, standardized and normalized. Ultimately this must change and Cloud and other forms of digital operating models provide the answer—both of which will require more investments.

However, on balance, a review of DoD spending on AI and autonomous system reveals a glass half full. DoD appears to be "putting its money where its mouth is" when it comes to pursuing Third Offset technologies. Hopefully, this report will help the new Under Secretary of Defense for Research and Development take stock of the Department's AI research and development portfolio and make the necessary changes to ensure continued progress in this important military arena.

These changes should be informed by the following question: are we spending enough on AI and autonomous systems, in the right areas, for the right outcomes? Both to improve its economy and its own military's importance, China recently released a national strategy to surpass the U.S. and become the world leader in AI theories, technologies and applications by 2030. Whether it wants it or not, the U.S. now finds itself in a major technological competition with a formidable rival. As Bob Work has asked, how will the U.S. respond to this "Sputnik moment"? Will the Chinese national plan be met with one of our own? Given the high stakes, one hopes so, as this competition will have very real consequences both in economic and military terms.

One thing is certain: Any national response must be driven by hard, accurate decision-grade information.

Methodology

Govini creates decision-grade information that allows clients to tackle their most difficult problems. Govini takes a unique taxonomic approach to breaking apart the market and its players, and provide insights only available through its Strategic Intelligence Platform. These analytic reports are designed to categorize Federal Government contract obligations and budgets into segments and sub-segments. Because some contracts are broad in scope, they may be included under multiple categories within a taxonomy to ensure an accurate, granular and evidence-based reflection of the market.

Govini is a big data and analytics firm committed to transforming the business of government through data science. The company's insights and analyses are utilized by Federal Contractors, Federal Agencies, Private Equity Firms and Hedge Funds to guide their strategies and uncover opportunities. Govini was founded in 2011 and has offices in Arlington, Virginia and San Francisco, California.

.govini™

Computing Enrollment and PhD Data -- for NSC AI

Prepared by the

Computing Research Association

May 8, 2019

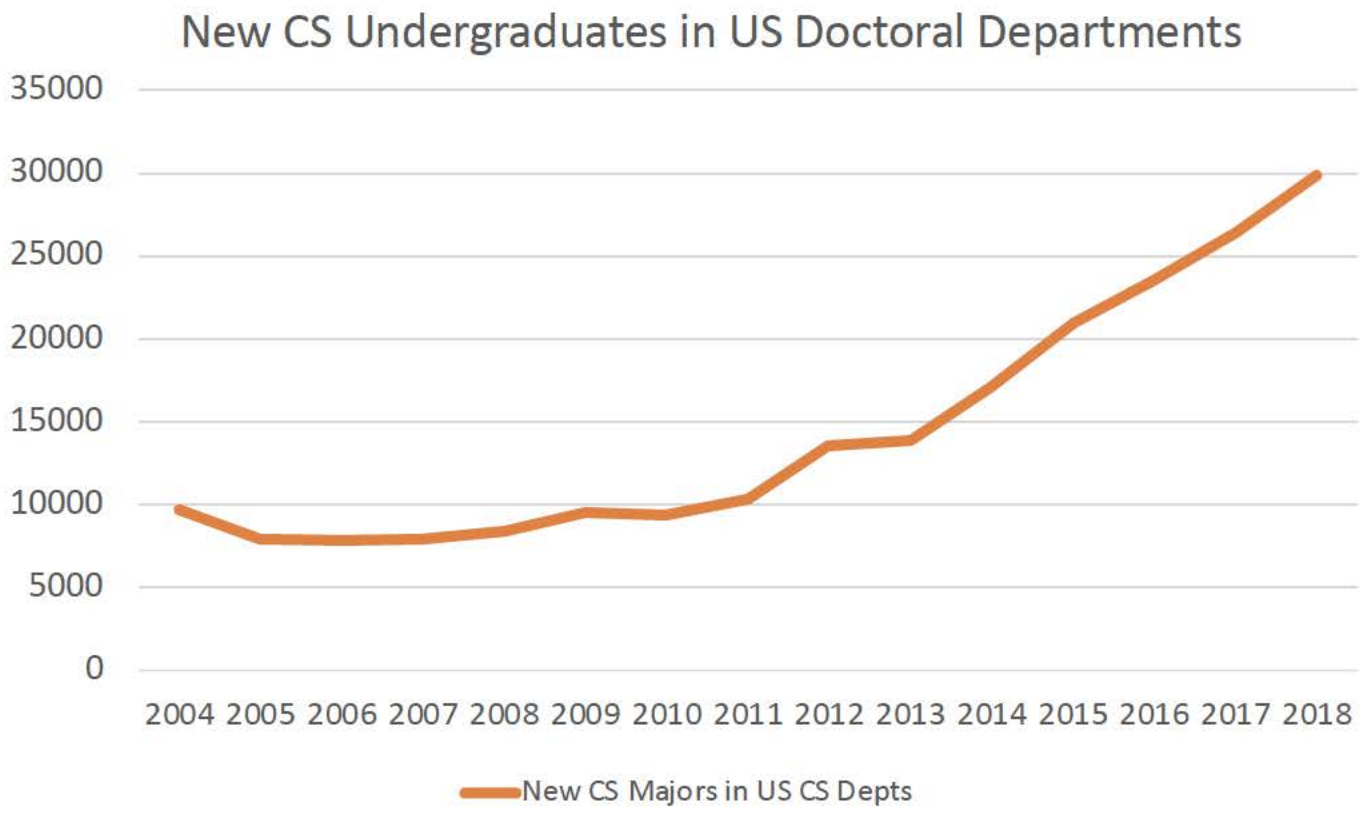
CRA Computing Research Association

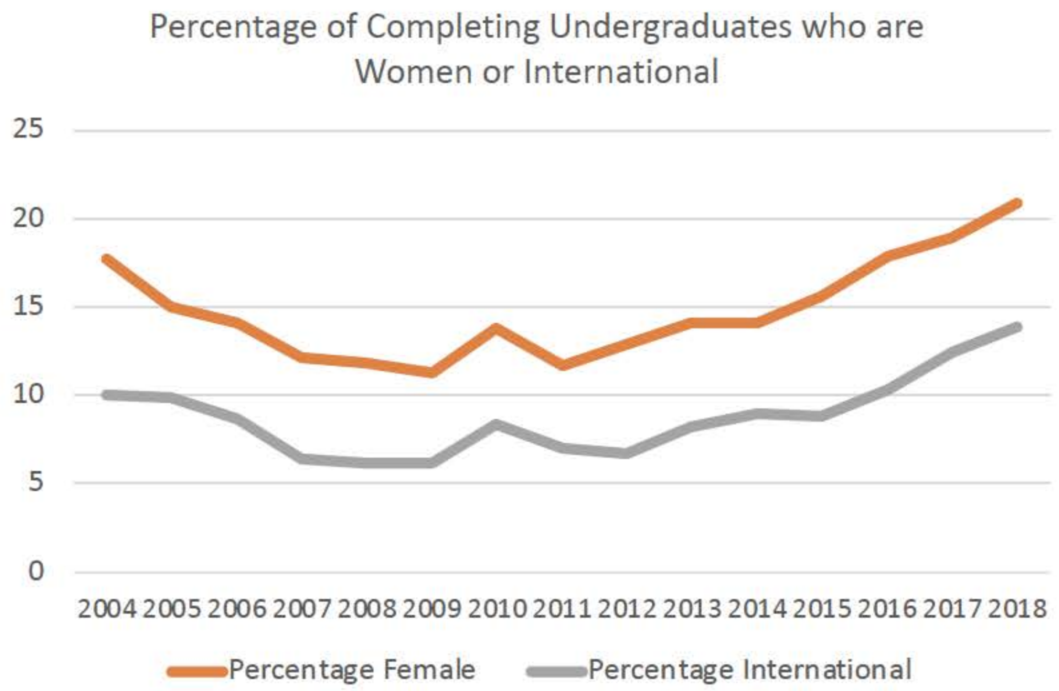
About the Data

Data for these charts comes primarily from The CRA Taulbee Survey (https://cra.org/resources/taulbee-survey/), conducted each fall since 1974. The CRA Taulbee Survey is the principal source of information on the enrollment, production, and employment of Ph.D.s in information, computer science and computer engineering, and in providing salary and demographic data for faculty in I, CS, and CE in North America. CRA surveys approximately 280 North American Ph.D-granting departments of computer science and computer engineering to generate the Taulbee results.

Historically Taulbee covers 1/4 to 1/3 of total undergraduate computer science graduates in the U.S. The percent of women earning bachelors' degrees is lower in the Taulbee schools than overall. Taulbee does track trends in overall computer science production.

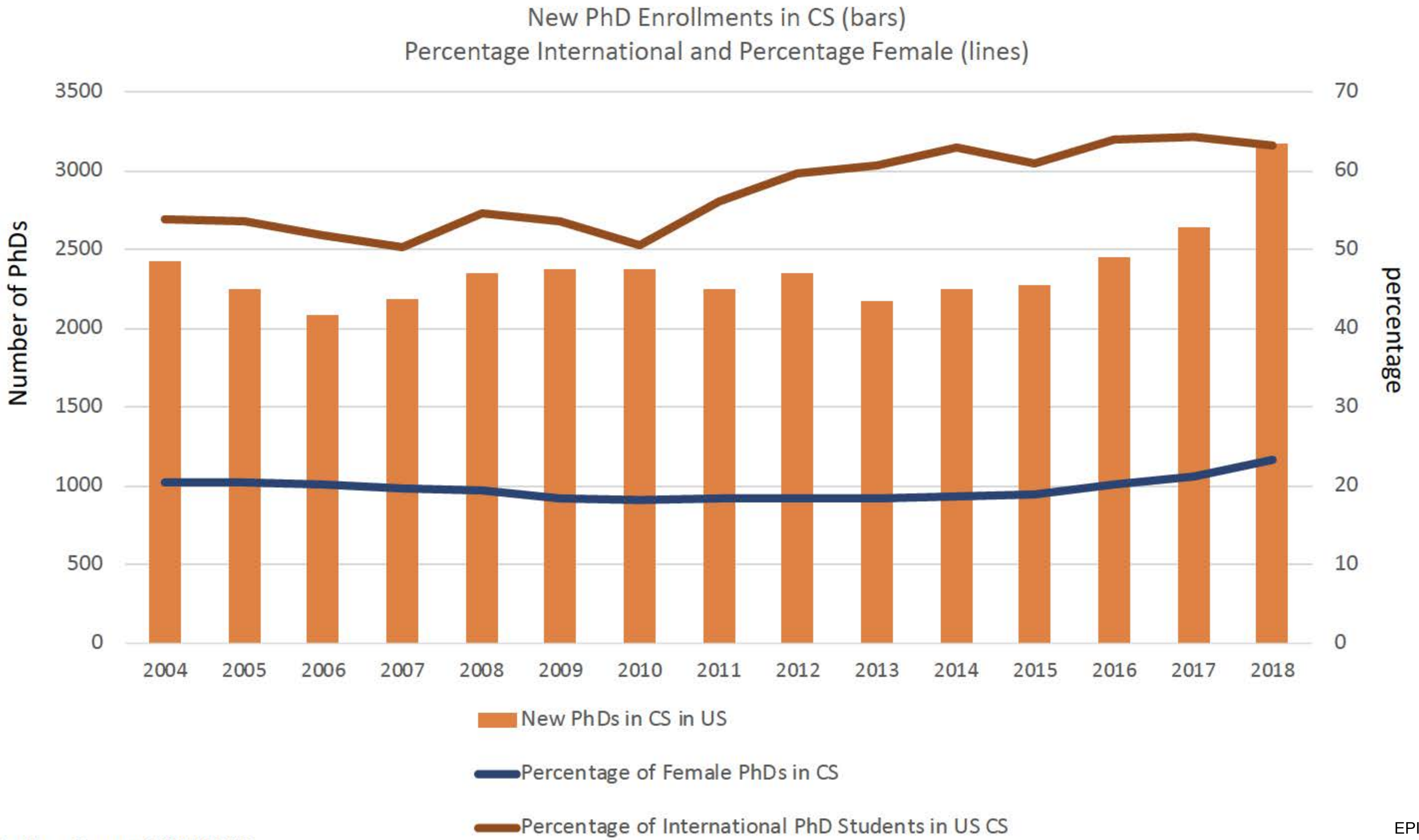
Undergraduate Enrollments in Computer Science





Source: CRA Taulbee Survey, 2004-2018

New PhD Enrollments in Computer Science



Source: CRA Taulbee Survey, 2004-2018

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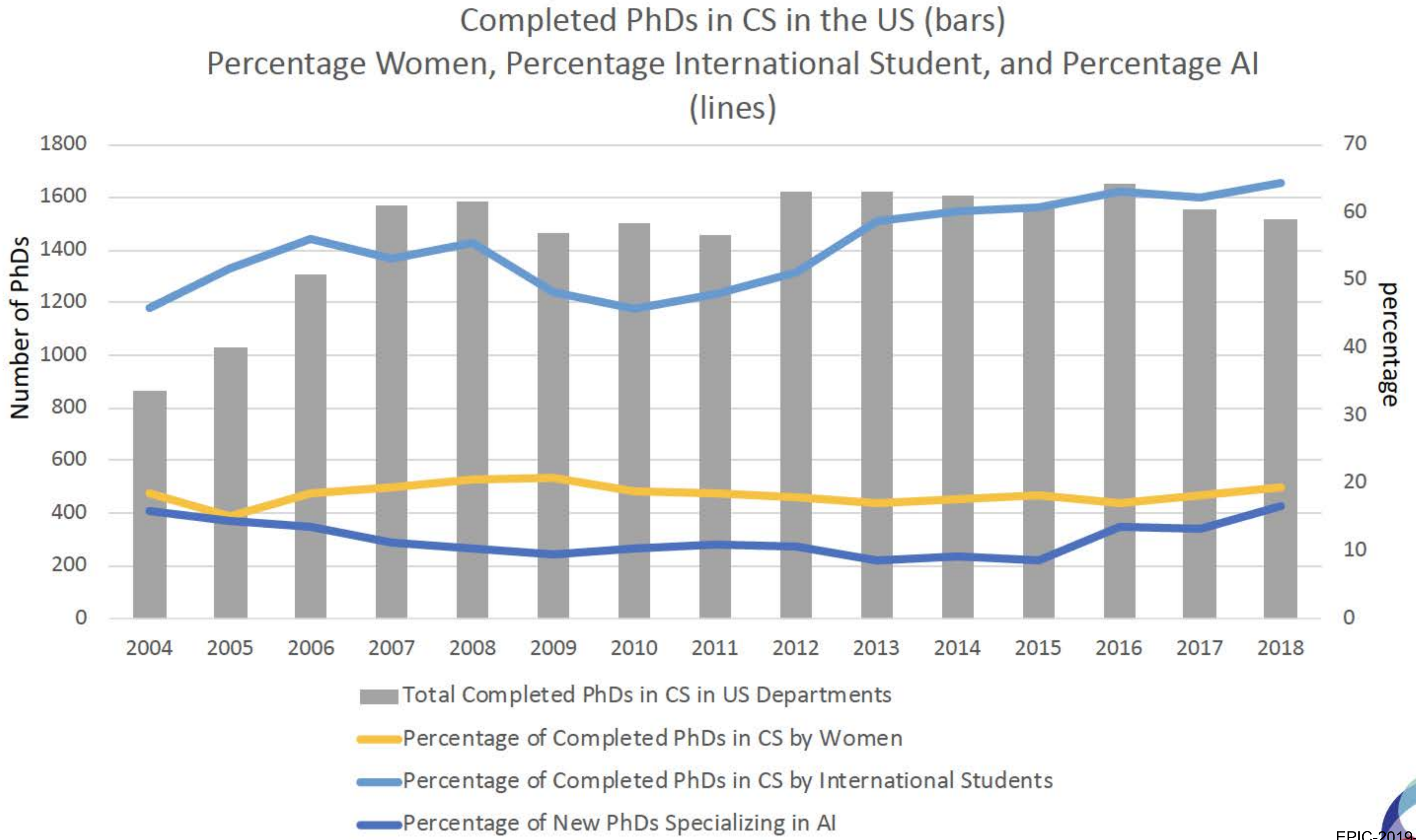
Completed PhDs in Computer Science



Source: CRA Taulbee Survey, 2004-2018

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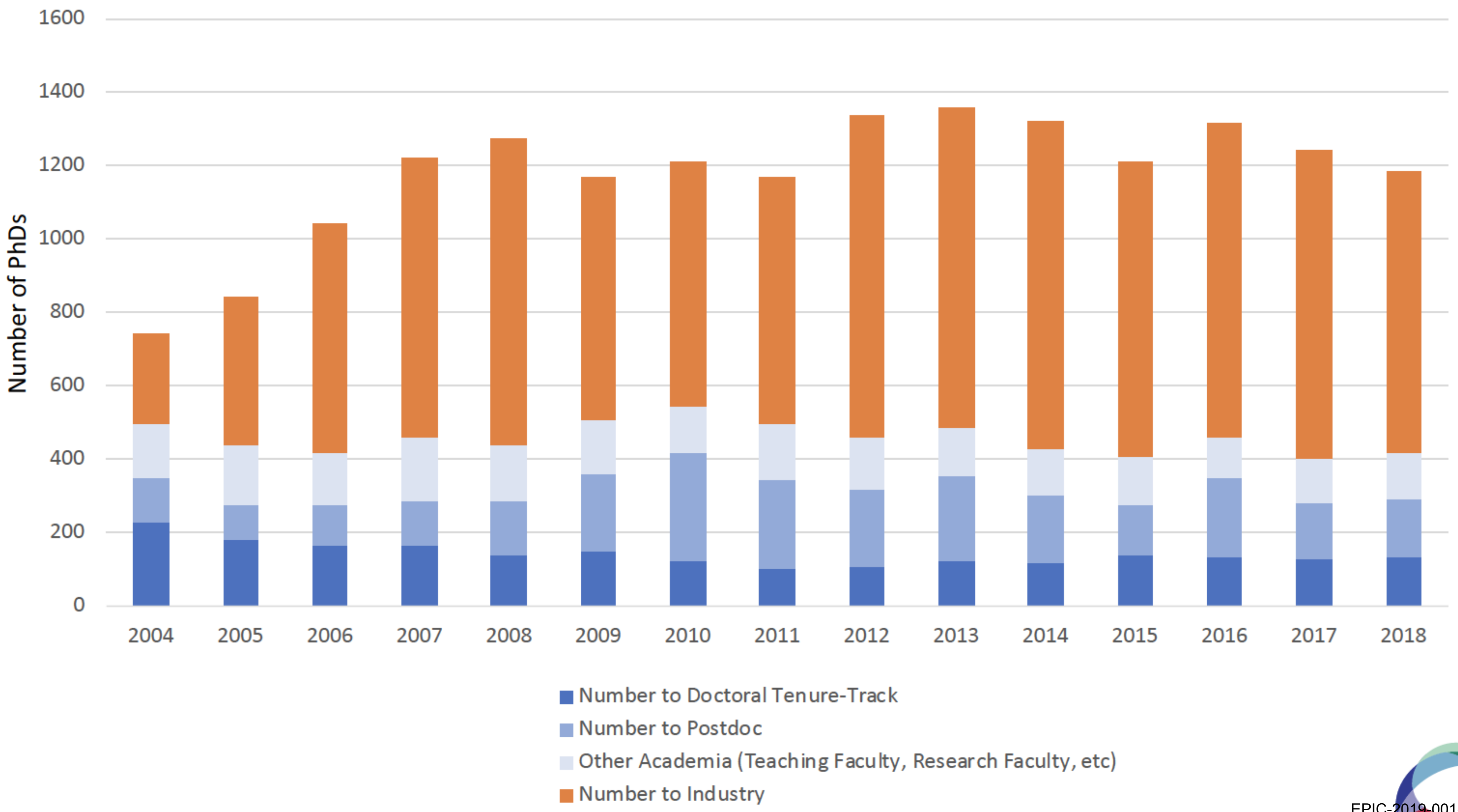
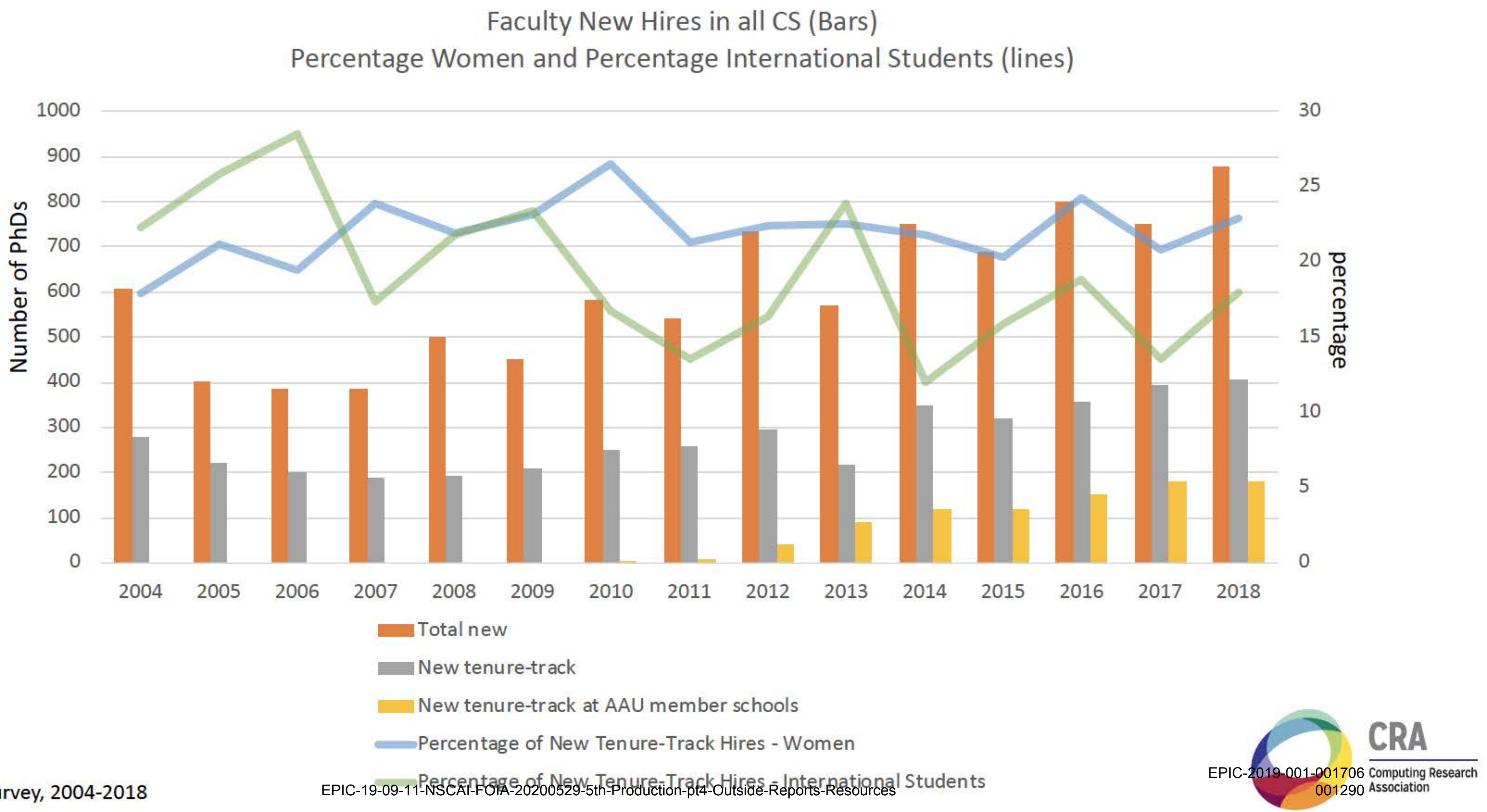
Employment of New PhDs (all Computing Fields)



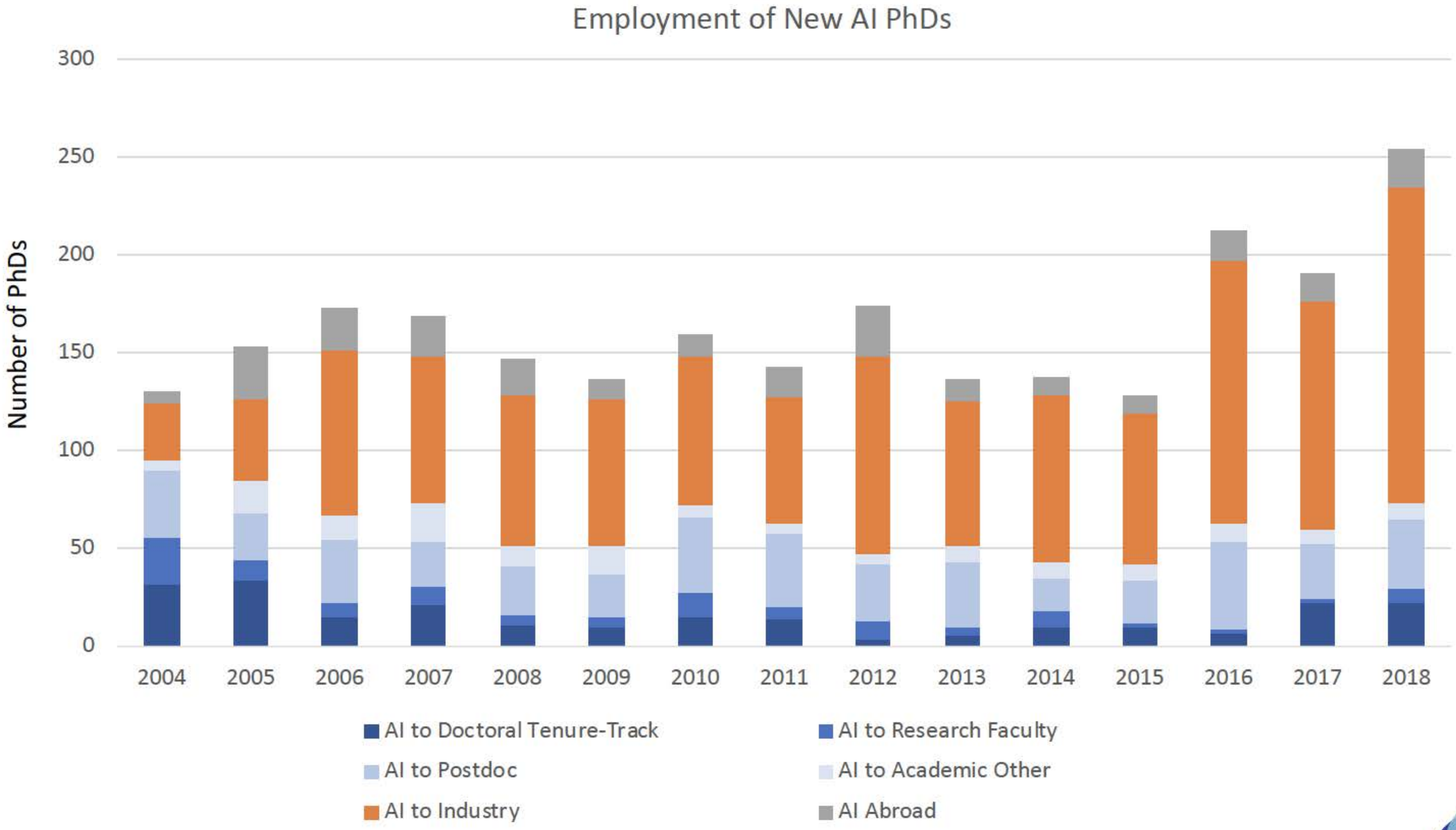
Source: CRA Taulbee Survey, 2004-2018

Faculty New Hires of PhDs (all Computing Fields)



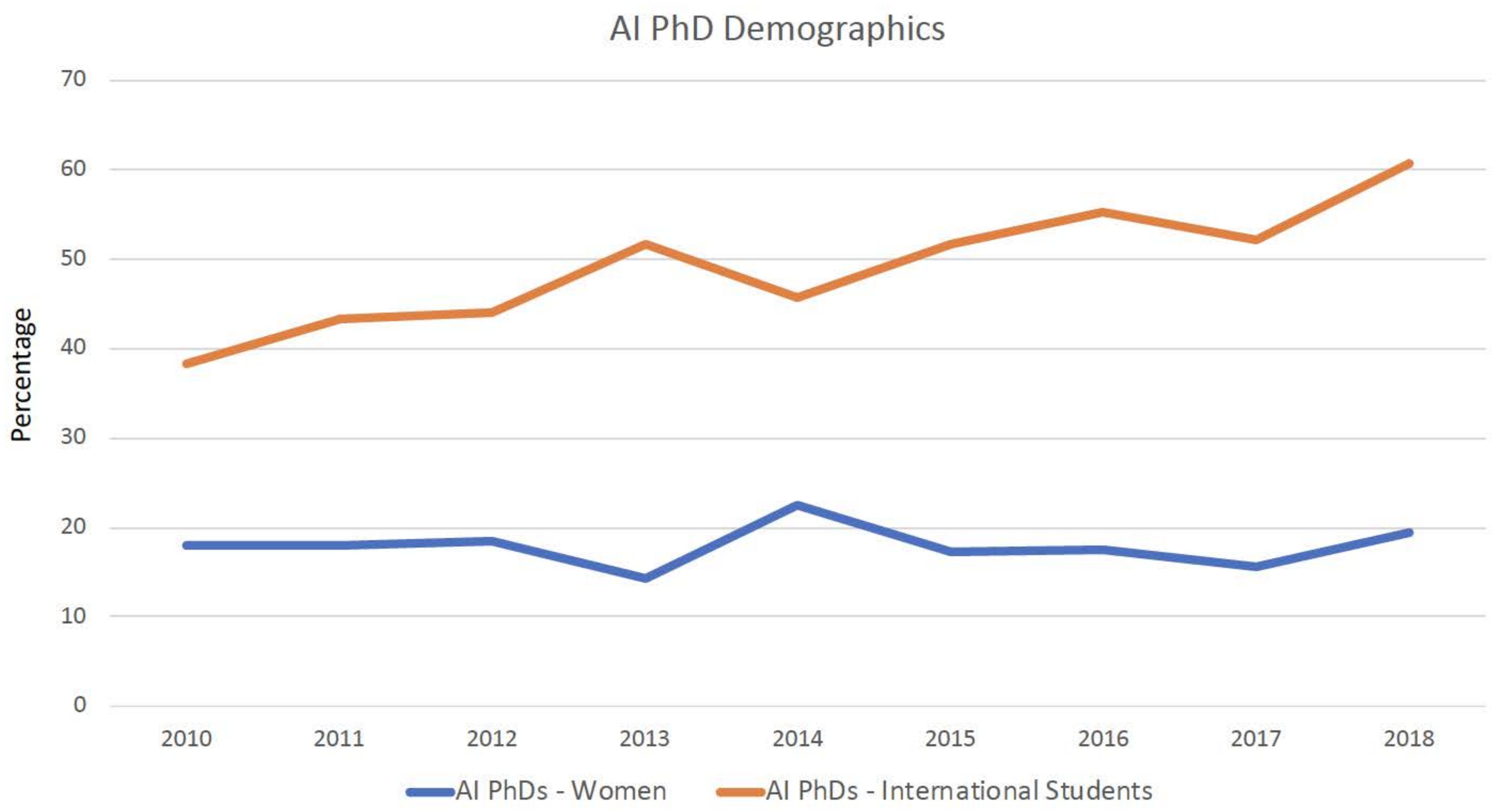
Source: CRA Taulbee Survey, 2004-2018

Employment of Newly Completed PhDs in Artificial Intelligence



Source: CRA Taulbee Survey, 2004-2018

Demographics of Newly Completed PhDs in Artificial Intelligence



Source: CRA Taulbee Survey, 2010-2018

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artificial intelligence index

National Security Commission on AI
May 8th, 2019

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Stanford | One Hundred Year Study on Artificial Intelligence (AI100)

HAI Human-Centered Artificial Intelligence
Stanford University

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Harvard

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AI Index PM

AI Index - Data Summary

	LOW
	MEDIUM
	HIGH
	NA
	Unknown
	Leaderboard specific

id	AI Attribute	Public (P), Company (C), Survey (S), Government (G)	Accessibility Central (C) or Distributed (D)	Countries covered	Years available	Data Quality	Agreement on analysis	Strategic importance
1	Research	P & C	C					
2	Innovation	C	C					
3	Education	S	D					
4	Conference	S	D					
5	Jobs	C	C					
6	Startup Activity	C & P	D					
7	Company Investment	C & S	D					
8	Public Investment	P	D					
9	Public Perception	C	C					
10	Technical Performance	Papers and Leaderboards	C & D					
11	Industrial Strategies	C, S & G	C					
12	National AI Plans	P, C, & G	D					
13	Regulatory Environment	P & C	C					
14	Human Predictions	NA	NA					
15	Ethics and Fairness	S	D					

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Worldwide AI Index - Vision

id	AI Attribute	USA	GREAT BRITAIN	CHINA	RUSSIA	CANADA
1	Research	AAA	AA+	AAA	A	AAA
2	Innovation	AA+	AA	AA+	BBB	AAA
3	Education	AAA	A	AAA	BBB-	AAA
4	Conferences	AAA	A+	AA+	B-	AAA
5	Jobs	AAA	AA+	Unknown	Unknown	AA
6	Startup Activity	AAA	AA+	AA+	BB	AA-
7	Company Investment	Unknown	Unknown	Unknown	Unknown	Unknown
8	Public Investment	AA	AA+	AA+	BBB+	AA-
9	Public Perception	AA	AA	AA-	B-	A+
10	Technical Performance	NA	NA	NA	NA	NA
11	Industrial Strategies	A+	AAA	AA+	BBB+	A-
12	National AI Plans	A	AAA	A	BBB	A-
13	Regulatory Environment	BBB+	A-	BBB	BBB-	A+
14	Ethics and Fairness	A-	BBB	B-	BB	AAA

Note: The above ratings are purely for illustration purpose and do not reflect any actual data gathering. The goal is to generate data-driven framework to directly aid policy decision-making.

Priority Policy Issues

- “Para-AI” issues — e.g., **ethics, security, privacy, bias, liability, impact on jobs** — are gating the deployment of AI systems, especially in critical applications.
- Detailed analyses of **investment** in and **outcomes** from US universities exist for ICT, but not for AI.
    - **R&D funding** for AI
    - Demands of the **job market** for AI practitioners
    - Consequences on universities of **academics leaving for industry**, full or part-time
    - Availability of qualified undergraduate **teaching staff**
    - Consequences of not retaining **foreign-born students** after graduation
    - Growing demand for **computational and data resources** in universities

US Government and AI

- USG (esp. NSF, DARPA) has long been the major funder of AI research
  - Seminal work on Deep Learning from Canada quickly adopted in US
  - Growing concern with “para” issues (DARPA Brandeis, Explainable AI; IARPA TrojAI)
- Reliable R&D funding data hard to find
- Significant R&D transitions to USG operations
  - Not always clear who is responsible for making them happen
- AI/ML transfer is challenging
  - Few commercial applications can be used as is
  - Lots of data, but not much labelled
  - Operating conditions often difficult
  - Civilian agency budgets are stretched

Thank you!

APPENDIX

Selected Collaborators

ELSEVIER Scopus
arXiv
Microsoft
Microsoft Academic Graph (MAG) Analytics
crunchbase
indeed
WiML Women in Machine Learning

SH SANDHILL ECONOMETRICS
Google
YouTube
LinkedIn
THE ECONOMIC GRAPH
WFP
MONSTER

WIPO WORLD INTELLECTUAL PROPERTY ORGANIZATION
Bloomberg
burningglass TECHNOLOGIES
unicri United Nations Interregional Crime and Justice Research Institute
prattle

GDELT Project
Quid
OECD
APL
amplified
McKinsey&Company
PRIME MINISTER'S OFFICE SINGAPORE

AI
pwc
Joint Research Centre JRC
nesta
Carnegie Mellon University
ICML
UWNLP
China AI Index

What is the AI Index?

- A set of measures that capture the state of AI and track it over time
- Aims to be well informed and provide quantitative basis for AI discussions
- Ground public narrative on AI using a data-driven approach

Target audiences

- Researchers in AI and other fields
- Industry
- Policymakers
- Media and general public

Indices are diverse

Higher Education Price Index

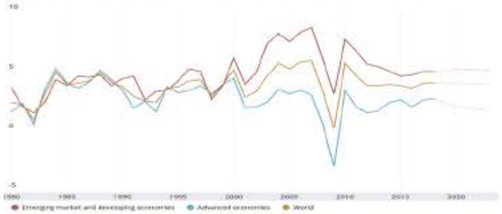
HISTORICAL SUMMARY OF HIGHER EDUCATION PRICE INDEX AND CONSUMER PRICE INDEX

Fiscal Years 1961 to 2016

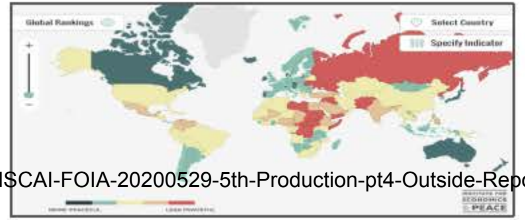
	College and university operations		Consumer prices			College and university operations		Consumer prices	
Fiscal year	HEPI Index Value 1983 = 100	Yearly % Change	CPI Index Value 1983 = 100	Yearly % Change	Fiscal year	HEPI Index Value 1983 = 100	Yearly % Change	CPI Index Value 1983 = 100	Yearly % Change
1961	25.6	-	30.3	-	1991	148.2	5.2%	136.4	5.4%
1962	26.5	3.7%	30.6	1.0%	1992	153.5	3.6%	140.8	3.2%
1963	27.6	4.0%	31.0	1.1%	1993	157.9	2.9%	145.2	3.1%
1964	28.6	3.8%	31.4	1.4%	1994	163.3	3.4%	148.8	2.5%
1965	29.8	4.1%	31.8	1.3%	1995	168.1	2.9%	153.2	3.0%
1966	31.3	4.9%	32.6	2.3%	1996	173.0	2.9%	157.4	2.7%
1967	32.9	5.4%	33.5	3.0%	1997	178.4	3.2%	161.9	2.9%
1968	34.9	5.9%	34.6	3.3%	1998	184.7	3.5%	164.8	1.8%
1969	37.1	6.3%	36.3	4.8%	1999	189.1	2.4%	167.6	1.7%
1970	39.5	6.7%	38.5	5.9%	2000	196.9	4.1%	172.5	2.9%
1971	42.1	6.4%	40.5	5.2%	2001	208.7	6.0%	178.4	3.4%
1972	44.3	5.3%	41.9	3.6%	2002	212.7	1.9%	181.6	1.8%
1973	46.7	5.3%	43.6	3.9%	2003	223.5	5.1%	185.5	2.2%
1974	49.9	6.9%	47.5	8.9%	2004	231.7	3.7%	189.6	2.2%
1975	54.3	8.8%	52.8	11.2%	2005	240.8	3.9%	195.3	3.0%
1976	57.8	6.4%	56.5	7.1%	2006	253.1	5.1%	202.7	3.8%
[illegible]	[illegible]	6.4%	59.8	5.8%	2007	260.3	2.8%	[illegible]	[illegible]
1978	65.7	6.8%	63.8	6.8%	2008	273.2	5.0%	215.7	3.7%
1979	70.5	7.3%	69.8	9.3%	2009	279.3	2.3%	218.7	1.4%

Stock Market Indices

Cross-country GDP growth



Global Peace Index



Social Progress Index

SOCIAL PROGRESS SUMMARY X

United States Score 86.43 Rank 18

High Social Progress

See scorecard

Dimensions

BASIC HUMAN NEEDS	FOUNDATIONS OF WELLBEING	OPPORTUNITY
93.42	84.19	81.68

Highest component scores

Nutrition and Basic Medical Care	98.96
Water and Sanitation	98.77
Access to Basic Knowledge	97.95
Access to Advanced Education	89.55
Shelter	89.18

Lowest component scores

Tolerance and Inclusion	68.30
Health and Wellness	75.88
Environmental Quality	78.31
Personal Freedom and Choice	79.88
Access to Information and Communications	84.63

Se

… but they typically

- Frame the conversation about a domain, provide broad picture
- Provide a quantified snapshot of the domain at any given time
- Capture historical trends
- Represent diverse dimensions
- Decomposability – by regions or sectors

AI Index - Annual Report

2017

2018

2019

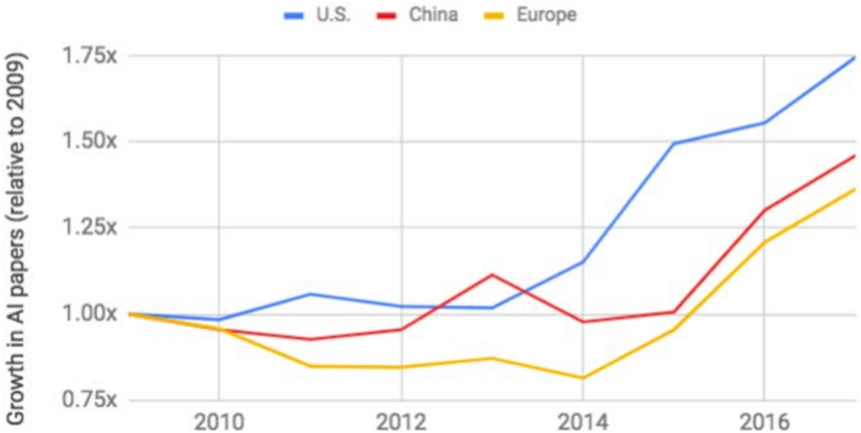
AI Index – Measures we track

- Volume and Quality of Activity
- Technical Performance
- Derivative Measures
- Economic and Human Impact

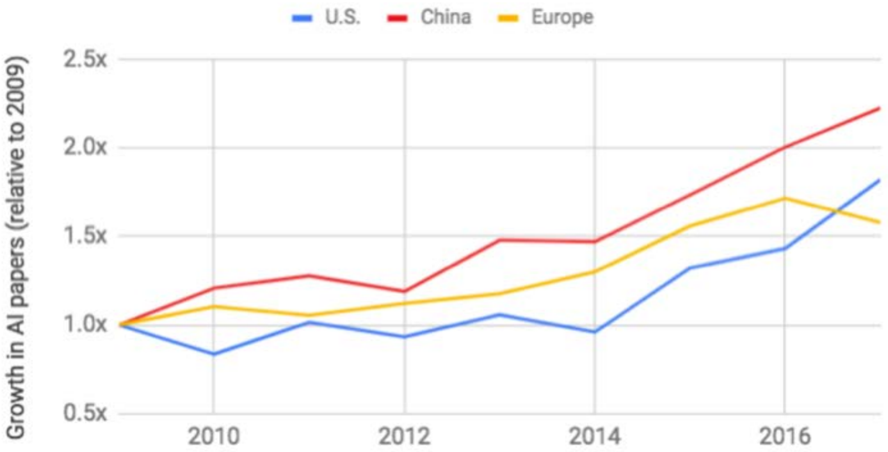
Longitudinal data to rank AI progress (or failure) metrics by domains, regions and sectors

Volume of Activity - Research affiliations

Growth in corporate-affiliated AI papers (2009—2017)
Source: Elsevier



Growth in government-affiliated AI papers (2009—2017)
Source: Elsevier

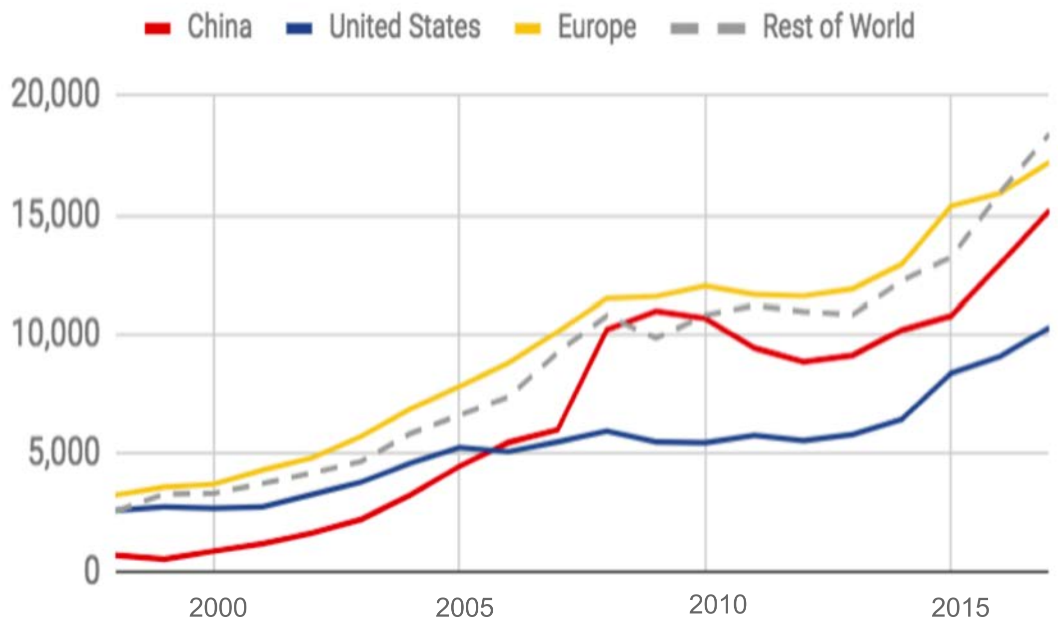


The number of Chinese government-affiliated AI papers has more than doubled since 2009

Meanwhile, the U.S. shows the greatest increase in corporate-affiliated AI papers. There were 1.7x as many corporate AI papers in 2017 as there were in 2009.

Volume of Activity - Research

Annually published AI papers by region (1998—2017)
Source: Elsevier

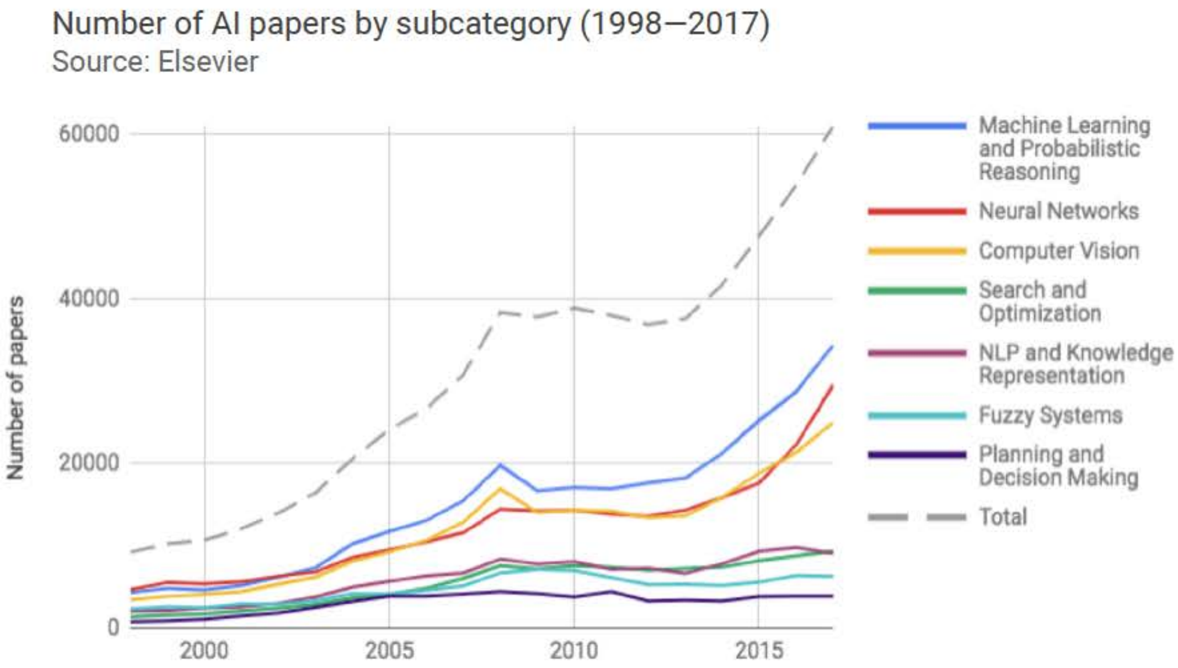


17%

Europe is the largest publisher of AI papers

In 2017, 28% of AI papers were affiliated with European authors, followed by China (25%) and the U.S. (17%).

Volume of Activity - Research Topics

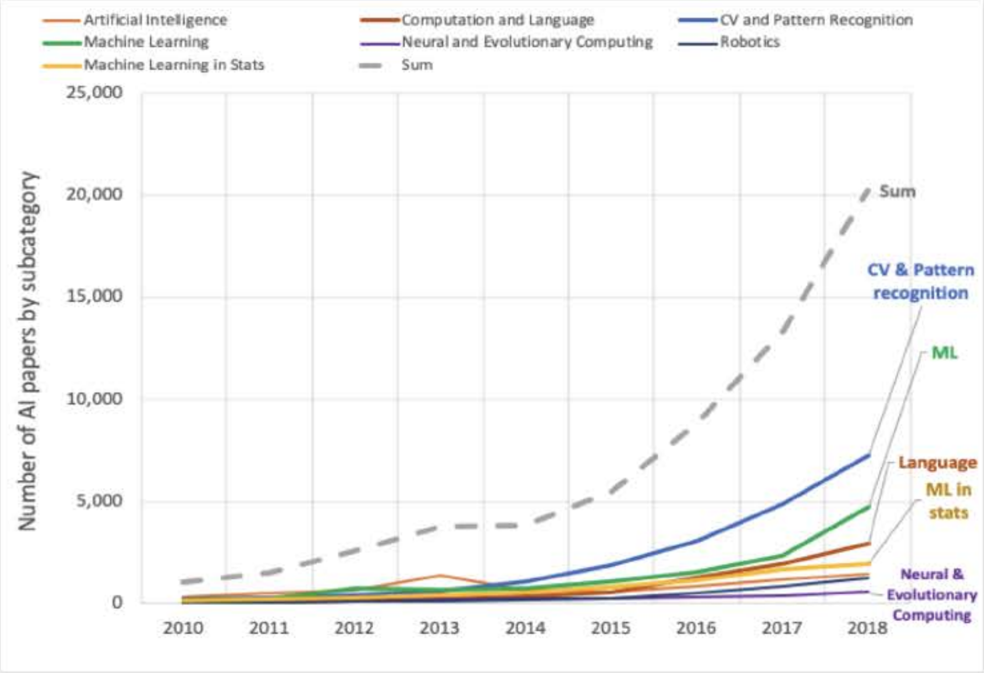


37%

The number of papers on Neural Networks had a CAGR of 37% from 2014 to 2017

Volume of Activity - arXiv categories

Number of AI papers on arXiv by subcategory (2010–2018)
Source: arXiv



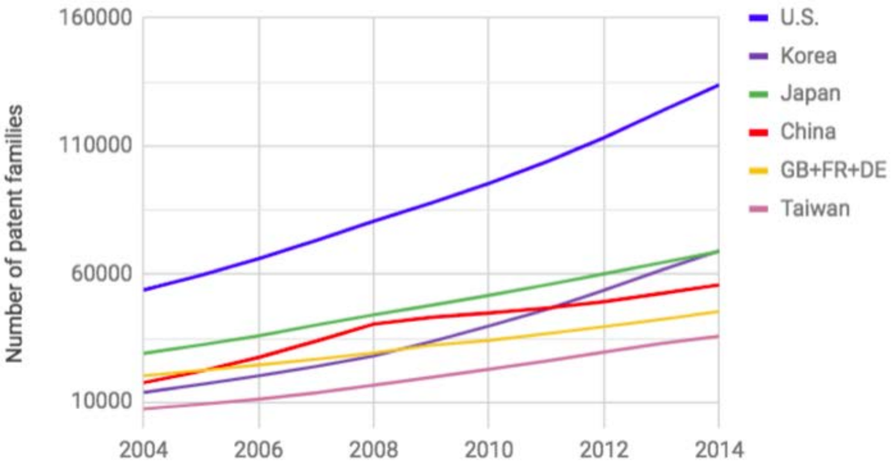
19x

*The total number of AI papers on arXiv has increased almost **19x** since 2010.*

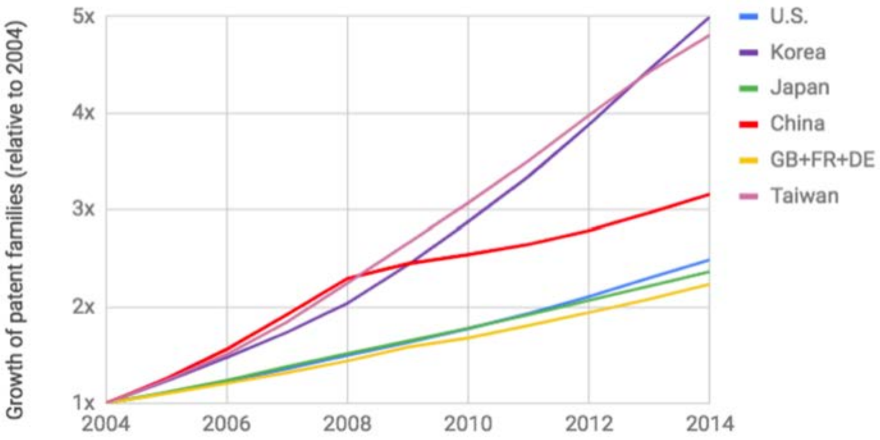
*Computation & Language papers grew the fastest over **44x** since 2010, followed by Machine Learning and CV and Pattern Recognition (**30x**)*

Volume of Activity - Patents

AI patents by inventor region (2004—2014)
Source: amplified



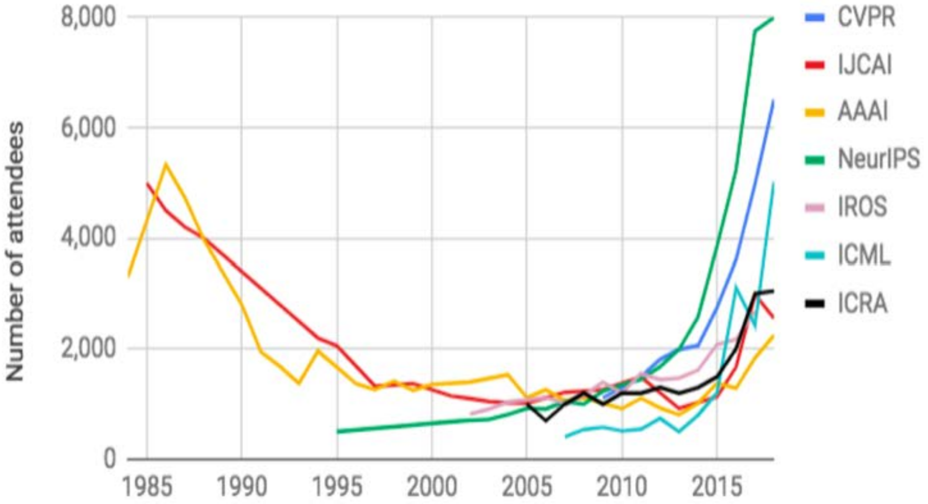
Growth of AI patents by inventor region (2004—2014)
Source: amplified



Note: GB + FR + DE refers to a combined number of patents from Great Britain, France, and Germany

Volume of Activity - Conferences

Attendance at large conferences (1984—2018)
Source: Conference provided data

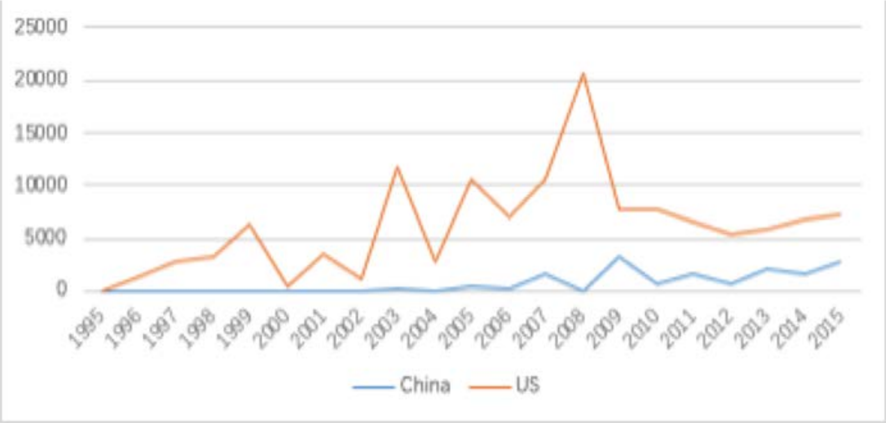


Shifting Focus

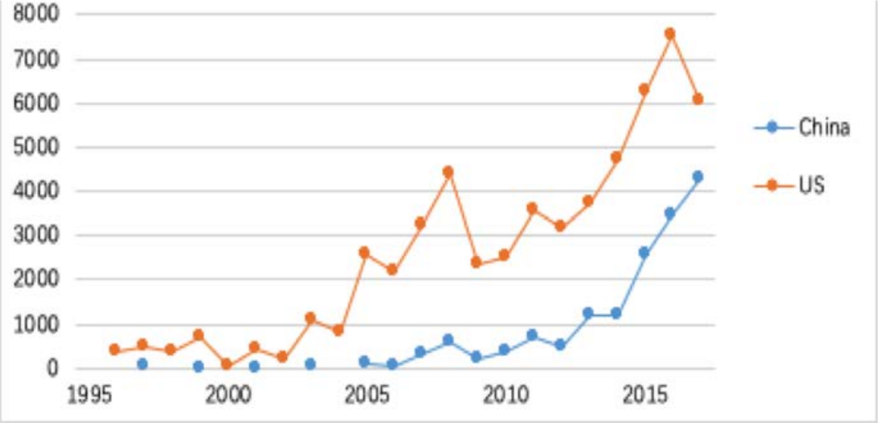
NeurIPS and ICML are growing at the fastest rate — ***4.8x*** and ***6.8x*** their 2012 attendance, respectively. This shows continued interest in ML as a subfield of AI. Meanwhile, conferences focusing on symbolic reasoning continue to show little relative growth.

US versus China - Conferences

Citations of conference papers: China vs. US (1995—2017)
Source: China AI Index, 2018.

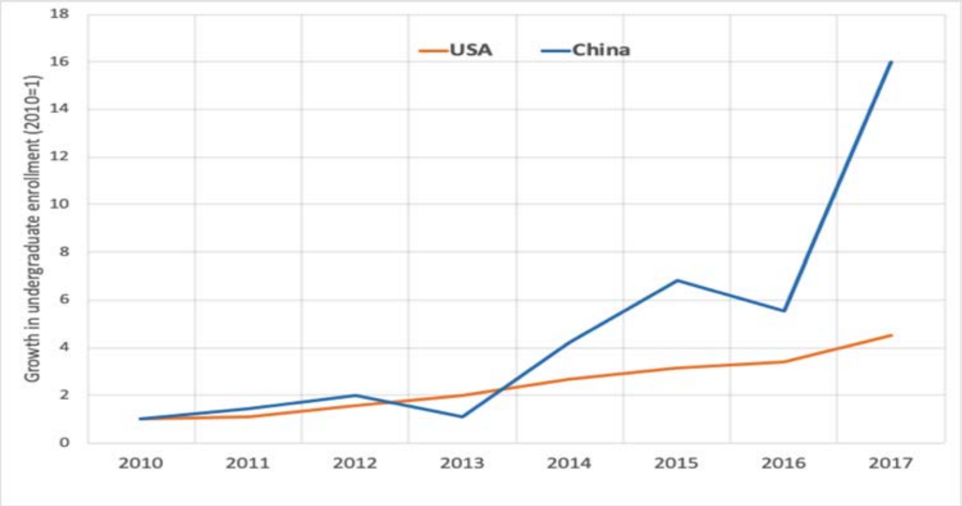


Participation to large conferences: China vs. US (1995—2017)
Source: China AI Index, 2018.



Volume of Activity - Course Enrollments

Growth in introductory AI+ML course enrollment (2010–2017)
Source: University provided data.

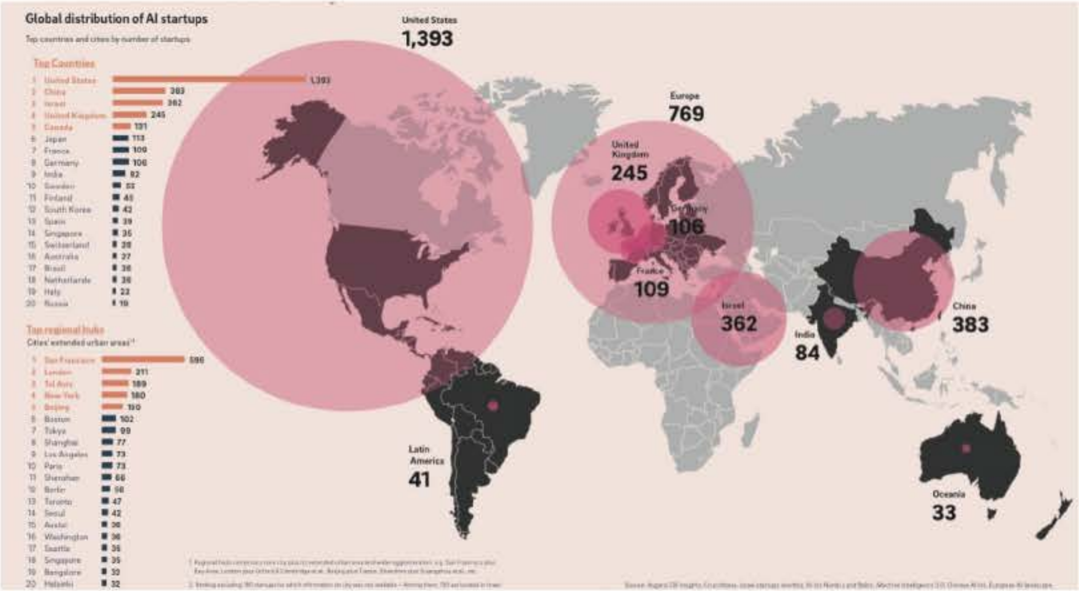


16x

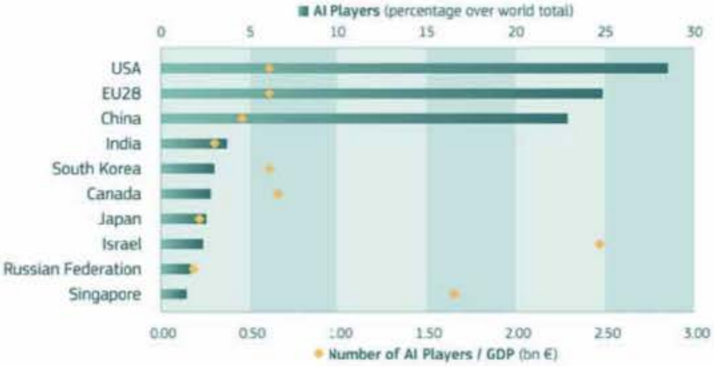
China refers to Tsinghua University only, USA is the sum of Stanford, GT, UIUC, UW, Berkeley, and CMU.

Volume of Activity - Startups

Global distribution of AI Startups
Source: Asgard and Roland Berger, 2018.

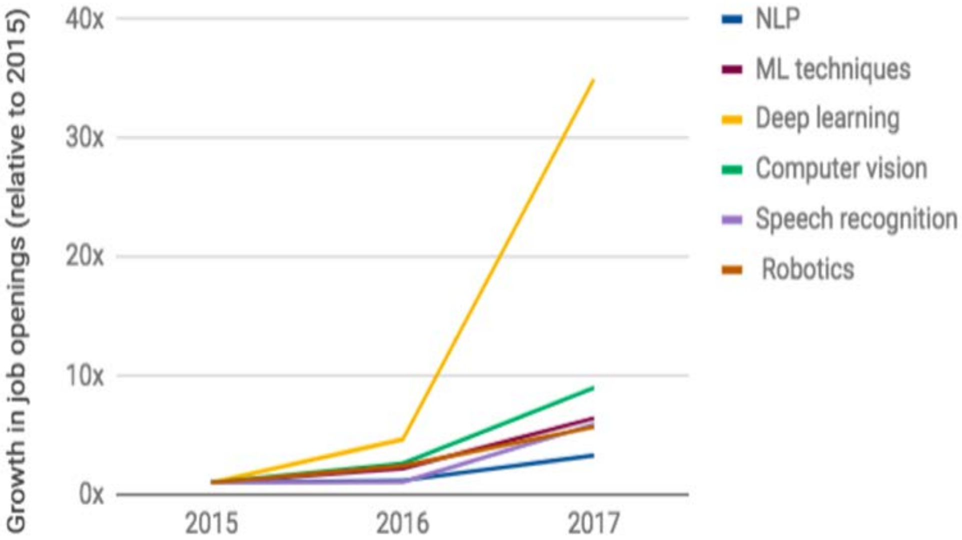


Top 10 AI players in the world and relation with GDP by geographical zones, 2009-2018
Source: JRC, 2018.



Volume of Activity - Job openings

Growth of job openings by AI skills required (2015 — 2017)
Source: Monster.com

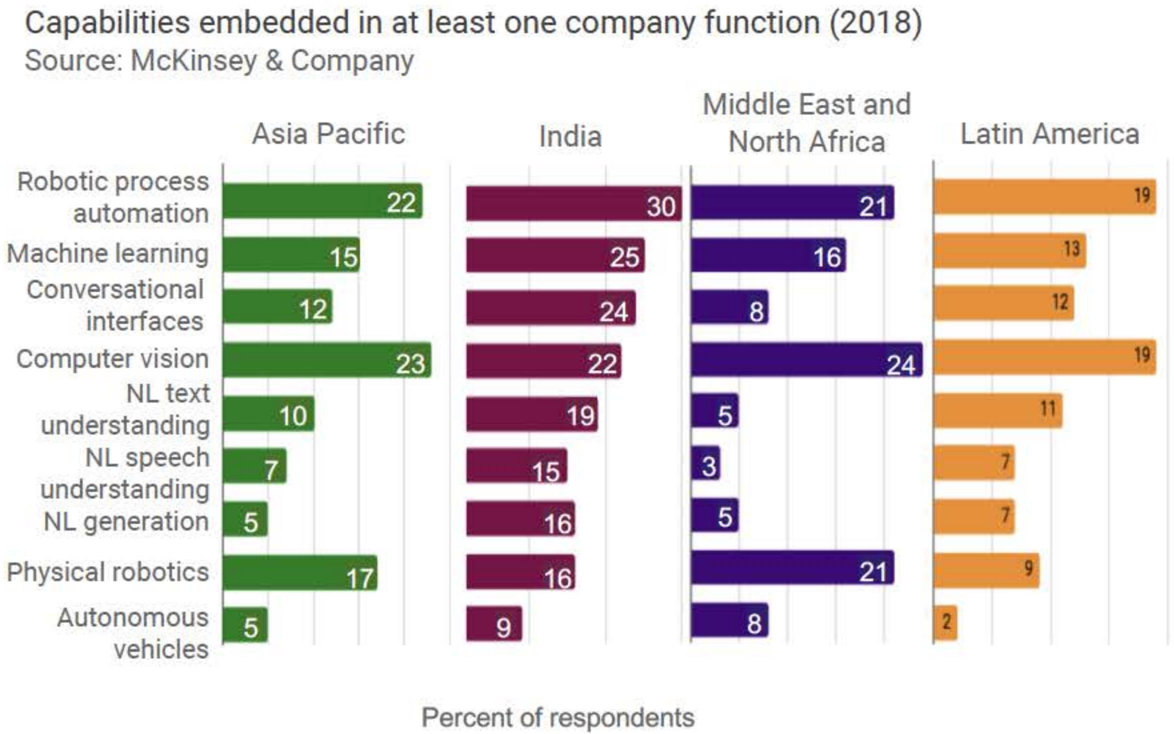


10x

*Average **AI job openings** in the US has grown **10x** since 2015.* While ML is the largest skill cited as a requirement, deep learning (DL) is growing at the fastest rate — from 2015 to 2017 the number of job openings requiring DL increased ***34x***.

*The **AI jobs gender ratio** for largest US cities is **70-30** (M-F).*

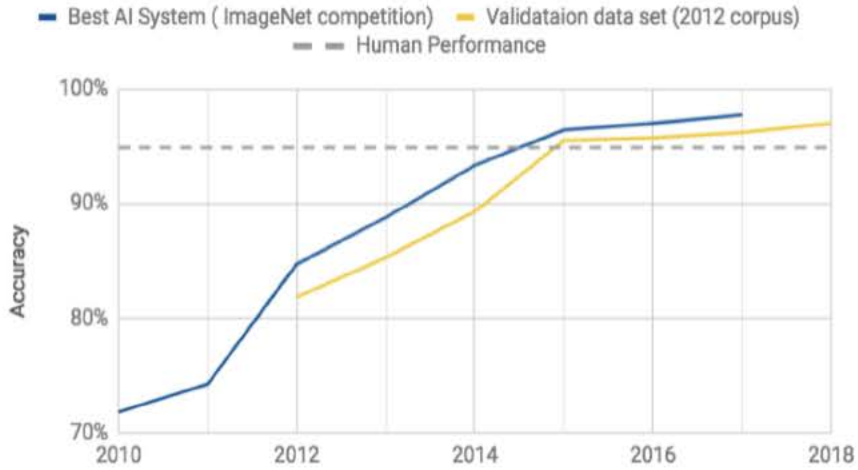
Industrial Strategies - Adoption and Capabilities



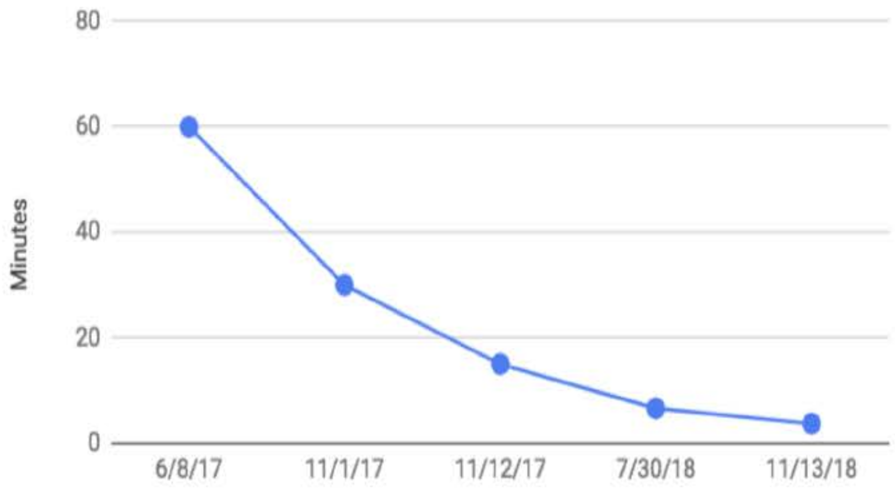
Note: The size of each bar is relative to the capabilities within each region; Asia–Pacific: N = 263; India: N = 197; Middle East and North Africa: N = 77; Latin America: N = 127. Based on survey of 2,135 respondents.

Technical Performance - ImageNet

ImageNet (2010 –2018)
Source: ImageNet.



ImageNet training time (June 2017 – November 2018)
Source: arXiv.org.



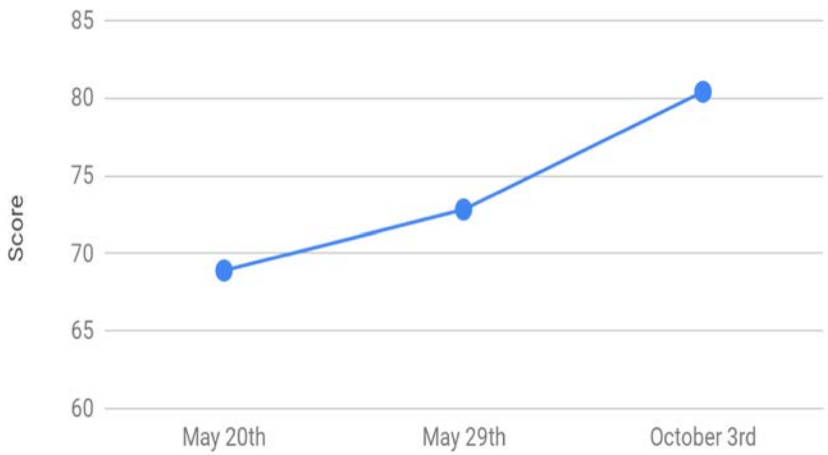
ImageNet training time in November 2018 was 16x the speed of that in June 2017. *Training time for best model on ImageNet reduced from 60 minutes to less than 3 minutes within 18 months*

Technical Performance - Challenges

ARC leaderboard (April 2018—November 2018)
Source: Allen Institute for Artificial Intelligence

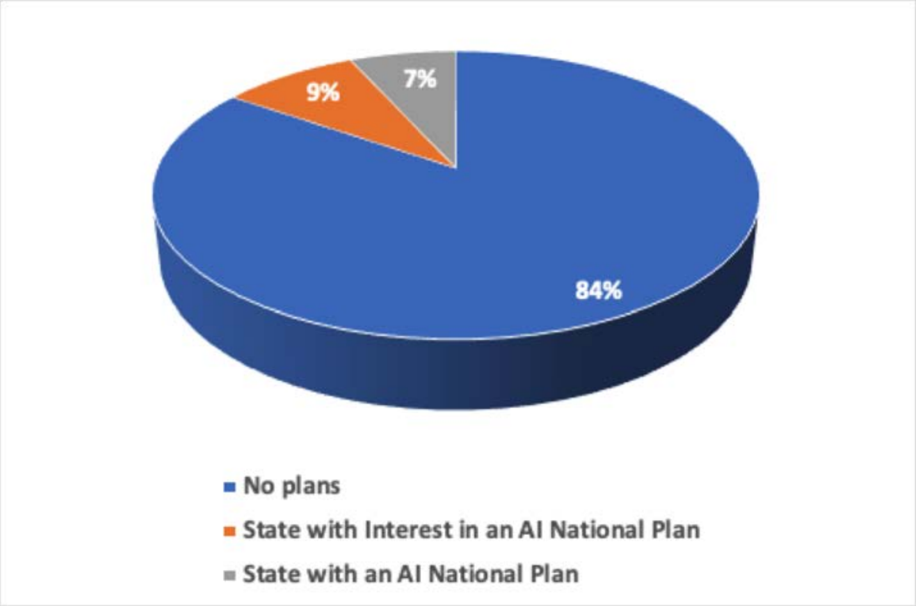
Note: This visual shows leading submissions connected by a trend line.

GLUE benchmark leaderboard (May 2018—October 2018)
Source: Gluebenchmark.com



National Strategies - States with AI plans or interest in plan

Proportion of countries with national AI plan
Source: UNICRI-FutureGrasp.



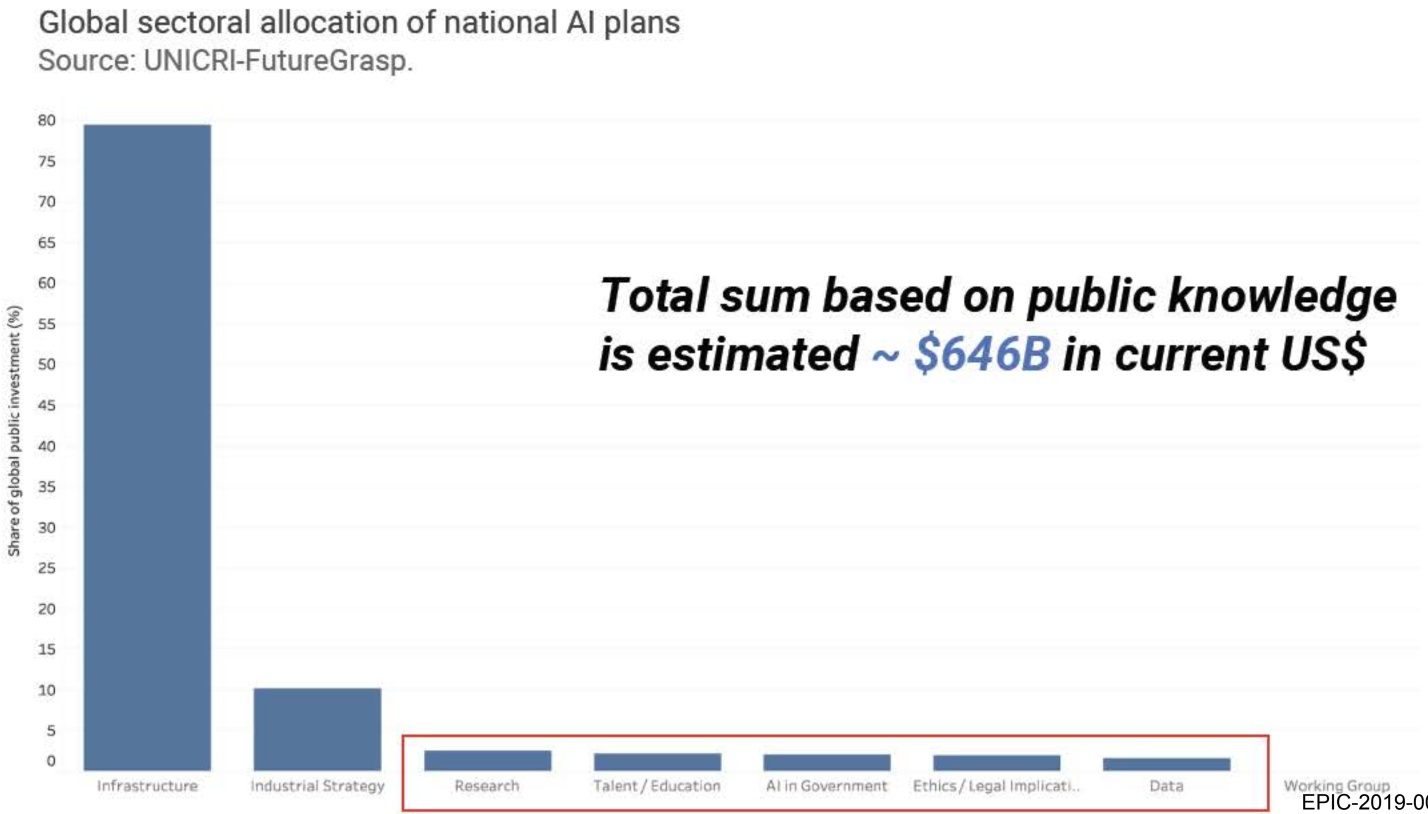
# of countries

# of countries	
14	National AI Plan
18	Interest in national AI plan
160+	No AI plan

National AI Strategies - A global perspective

World Map of stages of national AI plans
Source: UNICRI-FutureGrasp.

National AI Strategies - Sector breakdown

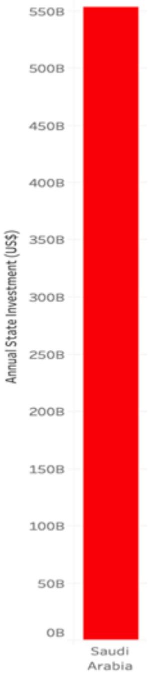


Total sum based on public knowledge is estimated ~ $646B in current US$

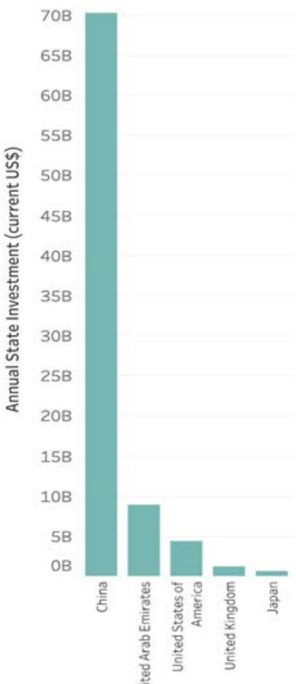
AI Public Investment - Country Public Knowledge

Public AI expenditure estimates (in current US$)
Source: UNICRI-FutureGrasp.

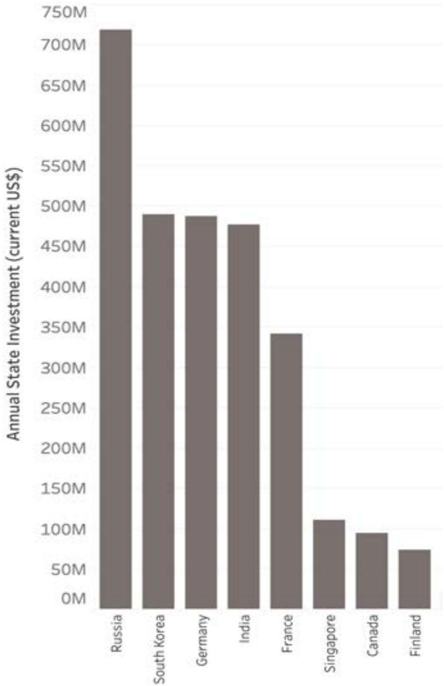
Mega



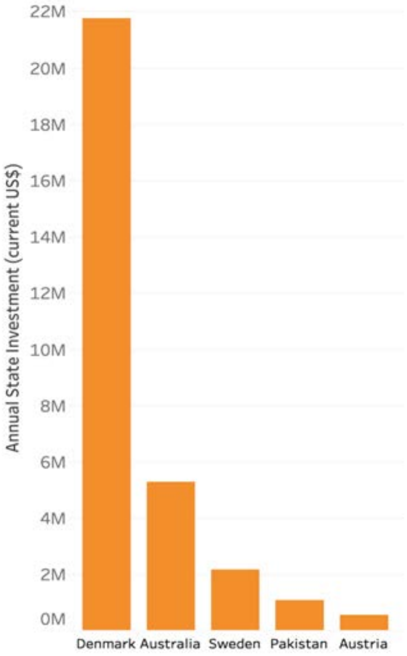
Large



Mid



Small



Thank you!

THE NATIONAL ARTIFICIAL INTELLIGENCE RESEARCH AND DEVELOPMENT STRATEGIC PLAN: 2019 UPDATE

A Report by the

SELECT COMMITTEE ON ARTIFICIAL INTELLIGENCE

of the

NATIONAL SCIENCE & TECHNOLOGY COUNCIL

JUNE 2019

Dear Colleagues,

In his State of the Union address on February 5, 2019, President Trump stressed the importance of ensuring American leadership in the development of emerging technologies, including artificial intelligence (AI), that make up the Industries of the Future. Reflecting this importance, on February 11, 2019, President Trump signed Executive Order 13859, which established the American Artificial Intelligence Initiative. This Initiative is a whole-of-government approach for maintaining American leadership in AI and ensuring that AI benefits the American people and reflects our Nation's values. The first directive in this Executive Order is for Federal agencies to prioritize AI research and development (R&D) in their annual budgeting and planning process. The attached *National AI R&D Strategic Plan: 2019 Update* highlights the key priorities for Federal investment in AI R&D.

Artificial intelligence presents tremendous opportunities that are leading to breakthroughs in improved healthcare, safer and more efficient transportation, personalized education, significant scientific discoveries, improved manufacturing, increased agricultural crop yields, better weather forecasting, and much more. These benefits are largely due to decades of long-term Federal investments in fundamental AI R&D, which have led to new theories and approaches for AI systems, as well as applied research that allows the translation of AI into practical applications.

The landscape for AI R&D is becoming increasingly complex, due to the significant investments that are being made by industry, academia, and nonprofit organizations. Additionally, AI advancements are progressing rapidly. The Federal Government must therefore continually reevaluate its priorities for AI R&D investments, to ensure that investments continue to advance the cutting edge of the field and are not unnecessarily duplicative of industry investments.

In August of 2018, the Administration directed the Select Committee on AI to refresh the 2016 *National AI R&D Strategic Plan*. This process began with the issuance of a Request for Information to solicit public input on ways that the strategy should be revised or improved. The responses to this RFI, as well as an independent agency review, informed this update to the Strategic Plan.

In this Strategic Plan, eight strategic priorities have been identified. The first seven strategies continue from the 2016 Plan, reflecting the reaffirmation of the importance of these strategies by multiple respondents from the public and government, with no calls to remove any of the strategies. The eighth strategy is new and focuses on the increasing importance of effective partnerships between the Federal Government and academia, industry, other non-Federal entities, and international allies to generate technological breakthroughs in AI and to rapidly transition those breakthroughs into capabilities.

While this Plan does not define specific research agendas for Federal agency investments, it does provide an expectation for the overall portfolio for Federal AI R&D investments. This coordinated Federal strategy for AI R&D will help the United States continue to lead the world in cutting-edge advances in AI that will grow our economy, increase our national security, and improve quality of life.

Sincerely,

Michael Kratsios
Deputy Assistant to the President for Technology Policy
June 21, 2019

Table of Contents

Executive Summary

Artificial intelligence (AI) holds tremendous promise to benefit nearly all aspects of society, including the economy, healthcare, security, the law, transportation, even technology itself. On February 11, 2019, the President signed Executive Order 13859, *Maintaining American Leadership in Artificial Intelligence*.[1] This order launched the American AI Initiative, a concerted effort to promote and protect AI technology and innovation in the United States. The Initiative implements a whole-of-government strategy in collaboration and engagement with the private sector, academia, the public, and like-minded international partners. Among other actions, key directives in the Initiative call for Federal agencies to prioritize AI research and development (R&D) investments, enhance access to high-quality cyberinfrastructure and data, ensure that the Nation leads in the development of technical standards for AI, and provide education and training opportunities to prepare the American workforce for the new era of AI.

In support of the American AI Initiative, this *National AI R&D Strategic Plan: 2019 Update* defines the priority areas for Federal investments in AI R&D. This 2019 update builds upon the first *National AI R&D Strategic Plan* released in 2016, accounting for new research, technical innovations, and other considerations that have emerged over the past three years. This update has been developed by leading AI researchers and research administrators from across the Federal Government, with input from the broader civil society, including from many of America's leading academic research institutions, nonprofit organizations, and private sector technology companies. Feedback from these key stakeholders affirmed the continued relevance of each part of the 2016 Strategic Plan while also calling for greater attention to making AI trustworthy, to partnering with the private sector, and other imperatives.

The *National AI R&D Strategic Plan: 2019 Update* establishes a set of objectives for Federally funded AI research, identifying the following eight strategic priorities:

Strategy 1: Make long-term investments in AI research. Prioritize investments in the next generation of AI that will drive discovery and insight and enable the United States to remain a world leader in AI.

Strategy 2: Develop effective methods for human-AI collaboration. Increase understanding of how to create AI systems that effectively complement and augment human capabilities.

Strategy 3: Understand and address the ethical, legal, and societal implications of AI. Research AI systems that incorporate ethical, legal, and societal concerns through technical mechanisms.

Strategy 4: Ensure the safety and security of AI systems. Advance knowledge of how to design AI systems that are reliable, dependable, safe, and trustworthy.

Strategy 5: Develop shared public datasets and environments for AI training and testing. Develop and enable access to high-quality datasets and environments, as well as to testing and training resources.

Strategy 6: Measure and evaluate AI technologies through standards and benchmarks. Develop a broad spectrum of evaluative techniques for AI, including technical standards and benchmarks.

Strategy 7: Better understand the national AI R&D workforce needs. Improve opportunities for R&D workforce development to strategically foster an AI-ready workforce.

Strategy 8: Expand public-private partnerships to accelerate advances in AI. Promote opportunities for sustained investment in AI R&D and for transitioning advances into practical capabilities, in collaboration with academia, industry, international partners, and other non-Federal entities.

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1 https://www.whitehouse.gov/presidential-actions/executive-order-maintaining-american-leadership-artificial-intelligence/

Introduction to the 2019 National AI R&D Strategic Plan

Artificial intelligence enables computers and other automated systems to perform tasks that have historically required human cognition and what we typically consider human decision-making abilities. Over the past several decades, AI has advanced tremendously and today promises better, more accurate healthcare; enhanced national security; improved transportation; and more effective education, to name just a few benefits. Increased computing power, the availability of large datasets and streaming data, and algorithmic advances in machine learning (ML) have made it possible for AI development to create new sectors of the economy and revitalize industries. As more industries adopt AI's fundamental technologies, the field will continue to drive profound economic impact and quality-of-life improvements worldwide.

These advancements have been driven primarily by Federal investments in AI R&D, the expertise of America's unsurpassed R&D institutions, and the collective creativity of many of America's most visionary technology companies and entrepreneurs.

In 2016 the Federal Government published first *National AI R&D Strategic Plan*, recognizing AI's tremendous promise and need for continued advancement. It was developed to guide the Nation in our AI R&D investments, provide a strategic framework for improving and leveraging America's AI capabilities, and ensure that those capabilities produce prosperity, security, and improved quality of life for the American people for years to come.

The Plan defined several key areas of priority focus for the Federal agencies that invest in AI. These focus areas, or strategies, include: 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 datasets and environments for AI training and testing; measuring and evaluating AI technologies through standards and benchmarks; and better understanding the Nation's AI R&D

2019 Update	**RFI responses inform the 2019 National AI R&D Strategic Plan**

In September 2018, the National Coordination Office for Networking and Information Technology Research and Development issued a Request for Information (RFI)[2] on behalf of the Select Committee on Artificial Intelligence, requesting input from all interested parties on the 2016 *National Artificial Intelligence Research and Development Strategic Plan*. Nearly 50 responses were submitted by researchers, research organizations, professional societies, civil society organizations, and individuals; these responses are available online.[3]

Many of the responses reaffirmed the analysis, organization, and approach outlined in the 2016 *National AI R&D Strategic Plan*. A significant number of responses noted the importance of investing in the application of AI in areas such as manufacturing and supply chains; healthcare; medical imaging; meteorology, hydrology, climatology, and related areas; cybersecurity; education; data-intensive physical sciences such as high-energy physics; and transportation. This interest in translational applications of AI technologies has certainly increased since the release of the 2016 *National AI R&D Strategic Plan*. Other common themes echoed in the RFI responses were the importance of developing trustworthy AI systems, including fairness, ethics, accountability, and transparency of AI systems; curated and accessible datasets; workforce considerations; and public-private partnerships for furthering AI R&D.

[2] https://www.nitrd.gov/news/RFI-National-AI-Strategic-Plan.aspx

[3] https://www.nitrd.gov/nitrdgroups/index.php?title=AI-RFI-Responses-2018

workforce needs. That work was prescient: today, countries around the world have followed suit and have issued their own versions of this plan.

In the three years since the *National AI R&D Strategic Plan* was produced, new research, technical innovations, and real-world deployments have progressed rapidly. The Administration initiated this 2019 update to the *National AI R&D Strategic Plan* to address these advancements, including a rapidly evolving international AI landscape.

Notably, this 2019 Update to the *National AI R&D Strategic Plan* is, by design, solely concerned with addressing the *research and development* priorities associated with advancing AI technologies. It does not describe or recommend policy or regulatory actions related to the governance or deployment of AI, although AI R&D will certainly inform the development of reasonable policy and regulatory frameworks.

AI as an Administration Priority

Since 2017, the Administration has addressed the importance of AI R&D by emphasizing its role for America's future across multiple major policy documents, including the *National Security Strategy*,[4] the *National Defense Strategy*,[5] and the FY 2020 R&D Budget Priorities Memo.[6]

In May 2018, the Office of Science and Technology Policy (OSTP) hosted the White House Summit on Artificial Intelligence for American Industry to begin discussing the promise of AI and the policies needed to realize that promise for the American people and maintain U.S. leadership in the age of AI. The Summit convened over 100 senior government officials, technical experts from top academic institutions, heads of industrial research laboratories, and American business leaders.

In his State of the Union address on February 5, 2019, President Trump stressed the importance of ensuring American leadership in the development of emerging technologies, including AI, that make up the Industries of the Future.

On February 11, 2019, the President signed Executive Order 13859, *Maintaining American Leadership in Artificial Intelligence*.[7] This order launched the American AI Initiative, a concerted effort to promote and protect AI technology and innovation in the United States. The Initiative implements a whole-of-government strategy in collaboration and engagement with the private sector, academia, the public, and like-minded international partners. Among other actions, key directives in the Initiative call for Federal agencies to prioritize AI R&D investments, enhance access to high-quality cyberinfrastructure and data, ensure that the Nation leads in the development of technical standards for AI, and provide education and training opportunities to prepare the American workforce for the new era of AI.

Development of the 2019 Update to the *National AI R&D Strategic Plan*

The 2016 *National AI R&D Strategic Plan* recommended that the many Federal agencies tasked with advancing or adopting AI collaborate to identify critical R&D opportunities and support effective coordination of Federal AI R&D activities, both intramural and extramural research. Reflecting the Administration's prioritization of AI, the National Science and Technology Council (NSTC) has established a new framework to implement this recommendation, consisting of three unique NSTC subgroups made up of members from across the Federal R&D agencies to cover (1) senior leadership

4 https://www.whitehouse.gov/wp-content/uploads/2017/12/NSS-Final-12-18-2017-0905.pdf

5 https://dod.defense.gov/Portals/1/Documents/pubs/2018-National-Defense-Strategy-Summary.pdf

6 https://www.whitehouse.gov/wp-content/uploads/2018/07/M-18-22.pdf

7 https://www.whitehouse.gov/presidential-actions/executive-order-maintaining-american-leadership-artificial-intelligence/

and strategic vision, (2) operational planning and tactical implementation, and (3) research and technical expertise. These subgroups are:

- The Select Committee on AI,[8] consisting of the heads of departments and agencies principally responsible for the government's AI R&D, advises the Administration on interagency AI R&D priorities; considers the creation of Federal partnerships with industry and academia; establishes structures to improve government planning and coordination of AI R&D; identifies opportunities to leverage Federal data and computational resources to support our national AI R&D ecosystem; and supports the growth of a technical, national AI workforce.
- The NSTC Subcommittee on Machine Learning and Artificial Intelligence (MLAI), consisting of agency AI leaders and administrators, serves as the operational and implementation arm of the Select Committee, responsible for fulfilling tasking from the Select Committee; creating and maintaining the *National AI R&D Strategic Plan*; identifying and addressing important policy issues related to AI research, testing, standards, education, implementation, outreach, and related areas; and related activities.
- The AI R&D Interagency Working Group, operating under the NSTC's Networking and Information Technology R&D (NITRD) Subcommittee and consisting of research program managers and technical experts from across the Federal Government, reports to the MLAI Subcommittee; helps coordinate interagency AI R&D programmatic efforts; serves as the interagency AI R&D community of practice; and reports government-wide AI R&D spending through the NITRD Subcommittee's annual Supplement to the President's Budget.

In September 2018, the Select Committee initiated an update to the 2016 Strategic Plan, beginning with an RFI seeking broad community input on whether and how the seven strategies of the 2016 *National AI R&D Strategic Plan* merited revision or replacement (see sidebar). Independently, Federal departments and agencies performing or funding AI R&D undertook their own assessments.

An Overview of the 2019 Update to the 2016 *National AI R&D Strategic Plan*

Together, the Select Committee on AI, the NSTC Subcommittee on Machine Learning and AI, and the AI R&D Interagency Working Group of NITRD reviewed the input regarding the *National AI R&D Strategic Plan.* Each of the original seven focus areas or strategies of the 2016 Plan was reaffirmed by multiple respondents from the public and government, with no calls to remove any one strategy. These strategies, updated in this 2019 Update to the Strategic Plan to reflect the current state of the art, are:

Strategy 1: Make long-term investments in AI research;

Strategy 2: Develop effective methods for human-AI collaboration;

Strategy 3: Understand and address the ethical, legal, and societal implications of AI;

Strategy 4: Ensure the safety and security of AI systems;

Strategy 5: Develop shared public datasets and environments for AI training and testing;

Strategy 6: Measure and evaluate AI technologies through standards and benchmarks; and

Strategy 7: Better understand the national AI R&D workforce needs.

8 https://www.whitehouse.gov/wp-content/uploads/2018/05/Summary-Report-of-White-House-AI-Summit.pdf

Many responses to the RFI called for greater Federal Government R&D engagement with the private sector, given the fast rise of privately funded AI R&D, and the rapid adoption of AI by industry. As a result, the 2019 Update incorporates a new, eighth strategy:

Strategy 8: Expand public-private partnerships to accelerate advances in AI.

Feedback from the public and Federal agencies identified a number of specific challenges to further AI development and adoption. These challenges, many of which cut across multiple agencies, provide enhanced insight into ways that this *National AI R&D Strategic Plan* can guide the course of AI R&D in America, and many closely relate to the themes addressed in the 2019 *Executive Order on Maintaining American Leadership in Artificial Intelligence.* Examples include the following:

- *Research at the frontiers.* Even though machine learning has brought phenomenal new capabilities in the past several years, continued research is needed to further push the frontiers of ML, as well as to develop additional approaches to the tough technical challenges of AI (Strategy 1).
- *Positive impact.* As AI capabilities grow, the United States must place increased emphasis on developing new methods to ensure that AI's impacts are robustly positive into the future (Strategies 1, 3, and 4).
- *Trust and explainability.* Truly trustworthy AI requires explainable AI, especially as AI systems grow in scale and complexity; this requires a comprehensive understanding of the AI system by the human user and the human designer (Strategies 1, 2, 3, 4, and 6).
- *Safety and security*. Researchers must devise methods to keep AI systems and the data they use secure so that the Nation can leverage the opportunities afforded by this technology while also maintaining confidentiality and safety (Strategies 4, 5, and 6).
- *Technical standards.* As the Nation develops techniques to expand both AI abilities and assurance, it must test and benchmark them; when the techniques are ready, they should be turned into technical standards for the world (Strategy 6).
- *Workforce capability.* Accomplishing these goals will require growing a skilled AI R&D workforce that is currently limited and in high demand; the United States must be creative and bold in training and acquiring the skilled workforce it needs to lead the world in AI research and applications (Strategy 7).
- *Partnerships.* Advances in AI R&D increasingly require effective partnerships between the Federal Government and academia, industry, and other non-Federal entities to generate technological breakthroughs in AI and to rapidly transition those breakthroughs into capabilities (Strategy 8).
- *Cooperation with allies.* Additionally, the Plan recognizes the importance of international cooperation for successful implementation of these goals, while protecting the American AI R&D enterprise from strategic competitors and adversarial nations.

Structure of this 2019 Update to the 2016 *National AI R&D Strategic Plan*

This updated *National AI R&D Strategic Plan* incorporates the original text from the 2016 version, including the following section on R&D Strategy (except for minor edits) and the original 2016 wording of the first seven strategies. For each strategy, *2019 updates to the 2016 National R&D Strategic Plan are provided in shaded boxes at the top of the original seven strategies; these highlight updated imperatives and/or new focus areas for the strategies.* Text below the shaded boxes is *as it originally appeared* in the 2016 *National AI R&D Strategic Plan*, providing observations and context that remain important today (note that some of the original details may have become out of date in the intervening period). In addition, as noted previously, a new eighth strategy is added in this 2019 Update, on expanding public-private partnerships in AI R&D.

AI R&D Strategy

The research priorities outlined in this AI R&D Strategic Plan focus on areas that industry is unlikely to address on their own, and thus, areas that are most likely to benefit from Federal investment. These priorities cut across all of AI to include needs common to the AI sub-fields of perception, automated reasoning/planning, cognitive systems, machine learning, natural language processing, robotics, and related fields. Because of the breadth of AI, these priorities span the entire field, rather than only focusing on individual research challenges specific to each sub-domain. To implement the plan, detailed roadmaps should be developed that address the capability gaps consistent with the plan.

One of the most important Federal research priorities, outlined in Strategy 1, is for sustained long-term research in AI to drive discovery and insight. Many of the investments by the U.S. Federal Government in high-risk, high-reward[9] fundamental research have led to revolutionary technological advances we depend on today, including the Internet, GPS, smartphone speech recognition, heart monitors, solar panels, advanced batteries, cancer therapies, and much, much more. The promise of AI touches nearly every aspect of society and has the potential for significant positive societal and economic benefits. Thus, to maintain a world leadership position in this area, the United States must focus its investments on high-priority fundamental and long-term AI research.

Many AI technologies will work with and alongside humans, thus leading to important challenges in how to best create AI systems that work with people in intuitive and helpful ways.[10] The walls between humans and AI systems are slowly beginning to erode, with AI systems augmenting and enhancing human capabilities. Fundamental research is needed to develop effective methods for human-AI interaction and collaboration, as outlined in Strategy 2.

AI advancements are providing many positive benefits to society and are increasing U.S. national competitiveness.[11] However, as with most transformative technologies, AI presents some societal risks in several areas, from jobs and the economy to safety, ethical, and legal questions. Thus, as AI science and technology develop, the Federal Government must also invest in research to better understand what the implications are for AI for all these realms, and to address these implications by developing AI systems that align with ethical, legal, and societal goals, as outlined in Strategy 3.

A critical gap in current AI technology is a lack of methodologies to ensure the safety and predictable performance of AI systems. Ensuring the safety of AI systems is a challenge because of the unusual complexity and evolving nature of these systems. Several research priorities address this safety challenge. First, Strategy 4 emphasizes the need for explainable and transparent systems that are trusted by their users, perform in a manner that is acceptable to the users, and can be guaranteed to act as the user intended. The potential capabilities and complexity of AI systems, combined with the wealth of possible interactions with human users and the environment, makes it critically important to invest in research that increases the security and control of AI technologies. Strategy 5 calls on the Federal Government to invest in shared public datasets for AI training and testing to advance the progress of AI research and to enable a more effective comparison of alternative solutions.

Strategy 6 discusses how standards and benchmarks can focus R&D to define progress, close gaps, and drive innovative solutions for specific problems and challenges. Standards and benchmarks are

[9] "High-risk, high-reward" research refers to visionary research that is intellectually challenging but has the potential to make deeply positive, transformative impacts on the field of study.

[10] See *2016 Report of the One Hundred Year Study on Artificial Intelligence*, which focuses on the anticipated uses and impacts of AI in the year 2030; https://ai100.stanford.edu/2016-report.

[11] J. Furman, "Is This Time Different? The Opportunities and Challenges of Artificial Intelligence," Council of Economic Advisors remarks, New York University: AI Now Symposium, July 7, 2016.

essential for measuring and evaluating AI systems and ensuring that AI technologies meet critical objectives for functionality and interoperability.

Finally, the growing prevalence of AI technologies across all sectors of society creates new pressures for AI R&D experts. Opportunities abound for core AI scientists and engineers with a deep understanding of the technology who can generate new ideas for advancing the boundaries of knowledge in the field. The Nation should take action to ensure a sufficient pipeline of AI-capable talent. Strategy 7 addresses this challenge.

Figure 1 (*updated in this 2019 version of the Plan*) provides a graphical illustration of the overall organization of this AI R&D Strategic Plan. Across the bottom row of boxes are the crosscutting, underlying foundations that affect the development of all AI systems; these foundations are described in Strategies 3-7 and the new Strategy 8. The next layer higher (middle row of boxes) includes many areas of research that are needed to advance AI. These R&D areas (including use-inspired basic research) are outlined in Strategies 1-2.[12] Across the top row of boxes in the graphic are examples of applications that are expected to benefit from advances in AI. Together, these components of the AI R&D Strategic Plan define a high-level framework for Federal investments that can lead to impactful advances in the field and positive societal benefits.

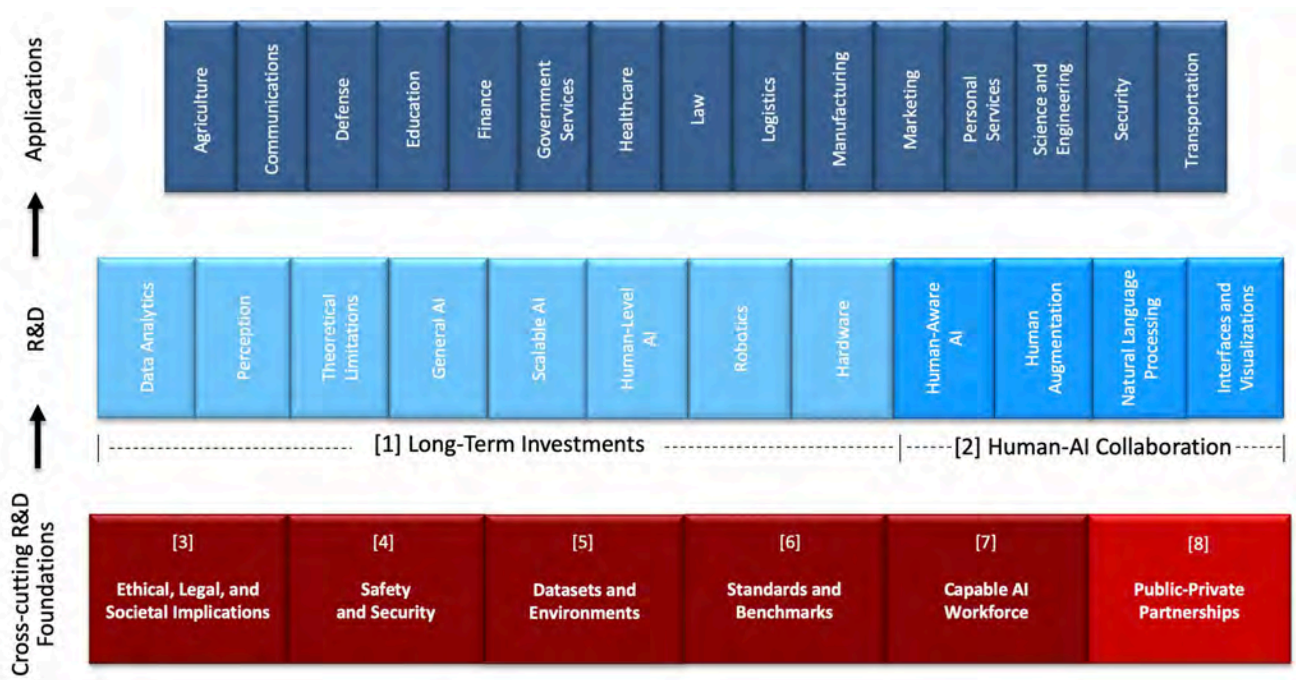

Figure 1. Organization of the AI R&D Strategic Plan (2019 update, to include Strategy 8). A combination of crosscutting R&D foundations (*in the lower row*) are important for all AI research. Many AI R&D areas (*in the middle row*) can build upon these crosscutting foundations to impact a wide array of societal applications (*in the top row*). The numbers in brackets indicate the number of the Strategy in this plan that further develops each topic. The ordering of these strategies does not indicate a priority of importance.

[12] Throughout this document, "basic research" includes both pure basic research and use-inspired basic research—the so-called Pasteur's Quadrant defined by Donald Stokes in his 1997 book of the same name—referring to basic research that has use for society in mind. For example, the fundamental NIH investments in IT are often called use-inspired basic research.

Strategy 1: Make Long-Term Investments in AI Research

2019 Update	**Sustaining long-term investments in fundamental AI research**

Since the release of the 2016 *National AI R&D Strategic Plan*, powerful new capabilities, primarily ML applications to well-defined tasks, have continued to emerge. These capabilities have demonstrated impacts in a diverse array of applications, such as classifying genetic sequences,[20,21] managing limited wireless spectrum resources,[22] interpreting medical images,[23] and grading cancers.[24] These rapid advances required decades of research for the technologies and applications to mature.[25] To maintain this progress in ML to achieve advancements in other areas of AI, and to strive toward the long-term goal of general-purpose AI, the Federal Government must continue to foster long-term, fundamental research in ML and AI. This research will give rise to transformational technologies and, in turn, breakthroughs across all sectors of society.

Much of the current progress in the field has been in specialized, well-defined tasks often driven by statistical ML, such as *classification*, *recognition*, and *regression* (i.e., "narrow AI systems"). Surveys of the

Long-term, fundamental AI research: Recent agency R&D programs

Since the release of the 2016 *National AI R&D Strategic Plan*, a number of agencies have initiated AI R&D programs for Strategy 1:

- NSF has continued to fund foundational research in AI, spanning ML, reasoning and representation, computer vision, computational neuroscience, speech and language, robotics, and multi-agent systems. NSF has launched new joint funding opportunities with other agencies—notably with DARPA in the area of high-performance, energy-efficient hardware for real-time ML[13] and with USDA-NIFA on AI for agricultural science[14]—and with industry.[15,16] In addition, NSF's Harnessing the Data Revolution Big Idea[17] supports research on the foundations of data science, which will serve as a driver of future ML and AI systems.
- DARPA announced in September 2018 a multiyear investment in new and existing programs called the "AI Next" campaign.[18] Key campaign areas include improving the robustness and reliability of AI systems; enhancing the security and resiliency of ML/AI technologies; reducing power, data, and performance inefficiencies; and pioneering the next generation of AI algorithms and applications, such as explainability and commonsense reasoning.
- The *NIH Strategic Plan for Data Science*[19] of September 2018 aims to advance access to data science technology and ML/AI capability for the biomedical research community toward data-driven healthcare research.

13 https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=505640&org=NSF
14 https://www.nsf.gov/pubs/2019/nsf19051/nsf19051.jsp
15 https://www.nsf.gov/pubs/2019/nsf19018/nsf19018.jsp
16 https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=505651
17 https://www.nsf.gov/cise/harnessingdata/
18 https://www.darpa.mil/work-with-us/ai-next-campaign
19 https://datascience.nih.gov/strategicplan
20 https://ai.googleblog.com/2017/12/deepvariant-highly-accurate-genomes.html
21 https://irp.nih.gov/catalyst/v26i4/machine-learning
22 https://www.spectrumcollaborationchallenge.com/
23 https://news-medical.net/news/20190417/Workshop-explores-the-future-of-artificial-intelligence-in-medical-imaging.aspx
24 https://www.nature.com/articles/nature21056
25 https://www.nitrd.gov/rfi/ai/2018/AI-RFI-Response-2018-Yolanda-Gil-AAAI.pdf

field have noted that long-term investments in fundamental research are needed to continue building on these advances in ML. Further, parallel sustained efforts are required to fully realize the vision of "general-purpose AI"—systems that exhibit the flexibility and versatility of human intelligence in a broad range of cognitive domains.[26,27,28,29]

Emphasis is needed on the development of further ML capabilities to interactively and persistently learn, the connection between perception and attention, and the incorporation of learned models into comprehensive reasoning architectures.[30] Beyond ML, critical research is also needed in other core areas of AI, including in commonsense reasoning and problem solving, probabilistic reasoning, combinatorial optimization, knowledge representation, planning and scheduling, natural language processing, decision making, and human-machine interaction. Advances in these areas will in turn enable collaborative robotics and shared and fully autonomous systems (see Strategy 2). The grand challenge of understanding human intelligence requires significant investments in shared resources and infrastructure.[25] Broad consensus exists for foundational investments in drivers of ML and AI as well, including data provenance and quality, novel software and hardware paradigms and platforms, and the security of AI systems.[31,32] For example, as AI software performs increasingly complex functions in all aspects of daily life and all sectors of the economy, existing software development paradigms will need to evolve to meet software productivity, quality, and sustainability requirements.

Recent Federal investments have prioritized these areas of fundamental ML and AI research (see sidebar) as well as the use of ML and AI across numerous application sectors, including defense, security, energy, transportation, health, agriculture, and telecommunications. Ultimately, AI technologies are critical for addressing a range of long-term challenges, such as constructing advanced healthcare systems, a robust intelligent transportation system, and resilient energy and telecommunication networks.

For AI applications to become widespread, they must be explainable and understandable (see Strategy 3). These challenges are particularly salient for fostering collaborative human-AI relationships (see Strategy 2). Today, the ability to understand and analyze the decisions of AI systems and measure their accuracy, reliability, and reproducibility is limited. Sustained R&D investments are needed to advance trust in AI systems to ensure they meet society's needs and adequately address requirements for robustness, fairness, explainability, and security.

A long-term commitment to AI R&D is essential to continue and expand current technical advances and more broadly ensure that AI enriches the human experience. Indeed, the 2019 ***Executive Order on Maintaining American Leadership in Artificial Intelligence*** notes:

> Heads of implementing agencies that also perform or fund R&D (AI R&D agencies), shall consider AI as an agency R&D priority, as appropriate to their respective agencies' missions… Heads of such agencies shall take this priority into account when developing budget proposals and planning for the use of funds in Fiscal Year 2020 and in future years. Heads of these agencies shall also consider appropriate administrative actions to increase focus on AI for 2019.

[26] https://ai100.stanford.edu/sites/g/files/sbiybj9861/f/ai100report10032016fnl_singles.pdf
[27] http://cdn.aiindex.org/2018/AI%20Index%202018%20Annual%20Report.pdf
[28] https://cra.org/ccc/visioning/visioning-activities/2018-activities/artificial-intelligence-roadmap/
[29] https://www.microsoft.com/en-us/research/research-area/artificial-intelligence/
[30] https://cra.org/ccc/events/artificial-intelligence-roadmap-workshop-3-learning-and-robotics/
[31] https://cra.org/ccc/wp-content/uploads/sites/2/2016/04/AI-for-Social-Good-Workshop-Report.pdf
[32] https://openai.com/blog/ai-and-compute/

AI research investments are needed in areas with potential long-term payoffs. While an important component of long-term research is incremental research with predictable outcomes, long-term sustained investments in high-risk research can lead to high-reward payoffs. These payoffs can be seen in 5 years, 10 years, or more. A 2012 National Research Council report emphasizes the critical role of Federal investments in long-term research, noting "the long, unpredictable incubation period—requiring steady work and funding—between initial exploration and commercial deployment."[33] It further notes that "the time from first concept to successful market is often measured in decades." Well-documented examples of sustained fundamental research efforts that led to high-reward payoffs include the World Wide Web and deep learning. In both cases, the basic foundations began in the 1960s; it was only after 30+ years of continued research efforts that these ideas materialized into the transformative technologies witnessed today in many categories of AI.

The following subsections highlight some of these areas. Additional categories of important AI research are discussed in Strategies 2 through 6.

Advancing data-focused methodologies for knowledge discovery

As discussed in the 2016 *Federal Big Data Research and Development Strategic Plan*,[34] many fundamental new tools and technologies are needed to achieve intelligent data understanding and knowledge discovery. Further progress is needed in the development of more advanced machine learning algorithms that can identify all the useful information hidden in big data. Many open research questions revolve around the creation and use of data, including its veracity and appropriateness for AI system training. The veracity of data is particularly challenging when dealing with vast amounts of data, making it difficult for humans to assess and extract knowledge from it. While much research has dealt with veracity through data quality assurance methods to perform data cleaning and knowledge discovery, further study is needed to improve the efficiency of data cleaning techniques, to create methods for discovering inconsistencies and anomalies in the data, and to develop approaches for incorporating human feedback. Researchers need to explore new methods to enable data and associated metadata to be mined simultaneously.

Many AI applications are interdisciplinary in nature and make use of heterogeneous data. Further investigation of multimodality machine learning is needed to enable knowledge discovery from a wide variety of different types of data (e.g., discrete, continuous, text, spatial, temporal, spatio-temporal, graphs). AI investigators must determine the amount of data needed for training and to properly address large-scale versus long-tail data needs. They must also determine how to identify and process rare events beyond purely statistical approaches; to work with knowledge sources (i.e., any type of information that explains the world, such as knowledge of the law of gravity or of social norms) as well as data sources, integrating models and ontologies in the learning process; and to obtain effective learning performance with little data when big data sources may not be available.

Enhancing the perceptual capabilities of AI systems

Perception is an intelligent system's window into the world. Perception begins with (possibly distributed) sensor data, which comes in diverse modalities and forms, such as the status of the system itself or information about the environment. Sensor data are processed and fused, often along with *a priori* knowledge and models, to extract information relevant to the AI system's task such as

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[33] National Research Council Computer Science Telecommunications Board, *Continuing Innovation in Information Technology* (The National Academies Press, Washington, D.C., 2012), 11; https://doi.org/10.17226/13427.

[34] https://www.nitrd.gov/PUBS/bigdatardstrategicplan.pdf

geometric features, attributes, location, and velocity. Integrated data from perception forms situational awareness to provide AI systems with the comprehensive knowledge and a model of the state of the world necessary to plan and execute tasks effectively and safely. AI systems would greatly benefit from advancements in hardware and algorithms to enable more robust and reliable perception. Sensors must be able to capture data at longer distances, with higher resolution, and in real time. Perception systems need to be able to integrate data from a variety of sensors and other sources, including the computational cloud, to determine what the AI system is currently perceiving and to allow the prediction of future states. Detection, classification, identification, and recognition of objects remain challenging, especially under cluttered and dynamic conditions. In addition, perception of humans must be greatly improved by using an appropriate combination of sensors and algorithms, so that AI systems can work more effectively with people.[10] A framework for calculating and propagating uncertainty throughout the perception process is needed to quantify the confidence level that the AI system has in its situational awareness and to improve accuracy.

Understanding theoretical capabilities and limitations of AI

While the ultimate goal for many AI algorithms is to address open challenges with human-like solutions, we do not have a good understanding of what the theoretical capabilities and limitations are for AI and the extent to which such human-like solutions are even possible with AI algorithms. Theoretical work is needed to better understand why AI techniques—especially machine learning—often work well in practice. While different disciplines (including mathematics, control sciences, and computer science) are studying this issue, the field currently lacks unified theoretical models or frameworks to understand AI system performance. Additional research is needed on computational solvability, which is an understanding of the classes of problems that AI algorithms are theoretically capable of solving, and likewise, those that they are not capable of solving. This understanding must be developed in the context of existing hardware, in order to see how the hardware affects the performance of these algorithms. Understanding which problems are theoretically unsolvable can lead researchers to develop approximate solutions to these problems, or even open up new lines of research on new hardware for AI systems. For example, when invented in the 1960s, Artificial Neural Networks (ANNs) could only be used to solve very simple problems. It only became feasible to use ANNs to solve complex problems after hardware improvements such as parallelization were made, and algorithms were adjusted to make use of the new hardware. Such developments were key factors in enabling today's significant advances in deep learning.

Pursuing research on general-purpose artificial intelligence

AI approaches can be divided into "narrow AI" and "general AI." Narrow AI systems perform individual tasks in specialized, well-defined domains, such as speech recognition, image recognition, and translation. Several recent, highly-visible, narrow AI systems, including IBM Watson and DeepMind's AlphaGo, have achieved major feats.[35,36] Indeed, these particular systems have been labeled "superhuman" because they have outperformed the best human players in Jeopardy! and Go, respectively. But these systems exemplify narrow AI, since they can only be applied to the tasks for which they are specifically designed. Using these systems on a wider range of problems requires a significant re-engineering effort. In contrast, the long-term goal of general AI is to create systems that

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[35] In 2011, IBM Watson defeated two players considered among the best human players in the Jeopardy! game.

[36] In 2016, AlphaGo defeated the reigning world champion of Go, Lee Se-dol. Notably, AlphaGo combines deep learning and Monte Carlo search—a method developed in the 1980s—which itself builds on a probabilistic method discovered in the 1940s.

exhibit the flexibility and versatility of human intelligence in a broad range of cognitive domains, including learning, language, perception, reasoning, creativity, and planning. Broad learning capabilities would provide general AI systems the ability to transfer knowledge from one domain to another and to interactively learn from experience and from humans. General AI has been an ambition of researchers since the advent of AI, but current systems are still far from achieving this goal. The relationship between narrow and general AI is currently being explored; it is possible that lessons from one can be applied to improve the other and vice versa. While there is no general consensus, most AI researchers believe that general AI is still decades away, requiring a long-term, sustained research effort to achieve it.

Developing scalable AI systems

Groups and networks of AI systems may be coordinated or autonomously collaborate to perform tasks not possible with a single AI system, and may also include humans working alongside or leading the team. The development and use of such multi-AI systems creates significant research challenges in planning, coordination, control, and scalability of such systems. Planning techniques for multi-AI systems must be fast enough to operate and adapt in real time to changes in the environment. They should adapt in a fluid manner to changes in available communications bandwidth or system degradation and faults. Many prior efforts have focused on centralized planning and coordination techniques; however, these approaches are subject to single points of failure, such as the loss of the planner, or loss of the communications link to the planner. Distributed planning and control techniques are harder to achieve algorithmically, and are often less efficient and incomplete, but potentially offer greater robustness to single points of failure. Future research must discover more efficient, robust, and scalable techniques for planning, control, and collaboration of teams of multiple AI systems and humans.

Fostering research on human-like AI

Attaining human-like AI requires systems to explain themselves in ways that people can understand. This will result in a new generation of intelligent systems, such as intelligent tutoring systems and intelligent assistants that are effective in assisting people when performing their tasks. There is a significant gap, however, between the way current AI algorithms work and how people learn and perform tasks. People are capable of learning from just a few examples, or by receiving formal instruction and/or “hints” to performing tasks, or by observing other people performing those tasks. Medical schools take this approach, for example, when medical students learn by observing an established doctor performing a complex medical procedure. Even in high-performance tasks such as world-championship Go games, a master-level player would have played only a few thousand games to train him/herself. In contrast, it would take hundreds of years for a human to play the number of games needed to train AlphaGo. More foundational research on new approaches for achieving human-like AI would bring these systems closer to this goal.

Developing more capable and reliable robots

Significant advances in robotic technologies over the last decade are leading to potential impacts in a multiplicity of applications, including manufacturing, logistics, medicine, healthcare, defense and national security, agriculture, and consumer products. While robots were historically envisioned for static industrial environments, recent advances involve close collaborations between robots and humans. Robotics technologies are now showing promise in their ability to complement, augment, enhance, or emulate human physical capabilities or human intelligence. However, scientists need to make these robotic systems more capable, reliable, and easy-to-use.

Researchers need to better understand robotic perception to extract information from a variety of sensors to provide robots with real-time situational awareness. Progress is needed in cognition and reasoning to allow robots to better understand and interact with the physical world. An improved ability to adapt and learn will allow robots to generalize their skills, perform self-assessment of their current performance, and learn a repertoire of physical movements from human teachers. Mobility and manipulation are areas for further investigation so that robots can move across rugged and uncertain terrain and handle a variety of objects dexterously. Robots need to learn to team together in a seamless fashion and collaborate with humans in a way that is trustworthy and predictable.

Advancing hardware for improved AI

While AI research is most commonly associated with advances in software, the performance of AI systems has been heavily dependent on the hardware upon which it runs. The current renaissance in deep machine learning is directly tied to progress in GPU-based hardware technology and its improved memory,[37] input/output, clock speeds, parallelism, and energy efficiency. Developing hardware optimized for AI algorithms will enable even higher levels of performance than GPUs. One example is "neuromorphic" processors that are loosely inspired by the organization of the brain and, in some cases, optimized for the operation of neural networks.[38]

Hardware advances can also improve the performance of AI methods that are highly data-intensive. Further study of methods to turn on and off data pipelines in controlled ways throughout a distributed system is called for. Continued research is also needed to allow machine learning algorithms to efficiently learn from high-velocity data, including distributed machine learning algorithms that simultaneously learn from multiple data pipelines. More advanced machine learning-based feedback methods will allow AI systems to intelligently sample or prioritize data from large-scale simulations, experimental instruments, and distributed sensor systems, such as Smart Buildings and the Internet of Things (IoT). Such methods may require dynamic I/O decision-making, in which choices are made in real time to store data based on importance or significance, rather than simply storing data at fixed frequencies.

Creating AI for improved hardware

While improved hardware can lead to more capable AI systems, AI systems can also improve the performance of hardware.[39] This reciprocity will lead to further advances in hardware performance, since physical limits on computing require novel approaches to hardware designs.[40] AI-based methods could be especially important for improving the operation of high-performance computing (HPC) systems. Such systems consume vast quantities of energy. AI is being used to predict HPC performance and resource usage, and to make online optimization decisions that increase efficiency; more advanced AI techniques could further enhance system performance. AI can also be used to create

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[37] GPU stands for graphics processing unit, which is a power- and cost-efficient processor incorporating hundreds of processing cores; this design makes it especially well suited for inherently parallel applications, including most AI systems.

[38] Neuromorphic computing refers to the ability of hardware to learn, adapt, and physically reconfigure, taking inspiration from biology or neuroscience.

[39] M. Milano and L. Benini, "Predictive Modeling for Job Power Consumption in HPC Systems," In *Proceedings of High Performance Computing: 31st International Conference, ISC High Performance 2016* (Springer Vol. 9697, 2016).

[40] These physical limits on computing are called *Dennard scaling*, and lead to high on-chip power densities and the phenomenon called "dark silicon", where different parts of a chip need to be turned off in order to limit temperatures and ensure data integrity.

self-reconfigurable HPC systems that can handle system faults when they occur, without human intervention.[41]

Improved AI algorithms can increase the performance of multi-core systems by reducing data movements between processors and memory—the primary impediment to exascale computing systems that operate 10 times faster than today's supercomputers.[42] In practice, the configuration of executions in HPC systems are never the same, and different applications are executed concurrently, with the state of each different software code evolving independently in time. AI algorithms need to be designed to operate online and at scale for HPC systems.

[41] A. Cocaña-Fernández, J. Ranilla, and L. Sánchez, "Energy-efficient allocation of computing node slots in HPC clusters through parameter learning and hybrid genetic fuzzy system modeling," *Journal of Supercomputing* 71 (2015):1163-1174.

[42] Exascale computing systems can achieve at least a billion billion calculations per second.

Strategy 2: Develop Effective Methods for Human-AI Collaboration

2019 Update	**Developing AI systems that complement and augment human capabilities, with increasing focus on the future of work**

Since the release of the 2016 *National AI R&D Strategic Plan*, national interest has grown in human-AI collaboration. When AI systems complement and augment human capabilities, humans and AI become partners across a range of shared to fully autonomous scenarios. In particular, human-AI collaboration has been elevated as both a challenge and an opportunity in the context of the future of work.

In the past three years, newly established as well as longstanding conferences, workshops, and task forces have prioritized human-AI collaboration broadly. For example, the Conference on Human Computation and Crowdsourcing has grown from a workshop to a major international conference that fosters research in the intersection of AI and human-computer interaction (HCI).[45] In 2018, the Association for the Advancement of Artificial Intelligence selected human-AI collaboration as the emerging topic for its annual conference.[46] In May 2019, the largest conference on human-computer interaction, CHI, included a workshop on "Bridging the Gap Between AI and HCI."[47] The journal *Human-Computer Interaction* put out a call in March 2019 for submissions for a special issue on "unifying human-computer interaction and artificial intelligence."[48]

Human-AI Collaboration: Recent agency R&D programs

Since the release of the 2016 *National AI R&D Strategic Plan*, several agencies have initiated efforts for Strategy 2:

- NSF's Future of Work at the Human-Technology Frontier[43] Big Idea is supporting socio-technical research enabling a future where intelligent technologies collaborate synergistically with humans to achieve broad participation in the workforce and improve the social, economic, and environmental benefits across a range of work settings.
- NOAA (National Oceanographic and Atmospheric Administration) is advancing human-AI collaboration for hurricane, tornado, and other severe weather predictions where the human forecaster and an AI system work together to improve severe weather warning generation and to identify distinct patterns that are precursors to extreme events. Sometimes referred to as "humans above the loop," human forecasters oversee the AI system's predictions and direct the outcomes.
- NIH has ongoing research in natural language processing based on a database of 96.3 million facts extracted from all MEDLINE citations maintained by the National Library of Medicine.
- A 2019 DOE workshop report on Scientific Machine Learning identified priority research directions, major scientific use cases, and the emerging trend that human-AI collaborations will transform the way science is done.[44]

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[43] https://www.nsf.gov/eng/futureofwork.jsp

[44] DOE workshop report, *Basic Research Needs for Scientific Machine Learning: Core Technologies for Artificial Intelligence*: https://www.osti.gov/biblio/1478744.

[45] Welcome to HCOMP 2019: https://www.humancomputation.com/.

[46] AAAI-18 Emerging Topic Human-AI Collaboration: http://www.aaai.org/Conferences/AAAI/2018/aaai18emergingcall.php.

[47] Where is the Human? Bridging the Gap Between AI and HCI: CHI 2019 Workshop: https://michae.lv/ai-hci-workshop/.

[48] Call: "Unifying Human Computer Interaction and Artificial Intelligence" issue of *Human-Computer Interaction*: https://ispr.info/2019/02/20/call-unifying-human-computer-interaction-and-artificial-intelligence-issue-of-human-computer-interaction/.

In the context of work, conferences have emerged exploring the role of the human, the machine, and their partnership, such as MIT's Computer Science and Artificial Intelligence Lab (CSAIL) and the Initiative on the Digital Economy that launched the Annual AI and the Future of Work Congress.[49,50] As part of *A 20-Year Community Roadmap for Artificial Intelligence Research in the U.S.*,[51] in 2019 the Computing Community Consortium (CCC) held a workshop focused on meaningful interaction between humans and AI systems.[52] Additionally, the CCC operated the Human Technology Frontier task force in 2017-2018 to focus on the potential of technology to augment human performance in, including but not limited to, the workplace, the classroom, and the healthcare system.[53]

The cross-strategy principle in the 2016 *National AI R&D Strategic Plan*, "appropriate trust of AI systems requires explainability, especially as the AI grows in scale and complexity," has seen an R&D call to action in the context of human-AI collaborations. This principle has been identified by a number of professional societies and agencies as a priority area (see sidebar). This research area reflects the intersection of Strategies 2 and 3, as explainability, fairness, and transparency are key principles for AI systems to effectively collaborate with humans. Likewise, the challenge of understanding and designing human-AI ethics and value alignment into systems remains an open research area. In parallel, the private sector has responded with principles for effective human-AI collaboration.[54,55]

As Federal agencies have increased AI investments in the past three years along mission objectives, they have shared a common emphasis on human-machine cognition, autonomy, and agency, such as in decision support, risk modeling, situational awareness, and trusted machine intelligence (see sidebar). Through such R&D investments, research partnerships are growing across a number of axes, bringing together computational scientists; behavioral, cognitive, and psychological scientists; and scientists and engineers from other domains. New collaborations have formed between academic researchers and users of AI systems inside and outside the workplace.

Moving forward, it is critical that Federal agencies continue to foster AI R&D in the open world to promote the design of AI systems that incorporate and accommodate the situations and goals of users so that AI systems and users can work collaboratively in both anticipated and unanticipated circumstances.

While completely autonomous AI systems will be important in some application domains (e.g., underwater or deep space exploration), many other application areas (e.g., disaster recovery and medical diagnostics) are most effectively addressed by a combination of humans and AI systems working together to achieve application goals. This collaborative interaction takes advantage of the complementary nature of humans and AI systems. While effective approaches for human-AI collaboration already exist, most of these are "point solutions" that only work in specific environments using specific platforms toward specific goals. Generating point solutions for every possible application instance does not scale; more work is thus needed to go beyond these point solutions toward more

[49] https://futureofwork.csail.mit.edu/.

[50] AI and Future of Work Innovation Summit 2019: https://analyticsevent.com/.

[51] https://cra.org/ccc/wp-content/uploads/sites/2/2019/03/AI_Roadmap_Exec_Summary-FINAL-.pdf

[52] Artificial Intelligence Roadmap Workshop 2 – Interaction: https://cra.org/ccc/events/artificial-intelligence-roadmap-workshop-2-interaction/.

[53] https://cra.org/ccc/human-technology-frontier/

[54] https://www.microsoft.com/en-us/research/uploads/prod/2019/01/Guidelines-for-Human-AI-Interaction-camera-ready.pdf

[55] https://www.partnershiponai.org/about/#our-work

general methods of human-AI collaboration. The tradeoffs must be explored between designing general systems that work in all types of problems, requiring less human effort to build and greater facility for switching between applications, versus building a large number of problem-specific systems that may work more effectively for each problem.

Future applications will vary considerably in the functional role divisions between humans and AI systems, the nature of the interactions between humans and AI systems, the number of humans and other AI systems working together, and how humans and AI systems will communicate and share situational awareness. Functional role divisions between humans and AI systems typically fall into one of the following categories:

1. *AI performs functions alongside the human*: AI systems perform peripheral tasks that support the human decision maker. For example, AI can assist humans with working memory, short or long-term memory retrieval, and prediction tasks.
2. *AI performs functions when the human encounters high cognitive overload*: AI systems perform complex monitoring functions (such as ground proximity warning systems in aircraft), decision making, and automated medical diagnoses when humans need assistance.
3. *AI performs functions in lieu of a human*: AI systems perform tasks for which humans have very limited capabilities, such as for complex mathematical operations, control guidance for dynamic systems in contested operational environments, aspects of control for automated systems in harmful or toxic environments, and in situations where a system should respond very rapidly (e.g., in nuclear reactor control rooms).

Achieving effective interactions between humans and AI systems requires additional R&D to ensure that the system design does not lead to excessive complexity, undertrust, or overtrust. The familiarity of humans with AI systems can be increased through training and experience, to ensure that the human has a good understanding of the AI system's capabilities and what the AI system can and cannot do. To address these concerns, certain human-centered automation principles should be used in the design and development of these systems:[56]

1. Employ intuitive, user-friendly design of human-AI system interfaces, controls, and displays.
2. Keep the operator informed. Display critical information, states of the AI system, and changes to these states.
3. Keep the operator trained. Engage in recurrent training for general knowledge, skills, and abilities (KSAs), as well as training in algorithms and logic employed by AI systems and the expected failure modes of the system.
4. Make automation flexible. Deploying AI systems should be considered as a design option for operators who wish to decide whether they want to use them or not. Also important is the design and deployment of adaptive AI systems that can be used to support human operators during periods of excessive workload or fatigue.[57,58]

Many fundamental challenges arise for researchers when creating systems that work effectively with humans. Several of these important challenges are outlined in the following subsections.

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[56] C. Wickens and J. G. Hollands, "Attention, time-sharing, and workload." In *Engineering, Psychology and Human Performance* (London: Pearson PLC, 1999), 439-479.

[57] https://www.nasa.gov/mission_pages/SOFIA/index.html

[58] https://cloud1.arc.nasa.gov/intex-na/

Seeking new algorithms for human-aware AI

Over the years, AI algorithms have become able to solve problems of increasing complexity. However, there is a gap between the capabilities of these algorithms and the usability of these systems by humans. *Human-aware* intelligent systems are needed that can interact intuitively with users and enable seamless machine-human collaborations. Intuitive interactions include shallow interactions, such as when a user discards an option recommended by the system; model-based approaches that take into account the users' past actions; or even deep models of user intent that are based upon accurate human cognitive models. Interruption models must be developed that allow an intelligent system to interrupt the human only when necessary and appropriate. Intelligent systems should also have the ability to augment human cognition, knowing which information to retrieve when the user needs it, even when they have not prompted the system explicitly for that information. Future intelligent systems must be able to account for human social norms and act accordingly. Intelligent systems can more effectively work with humans if they possess some degree of emotional intelligence, so that they can recognize their users' emotions and respond appropriately. An additional research goal is to go beyond interactions of one human and one machine, toward a "systems-of-systems", that is, teams composed of multiple machines interacting with multiple humans.

Human-AI system interactions have a wide range of objectives. AI systems need the ability to represent a multitude of goals, actions that they can take to reach those goals, constraints on those actions, and other factors, as well as easily adapt to modifications in the goals. In addition, humans and AI systems must share common goals and have a mutual understanding of them and relevant aspects of their current states. Further investigation is needed to generalize these facets of human-AI systems to develop systems that require less human engineering.

Developing AI techniques for human augmentation

While much of the prior focus of AI research has been on algorithms that match or outperform people performing narrow tasks, more work is needed to develop systems that augment human capabilities across many domains. Human augmentation research includes algorithms that work on a stationary device (such as a computer); wearable devices (such as smart glasses); implanted devices (such as brain interfaces); and in specific user environments (such as specially tailored operating rooms). For example, augmented human awareness could enable a medical assistant to point out a mistake in a medical procedure, based on data readings combined from multiple devices. Other systems could augment human cognition by helping the user recall past experiences applicable to the user's current situation.

Another type of collaboration between humans and AI systems involves active learning for intelligent data understanding. In active learning, input is sought from a domain expert and learning is only performed on data when the learning algorithm is uncertain. This is an important technique to reduce the amount of training data that needs to be generated in the first place, or the amount that needs to be learned. Active learning is also a key way to obtain domain expert input and increase trust in the learning algorithm. Active learning has so far only been used within supervised learning; further research is needed to incorporate active learning into unsupervised learning (e.g., clustering, anomaly detection) and reinforcement learning.[59] Probabilistic networks allow domain knowledge to be included in the form of prior probability distributions. General ways of allowing machine learning algorithms to incorporate domain knowledge must be sought, whether in the form of mathematical models, text, or others.

[59] While supervised learning requires humans to provide the ground-truth answers, reinforcement learning and unsupervised learning do not.

Developing techniques for visualization and human-AI interfaces

Better visualization and user interfaces are additional areas that need much greater development to help humans understand large-volume modern datasets and information coming from a variety of sources. Visualization and user interfaces must clearly present increasingly complex data and information derived from them in a human-understandable way. Providing real-time results is important in safety-critical operations and may be achieved with increasing computational power and connected systems. In these types of situations, users need visualization and user interfaces that can quickly convey the correct information for real-time response.

Human-AI collaboration can be applied in a wide variety of environments, and where there are constraints on communication. In some domains, human-AI communication latencies are low and communication is rapid and reliable. In other domains (e.g., NASA's deployment of the rovers Spirit and Opportunity to Mars), remote communication between humans and the AI system has a very high latency (e.g., round trip times of 5-20 minutes between Earth and Mars), thus requiring the deployed platform(s) to operate largely autonomously, with only high-level strategic goals communicated to the platform. These communications requirements and constraints are important considerations for the R&D of user interfaces.

Developing more effective language processing systems

Enabling people to interact with AI systems through spoken and written language has long been a goal of AI researchers. While significant advances have been made, considerable open research challenges must be addressed in language processing before humans can communicate as effectively with AI systems as they do with other humans. Much recent progress in language processing has been credited to the use of data-driven machine learning approaches, which have resulted in successful systems that, for example, successfully recognize fluent English speech in quiet surroundings in real time. These achievements, however, are only first steps toward reaching longer-term goals. Current systems cannot deal with real-world challenges such as speech in noisy surroundings, heavily accented speech, children's speech, impaired speech, and speech for sign languages. The development of language processing systems capable of engaging in real-time dialogue with humans is also needed. Such systems will need to infer the goals and intentions of its human interlocutors, use the appropriate register, style and rhetoric for the situation, and employ repair strategies in case of dialogue misunderstandings. Further research is needed on developing systems that more easily generalize across different languages. Additionally, more study is required on acquiring useful structured domain knowledge in a form readily accessible by language processing systems.

Language processing advances in many other areas are also needed to make interactions between humans and AI systems more natural and intuitive. Robust computational models must be built for patterns in both spoken and written language that provide evidence for emotional state, affect, and stance, and for determining the information that is implicit in speech and text. New language processing techniques are needed for grounding language in the environmental context for AI systems that operate in the physical world, such as in robotics. Finally, since the manner in which people communicate in online interactions can be quite different from voice interactions, models of languages used in these contexts must be perfected so that social AI systems can interact more effectively with people.

Strategy 3: Understand and Address the Ethical, Legal, and Societal Implications of AI

2019 Update	**Addressing ethical, legal, and societal considerations in AI**

Since the release of the 2016 *National AI R&D Strategic Plan*, R&D activities addressing the ethical, legal, and societal implications of AI system development and deployment have increased. There is a growing realization that AI systems must be "trustworthy," and that AI could transform many sectors of social and economic life, including employment, healthcare, and manufacturing. International organizations such as the Organisation for Economic Co-operation and Development (OECD)[63] and the G7 Innovation Ministers[64] have encouraged R&D to increase trust in and adoption of AI.

The 2016 *National AI R&D Strategic Plan* was prescient in identifying research themes in privacy; improving fairness, transparency, and accountability of AI systems by design; and designing architectures for ethical AI. Research conferences dedicated to fairness, accountability, and transparency in ML and AI systems have flourished.[65] Federal agencies have responded with a variety of new research programs and meetings focused on these critical areas (see sidebar).

Explainability, fairness, and transparency: Recent agency R&D programs

Since the release of the 2016 *National AI R&D Strategic Plan*, a number of agencies have initiated AI R&D programs for Strategy 3:

- DARPA's Explainable AI (XAI) program[60] aims to create a suite of ML techniques that produce more explainable AI systems while maintaining a high level of learning performance (prediction accuracy). XAI will also enable human users to understand, appropriately trust, and effectively manage the emerging generation of AI systems. More generally, DoD is committed to "leading in military ethics and AI safety" as one of five key actions outlined in the strategic approach that guides its efforts to accelerate the adoption of AI systems.[61]
- NSF and Amazon are collaborating[62] to jointly support research focused on AI fairness with the goal of contributing to trustworthy AI systems that are readily accepted and deployed to tackle grand challenges facing society. Specific topics of interest include, but are not limited to, transparency, explainability, accountability, potential adverse biases and effects, mitigation strategies, validation of fairness, and considerations of inclusivity.

[60] https://www.darpa.mil/program/explainable-artificial-intelligence
[61] "Summary of the 2018 Department of Defense Artificial Intelligence Strategy": https://media.defense.gov/2019/Feb/12/2002088963/-1/-1/1/SUMMARY-OF-DOD-AI-STRATEGY.PDF.
[62] https://www.nsf.gov/pubs/2019/nsf19571/nsf19571.htm
[63] "OECD Initiatives on AI": http://www.oecd.org/going-digital/ai/oecd-initiatives-on-ai.htm.
[64] "G7 Innovation Ministers' Statement on AI": http://www.g8.utoronto.ca/employment/2018-labour-annex-b-en.html.
[65] http://www.fatml.org/; https://fatconference.org/; http://www.aies-conference.com/

The 2019 *Executive Order on Maintaining American Leadership in Artificial Intelligence* emphasizes that maintaining American leadership in AI requires a concerted effort to promote advancements in technology and innovation, while protecting civil liberties, privacy, and American values:[1]

> The United States must foster public trust and confidence in AI technologies and protect civil liberties, privacy, and American values in their application in order to fully realize the potential of AI technologies for the American people.

More R&D is needed to develop AI architectures that incorporate ethical, legal, and societal concerns through technical mechanisms such as transparency and explainability. This R&D will require intensive collaboration among technical experts as well as stakeholders and specialists in other fields including the social and behavioral sciences, law, ethics, and philosophy. Since ethical decisions may also be heavily context- or application-dependent, collaboration with domain experts could be required as well. This interdisciplinary approach could be incorporated in the training, design, testing, evaluation, and implementation of AI in the interests of understanding and accounting for AI-induced decisions and actions and mitigating unintended consequences.

Federal agencies should therefore continue to foster the growing community of interest in further R&D of these issues by sponsoring research and convening experts and stakeholders.

When AI agents act autonomously, we expect them to behave according to the formal and informal norms to which we hold our fellow humans. As fundamental social ordering forces, law and ethics therefore both inform and adjudge the behavior of AI systems. The dominant research needs involve both understanding the ethical, legal, and social implications of AI, as well as developing methods for AI design that align with ethical, legal, and social principles. Privacy concerns must also be taken into account; further information on this issue can be found in the *National Privacy Research Strategy*.[66]

As with any technology, the acceptable uses of AI will be informed by the tenets of law and ethics; the challenge is how to apply those tenets to this new technology, particularly those involving autonomy, agency, and control.

As illuminated in "Research Priorities for Robust and Beneficial Artificial Intelligence,"[67]

> In order to build systems that robustly behave well, we of course need to decide what good behavior means in each application domain. This ethical dimension is tied intimately to questions of what engineering techniques are available, how reliable these techniques are, and what trade-offs are made—all areas where computer science, machine learning, and broader AI expertise is valuable.

Research in this area can benefit from multidisciplinary perspectives that involve experts from computer science, social and behavioral sciences, ethics, biomedical science, psychology, economics, law, and policy research. Further investigation is needed in areas both inside and outside of the NITRD-relevant IT domain (i.e., in information technology, as well as in the disciplines mentioned previously) to inform the R&D and use of AI systems and their impacts on society.

The following subsections explore key information technology research challenges in this area.

[66] https://www.nitrd.gov/pubs/NationalPrivacyResearchStrategy.pdf

[67] "An Open Letter: Research Priorities for Robust and Beneficial Artificial Intelligence" (Future of Life Institute): http://futureoflife.org/ai-open-letter/.

Improving fairness, transparency, and accountability by design

Many concerns have been voiced about the susceptibility of data-intensive AI algorithms to error and misuse, and the possible ramifications for gender, age, racial, or economic classes. The proper collection and use of data for AI systems, in this regard, represent an important challenge. Beyond purely data-related issues, however, larger questions arise about the design of AI to be inherently just, fair, transparent, and accountable. Researchers must learn how to design these systems so that their actions and decision-making are transparent and easily interpretable by humans, and thus can be examined for any bias they may contain, rather than just learning and repeating these biases. There are serious intellectual issues about how to represent and "encode" value and belief systems. Scientists must also study to what extent justice and fairness considerations can be designed into the system, and how to accomplish this within the bounds of current engineering techniques.

Building ethical AI

Beyond fundamental assumptions of justice and fairness are other concerns about whether AI systems can exhibit behavior that abides by general ethical principles. How might advances in AI frame new "machine-relevant" questions in ethics, or what uses of AI might be considered unethical? Ethics is inherently a philosophical question while AI technology depends on, and is limited by, engineering. Within the limits of what is technologically feasible, therefore, researchers must strive to develop algorithms and architectures that are verifiably consistent with, or conform to, existing laws, social norms and ethics—clearly a very challenging task. Ethical principles are typically stated with varying degrees of vagueness and are hard to translate into precise system and algorithm design. There are also complications when AI systems, particularly with new kinds of autonomous decision-making algorithms, face moral dilemmas based on independent and possibly conflicting value systems. Ethical issues vary according to culture, religion, and beliefs. However, acceptable ethics reference frameworks can be developed to guide AI system reasoning and decision-making in order to explain and justify its conclusions and actions. A multidisciplinary approach is needed to generate datasets for training that reflect an appropriate value system, including examples that indicate preferred behavior when presented with difficult moral issues or with conflicting values. These examples can include legal or ethical "corner cases," labeled by an outcome or judgment that is transparent to the user.[68] AI needs adequate methods for values-based conflict resolution, where the system incorporates principles that can address the realities of complex situations where strict rules are impracticable.

Designing architectures for ethical AI

Additional progress in fundamental research must be made to determine how to best design architectures for AI systems that incorporate ethical reasoning. A variety of approaches have been suggested, such as a two-tier monitor architecture that separates the operational AI from a monitor agent that is responsible for the ethical or legal assessment of any operational action.[68] An alternative view is that safety engineering is preferred, in which a precise conceptual framework for the AI agent architecture is used to ensure that AI behavior is safe and not harmful to humans.[69] A third method is to formulate an ethical architecture using set theoretic principles, combined with logical constraints

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68 A. Etzioni and O. Etzioni, "Designing AI Systems that Obey Our Laws and Values," *Communications of the ACM* 59(9) (2016):29-31.

69 R. Y. Yampolsky, "Artificial Intelligence Safety Engineering: Why Machine Ethics is a Wrong Approach." In *Philosophy and Theory of Artificial Intelligence,* ed. V.C. Muller (Heidelberg: Springer Verlag, 2013), 389-396.

on AI system behavior that restrict action to conform to ethical doctrine.[70] As AI systems become more general, their architectures will likely include subsystems that can take on ethical issues at multiple levels of judgment, including:[71] rapid response pattern matching rules, deliberative reasoning for slower responses for describing and justifying actions, social signaling to indicate trustworthiness for the user, and social processes that operate over even longer time scales to enable the system to abide by cultural norms. Researchers will need to focus on how to best address the overall design of AI systems that align with ethical, legal, and societal goals.

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[70] R. C. Arkin, "Governing Legal Behavior: Embedding Ethics in a Hybrid Deliberative/Reactive Robot Architecture," Georgia Institute of Technology Technical Report, GIT-GVU-07-11, 2007.

[71] B. Kuipers, "Human-like Morality and Ethics for Robots," AAAI-16 Workshop on AI, Ethics and Society, 2016; https://web.eecs.umich.edu/~kuipers/papers/Kuipers-aaaiws-16.pdf

Strategy 4: Ensure the Safety and Security of AI Systems

2019 Update	**Creating robust and trustworthy AI systems**

Since the 2016 release of the *National AI R&D Strategic Plan*, there has been rapid growth in scientific and societal understanding of AI security and safety. Much of this new knowledge has helped identify new problems: it is more evident now how AI systems can be made to do the wrong thing, learn the wrong thing, or reveal the wrong thing, for example, through adversarial examples, data poisoning, and model inversion, respectively. Unfortunately, technical solutions for these AI safety and security problems remain elusive.

To address all of these problems, the safety and security of AI systems must be considered in all stages of the AI system lifecycle, from the initial design and data/model building, to verification and validation, deployment, operation, and monitoring. Indeed, the notion of "safety (or security) by design" might impart an incorrect notion that these are only concerns of system designers; instead, they must be considered throughout the system lifecycle, not just at the design stage, and so must be an important part of the AI R&D portfolio.

When AI components are connected to other systems or information that must be safe or secure, the AI vulnerabilities and performance requirements (e.g., very low false-positive and false-negative rates, when operating over high volumes of data)

AI safety and security: Recent agency R&D programs

Since the release of the 2016 *National AI R&D Strategic Plan*, a number of agencies have initiated efforts supporting Strategy 4:

- DOT published new Federal guidance for automated vehicles in October 2018 supporting the safe integration of automation into the broad multimodal surface transportation system. *Preparing for the Future of Transportation: Automated Vehicles 3.0*[72] advances DOT's principles for safe integration of automated vehicles. The document also reiterates prior safety guidance, provides new multimodal safety guidance, and outlines a process for working with DOT as this new technology evolves. As of May 2019, fourteen companies had released Voluntary Safety Self-Assessments detailing how they will incorporate safety into their design and testing of automated driving systems.[73]
- In December 2018, IARPA announced two programs on AI security: Secure, Assured, Intelligent Learning Systems (SAILS)[74] and Trojans in Artificial Intelligence (TrojAI).[75] DARPA announced another program in February 2019, Guaranteeing AI Robustness against Deception (GARD).[76] Together, these programs aim to combat a range of attacks on AI systems.
- As noted in Strategy 3, DoD is committed to "leading in military ethics and AI safety" as one of five key actions outlined in the strategic approach that guides its efforts to accelerate the adoption of AI systems.[77]

[72] https://www.transportation.gov/av/3
[73] https://www.nhtsa.gov/automated-driving-systems/voluntary-safety-self-assessment
[74] https://www.iarpa.gov/index.php/research-programs/sails
[75] https://www.iarpa.gov/index.php/research-programs/trojai
[76] https://www.darpa.mil/news-events/2019-02-06
[77] "Summary of the 2018 Department of Defense Artificial Intelligence Strategy": https://media.defense.gov/2019/Feb/12/2002088963/-1/-1/1/SUMMARY-OF-DOD-AI-STRATEGY.PDF.

are inherited by the larger systems. These challenges are not static; as AI systems continue to grow in capabilities, they will likely grow in complexity, making it ever harder for correct performance or privacy of information to be verified and validated. This complexity may also make it increasingly difficult to explain decisions in ways that justify high levels of trust from human users (see Strategy 3).

Making AI trustworthy—now and into the future—is a critical issue that requires Federal Government R&D investments (see sidebar), along with collaborative efforts among government, industry, academia, and civil society. Engineering trustworthy AI systems may benefit from borrowing existing practices in safety engineering in other fields that have learned how to account for potential misbehavior of non-AI autonomous or semi-autonomous systems. However, AI-specific problems mean that novel techniques for program analysis, testing, formal verification, and synthesis will be critical to establish that an AI-based system meets its specifications—that is, that the system does exactly what it is supposed to do and no more. These problems are exacerbated in AI-based systems that can be easily fooled, evaded, and misled in ways that can have profound security implications. An emerging research area is adversarial ML, which explores both the analysis of vulnerabilities in ML algorithms as well as algorithmic techniques that yield more robust learning. Well-known attacks on ML include adversarial classifier evasion attacks, where the attacker changes behavior to escape being detected, and poisoning attacks, where training data itself is corrupted. There is growing need for research that systematically explores the space of adversaries that attack ML and other AI-based systems and to design algorithms that provide provable robustness guarantees against classes of adversaries.

Methods must be developed to make safe and secure the creation, evaluation, deployment, and containment of AI, and these methods must scale to match the capability and complexity of AI. Evaluating these methods will require new metrics, control frameworks, and benchmarks for testing and assessing the safety of increasingly powerful systems. Both methods and metrics must incorporate human factors, with safe AI objectives defined by human designers' goals, safe AI operations defined by human users' habits, and safe AI metrics defined by human evaluators' understanding. Producing human-driven and human-understandable methods and metrics for the safety of AI systems will enable policymakers, the private sector, and the public to accurately judge the evolving AI safety landscape and appropriately proceed within it.

Before an AI system is put into widespread use, assurance is needed that the system will operate safely and securely, in a controlled manner. Research is needed to address this challenge of creating AI systems that are reliable, dependable, and trustworthy. As with other complex systems, AI systems face important safety and security challenges due to:[78]

- *Complex and uncertain environments*: In many cases, AI systems are designed to operate in complex environments, with a large number of potential states that cannot be exhaustively examined or tested. A system may confront conditions that were never considered during its design.
- *Emergent behavior*: For AI systems that learn after deployment, a system's behavior may be determined largely by periods of learning under unsupervised conditions. Under such conditions, it may be difficult to predict a system's behavior.
- *Goal misspecification*: Due to the difficulty of translating human goals into computer instructions, the goals that are programmed for an AI system may not match the goals that were intended by the programmer.

[78] J. Bornstein, "DoD Autonomy Roadmap – Autonomy Community of Interest," Presentation at NDIA 16th Annual Science & Engineering Technology Conference, March 2015.

- *Human-machine interactions*: In many cases, the performance of an AI system is substantially affected by human interactions. In these cases, variation in human responses may affect the safety of the system.[79]

To address these issues and others, additional investments are needed to advance AI safety and security,[80] including explainability and transparency, trust, verification and validation, security against attacks, and long-term AI safety and value-alignment.

Improving explainability and transparency

A key research challenge is increasing the "explainability" or "transparency" of AI. Many algorithms, including those based on deep learning, are opaque to users, with few existing mechanisms for explaining their results. This is especially problematic for domains such as healthcare, where doctors need explanations to justify a particular diagnosis or a course of treatment. AI techniques such as decision-tree induction provide built-in explanations but are generally less accurate. Thus, researchers must develop systems that are transparent, and intrinsically capable of explaining the reasons for their results to users.

Building trust

To achieve trust, AI system designers need to create accurate, reliable systems with informative, user-friendly interfaces, while the operators must take the time for adequate training to understand system operation and limits of performance. Complex systems that are widely trusted by users, such as manual controls for vehicles, tend to be transparent (the system operates in a manner that is visible to the user), credible (the system's outputs are accepted by the user), auditable (the system can be evaluated), reliable (the system acts as the user intended), and recoverable (the user can recover control when desired). A significant challenge to current and future AI systems remains the inconsistent quality of software production technology. As advances bring greater linkages between humans and AI systems, the challenge in the area of trust is to keep pace with changing and increasing capabilities, anticipate technological advances in adoption and long-term use, and establish governing principles and policies for the study of best practices for design, construction, and use, including proper operator training for safe operation.

Enhancing verification and validation

New methods are needed for verification and validation of AI systems. "Verification" establishes that a system meets formal specifications, while "validation" establishes that a system meets the user's operational needs. Safe AI systems may require new means of *assessment* (determining if the system is malfunctioning, perhaps when operating outside expected parameters), *diagnosis* (determining the causes for the malfunction), and *repair* (adjusting the system to address the malfunction). For systems operating autonomously over extended periods of time, system designers may not have considered every condition the system will encounter. Such systems may need to possess capabilities for self-assessment, self-diagnosis, and self-repair in order to be robust and reliable.

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79 J. M. Bradshaw, R. R. Hoffman, M. Johnson, and D. D. Woods, "The Seven Deadly Myths of Autonomous Systems," *IEEE Intelligent Systems* 28(3)(2013):54-61.

80 See, for instance: D. Amodei, C. Olah, J. Steinhardt, P. Christiano, J. Schulman, and D. Mane, "Concrete Problems in AI Safety," 2016, arXiv: 1606.06565v2; S. Russell, D. Dewey, and M. Tegmark, "Research Priorities for Robust and Beneficial Artificial Intelligence," 2016, arXiv: 1602.03506; T. G. Dietterich and E. J. Horvitz, "Rise of Concerns about AI: Reflections and Directions," *Communications of the ACM*, 58(10)(2015); and K. Sotala and R. Yampolskiy, "Responses to catastrophic AGI risk: A survey," *Physica Scripta*, 90(1), 19 December 2014.

Securing against attacks

AI embedded in critical systems must be robust in order to handle accidents but should also be secure to a wide range of intentional cyber attacks. Security engineering involves understanding the vulnerabilities of a system and the actions of actors who may be interested in attacking it. While cybersecurity R&D needs are addressed in greater detail in the NITRD 2016 *Federal Cybersecurity R&D Strategic Plan*,[81] some cybersecurity risks are specific to AI systems. For example, one key research area is "adversarial machine learning" that explores the degree to which AI systems can be compromised by "contaminating" training data, by modifying algorithms, or by making subtle changes to an object that prevent it from being correctly identified (e.g., prosthetics that spoof facial recognition systems). The implementation of AI in cybersecurity systems that require a high degree of autonomy is also an area for further study. One recent example of work in this area is DARPA's Cyber Grand Challenge that involved AI agents autonomously analyzing and countering cyber attacks.[82]

Achieving long-term AI safety and value-alignment

AI systems may eventually become capable of "recursive self-improvement," in which substantial software modifications are made by the software itself, rather than by human programmers. To ensure the safety of self-modifying systems, additional research is called for to develop: self-monitoring architectures that check systems for behavioral consistency with the original goals of human designers; confinement strategies for preventing the release of systems while they are being evaluated; value learning, in which the values, goals, or intentions of users can be inferred by a system; and value frameworks that are provably resistant to self-modification.

[81] https://www.nitrd.gov/pubs/2016-Federal-Cybersecurity-Research-and-Development-Strategic-Plan.pdf; this is being updated in 2019.

[82] https://archive.darpa.mil/CyberGrandChallenge_CompetitorSite/

Strategy 5: Develop Shared Public Datasets and Environments for AI Training and Testing

2019 Update	**Increasing access to datasets and associated challenges**

At the time of the 2016 *National AI R&D Strategic Plan*'s release, publicly available datasets and environments were already playing a critical role in pushing forward AI R&D, particularly in areas such as computer vision, natural language processing, and speech recognition. ImageNet,[84] with more than 14 million labeled objects, along with associated computer vision community challenges (e.g., the ImageNet Large Scale Visual Recognition Challenge[85] that evaluates algorithms for object detection and image classification), have played an especially vital role in the community. As translational applications for ML are being found in myriad application areas such as healthcare, medicine, and smart and connected communities, the need has grown for publicly available datasets in domain-specific areas.

The importance of datasets and models – in particular, those of the Federal Government – is explicitly called out in the 2019 *Executive Order on Maintaining American Leadership in Artificial Intelligence*:[1]

> Heads of all agencies shall review their Federal data and models to identify opportunities to increase access and use by the greater non-Federal AI research community in a manner that benefits that community, while protecting safety, security, privacy, and confidentiality. Specifically, agencies shall improve data and model inventory documentation to enable discovery and usability, and shall

Shared Public Datasets and Environments for AI Training and Testing: Recent agency R&D programs

Since the release of the 2016 *National AI R&D Strategic Plan*, a number of agencies have initiated efforts supporting Strategy 5:

- DOT sponsored the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS),[83] which recorded more than 5.4 million trips taken by more than 3,400 drivers and vehicles. An in-vehicle data acquisition system (DAS) unit gathered and stored data from forward radar, four video cameras, accelerometers, vehicle network information, a geographic positioning system, and an onboard lane tracker. Data from the DAS were recorded continuously while participants' vehicles were operating. Whereas summaries of the NDS data are public, access to the detailed datasets requires qualified research ethics training.
- The VA Data Commons is creating the largest linked medical–genomics dataset in the world with tools for enabling ML and AI, and guided by veterans' preferences. This effort is leveraging applicable NIST standards, laws, and executive orders.
- GSA (General Services Administration) is working to enable the use of cloud computing resources for federally funded AI R&D. Data.gov and code.gov, housed at GSA, contain over 246,000 datasets and code from across agencies and automatically harvest datasets released by agencies.
- The NIH Science and Technology Research Infrastructure for Discovery, Experimentation, and Sustainability (STRIDES) initiative, a partnership with industry-leading cloud service providers, is enabling researcher access to major data assets that are funded across NIH and that are stored in cloud environments.

83 https://insight.shrp2nds.us/
84 http://www.image-net.org/
85 http://www.image-net.org/challenges/LSVRC/

prioritize improvements to access and quality of AI data and models based on the AI research community's feedback.

A new NSTC Subcommittee on Open Science was created in 2018 to coordinate Federal efforts on open and FAIR (findable, accessible, interoperable, and reusable) data. R&D investments will be needed to develop tools and resources that make it easier to identify, use, and manipulate relevant datasets (including Federal datasets), verify data provenance, and respect appropriate use policy. Many of these datasets themselves may be of limited use in an AI context without an investment in labeling and curation. Federal agencies should engage and work with AI stakeholders to ensure that appropriately vetted datasets and models that are released for sharing are ready and fit for use and that they are maintained as standards and norms evolve. Ultimately, development and adoption of best practices and standards in documenting dataset and model provenance will enhance trustworthiness and responsible use of AI technologies.

Since 2016, there have also been increased concerns about data content, such as potential bias (see Strategy 3)[86,87] or private information leakage. The 2016 *National AI R&D Strategic Plan* noted that "dataset development and sharing must … follow applicable laws and regulations and be carried out in an ethical manner." The DOT-supported InSight project provides such carefully structured access to data collected during the Naturalistic Driving Study (see sidebar). The 2016 *National AI R&D Strategic Plan* also noted that new "technologies are needed to ensure safe sharing of data, since data owners take on risk when sharing their data with the research community." For example, CryptoNets[88] allows neural networks to operate over encrypted data, ensuring that data remain confidential, because decryption keys are not needed in neural networks. Researchers have also begun developing new ML techniques that use a differential privacy framework to provide quantifiable privacy guarantees over the used data.[89] At the same time, privacy methods must remain sufficiently explainable and transparent to help researchers correct them and make them safe, efficient, and accurate. Furthermore, AI could reveal discoveries beyond the original or intended scope; therefore, researchers must remain cognizant of the potential dangers in access to data or discoveries by adversaries.

Data alone are of little use without the ability to bring computational resources to bear on large-scale public datasets. The importance of computational resources to AI R&D is called out in the 2019 *Executive Order on Maintaining American Leadership in Artificial Intelligence*:[1]

> The Secretaries of Defense, Commerce, Health and Human Services, and Energy, the Administrator of the National Aeronautics and Space Administration, and the Director of the National Science Foundation shall, to the extent appropriate and consistent with applicable law, prioritize the allocation of high-performance computing resources for AI-related applications through: (i) increased assignment of discretionary allocation of resources and resource reserves; or (ii) any other appropriate mechanisms.

86 Emily M. Bender and Batya Friedman, "Data Statements for NLP: Toward Mitigating System Bias and Enabling Better Science," *Transactions of the Association for Computational Linguistics* 6 (2018):587-604.

87 Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan, "Semantics derived automatically from language corpora contain human-like biases," *Science* 356(6334):183-186, 14 Apr 2017.

88 Ran Gilad-Bachrach, Nathan Dowlin, Kim Laine, Kristin Lauter, Michael Naehrig, John Wernsing, "CryptoNets: Applying neural networks to encrypted data with high throughput and accuracy," *2016 International Conference on Machine Learning* 48:201-210; http://proceedings.mlr.press/v48/.

89 Martin Abadi, Andy Chu, Ian Goodfellow, H. Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang, "Deep Learning with Differential Privacy," *23rd ACM Conference on Computer and Communications Security*," 2016: 308-318.

and:

> …the Select Committee, in coordination with the General Services Administration (GSA), shall submit a report to the President making recommendations on better enabling the use of cloud computing resources for federally funded AI R&D.

The need for computational capacity for many AI challenges has been increasing rapidly.[32] Federal funding may provide computational capabilities for Federally-funded research. Some companies and universities, however, may have additional computational demands. Overall, there is a national need to study and invest in shared computational resources to promote AI R&D.

The benefits of AI will continue to accrue, but only to the extent that training and testing resources for AI are developed and made available. The variety, depth, quality, and accuracy of training datasets and other resources significantly affects AI performance. Many different AI technologies require high-quality data for training and testing, as well as dynamic, interactive testbeds and simulation environments. More than just a technical question, this is a significant "public good" challenge, as progress would suffer if AI training and testing is limited to only a few entities that already hold valuable datasets and resources, yet we must simultaneously respect commercial and individual rights and interests in the data. Research is needed to develop high-quality datasets and environments for a wide variety of AI applications and to enable responsible access to good datasets and testing and training resources. Additional open-source software libraries and toolkits are also needed to accelerate the advancement of AI R&D. The following subsections outline these key areas of importance.

Developing and making accessible a wide variety of datasets to meet the needs of a diverse spectrum of AI interests and applications

The integrity and availability of AI training and testing datasets is crucial to ensuring scientifically reliable results. The technical as well as the socio-technical infrastructure necessary to support reproducible research in the digital area has been recognized as an important challenge—and is essential to AI technologies as well. The lack of vetted and openly available datasets with identified provenance to enable reproducibility is a critical factor to confident advancement in AI.[90] As in other data-intensive sciences, capturing data provenance is critical. Researchers must be able to reproduce results with the same as well as different datasets. Datasets must be representative of challenging real-world applications, and not just simplified versions. To make progress quickly, emphasis should be placed on making available already existing datasets held by government, those that can be developed with Federal funding, and, to the extent possible, those held by industry.

The machine learning aspect of the AI challenge is often linked with "big data" analysis. Considering the wide variety of relevant datasets, it remains a growing challenge to have appropriate representation, access, and analysis of unstructured or semi-structured data. How can the data be represented—in absolute as well as relative (context-dependent) terms? Current real-world databases can be highly susceptible to inconsistent, incomplete, and noisy data. Therefore, a number of data preprocessing techniques (e.g., data cleaning, integration, transformation, reduction, and representation) are important to establishing useful datasets for AI applications. How does the data preprocessing impact data quality, especially when additional analysis is performed?

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[90] Toward this end, in 2016 the Intelligence Advanced Research Projects Activity issued a Request for Information on novel training datasets and environments to advance AI. See https://iarpa.gov/index.php/working-with-iarpa/requests-for-information/novel-training-datasets-and-environments-to-advance-artificial-intelligence.

Encouraging the sharing of AI datasets—especially for government-funded research—would likely stimulate innovative AI approaches and solutions. However, technologies are needed to ensure safe sharing of data, since data owners take on risk when sharing their data with the research community. Dataset development and sharing must also follow applicable laws and regulations and be carried out in an ethical manner. Risks can arise in various ways: inappropriate use of datasets, inaccurate or inappropriate disclosure, and limitations in data de-identification techniques to ensure privacy and confidentiality protections.

Making training and testing resources responsive to commercial and public interests

With the continuing explosion of data, data sources, and information technology worldwide, both the number and size of datasets are increasing. The techniques and technologies to analyze data are not keeping up with the high volume of raw information sources. Data capture, curation, analysis, and visualization are all key research challenges, and the science needed to extract valuable knowledge from enormous amounts of data is lagging behind. While data repositories exist, they are often unable to deal with the scaling up of datasets, have limited data provenance information, and do not support semantically rich data searches. Dynamic, agile repositories are needed.

One example of the kind of open/sharing infrastructure program that is needed to support the needs of AI research is the IMPACT program (Information Marketplace for Policy and Analysis of Cyber-risk & Trust) developed by the Department of Homeland Security (DHS).[91] This program supports the global cyber security risk research effort by coordinating and developing real-world data and information sharing capabilities, including tools, models, and methodologies. IMPACT also supports empirical data sharing between the international cybersecurity R&D community, critical infrastructure providers, and their government supporters. AI R&D would benefit from comparable programs across all AI applications.

Developing open-source software libraries and toolkits

The increased availability of open-source software libraries and toolkits provides access to cutting-edge AI technologies for any developer with an Internet connection. Resources such as the Weka toolkit,[92] MALLET,[93] and OpenNLP,[94] among many others, have accelerated the development and application of AI. Development tools, including free or low-cost code repository and version control systems, as well as free or low-cost development languages (e.g., R, Octave, and Python) provide low barriers to using and extending these libraries. In addition, for those who may not want to integrate these libraries directly, any number of cloud-based machine learning services exist that can perform tasks such as image classification on demand through low-latency web protocols that require little or no programming for use. Finally, many of these web services also offer the use of specialized hardware, including GPU-based systems. It is reasonable to assume that specialized hardware for AI algorithms, including neuromorphic processors, will also become widely available through these services.

Together, these resources provide an AI technology infrastructure that encourages marketplace innovation by allowing entrepreneurs to develop solutions that solve narrow domain problems without requiring expensive hardware or software, without requiring a high level of AI expertise, and permitting rapid scaling-up of systems on demand. For narrow AI domains, barriers to marketplace innovation are extremely low relative to many other technology areas.

[91] https://www.dhs.gov/csd-impact

[92] https://sourceforge.net/projects/weka/

[93] http://mallet.cs.umass.edu

[94] https://opennlp.apache.org

To help support a continued high level of innovation in this area, the U.S. Government can boost efforts in the development, support, and use of open AI technologies. Particularly beneficial would be open resources that use standardized or open formats and open standards for representing semantic information, including domain ontologies when available.

Government may also encourage greater adoption of open AI resources by accelerating the use of open AI technologies within the government itself, and thus help to maintain a low barrier to entry for innovators. Whenever possible, government should contribute algorithms and software to open source projects. Because government has specific concerns, such as a greater emphasis on data privacy and security, it may be necessary for the government to develop mechanisms to ease government adoption of AI systems. For example, it may be useful to create a task force that can perform a "horizon scan" across government agencies to find particular AI application areas within departments, and then determine specific concerns that would need to be addressed to permit adoption of such techniques by these agencies.

Strategy 6: Measure and Evaluate AI Technologies through Standards and Benchmarks

2019 Update	**Supporting development of AI technical standards and related tools**

The 2016 *National AI R&D Strategic Plan* states that "Standards, benchmarks, testbeds, and their adoption by the AI community are essential for guiding and promoting R&D of AI technologies." In the intervening three years, emphasis on standards and benchmarks has continued to rise in the U.S. and globally. The 2019 *Executive Order on Maintaining American Leadership in Artificial Intelligence* explicitly calls out the importance of such standards:[1]

> …[T]he Secretary of Commerce, through the Director of [NIST], shall issue a plan for Federal engagement in the development of technical standards and related tools in support of reliable, robust, and trustworthy systems that use AI technologies.

With AI innovation potentially impacting all sectors and domains of society, many standards development organizations have new AI-related considerations and work items underway, including activities related to AI ethics and trustworthy AI systems (see Strategy 3). The International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) have convened a joint technical subcommittee on AI (ISO/IEC Joint Technical Committee 1, Subcommittee 42 on Artificial Intelligence[95]) to develop standards for AI systems and associated considerations. It is critical that Federal, industry, and academic researchers continue to inform these activities, particularly as AI advances and systems reach into areas such as transportation, health care, and food that align with the missions of government agencies.

Standards, benchmarks, and related tools: Recent agency R&D programs

Since the release of the 2016 *National AI R&D Strategic Plan*, NIST in particular has initiated efforts for Strategy 6:

- NIST is engaged in the standardization program of ISO/IEC JTC 1 SC 42 on Artificial Intelligence.[95] A NIST expert is the convener for the Big Data work effort in SC 42. The U.S. delegation to SC 42 includes NIST and other Federal agency experts, as well as representatives from industry and academia. U.S. input to SC 42 is facilitated by the International Committee for Information Technology Standards (INCITS).
- NIST staff participate in additional AI standards activities through standards organizations, such as the American Society of Mechanical Engineers, IEEE, and ISO/IEC. Their activities cover such topics as computational modeling for advanced manufacturing, ontologies for robotics and automation, personal data privacy, and algorithmic bias.
- NIST experts are raising awareness about the importance of consensus standards for AI in multilateral fora, including bodies such as G20 and G7.[96] NIST brings unique Federal Government expertise that grounds policy discussions in practice, in particular, through close collaboration with the private sector. Similarly, NIST lends its standards and related experience to intergovernmental bilateral discussions.

Since 2016, the surge in AI-related standards activities has outpaced the launch of new AI-focused benchmarks and evaluations, particularly as related to trustworthiness of AI systems. In the

[95] https://www.iso.org/committee/6794475.html

[96] https://home.treasury.gov/policy-issues/international/g-7-and-g-20

intervening time, however, considerations of fairness and bias in benchmark datasets have become increasingly important, with researchers pursuing new facial recognition datasets that seek to minimize bias. Much more plentiful are benchmarks that test the application-level performance of AI algorithms (e.g., false-positive or false-negative rates for classification algorithms) and benchmarks that quantify the compute-level performance of AI software and hardware systems. Two such recent activities are MLPerf[97] and DAWNbench.[98]

Assessing, promoting, and assuring all aspects of AI trustworthiness requires measuring and evaluating AI technology performance through benchmarks and standards. Beyond being safe, secure, reliable, resilient, explainable, and transparent, trustworthy AI must preserve privacy while detecting and avoiding inappropriate bias. As AI technologies evolve, so will the need to develop new metrics and testing requirements for validation of these essential characteristics.

Standards, benchmarks, testbeds, and their adoption by the AI community are essential for guiding and promoting R&D of AI technologies. The following subsections outline areas where additional progress must be made.

Developing a broad spectrum of AI standards

The development of standards must be hastened to keep pace with the rapidly evolving capabilities and expanding domains of AI applications. Standards provide requirements, specifications, guidelines, or characteristics that can be used consistently to ensure that AI technologies meet critical objectives for functionality and interoperability, and that they perform reliably and safely. Adoption of standards brings credibility to technology advancements and facilitates an expanded interoperable marketplace. One example of an AI-relevant standard that has been developed is P1872-2015 (Standard Ontologies for Robotics and Automation), developed by the Institute of Electrical and Electronics Engineers. This standard provides a systematic way of representing knowledge and a common set of terms and definitions. These allow for unambiguous knowledge transfer among humans, robots, and other artificial systems, as well as provide a foundational basis for the application of AI technologies to robotics. Additional work in AI standards development is needed across all subdomains of AI.

Standards are needed to address:

- *Software engineering*: to manage system complexity, sustainment, security, and to monitor and control emergent behaviors;
- *Performance*: to ensure accuracy, reliability, robustness, accessibility, and scalability;
- *Metrics*: to quantify factors impacting performance and compliance to standards;
- *Safety*: to evaluate risk management and hazard analysis of systems, human computer interactions, control systems, and regulatory compliance;
- *Usability*: to ensure that interfaces and controls are effective, efficient, and intuitive;
- *Interoperability*: to define interchangeable components, data, and transaction models via standard and compatible interfaces;
- *Security*: to address the confidentiality, integrity, and availability of information, as well as cybersecurity;
- *Privacy*: to control for the protection of information while being processed, when in transit, or being stored;

97 https://mlperf.org/

98 https://dawn.cs.stanford.edu/benchmark/

- *Traceability*: to provide a record of events (their implementation, testing, and completion), and for the curation of data; and
- *Domains*: to define domain-specific standard lexicons and corresponding frameworks.

Establishing AI technology benchmarks

Benchmarks, made up of tests and evaluations, provide quantitative measures for developing standards and assessing compliance to standards. Benchmarks drive innovation by promoting advancements aimed at addressing strategically selected scenarios; they additionally provide objective data to track the evolution of AI science and technologies. To effectively evaluate AI technologies, relevant and effective testing methodologies and metrics must be developed and standardized. Standard testing methods will prescribe protocols and procedures for assessing, comparing, and managing the performance of AI technologies. Standard metrics are needed to define quantifiable measures in order to characterize AI technologies, including but not limited to: accuracy, complexity, trust and competency, risk and uncertainty, explainability, unintended bias, comparison to human performance, and economic impact. It is important to note that benchmarks are data driven. Strategy 5 discusses the importance of datasets for training and testing.

As a successful example of AI-relevant benchmarks, the National Institute of Standards and Technology has developed a comprehensive set of standard test methods and associated performance metrics to assess key capabilities of emergency response robots. The objective is to facilitate quantitative comparisons of different robot models by making use of statistically significant data on robot capabilities that was captured using the standard test methods. These comparisons can guide purchasing decisions and help developers to understand deployment capabilities. The resulting test methods are being standardized though the ASTM International Standards Committee on Homeland Security Applications for robotic operational equipment (referred to as standard E54.08.01).[99] Versions of the test methods are used to challenge the research community through the RoboCup Rescue Robot League competitions,[100] which emphasize autonomous capabilities. Another example is the IEEE Agile Robotics for Industrial Automation Competition (ARIAC),[101] a joint effort between IEEE and NIST,[102] which promotes robot agility by utilizing the latest advances in artificial intelligence and robot planning. A core focus of this competition is to test the agility of industrial robot systems, with the goal of enabling those on the shop floors to be more productive, more autonomous, and requiring less time from shop floor workers.

While these efforts provide a strong foundation for driving AI benchmarking forward, they are limited by being domain-specific. Additional standards, testbeds, and benchmarks are needed across a broader range of domains to ensure that AI solutions are broadly applicable and widely adopted.

Increasing the availability of AI testbeds

The importance of testbeds was stated in the *Cyber Experimentation of the Future* report: "Testbeds are essential so that researchers can use actual operational data to model and run experiments on real-world system[s] … and scenarios in good test environments."[103] Having adequate testbeds is a

[99] 2019 update: The resulting test methods are now standards issued by ASTM International Standards Committee on Homeland Secruity Applications for Response Robots (referred to as E54.09).

[100] http://www.robocup2016.org/en/

[101] http://robotagility.wixsite.com/competition

[102] 2019 update: IEEE is no longer a partner of ARIAC, which is now in its third year.

[103] SRI International and USC Information Sciences Institute, "Cybersecurity Experimentation of the Future (CEF): Catalyzing a New Generation of Experimental Cybersecurity Research," Final Report, July 31, 2015.

need across all areas of AI. The government has massive amounts of mission-sensitive data unique to government, but much of this data cannot be distributed to the outside research community. Appropriate programs could be established for academic and industrial researchers to conduct research within secured and curated testbed environments established by specific agencies. AI models and experimental methods could be shared and validated by the research community by having access to these test environments, affording AI scientists, engineers, and students unique research opportunities not otherwise available.

Engaging the AI community in standards and benchmarks

Government leadership and coordination is needed to drive standardization and encourage its widespread use in government, academia, and industry. The AI community—made up of users, industry, academia, and government—must be energized to participate in developing standards and benchmark programs. As each government agency engages the community in different ways based on its role and mission, community interactions can be leveraged through coordination in order to strengthen their impact. This coordination is needed to collectively gather user-driven requirements, anticipate developer-driven standards, and promote educational opportunities. User-driven requirements shape the objectives and design of challenge problems and enable technology evaluation. Having community benchmarks focuses R&D to define progress, close gaps, and drive innovative solutions for specific problems. These benchmarks must include methods for defining and assigning ground truth. The creation of benchmark simulation and analysis tools will also accelerate AI developments. The results of these benchmarks also help match the right technology to the user's need, forming objective criteria for standards compliance, qualified product lists, and potential source selection.

Industry and academia are the primary sources for emerging AI technologies. Promoting and coordinating their participation in standards and benchmarking activities are critical. As solutions emerge, opportunities abound for anticipating developer- and user-driven standards through sharing common visions for technical architectures, developing reference implementations of emerging standards to show feasibility, and conducting precompetitive testing to ensure high-quality and interoperable solutions, as well as to develop best practices for technology applications.

One successful example of a high-impact, community-based, AI-relevant benchmark program is the Text Retrieval Conference (TREC),[104] which was started by NIST in 1992 to provide the infrastructure necessary for large-scale evaluation of information retrieval methodologies. More than 250 groups have participated in TREC, including academic and commercial organizations both large and small. The standard, widely available, and carefully constructed set of data put forth by TREC has been credited with revitalizing research on information retrieval.[105,106] A second example is the NIST periodic benchmark program in the area of machine vision applied to biometrics,[107] particularly face recognition.[108] This began with the Face Recognition Technology (FERET) evaluation in 1993, which provided a standard dataset of face photos designed to support face recognition algorithm development as well as an evaluation protocol. This effort has evolved over the years into the Face

[104] http://trec.nist.gov

[105] E. M. Voorhees and D. K. Harman, *TREC Experiment and Evaluation in Information Retrieval* (Cambridge: MIT Press, 2005).

[106] http://googleblog.blogspot.com/2008/03/why-data-matters.html

[107] http://biometrics.nist.gov

[108] http://face.nist.gov

Recognition Vendor Test (FRVT),[109] involving the distribution of datasets, hosting of challenge problems, and conducting of sequestered technology evaluations. This benchmark program has contributed greatly to the improvement of facial recognition technology. Both TREC and FRVT can serve as examples of effective AI-relevant community benchmarking activities, but similar efforts are needed in other areas of AI.

It is important to note that developing and adopting standards, as well as participating in benchmark activities, comes with a cost. R&D organizations are incentivized when they see significant benefit. Updating acquisition processes across agencies to include specific requirements for AI standards in requests for proposals will encourage the community to further engage in standards development and adoption. Community-based benchmarks, such as TREC and FRVT, also lower barriers and strengthen incentives by providing types of training and testing data otherwise inaccessible, fostering healthy competition between technology developers to drive best-of-breed algorithms, and providing objective and comparative performance metrics for relevant source selections.

[109] P. J. Phillips, "Improving Face Recognition Technology," *Computer* 44(3)(2011): 84-96.

Strategy 7: Better Understand the National AI R&D Workforce Needs

2019 Update	**Advancing the AI R&D workforce, including those working on AI systems and those working alongside them, to sustain U.S. leadership**

Since the release of the 2016 *National AI R&D Strategic Plan*, the demand for AI researchers and practitioners has grown rapidly. Studies have shown that the number of hiring opportunities is expected to rise into the millions over the next decade. As one data point, the U.S. Bureau of Labor Statistics projects that the number of positions for computer and information scientists and engineers will grow by 19% from 2016 to 2026, almost three times faster than the average for all occupations.[111] Moreover, through 2028, AI researchers are expected contribute to as much as $11.5 trillion of cumulative growth promised by intelligent technologies in the G20 countries alone.[112]

U.S. academic institutions are struggling to keep pace with the explosive growth in student interest and enrollment in AI.[113,114,115] At the same time, industry, with its sustained financial support and access to advanced computing facilities and datasets, exerts a strong pull on academic research and teaching talent.[116]

It is critical to maintain a robust academic research ecosystem in AI that, in collaboration with industry R&D, can continue to deliver tremendous dividends[117] by advancing national health, prosperity, and welfare, and securing the national defense.

National AI R&D workforce: Recent agency activities

Since the release of the 2016 *National AI R&D Strategic Plan*, a number of agencies have initiated efforts supporting Strategy 7:

- Apart from supporting undergraduate and graduate students through standard AI research grants, agencies are prioritizing computational- and data-enabled science and engineering in their graduate fellowship programs. For example, in 2018, DOE added a new track to its Computational Science Graduate Fellowship program. This track supports students pursuing advanced degrees in applied mathematics, statistics, or computer science, and promotes more effective use of high-performance systems, including in the areas of AI, ML, and deep learning.[44,110] Also in 2018, NSF began prioritizing computational and data-enabled science and engineering in a subset of awardees of its Graduate Research Fellowships Program.
- The Census Bureau has created the Statistical Data Modernization (SDM) project to bring its workforce, operations, and technologies up to the current state of the art and set the standard for statistical agencies in today's data-driven society. SDM's workforce transformation component will enable the hiring of new data scientists with expertise in new methods and analytics, including the use of AI methods and tools to process and analyze big data. The workforce transformation will also address the upskilling of the current data science workforce.

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[110] https://www.krellinst.org/csgf/math-cs
[111] https://www.bls.gov/ooh/computer-and-information-technology/computer-and-information-research-scientists.htm
[112] https://www.accenture.com/t20180920T094705Z__w__/us-en/_acnmedia/Thought-Leadership-Assets/PDF/Accenture-Education-and-Technology-Skills-Research.pdf
[113] https://cra.org/data/generation-cs/
[114] https://cra.org/wp-content/uploads/2018/05/2017-Taulbee-Survey-Report.pdf
[115] http://web.cs.wpi.edu/~cew/papers/CSareas19.pdf
[116] https://www.nitrd.gov/rfi/ai/2018/AI-RFI-Response-2018-Yolanda-Gil-AAAI.pdf
[117] https://www.nap.edu/catalog/13427/continuing-innovation-in-information-technology

In the three years since the release of the 2016 *National AI R&D Strategic Plan*, various reports have called for continued support for the development of instructional materials and teacher professional development in computer science at all levels. Emphasis is needed at the K–12 levels to feed the Nation's pipeline of AI researchers over many decades.[118] At the undergraduate level, there is a need to focus on integrating advanced computational skills and methods with domain-specific knowledge from other disciplines, given the growing role of computing across disciplines.[119] Sustained support is also needed at the graduate level, where students are conducting fundamental research in ML and AI. Indeed, the 2019 *Executive Order on Maintaining American Leadership in Artificial Intelligence* requires that:[1]

> Heads of implementing agencies that also provide educational grants shall, to the extent consistent with applicable law, consider AI as a priority area within existing Federal fellowship and service programs … [including] … (A) high school, undergraduate, and graduate fellowship; alternative education; and training programs; (B) programs to recognize and fund early-career university faculty who conduct AI R&D, including through Presidential awards and recognitions; (C) scholarship for service programs; (D) direct commissioning programs of the United States Armed Forces; and (E) programs that support the development of instructional programs and curricula that encourage the integration of AI technologies into courses in order to facilitate personalized and adaptive learning experiences for formal and informal education and training.

More broadly, the need for a firm grounding in computational thinking, including through computer science education, is also noted prominently in the Federal Government's December 2018 five-year strategic plan for science, technology, engineering, and mathematics (STEM) education.[120]

In addition, it is imperative to broaden the participation among groups traditionally underrepresented in computing and related fields.

Finally, the AI R&D workforce will consist of multidisciplinary teams comprising not just computer and information scientists and engineers, but also experts from other fields key to AI and ML innovation and its application, including cognitive science and psychology, economics and game theory, engineering and control theory, ethics, linguistics, mathematics, philosophy, and the many domains in which AI may be applied.

Federal agencies are giving priority to training and fellowship programs at all levels to prepare the workforce with requisite AI R&D skills through apprenticeships, skills programs, fellowships, and course work in relevant disciplines (see sidebar). Such training opportunities target both scientists and engineers who contribute to AI R&D innovations and users of AI R&D who may possess relevant domain knowledge. In the case of the former, long-term Federal investment in AI R&D, as described in Strategy 1, further supports the growth of this workforce, both through training the next generation of researchers and by making faculty positions more attractive to current graduate and postdoctoral students. In the case of the latter, new programs are bringing AI-relevant skills to current and future users of AI systems (see sidebar). Federal agencies must therefore continue to strategically foster expertise in the AI R&D workforce that spans multiple disciplines and skill categories to ensure sustained national leadership.

[118] https://github.com/touretzkyds/ai4k12/wiki

[119] https://www.nap.edu/catalog/24926/assessing-and-responding-to-the-growth-of-computer-science-undergraduate-enrollments

[120] https://www.whitehouse.gov/wp-content/uploads/2018/12/STEM-Education-Strategic-Plan-2018.pdf

Attaining the needed AI R&D advances outlined in this strategy will require a sufficient AI R&D workforce. Nations with the strongest presence in AI R&D will establish leading positions in the automation of the future. They will become the frontrunners in competencies like algorithm creation and development; capability demonstration; and commercialization. Developing technical expertise will provide the basis for these advancements.

While no official AI workforce data currently exist, numerous recent reports from the commercial and academic sectors are indicating an increased shortage of available experts in AI. AI experts are reportedly in short supply,[121] with demand expected to continue to escalate.[122] High-tech companies are reportedly investing significant resources into recruiting faculty members and students with AI expertise.[123] Universities and industries are reportedly in a battle to recruit and retain AI talent.[124]

Additional studies are needed to better understand the current and future national workforce needs for AI R&D. Data is needed to characterize the current state of the AI R&D workforce, including the needs of academia, government, and industry. Studies should explore the supply and demand forces in the AI workplace, to help predict future workforce needs. An understanding is needed of the projected AI R&D workforce pipeline. Considerations of educational pathways and potential retraining opportunities should be included. Diversity issues should also be explored, since studies have shown that a diverse information technology workforce can lead to improved outcomes.[125] Once the current and future AI R&D workforce needs are better understood, then appropriate plans and actions can be considered to address any existing or anticipated workforce challenges.

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[121] "Startups Aim to Exploit a Deep-Learning Skills Gap," *MIT Technology Review*, January 6, 2016.

[122] "AI talent grab sparks excitement and concern," *Nature*, April 26, 2016.

[123] "Artificial Intelligence Experts are in High Demand," *The Wall Street Journal*, May 1, 2015.

[124] "Million dollar babies: As Silicon Valley fights for talent, universities struggle to hold on to their stars," *The Economist*, April 2, 2016.

[125] J. W. Moody, C. M. Beise, A. B. Woszczynski, and M. E. Myers, "Diversity and the information technology workforce: Barriers and opportunities," *Journal of Computer Information Systems* 43 (2003): 63-71.

Strategy 8: Expand Public–Private Partnerships to Accelerate Advances in AI

Strategy 8 is new in 2019 and reflects the growing importance of public-private partnerships enabling AI R&D.

American leadership in science and engineering research and innovation is rooted in the Nation's unique government-university-industry R&D ecosystem. As the American Association of Arts and Sciences has written, "America's standing as an innovation leader" relies upon "establishing a more robust national Government-University-Industry research partnership."[126] Since the release of the 2016 *National AI R&D Strategic Plan*, the Administration has amplified this vision of promoting "sustained investment in AI R&D in collaboration with academia, industry, international partners and allies, and other non-Federal entities to generate technological breakthroughs in AI and related technologies and to rapidly transition those breakthroughs into capabilities that contribute to U.S. economic and national security."[1]

Over the last several decades, fundamental research in information technology conducted at universities with Federal funding, as well as in industry, has led to new, multi-billion-dollar sectors of the Nation's economy.[127] Concurrent advances across government, universities, and industry have been mutually reinforcing and have led to an innovative, vibrant AI sector. Many of today's AI systems have been enabled by the American government-university-industry R&D ecosystem (see sidebar).

Advancing the Nation's AI innovation ecosystem, spanning government, universities, and industry

- Deep convolutional neural networks have proven to be a key innovation rooted in AI research. Although this modeling approach emerged from early Federal investments in the late 1980s, there were not enough data nor enough computational capabilities available at the time for neural networks to make accurate predictions. Through the combination of a rise in big data, today's data-intensive scientific methods, and conceptual advances in how to structure and optimize the networks, neural networks have re-emerged as a useful way to improve accuracy in AI models. Interactions between academia and the private sector, including government funding, in recent years have helped reduce the error rate in speech recognition systems, enabling innovations such as real-time translation.[126]
- Similarly, Federal investments in reinforcement learning in the 1980s and 1990s—an approach rooted in behavioral psychology that involves learning to associate behaviors with desired outcomes—have led to today's deep learning systems. Through interactions across sectors, computers are increasingly learning like humans, without explicit instruction, and reinforcement learning is driving progress in self-driving cars and other forms of automation where machines can hone skills through experience. Reinforcement learning was the key technology underlying AlphaGo, the program that defeated the world's best Go players, which has seen a growing number of victories over professional players since 2016.[126]

Since the release of the 2016 *National AI R&D Strategic Plan*, additional emphasis has been placed on the benefits of public-private partnerships. These benefits include strategically leveraging resources, including facilities, datasets, and expertise, to advance science and engineering innovations;

[126] *Restoring the Foundation: The Vital Role of Research in Preserving the American Dream* (American Academy of Arts and Sciences, Cambridge, MA, 2014); https://www.amacad.org/multimedia/pdfs/publications/researchpapersmonographs/AmericanAcad_RestoringtheFoundation_Brief.pdf.

[127] National Research Council Computer Science Telecommunications Board, *Continuing Innovation in Information Technology* (The National Academies Press, Washington, D.C., 2012); https://doi.org/10.17226/13427.

accelerating the transition of these innovations to practice; and enhancing education and training for next-generation researchers, technicians, and leaders. Government-university-industry R&D partnerships bring pressing, real-world challenges faced by industry to university researchers, enabling "use-inspired research"; leverage industry expertise to accelerate the transition of open and published research results into viable products and services in the marketplace for economic growth; and grow research and workforce capacity by linking university faculty and students with industry representatives, industry settings, and industry jobs (see sidebar).[126,128,129,130] These partnerships build upon joint engagements among Federal agencies that enable synergies in areas where agencies' missions intersect. The Nation also benefits from relationships between Federal agencies and international funders who can work together to address key challenges of mutual interest across a range of disciplines.

While there are many structures and mechanisms for public-private partnerships, some common categories for engagement include:

1. *Individual project-based collaborations.* These efforts enable engagement by university researchers with those in other sectors, including Federal agencies, industry, and international organizations, to identify and leverage synergies in areas of mutual interest.
2. *Joint programs to advance open, precompetitive, fundamental research*. Direct partnerships among organizations across sectors enable funding and support for open, precompetitive, fundamental research in areas of mutual interest to the partners. In general, non-Federal partners contributing research resources receive the same intellectual property rights afforded to the U.S. Government by the Bayh-Dole Act.[131]
3. *Collaborations to deploy and enhance research infrastructure*. Collaborations among Federal agencies, industry, and international organizations significantly enhance the potential for developing new and enhancing existing research infrastructure that in turn enables groundbreaking experimentation by researchers. Partners may offer financial and/or in-kind support to develop and/or enhance research infrastructure.
4. *Collaborations to enhance workforce development including broadening participation*. Multisector partnerships set the foundation for rigorous, engaging, and inspiring instructional materials that enhance workforce development and diversity in STEM professions.

In each of these cases, leveraging each partner's strengths for the benefit of all is vitally important to achieving success.

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[128] Mathematical Sciences Research Institute report, "*Partnerships: A Workshop on Collaborations between the NSF/MPS & Private Foundations,"* 2015; http://library.msri.org/msri/Partnerships.pdf.

[129] Computing Community Consortium, *"The Future of Computing Research: Industry-Academic Collaborations,"* 2016; http://cra.org/ccc/wp-content/uploads/sites/2/2016/06/15125-CCC-Industry-Whitepaper-v4-1.pdf.

[130] Computing Community Consortium, *"Evolving Academia/Industry Relations in Computing Research: Interim Report released by the CCC,"* 2019; https://www.cccblog.org/wp-content/uploads/2019/03/Industry-Interim-Report-w-footnotes.pdf.

[131] https://history.nih.gov/research/downloads/PL96-517.pdf

Advances in AI R&D stand to benefit from all of these types of public-private partnerships. Partnerships can promote open, precompetitive, fundamental AI R&D; enhance access to research resources such as datasets, models, and advanced computational capabilities; and foster researcher exchanges and/or joint appointments between government, universities, and industry to share AI R&D expertise. Partnerships can also promulgate the inherently interdisciplinary nature of AI R&D, which requires convergence between computer and information science, cognitive science and psychology, economics and game theory, engineering and control theory, ethics, linguistics, mathematics and statistics, and philosophy to drive the development and evaluation of future AI systems that are fair, transparent, and accountable, as well as safe and secure. Federal agencies are actively pursuing public-private partnerships to achieve these goals (*see sidebar*).

Federal agencies must therefore continue to pursue and strengthen public-private partnerships in AI R&D to drive technology development and economic growth by leveraging investments and expertise in areas of mutual interest to government, industry, and academia. In doing so, the U.S. Government will capitalize on a uniquely American innovation ecosystem that has transformed nearly every aspect of the Nation's economy and society over the last two decades through novel information technologies.[127]

Public-private partnerships: Recent agency R&D programs

A number of agencies have already initiated public-private partnerships in support of AI R&D:

- The Defense Innovation Unit (DIU)[132] is a DoD organization that solicits commercial solutions capable of addressing DoD needs. The DIU in turn provides pilot contracts, which can include hardware, software, or other unique services. If successful, pilot contracts lead to follow-on contracts between companies and any DoD entity. A key DIU feature is the rapid pace of the pilot and subsequent contracts.
- NSF and the Partnership on AI, a diverse, multistakeholder organization working to better understand AI's impacts, are partnering to jointly support high-risk, high-reward research at the intersection of the social and technical dimensions of AI.[15]
- The DHS Science and Technology Directorate's Silicon Valley Innovation Program (SVIP)[133] looks to harness commercial R&D innovation ecosystems across the Nation and around the world for technologies with government applications. SVIP employs a streamlined application and pitch process; brings government, entrepreneurs, and industry together to find cutting-edge solutions; and co-invests in and accelerates transition to market.
- The Department of Health and Human Services (HHS) piloted the Health Tech Sprint initiative, also known in its first iteration as "Top Health," modeled in part after the Census Bureau's Opportunity Project. This effort created a nimble framework to public-private collaborations around bidirectional data links. It piloted new models for iterating on data release for AI training and testing, and it developed a voluntary incentivization framework for a public–private AI ecosystem.
- The HHS Division of Research, Innovation, and Ventures is part of the Biomedical Advanced Research and Development Authority at the Office of the Assistant Secretary for Preparedness and Response. It oversees an accelerator network and is recruiting a nonprofit partner that can work with private investors to fund innovative technologies and products to solve systemic health security challenges, with AI applications being one area of interest. Accelerators will connect startups and other businesses with product development and business support services.

[132] https://www.diu.mil/

[133] https://www.dhs.gov/science-and-technology/svip

Abbreviations

AFOSR	Air Force Office of Scientific Research
AI	artificial intelligence
DARPA	Defense Advanced Research Projects Agency
DHS	Department of Homeland Security
DoD	Department of Defense
DOE	Department of Energy
DOT	Department of Transportation
FDA	Food and Drug Administration
FRVT	Face Recognition Vendor Test
GPS	Global Positioning System
GPU	graphics processing unit
GSA	General Services Administration
HHS	Department of Health and Human Services
HPC	high-performance computing
IARPA	Intelligence Advanced Research Projects Activity
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IMPACT	Information Marketplace for Policy and Analysis of Cyber-risk & Trust (DHS)
ISO	International Organization for Standardization
IT	information technology
IWG	interagency working group
ML	machine learning
MLAI	Machine Learning and Artificial Intelligence (Subcommittee of the NSTC)
NASA	National Aeronautics and Space Administration
NCO	National Coordination Office for NITRD
NDS	Naturalistic Driving Study (DOT)
NIFA	National Institute of Food and Agriculture (USDA)
NIH	National Institutes of Health
NIST	National Institute of Standards and Technology
NITRD	Networking and Information Technology Research and Development program
NLM	National Library of Medicine (NIH)
NSF	National Science Foundation
NSTC	National Science and Technology Council
NTIA	National Telecommunications and Information Administration
ODNI	Office of the Director of National Intelligence
OSTP	Office of Science and Technology Policy
R&D	research and development
RFI	Request for Information
STEM	science, technology, engineering, and mathematics
SVIP	Silicon Valley Innovation Program (DHS)
TREC	Text Retrieval Conference
USDA	U.S. Department of Agriculture
VA	U.S. Department of Veterans Affairs
XAI	explainable AI

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About the National Science and Technology Council

The National Science and Technology Council (NSTC) is the principal means by which the Executive Branch coordinates science and technology policy across the diverse entities that make up the Federal research and development enterprise. A primary objective of the NSTC is to ensure that science and technology policy decisions and programs are consistent with the President's stated goals. The NSTC prepares research and development strategies that are coordinated across Federal agencies aimed at accomplishing multiple national goals. The work of the NSTC is organized under committees that oversee subcommittees and working groups focused on different aspects of science and technology. More information is available at https://www.whitehouse.gov/ostp/nstc.

About the Office of Science and Technology Policy

The Office of Science and Technology Policy (OSTP) was established by the National Science and Technology Policy, Organization, and Priorities Act of 1976 to provide the President and others within the Executive Office of the President with advice on the scientific, engineering, and technological aspects of the economy, national security, homeland security, health, foreign relations, the environment, and the technological recovery and use of resources, among other topics. OSTP leads interagency science and technology policy coordination efforts, assists the Office of Management and Budget with an annual review and analysis of Federal research and development (R&D) in budgets, and serves as a source of scientific and technological analysis and judgment for the President with respect to major policies, plans, and programs of the Federal Government. More information is available at https://www.whitehouse.gov/ostp.

About the Select Committee on Artificial Intelligence

The Select Committee on Artificial Intelligence (AI) advises and assists the NSTC to improve the overall effectiveness and productivity of Federal R&D efforts related to AI to ensure continued U.S. leadership in this field. It addresses national and international policy matters that cut across agency boundaries, and it provides formal mechanisms for interagency policy coordination and development for Federal AI R&D activities, including those related to autonomous systems, biometric identification, computer vision, human-computer interactions, machine learning, natural language processing, and robotics. It also advises the Executive Office of the President on interagency AI R&D priorities; works to create balanced and comprehensive AI R&D programs and partnerships; leverages Federal data and computational resources across department and agency missions; and supports a technical, national AI workforce.

About the Subcommittee on Machine Learning and Artificial Intelligence

The Machine Learning and Artificial Intelligence (MLAI) Subcommittee monitors the state of the art in machine learning (ML) and artificial intelligence within the Federal Government, in the private sector, and internationally to watch for the arrival of important technology milestones in the development of AI, to coordinate the use of and foster the sharing of knowledge and best practices about ML and AI by the Federal Government, and to consult in the development of Federal MLAI R&D priorities. The MLAI Subcommittee reports to the Committee on Technology and the Select Committee on AI. The MLAI Subcommittee also coordinates AI taskings with the Artificial Intelligence Research & Development Interagency Working Group (see below).

About the Subcommittee on Networking & Information Technology Research & Development

The Networking and Information Technology Research and Development (NITRD) Program is the Nation's primary source of Federally funded work on pioneering information technologies (IT) in computing, networking, and software. The NITRD Subcommittee guides the multiagency NITRD Program in its work to provide the R&D foundations for assuring continued U.S. technological leadership and meeting the needs of the Nation for advanced IT. It reports to the NSTC Committee on Science and Technology Enterprise. The Subcommittee is supported by the interagency working groups that report to it and by its National Coordination Office. More information is available at https://www.nitrd.gov/about/.

About the Artificial Intelligence Research & Development Interagency Working Group

The NITRD AI R&D Interagency Working Group (IWG) coordinates Federal R&D in AI; it also supports and coordinates activities tasked by the Select Committee on AI and the NSTC Subcommittee on Machine Learning and Artificial Intelligence. This vital work promotes U.S. leadership and global competitiveness in AI R&D. The NITRD AI R&D IWG spearheaded the update of this National Artificial Intelligence Research and Development Strategic Plan. More information is available at https://www.nitrd.gov/groups/AI.

About this Document

This document includes the original text from the 2016 *National AI R&D Strategic Plan* with updates prepared in 2019 following Administration and interagency evaluation of the 2016 Plan and of community responses to a Request for Information on updating the Plan. The 2016 strategies were broadly determined to be valid going forward with some reemphases and with a call for a new strategy on Private-Public Partnerships in AI. A shaded call-out box has been inserted at the top of each strategy to highlight updated imperatives and/or new focus areas. The 2019 update adds an entirely new Strategy 8 on Private-Public Partnerships in AI.

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THE WHITE HOUSE

Applied Artificial Intelligence at Lincoln Laboratory

Robert A. Bond, CTO

21 August 2019

LINCOLN LABORATORY
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

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What is Artificial Intelligence?

	Observe	Orient	Decide	Act
HUMANS	Hear, See, Smell, Touch, Taste	Human Intelligence		Move, Speak
MACHINES	Collect Data	Artificial Intelligence		Actuate, Communicate

“Narrow AI”

Computer achieves human or superhuman intelligence on specific tasks or in limited environments

Today

“General AI”

Computer achieves human or superhuman intelligence over the full range of cognitive tasks

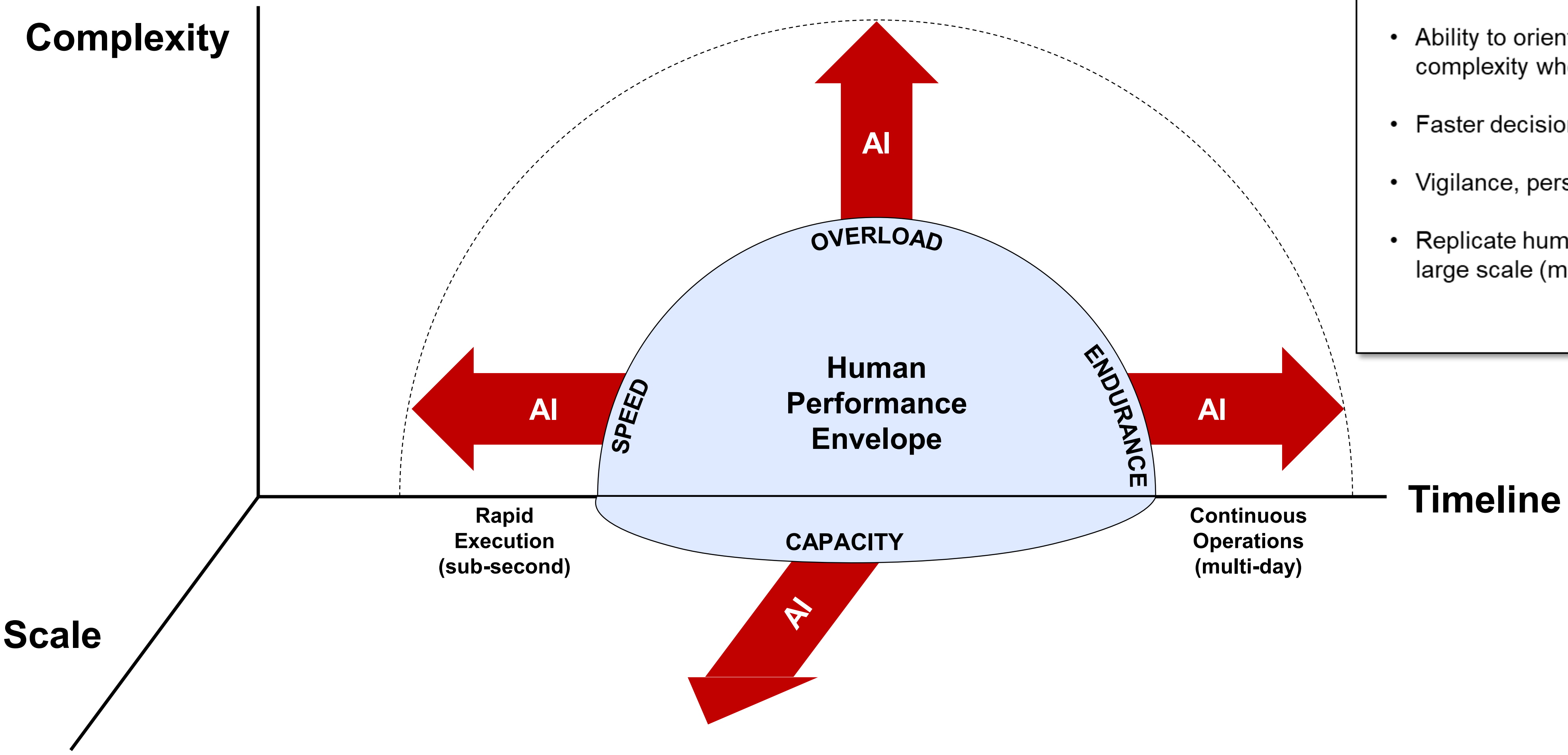
Decades from today?

Adapted from “Preparing for the Future of Artificial Intelligence,” National Science and Technology Council, Oct 2016

Outline

- Artificial Intelligence (AI) for National Security
- AI Technology Functional Viewpoint
- A Few Examples
- Strategic Viewpoint
- Summary

Recent AI Directions

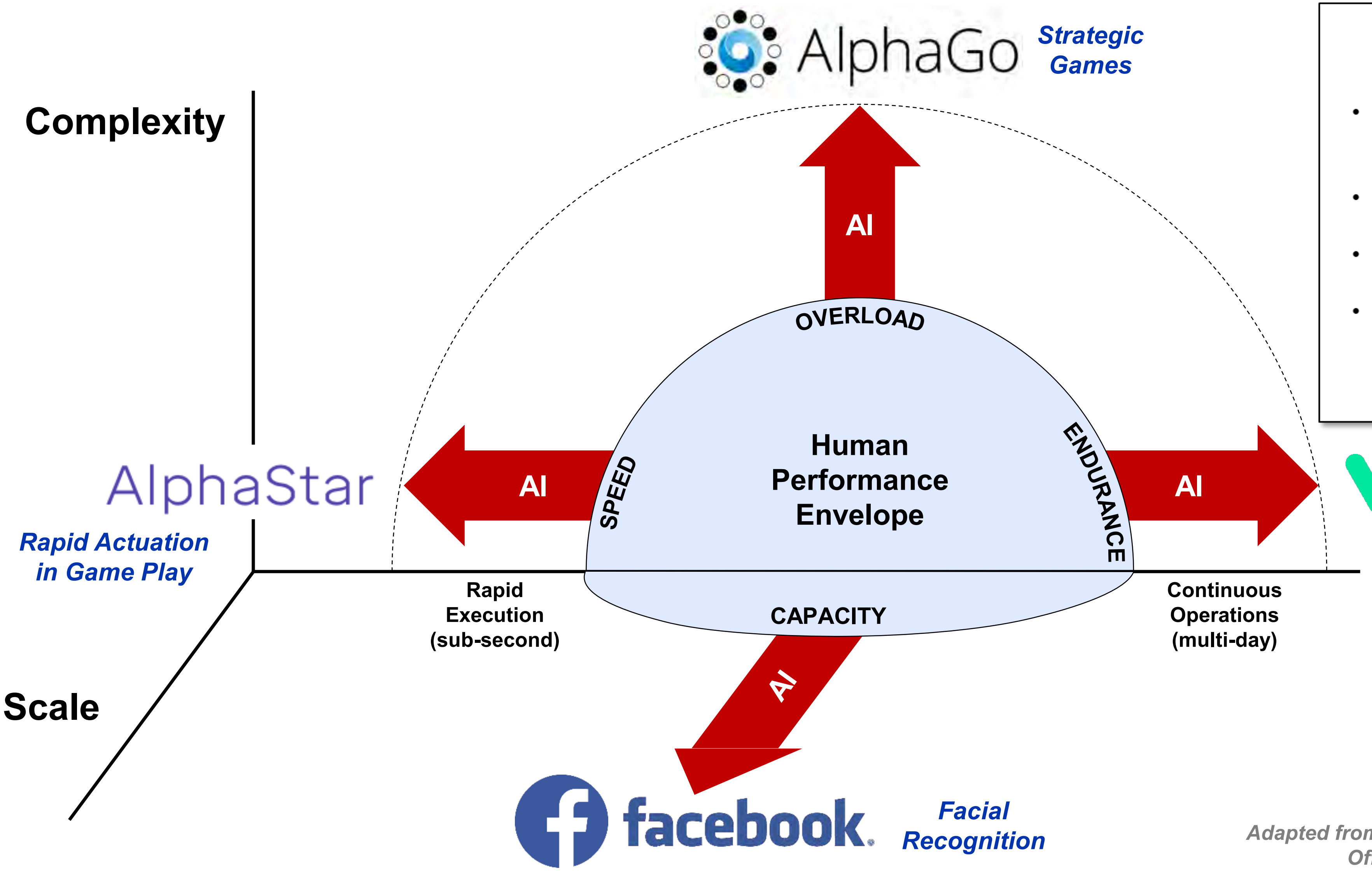


Key Benefits of AI

- Ability to orient & decide in complexity when humans cannot
- Faster decision making
- Vigilance, persistence, endurance
- Replicate human performance at a large scale (massing)

Adapted from "Technical Assessment: Autonomy," Office of Technical Intelligence, Feb 2015

Some Recent Commercial AI Advances



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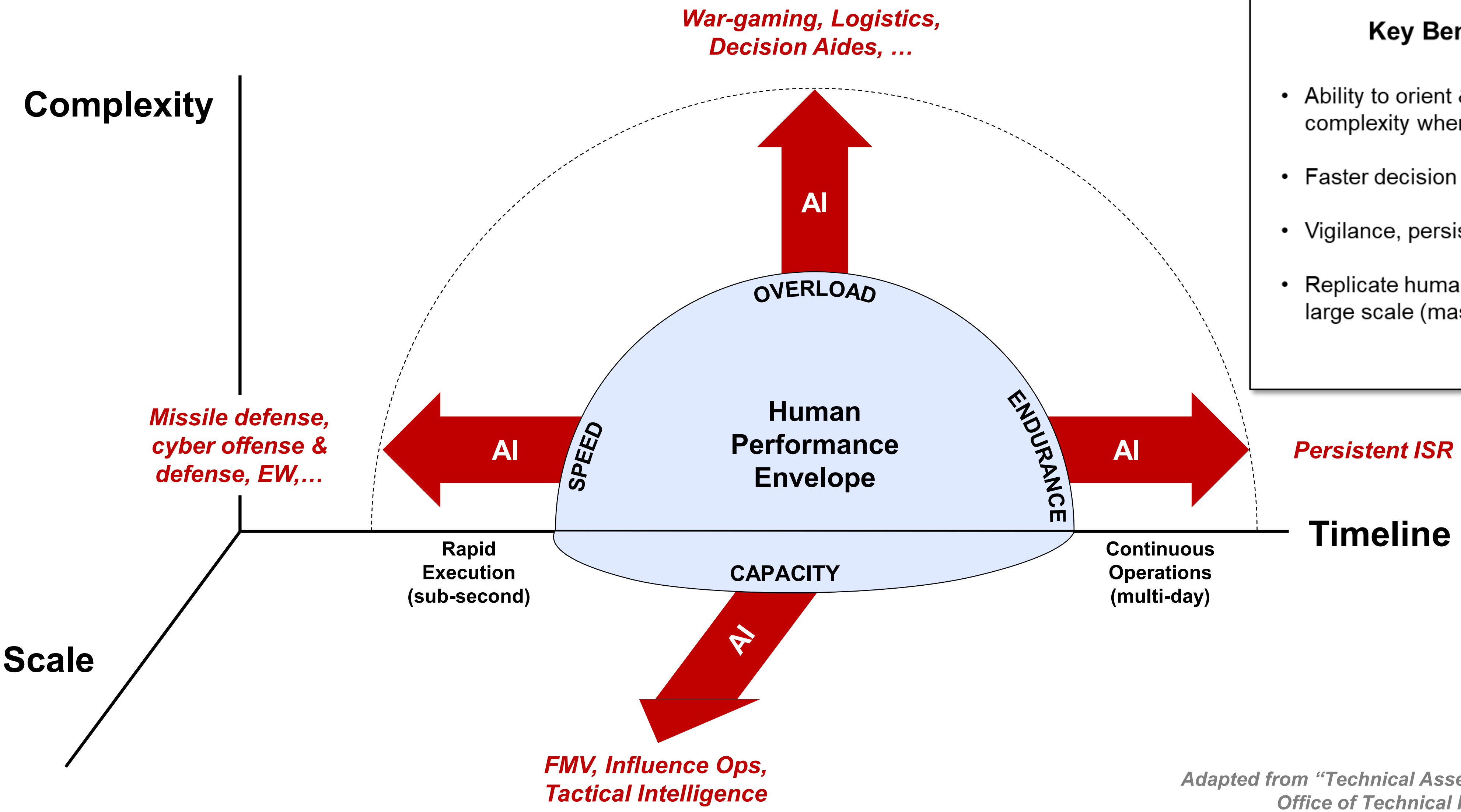
Example AI Applications for National Security



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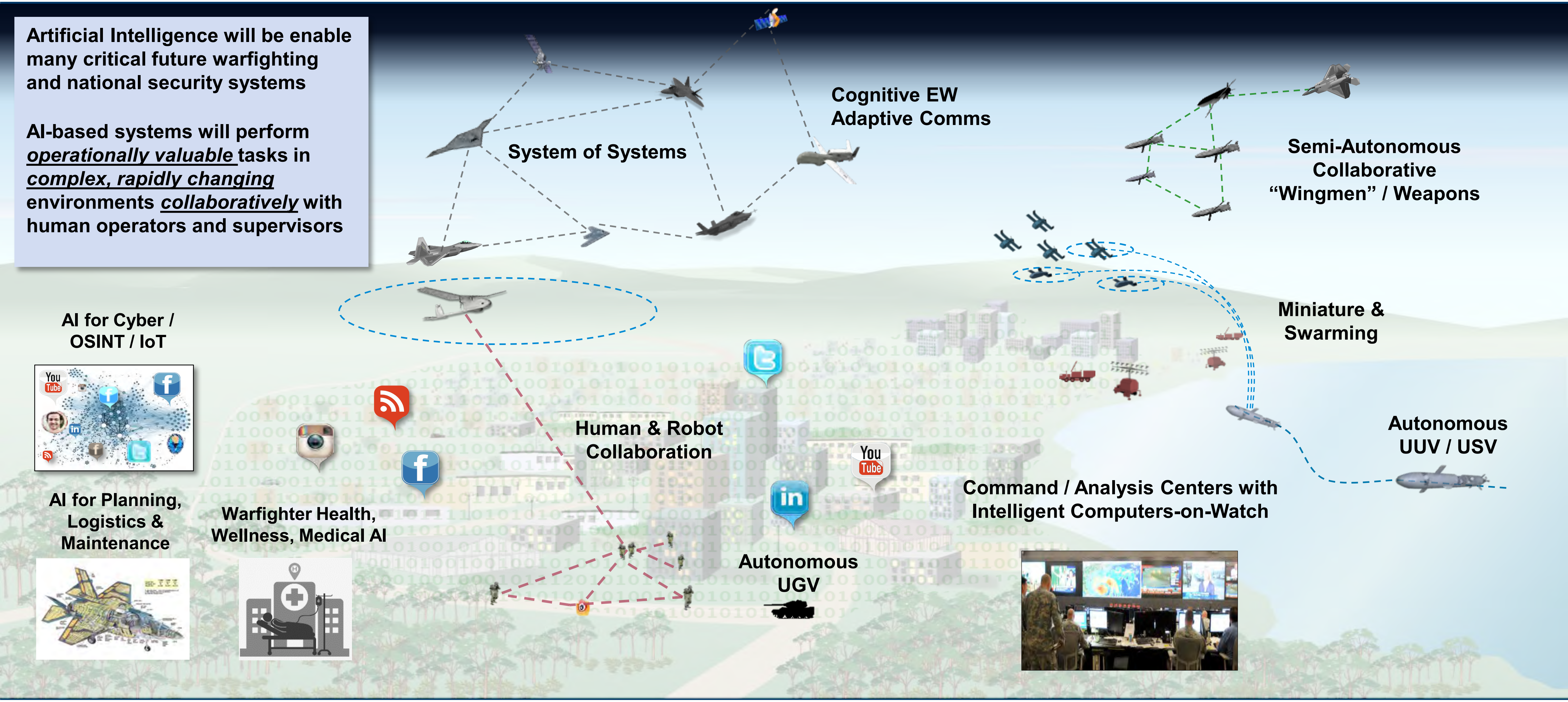
Military AI Systems Landscape of Tomorrow

Artificial Intelligence will be enable many critical future warfighting and national security systems

AI-based systems will perform *operationally valuable* tasks in *complex, rapidly changing* environments *collaboratively* with human operators and supervisors



Derived from the MIT LL Autonomous Systems Study, November 2016

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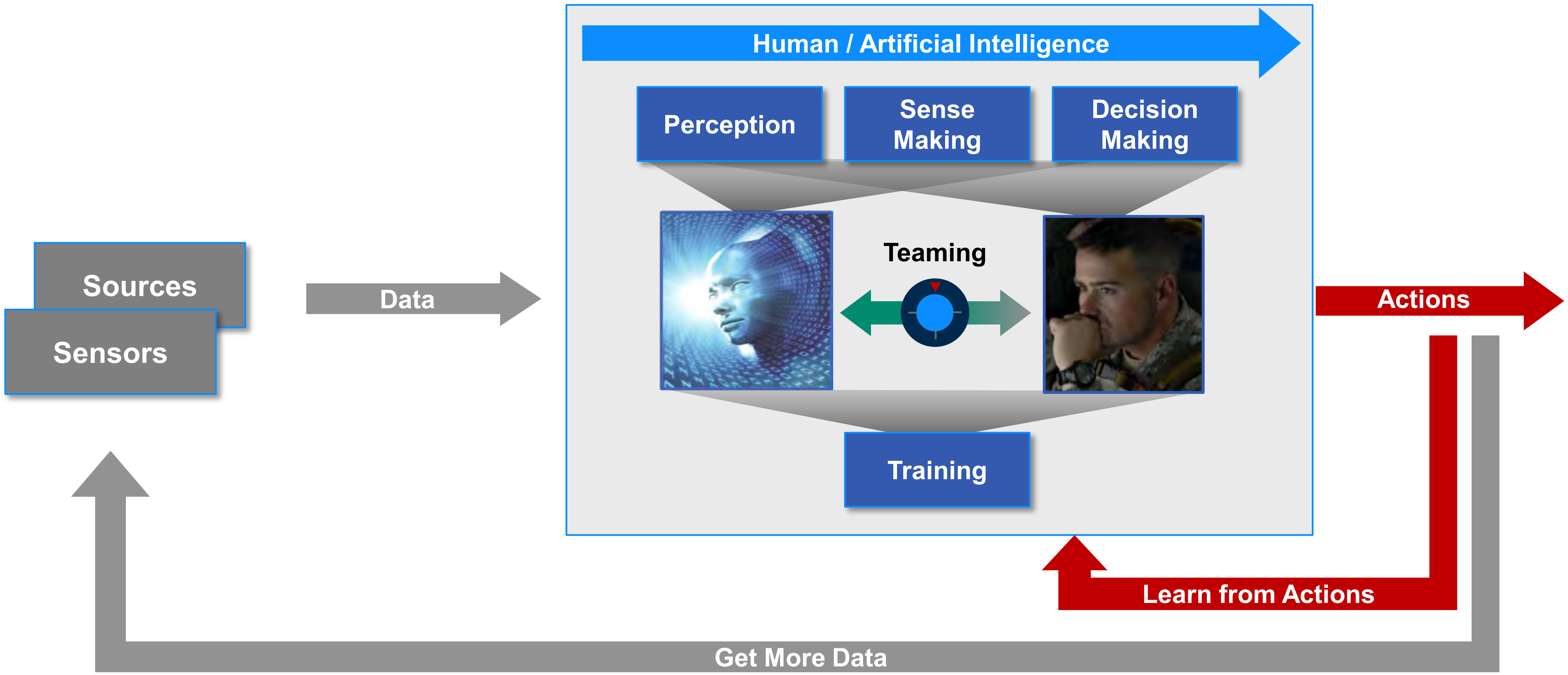
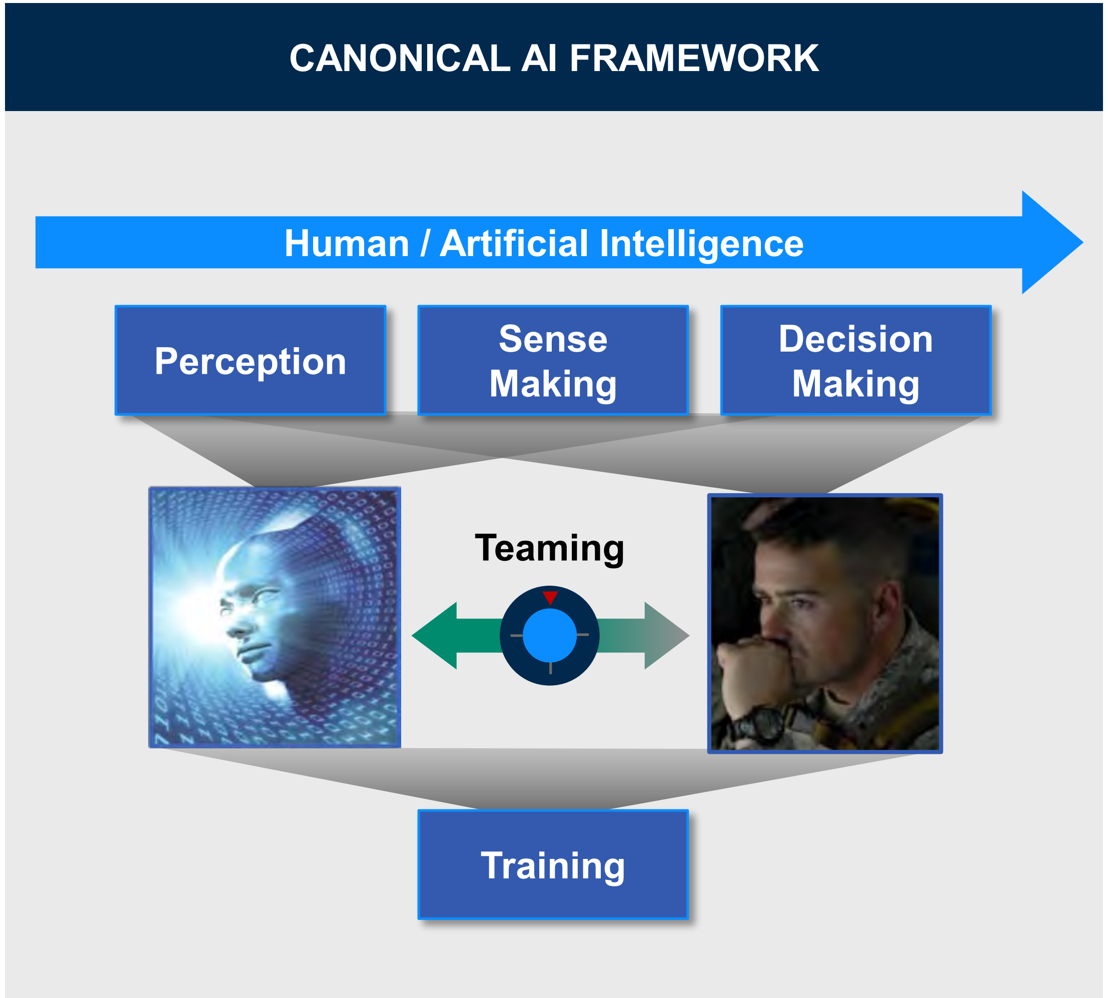
A Functional View of Artificial Intelligence

Human Intelligence and Artificial Intelligence working together as a Team



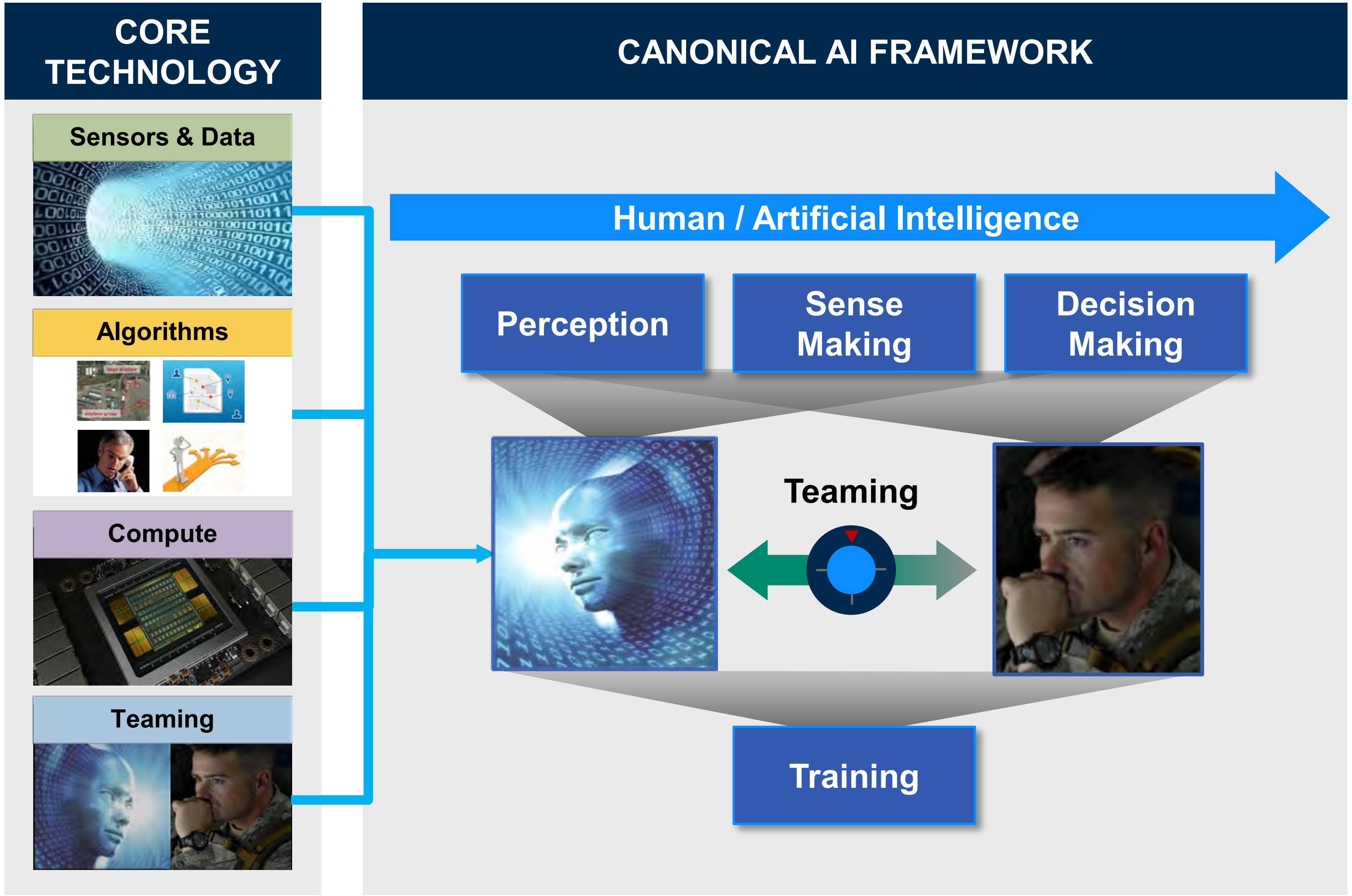
AI: Artificial Intelligence
ML: Machine Learning

Building the Framework for AI

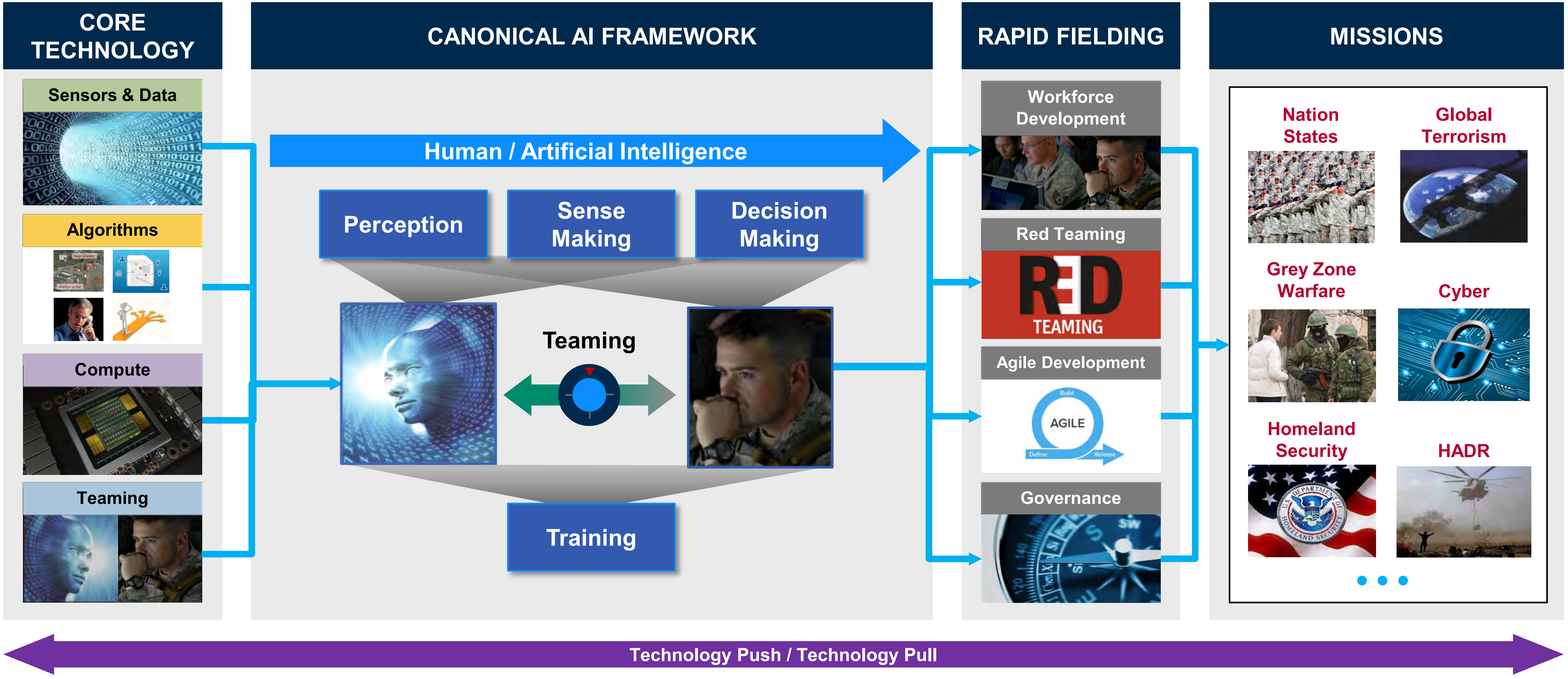


What are the core competencies that we need to build this AI framework?

Building the Framework for AI

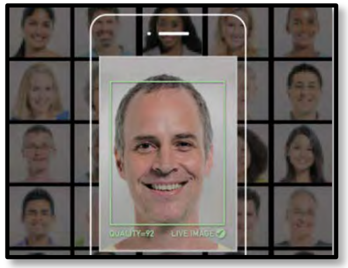
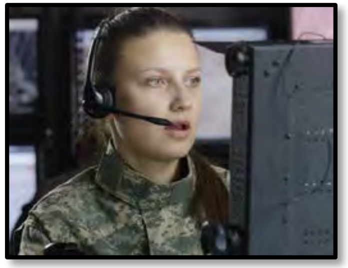


Building the Framework for AI



How National Security AI Differs from Commercial AI

Similar Tasks…

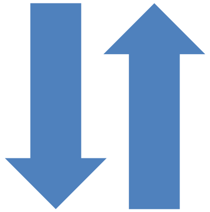
	Commercial	National Security
Image Analytics		
Language Processing		
Autonomy		

…Different Resources and Environment

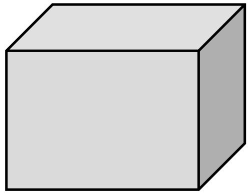
Commercial

Similar Sensors, Crowd-sourced, Pervasive Access, Ample Labeled data

High Capacity Datalinks



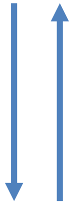
Centralized Computing



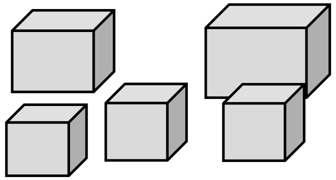
Cooperative Environment

National Security

Unique Sensors, Few Analysts, Limited Access Data-starved and/or countered



Low Capacity / Intermittent Datalinks



Isolated Computing

Adversarial Environment

Example Technology Gaps and Recommended Thrusts

	Commercial Space	DoD Space	Recommended Thrusts
Sensors & Data 	• Proliferation of new and improved sensors • Large, curated datasets for training AI	• Fusing multi-modal data from classified sensors & with commercial data streams • Data labeling of classified data streams, and data protection	**Dataset Management** • Manage and exploit commercial, classified data across security domains • Create & protect labeled data for missions
Algorithms 	• Large labeled datasets • Data is easy to collect • Labels are free or crowd source	• Large amounts of data, but little “truth” data to train on. • Data on events or objects of interest is rare	**Data-Starved AI** • Reduce data labeling burden • Develop algorithms that learn from limited data or learn from machines • Develop virtual environments to train AI
Compute 	• Centralized computing • Reliable communications • Emerging AI for IoT	• Premium on Size, Weight, and Power (SWAP) • Contested communications • Data processing and AI need to be delivered to the tactical edge	**Tactical Edge AI** • Specialized embedded processing for processing at speed and scale • Tactical clouds and reach-back enterprise clouds for for C2/PED and data fusion
Teaming 	• Adaptive and multi-modal Human-Machine Interfaces • Cognitive assistants for personal tasks • Consequences of being wrong are often not huge	• AI to assist in warfighting tasks in adversarial environments • Trust is key as consequences of bad decisions could be huge	**Trusted AI** • Explainability, Interpretability, and Transparency • Safe, secure, resilient, and robust AI • Training environments for joint human-machine training

C2 = Command and Control
PED = Processing, Exploitation, and Dissemination

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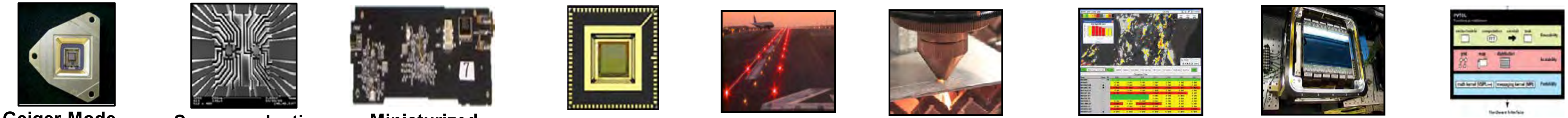
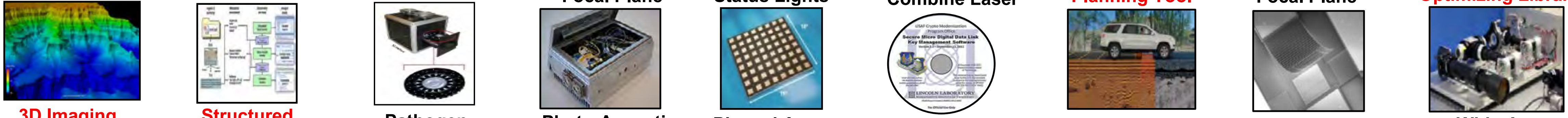
Lincoln Laboratory R&D 100 Awards Over 9 Years

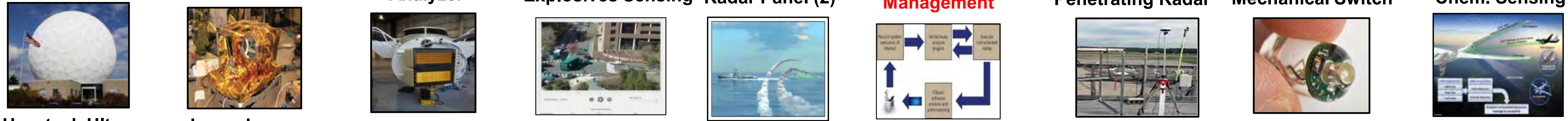
48 Awards, 23 Involving AI or Advanced Algorithms



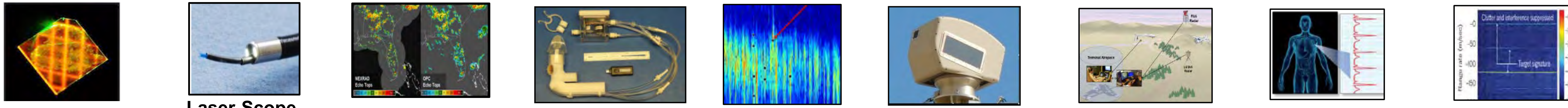
Geiger-Mode Single Photon Detector | Superconducting Nanowire Detector | Miniaturized RF Receiver | Digital-Pixel Focal Plane | Runway Status Lights | Wavelength Beam-Combine Laser | Air Route Planning Tool | Wide FOV Curved Focal Plane | Parallel Vector Tile Optimizing Library



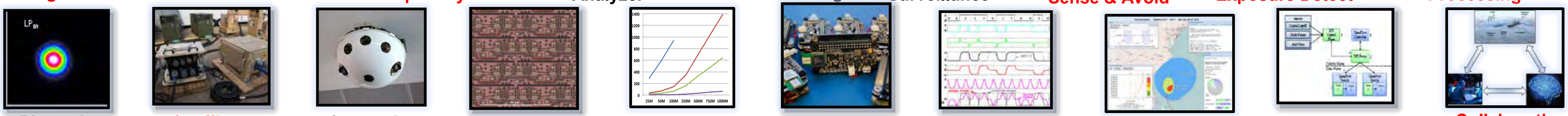
3D Imaging Airborne Ladar | Structured Knowledge Space | Pathogen Analyzer | Photo-Acoustic Explosives Sensing | Phased Array Radar Panel (2) | Crypto Key Management | Localizing Ground-Penetrating Radar | Micro Electro-Mechanical Switch | Wide-Area Chem. Sensing



Haystack Ultra-Wideband Radar | Lunar Laser Comm. (2) | Sense & Avoid Radar | Video Content Summarization | Distributed Engage/Coordinate | Dynamic Analysis Platform | Small Airport Surveillance | Ingestible Vital Sign Monitor | UAS Collision Avoidance System



Quantum Magnetometer | Laser-Scope Spinal Surgery | Offshore Precipitation Capability | CO_2/O_2 Breath Analyzer | Polarimetric Radar Tracking | Wide-Area IR Surveillance | UAS Ground-Based Sense & Avoid | Pre-Symptom Exposure Detect | Phase Diversity Processing



Photonic Fiber Lantern | Intelligent Power Distrib. | Immersive Imaging | VLSI for Super-Conducting Elect. | Ultrafast DNA Data Search | Peregrine GPS-Free Nav. | Multi-Rate DPSK Modem | Hurricane Evacuation Plan | Dynamic Flow Isolation | Collaborative Optimization

Red text indicates AI-based or Advanced Algorithm innovation

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AI Thrusts across Lincoln Laboratory

Air, Missile, and Maritime Defense Technology

- Ballistic Missile Defense
- Interceptor and Sensor Systems
- Undersea systems
- Advanced Technology

Homeland Protection and Air Traffic Control

- Transportation
- Homeland protection
- Bio-Engineering
- Humanitarian Assistance and Disaster Response

Cyber Security and Information Sciences

- Cyber Operations
- Human Language Tech.
- Secure Resilient system
- Cyber Analytics
- Supercomputing

Communication Systems

- Satellite Comm.
- Tactical Networking
- Lasercom / Quantum
- Spectrum Operations

Engineering

- Fabrication
- Energy Systems
- Control & Autonomous Systems
- Rapid Prototyping

Advanced Technology

- RF Technology / Lasers
- Imagers and novel sensors
- Quantum Computing
- Microelectronics

Space Systems and Technology

- Space Control
- Persistent surveillance
- Environmental monitoring
- Technology for IC

ISR and Tactical Systems

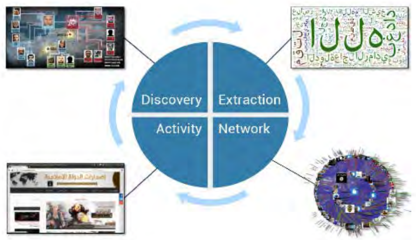
- Embedded AI and Open Architectures
- PED
- Autonomous Systems
- Red Teaming

Lincoln Laboratory is applying Artificial Intelligence technology across all mission areas

PED = Processing, Exploitation, and Dissemination
ISR = Intelligence, Surveillance and Reconnaissance

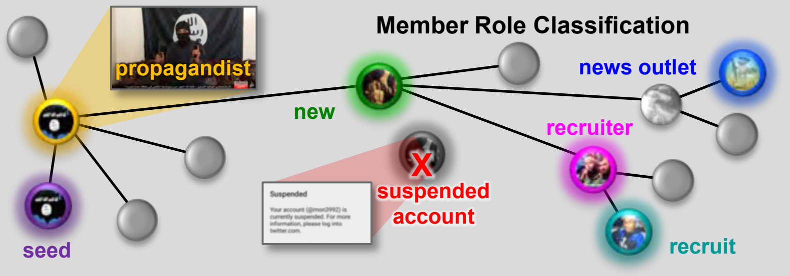
A Few National Security Applications of AI at Lincoln Laboratory

Human Dark Networks Analysis



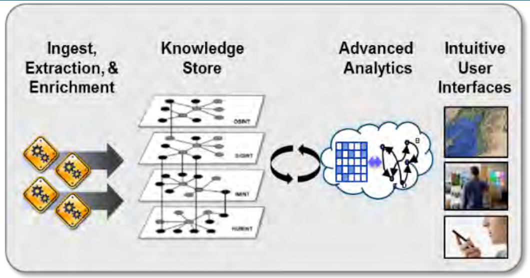
Next-generation human language and network analytics to uncover and understand dark network activities

Threat Network Detection and Tracking



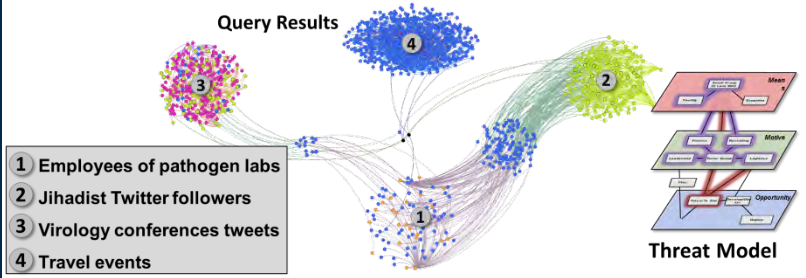
Enable analysts to automatically collect and characterize threat networks, actors, and activities on social media

Intelligent Computer on Watch



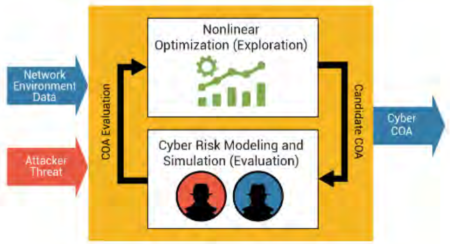
An autonomous processing, exploitation and dissemination system for imagery analysis

Indications and Warnings for BioWMD



Design and build a prototype of flexible early warning system that can be rapidly reconfigured to address emerging threats

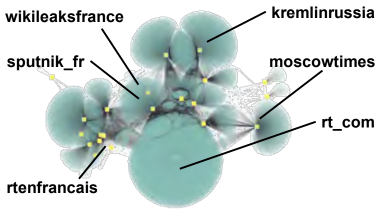
Automated Cyber Decision Engine



Build an automated AI decision engine to proactively defend networks

Monitoring Influence Operations

Top Twitter hashtags surrounding French elections

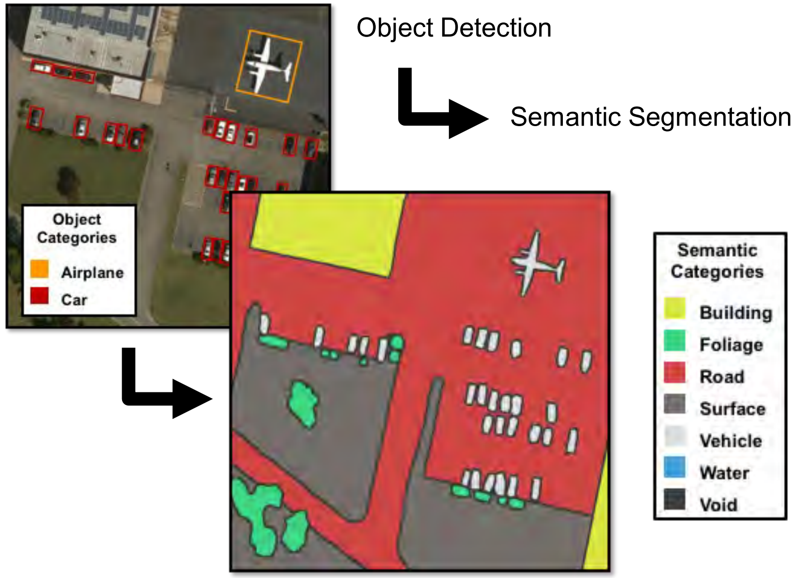


Twitter mention network of Russian-affiliated accounts

Detect Influence Operations in Publicly Available Information (PAI)

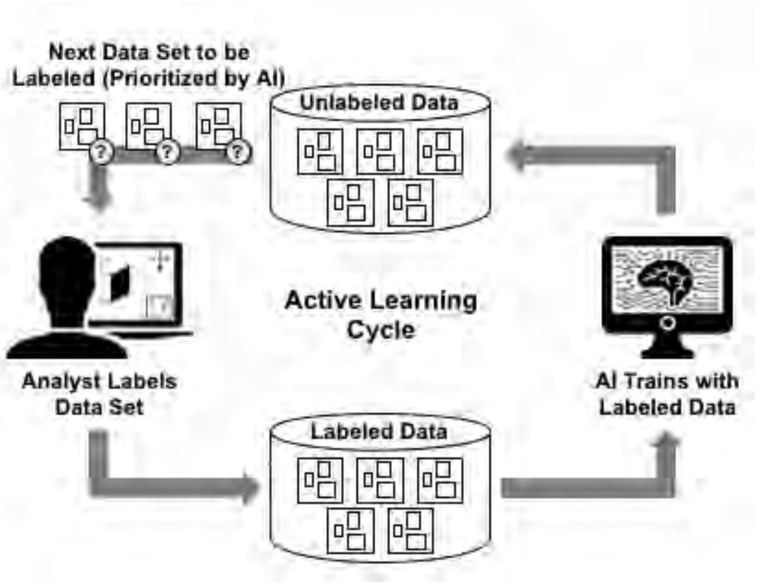
Computer-on-Watch AI Analytics

Learning from Limited Data



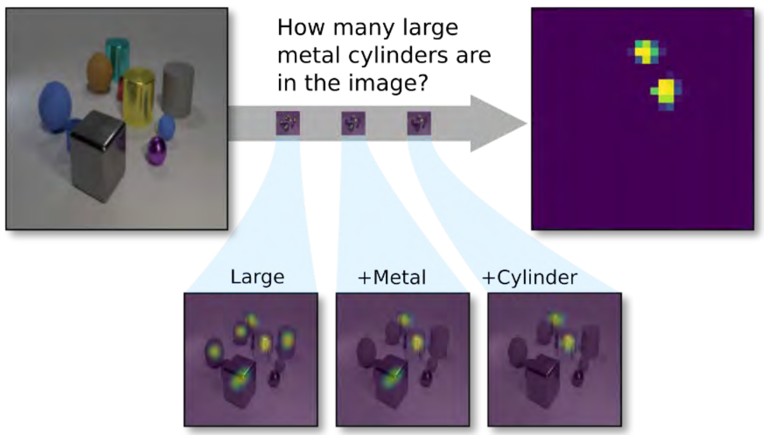
- Labeling at the sematic level increases labeling efficiency and allows higher-level reasoning

Efficiently Labeling Data



- Bayesian neural networks improve the effectiveness of active learning, robustness, and labeling efficiency

Interpretable Visual Reasoning



- Model transparency helps with understanding machine "thought processes" & diagnosing system errors

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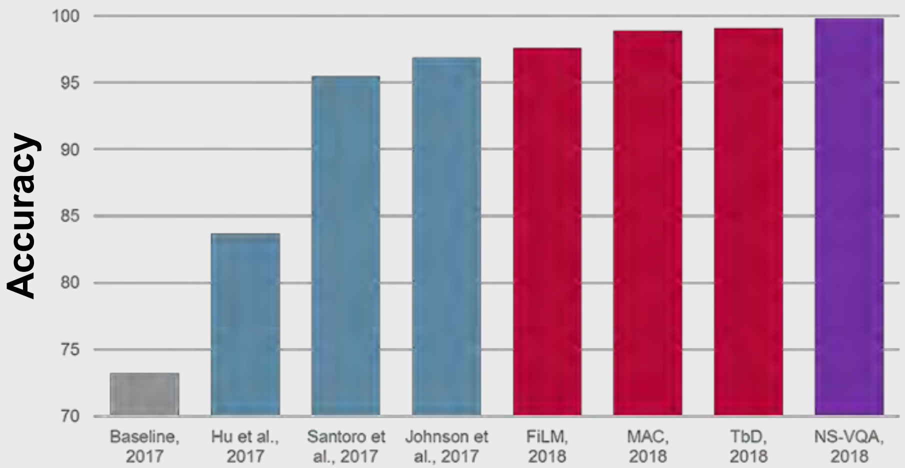
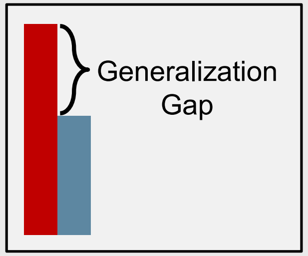
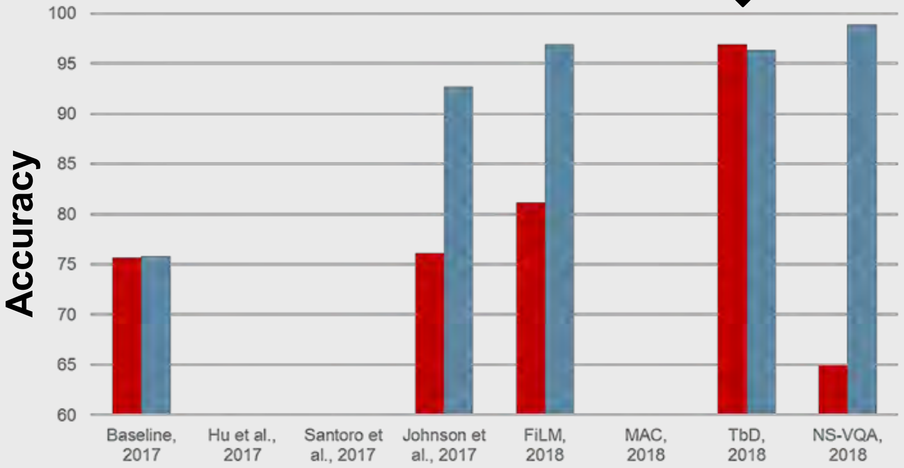
Interpretable Visual Reasoning



Performance on CLEVR dataset

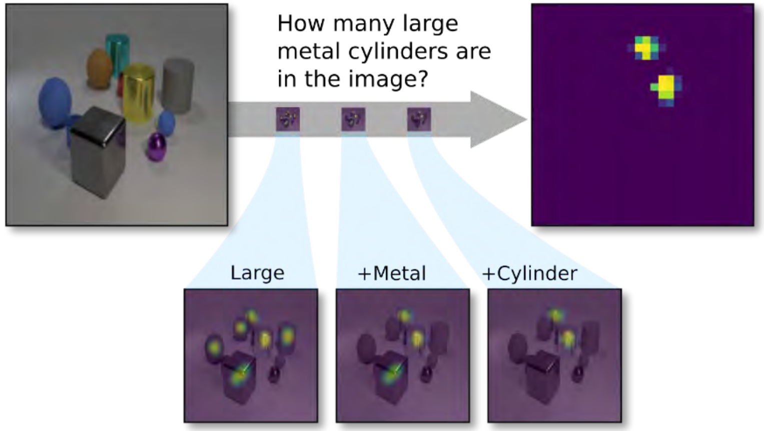


MIT LL approach



World's best generalization performance

Interpretable Visual Reasoning



- **Model transparency helps with diagnosing system errors**

Outline

- Artificial Intelligence (AI) for National Security
- AI Technology Functional Viewpoint
- A Few Lincoln Lab Examples
- Strategic Viewpoint
- Summary

AI for the National Security – Goals & Strategies

Goal 1: Get AI Now

*Identify** and pursue "quick wins"*

- **Develop AI-enabled DoD capabilities by adapting mature core AI technologies through rapid prototyping and field testing**
  - Increase collection, aggregation and curation of national security data… protect critical data!
  - Develop approaches to verify and validate AI performance
  - Red-team the capabilities
  - Engage the users
- **Fund existing Programs-of-Record to assess and acquire AI-based capabilities**
- **Standup and support dedicated AI organization i.e. JAIC and AIM charter**

Impact

Current Generation DoD AI

** Initially, the core technologies will come principally from the commercial private sector. Ultimately, a DoD AI ecosystem is needed to serve DoD specific needs and ensure national leadership

Time Horizon of Investment Impact

Note: chart says "DoD" but strategies apply across National Security organizations

AI for the National Security – Goals & Strategies

Goal 2:
Get Ahead in AI

*Accelerate** DoD acquisition of vanguard AI*

Impact

Next Generation DoD AI

- Pursue core AI technology development in potential berakthrough areas where National Security needs are unique or pressing
  - AI for data-starved scenarios
  - AI for the tactical edge
  - AI for national security data streams
  - AI robustness and countermeasures

- Engage leaders in AI from academia and private sector
  - Challenging problems & breakthrough research
- Leverage FFRDCs, UARCs & national labs
  - Rapidly apply advances to DoD context
- Establish DoD stakeholder buy-in and engage user-base early and often

** By transitioning technologies directly from early R&D in academia and private sector to DoD applications, DoD can field capabilities more rapidly than can our adversaries

Time Horizon of Investment Impact

Note: chart says "DoD" but strategies apply across National Security organizations

AI for the National Security – Goals & Strategies

Goal 3:
Stay Ahead in AI

Develop the enabling DoD ecosystem

- ***Cultivate DoD AI acquisition ecosystems***
  - *Create partnerships between academia, government labs, industry and DoD/IC*
  - *Develop technology pipeline to support DoD needs / opportunities*
  - *Engage the end users professionals*
  - *Fund balance between foundational, core, and applied AI*
  - *Adjust the acquisition process for rapid agile insertion of breakthroughs ahead of commercialization*
- ***Hire and educate the DoD AI workforce***
  - *Users, researchers, acquisition professionals*
  - *Lead conversation on ethical and societal implications*
- ***Create the AI infrastructure & policy***
  - *Provide scalable computing for organic capabilities*
  - *Clear policy guidelines for use and adoption of AI*

Future Generations of DoD AI

Impact

Time Horizon of Investment Impact

Note: chart says "DoD" but strategies apply across National Security organizations

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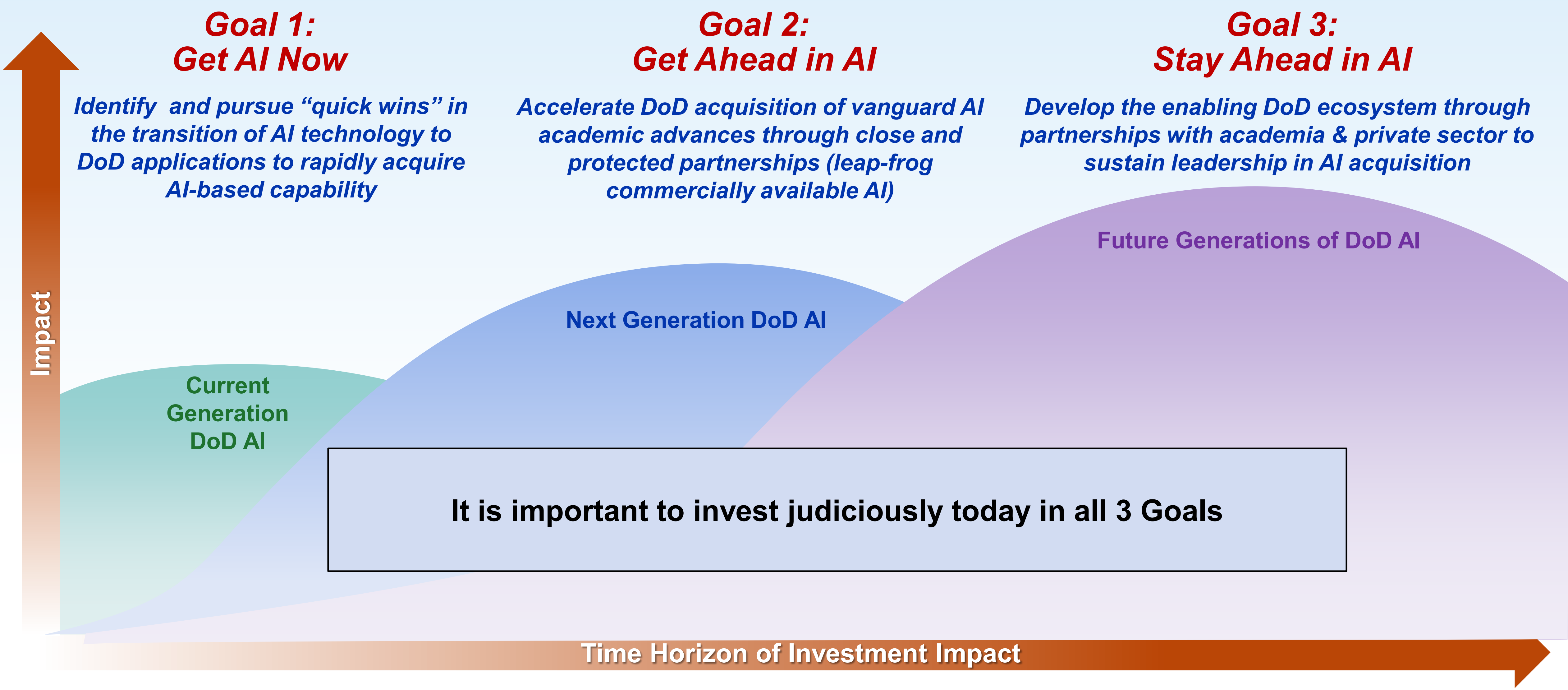
AI for the National Security – Goals & Strategies



Note: chart says "DoD" but strategies apply across National Security organizations

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Summary

- "Narrow" AI can provide near-term & sustained benefits to National Security
  - Speed of response
  - Throughput and scale of operations
  - Cognitive resilience and reduced cognitive overload
  - System and human endurance
- An AI technology functional viewpoint highlights
  - Importance of integrating the human with the machine (teamwork)
  - Need to focus on core technology differences and user involvement
- Lincoln Laboratory is applying AI across all of its mission areas
- An AI adoption strategy is needed that balance
  - Getting commercial AI into applications today
  - Developing and accelerating transition of vanguard AI to achieve leadership
  - Creating the national security AI ecosystems needed to sustain leadership

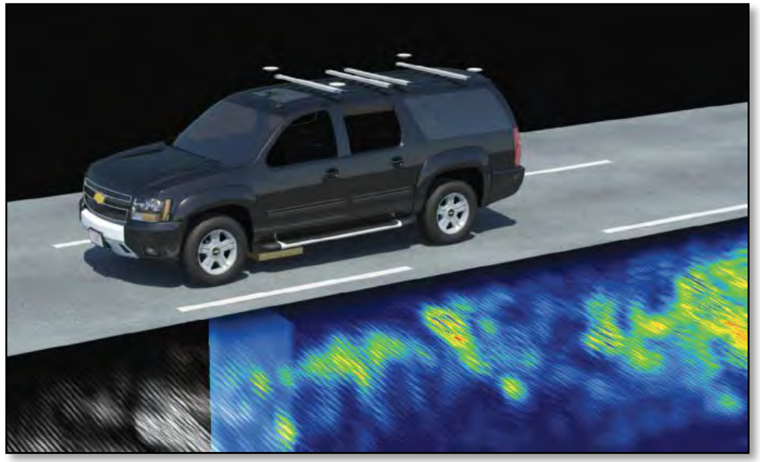
Backup

Guiding Questions

1. What is the state-of-the-art in AI R&D and application and where are future trends headed? How do you stay ahead of the curve on cutting edge advancements?
2. How will advances in AI impact the current national security environment and change the global threat landscape?
3. How can AI applications be used to enhance U.S. national security and defense and maintain our strategic advantage? What types of R&D is needed to support such applications today and in the future?
4. How can the U.S. government better support AI R&D and application fielding? What changes to current funding levels, acquisition mechanisms, or other systems/policies do you recommend?
5. What changes are required to close the gap between the current and desired competitive advantage for national security AI application?

A Few National Security Applications of Autonomous Systems at Lincoln Laboratory

Autonomous Ground Vehicles



- Prototype autonomous vehicle control using ground-penetrating radar
- Capable of operations in harsh weather conditions (e.g. snow)

Autonomous Air Vehicles

- Early-generation Perdix autonomous micro-air-vehicle
- Embedded AI designed to operate in swarming context

Autonomous Undersea Vehicles

- Early proof-of-concept for undersea high bandwidth laser communication system
- Enabling component for coordination in autonomous undersea vehicle applications

The Rocky Relationship Between Washington and Silicon Valley

Clearing the Path to Improved Collaboration

Center for a New American Security

copia

By Loren DeJonge Schulman, Alexandra Sander, and Madeline Christian

INTRODUCTION

The Trump administration inherited a decent foundation on which to build collaborative ties between Washington and hubs of American innovation like Silicon Valley. Both President Barack Obama and former Secretary of Defense Ash Carter invested heavily in improving government outreach to the tech industry, bringing Washington and Silicon Valley closer than they have been in decades on both policy substance and technology solutions in the national security space. But the relationship was far from perfect, and it is as yet unclear whether lessons, good and bad, from Obama's efforts have been taken seriously by their successors.

Serious work remains to be done in substantive collaborations on countering violent extremism, the future of encryption, cybersecurity threats, and surveillance. Furthermore, several minefields lay ahead – such as addressing the technical and foreign policy challenges of "fake news," the ongoing immigration debate, and the impact of automation on both domestic and international security matters.[1] At this stage, it is unclear whether there will be similar levels of engagement with the tech industry to collaborate on solutions to these challenges or if the relationship will be sustained.

President Donald Trump certainly appears to be interested in what technology leaders on the West Coast have to offer, recruiting contributors like Apple CEO Tim Cook, Salesforce CEO Marc Benioff, and Bill Gates to support the new White House Office of American Innovation, which is designed to bring "fresh business ideas to government."[2] This may prove to be a worthwhile initiative, but the outlook for serious engagement on hard problems of mutual interest is already marred by the administration's exclusionary immigration policies, which quickly provoked a backlash among technology companies.[3] Furthermore, in the run-up to the election, much of the tech industry publicly supported Hillary Clinton, making the dissipation of bicoastal tensions all the more difficult in the short term.

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1 Jessica Guynn, "Tech Workers Vow Not to Build Trump Muslim Registry," USA Today, December 13, 2016, https://www.usatoday.com/story/tech/news/2016/12/13/tech-workers-vow-not-build-trump-muslim-registry/95407242/

2 Emily Dreyfuss, "Innovation Can Fix Government, Sure. Either That or Break It," Wired, March 27, 2017, https://www.wired.com/2017/03/innovation-can-fix-government-sure-either-break/

3 Davey Alba, "The Silicon Valley Engineers Driving the Anti-Trump Train," Wired, February 3, 2017, https://www.wired.com/2017/02/silicon-valley-vs-trump-tech-workers-wield-real-power/

But this relationship has never been easy, and political change may have less impact than the long-standing cultural divides and differences in norms separating both communities. Serious policy and legal arguments have also divided them – such as the iPhone encryption debate and subsequent courtroom disputes. Despite that, Obama recognized "technology as an engine to improve lives and accelerate society more quickly than any government body," while Carter also saw vast potential for a synergistic relationship between the Department of Defense and startups, going so far as to set up the Defense Innovation Unit Experimental (DIUx) as a permanent West Coast outpost.[4] Though perhaps more warily, CEOs and founders have opened their doors to government delegations and invested serious time and resources in global challenges. And as American technology companies expand globally, they will almost certainly continue to touch on matters of international affairs – finding themselves caught between geopolitical actors and their bottom line, faced with unpredictable or hazardous uses of their product, or needing a government voice to protect their markets. Changes to leadership do not change this reality. Neither the technology community nor the international security policy community should give up on cross-sector collaboration in the many arenas that could yield mutual benefits.

A close look at why Silicon Valley–D.C. engagement on sensitive security policy issues has struggled, when it has worked, and the key ingredients to make it more productive is overdue. Like any couple with high demand, high stress day jobs and who have difficulty communicating, this relationship may benefit from a clear-eyed assessment and relationship counseling.

METHODOLOGY

The Center for a New American Security (CNAS) and the Copia Institute launched a qualitative, exploratory study to investigate the demand signal for better dialogue on issues intersecting the technology and international security policy communities.[5] The team used personal interviews and, later, a more detailed online survey with subject matter experts, policy leaders, academics, technology executives, and consultants. Next, they began to build an understanding of the communities' perceptions of each other and incentives for smaller startups, larger technology companies, and international policy experts to work together (or not).

Though a relatively small and nonscientific sample, the survey and interview participants were deliberately chosen for both their extensive experiences and their ability to discuss dynamics in their communities in an informed way. Both the survey and interviews were conducted on a not-for-named-attribution basis. The questions focused on drawing out the details of respondents' perceptions of cross-sector collaboration, experiences engaging with the "other" community, and anticipation of opportunities for productive dialogue.

Of note: All input was collected before the 2016 election. While the change in political context may have an impact

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4 Jenna Wortham, "Obama Brought Silicon Valley to Washington," The New York Times, October 25, 2016, https://www.nytimes.com/2016/10/30/magazine/barack-obama-brought-silicon-valley-to-washington-is-that-a-good-thing.html

5 CNAS and the Copia Institute defined the international security policy community to include nongovernmental and governmental organizations focused on influencing, developing, or implementing international security policy. They also defined the technology community to include organizations that are premised on creating value through disruption and are growing quickly, expanding, or exerting influence globally.

on how these communities engage, their core cultural differences and the nature of the challenges to be addressed remain constant.

Among the questions explored:

- What is your understanding of the policy-technology community relationship?
- What are substantive policy topics on which these communities might productively engage?
- Which collaborative methods are the most and least effective in bringing these communities together on policy matters?
- What sorts of participants are useful – or not – to these cross-sector engagements?
- What factors contribute to successful policy collaboration? What barriers prevent it?
- What specific experiences do you believe the communities could learn from?

CNAS and the Copia Institute also leveraged their prior research and experience analyzing and working in the spaces between the Washington, D.C., international security policy community and the Silicon Valley technology community.

FINDINGS

The findings from CNAS and the Copia Institute's exploratory study will not seem groundbreaking to those who work at the nexus of the technology and international security policy communities. The survey and interview responses confirm the conventional wisdom that the policy-technology relationship is strained and, at times, adversarial. Many predictable barriers stand between these communities and effective collaboration – barriers that will sound familiar to anyone who has sought professional relationship advice. So, if the problems are so obvious, why is it that neither community feels comfortable in the relationship?

Engagement between the technology and international security policy communities is occurring, but its effectiveness is not a given. For that reason, we sought views on key ingredients that make engagements succeed or fail. Some of the most critical determinants for improving collaboration included such factors as endorsement and involvement of leaders in any such project; the kinds of participants in any engagement; how the initiating question or task is framed; personal relationships between participants; and follow-up by participants.

This last issue – follow-up by participants – received the most attention throughout the study. Over and over, survey and interview participants described productive sessions – meetings, conferences, brainstorming – that ultimately went nowhere. In an earlier CNAS study of attempts by the Department of Defense (DoD) to partner with Silicon Valley, tech industry and government representatives alike lamented an increasingly frustrating phenomenon they called "tech tourism": government personnel seeking out generic meetings with technology companies without defined objectives and no plan for concrete results or further engagement.[6] Respondents in this project similarly characterized

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6 Ben FitzGerald and Loren DeJonge Schulman, "12 Months In – 8 Months Left: An Update on Secretary Carter's Innovation Agenda" (Center for a New American Security, April 2016), https://www.cnas.org/publications/reports/12-months-in-8-months-left-an-update-on-secretary-carters-innovation-agenda.

much of this failure in cross-sector engagement as largely, though not uniquely, a government problem – although, in general, the government being the "suitor," rather than the target, in the courtship could be an important factor.

To expand on this study, CNAS and the Copia Institute set out to identify specific steps that could improve collaboration between the technology and international security policy communities. Barriers to positive engagement may vary from one issue to the next but they share a pernicious point of commonality: poor communication and lack of shared understanding. The policy-technology relationship is not strained because of a lack of awareness of shared problems, but because productive dialogue is frequently derailed by divergent perspectives and mutual misjudgment.

The following themes, repeated by both survey and interview respondents, illustrate why common ground between these communities is in such short supply and suggests initial steps to diminish the barriers to policy-technology collaboration.

Preexisting tension between the technology and international security policy communities undermines the success of professional relationships and engagements between the groups. Unsurprisingly, very few respondents expressed positive views of the state of relations between Silicon Valley and Washington. Nearly 80 percent of survey respondents rated the current state of collaboration between the communities as "poor" or "very poor," with communication and coordination drawing similarly negative rebukes. Some respondents felt this bad blood was an elephant in the room and noted that open acknowledgment of tensions is a prerequisite for a positive working relationship. Politely whitewashing cultural differences is not viable, nor is ignoring past serious disputes. One of those surveyed highlighted the highly fraught Apple-FBI encryption debate and called for "apologies…for attacking patriotism or motives" as a first step for related discussions. Getting past these tensions requires establishing a baseline understanding of each other's goals and interests – and how they clash or overlap – to help "stakeholders focus on finding a common solution rather than defending existing positions," as one technology community respondent reported. Another warned that failing to take such steps to ameliorate "the current adversarial nature of the relationship can only lead to distrust and heightened aggression from each side."

The incentives for collaboration are understood differently across the technology and international security policy communities. Despite the frustration expressed over the current state of relations, all but two survey respondents reported that technology companies have something to gain from increased collaboration with the international security policy community, and every single survey respondent said the policy community would gain from increased cooperation. Whether due to potential gains or simply resignation, there is a sense of necessity for improving this partnership, particularly given the number of critical intersecting issues on the horizon. One survey respondent stated, "We can't not bridge these communities, [it's] too critical to the nation and the world." Nonetheless, members of both communities disagree about the specific benefits of collaboration.

Still, respondents from the technology community perceive uneven returns from engagement with their policy counterparts. Some further argued that the international security policy community has more to gain in terms of both actual capability and knowledge of trends. The utility of the tech sector working with the policy community in matters where they might act as advocates, political interpreters, or partners (e.g., trade negotiation or limiting harmful foreign regulation) was not raised, whether due to the makeup of the respondents, an unwillingness to acknowledge comparative advantages, or limited returns. To our surprise, some warned against the international security policy community trying to make the case that joint engagement on policy issues is primarily a business interest to those in the tech industry. As one respondent explained, "Businesses are focused on profits and growth and everything else is either an enabler or a distraction," so engaging on policy-related challenges may be worthwhile but not relevant to near-term business motives. In contrast, in interviews, the international security policy community was convinced that demonstrating that its work has business impact is key to getting in the door with Silicon Valley. Unsurprisingly, "we're from the government and we're here to help you" is not a welcome opener in technology centers. Explicitly and humbly disavowing this stereotype – being painstakingly clear on what policymakers are actually working toward – would be a welcome first step.

Fundamental differences between governmental and commercial approaches to problem solving undermine the success of cross-sector engagements. Collaboration between the technology and international security policy communities on hard problems is difficult because the purpose and pace of operations do not align was a common theme in both surveys and interviews. Though far from the only difference, an example that came up repeatedly suggested the two sides hold different understandings of the value of time and its link to change within formal processes. Meetings and reform processes, for example, tend to be lengthy, repetitive, and exploratory in the policy world, versus short, purposeful, and experimental in the technology world, generating frustration when the groups are mixed. "Destructive innovation can work well for a company…accountable only to its customers," whereas a democratic government by its nature must be held accountable to all of its citizens.[7] Frustration over these differences is particularly high within the technology community, because the opportunity cost of taking government meetings, especially those with no clear or immediate returns, is revenue.[8]

Such differences become all the more stressful if the knowledge base between the communities is drastically different when launching an engagement. Lack of technical know-how among policymakers was criticized regularly by tech participants. Interestingly, neither sector raised significant concerns in the survey about the technology community's relative inexperience or indifference to policy substance or process being much of a limitation, which perhaps reflects the (unrealistic and unhelpful) engineers-vs.-liberal-arts-majors meme haunting social media, with engineers generally attributed omni-competence compared with liberal arts majors' supposed inability to function in STEM fields. Regardless, such perceptions seem more a matter of stereotype than reality and are easily mitigable. Mutual goal setting, preparatory homework, flexibility, and candor regarding mutual problems and opportunities are potential fixes to these tensions.

The nature of the issues being addressed – and the framework for engagement – are critical determinants of whether cross-sector collaboration will succeed or fail. To scope their next phase of work, CNAS and the Copia

7 Dreyfuss, "Innovation Can Fix Government, Sure. Either That or Break It."

8 Billy Mitchell, "DoD Innovation Unit Hosting Pitch Events in Silicon Valley," FedScoop, November 4, 2015, https://www.fedscoop.com/dod-innovation-unit-hosting-pitch-events-in-silicon-valley/

Institute are particularly interested in what issue areas are most productive for bringing together the international security policy and technology communities – what's the "next big thing," or the issue currently lacking appropriate attention. In interviews, several respondents warned against trying to launch any additional policy discussions on highly contentious topics, particularly cybersecurity, encryption, and counterterrorism. At best, they judged this space to be too saturated and, at worst, too contaminated by bad blood to make new collaborative efforts worthwhile (such views may have been influenced by significant media attention to a series of tense engagements between Washington and large tech companies). In contrast, the survey data revealed the opposite. Even though these topics have created serious tensions, for obvious reasons they top the list of issues that would yield the most significant benefits from continued engagement: The greatest opportunity lies wherever there are the greatest points of friction. Former Secretary of Defense Carter, for example, spent the last months of his tenure encouraging cross-sector collaboration on cybersecurity and encryption, despite seemingly incompatible tech industry and government points of view. He emphasized the importance of striking a "balance between what the government says it needs (no encryption!) and what the tech community says it needs (encryption!)."[9] Though these and other issues generated interest, – like data localization, cryptocurrencies, technology and civil society, and the 'Internet of Things' – the specific topic seemed less important than the approach. Above all, study participants emphasized the importance of pursuing topics where both sides share not just mutual interest or frustration, but also a degree of certainty that collaboration will have a direct and positive impact on the issue at hand. Mutual admiration of a problem goes only so far. Survey respondents endorsed data localization, cryptocurrencies, technology and civil society, and "the Internet of Things" as promising topics, for example. But more than the issue, the kind of engagement – and who does it – matters.

Who participates in collaborative efforts between these communities can make or break the opportunity for positive engagement. In a prior study, CNAS encountered a view that when working together, neither the policy community nor the technology community involved the right kinds of people. One thing they have in common? Shared frustration over lawyers. The extent to which legal departments inhibit collaboration between the policy and technology communities was a common theme among study participants. Government respondents noted how difficult it was to acquire legal clearance to meet with individual companies without navigating a host of contractual requirements. And technology community respondents expressed similar frustration over the difficulty of "bypassing legal roadblocks" to engage with D.C. representatives or to avoid an "automatic no" when seeking follow-up engagements. For this and other comparable reasons, many highlighted the need for third-party stakeholders or organizations to host or separately engage communities on particularly sensitive issues. This is similar to Track 1.5 or Track 2 dialogues held within the foreign policy community, in which third parties use informal forums to bring together disparate groups for relationship building, learning about another perspective, and considering options for problem solving.[10] There seems to be an opportunity for third-party organizations to play a similar role.

In addition to lawyers, the press received similarly negative feedback for its involvement in policy discussions, particularly given the number of recent public disputes between the communities. Investors, international organizations,

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9 Jessi Hempell, "DoD Head Ashton Carter Enlists Silicon Valley to Transform the Military," Wired, November 19, 2015, https://www.wired.com/2015/11/secretary-of-defense-ashton-carter/

10 J. W. McDonald and D. B. Bendahmane, eds., Conflict Resolution: Track Two Diplomacy (Washington: Foreign Service Institute, U.S. Department of State, 1987) and industry associations were also unpopular participants.On a more positive note, there was enthusiasm around including engineers, technology policy leads, technology company leaders, government agencies, and think tanks in any international security policy engagements.

The format of the engagements themselves can impact the results. Of particular interest to CNAS and the Copia Institute was whether certain types of collaborations could bring together policy and technology professionals in a more productive manner. Nothing from the survey results stood out as a magic format, but there was a notable emphasis on the utility of executive-level meetings (to ensure leadership buy-in), informal interactions and informal requests for comment (to build relationships and keep pressure low), and simulations and exercises (to provide context and opportunity to see alternative perspectives on policy issues). The "Hacking for Defense" platform, launched at Stanford University and now available at six additional universities, is a particularly successful example of an educational exchange that draws policy and technical experts together to "develop technology solutions to help solve important national security problems."[11] On the other hand, conferences, formal requests for comment, and, surprisingly, hackathons proved the least popular forums among respondents.

THE KEY INGREDIENTS

Some immovable barriers present complex challenges to technology and policy professionals seeking to bridge the bicoastal divide. Even if the topic, the forum, the objective, and the participants are right, fundamental philosophical differences, a history of distrust, and the absence of leadership support can still stand in the way of productive collaboration. So, how can the technology and international security policy community move past these barriers?

With this question in mind, CNAS and the Copia Institute specifically asked survey and interview participants for examples of key takeaways from their experiences with collaboration. Respondents offered some practical lessons for those seeking to pursue such efforts in the future, including:

- Readiness to travel to Silicon Valley by the policy community
- Realism on timeline and objectives to avoid inertia and decision paralysis
- Deliberately including an appropriate range of perspectives
- Willingness to do advance homework and study the other's issues and perspectives
- Transparency on all sides
- Consistent follow-through, identification of action items, and allocation of responsibility

Overall, clearer communication, more purposeful engagement, and mutual understanding between these sectors will be critical to improving the policy-technology relationship on key policy issues. Respondents also focused on the need for informality, personal relationships, and honest, regular dialogue over the long term as core elements for successful and continuous future engagement. Specific, practical steps toward these ends should center on increasing

11 "Hacking 4 Defense (H4D)," Stanford H4D, accessed April 24, 2017, http://hacking4defense.stanford.edu/

the flow of ideas and people between the technology and the policy worlds.

As in Track 1.5 and Track 2 diplomacy, experts who have worked in or with these communities can serve as highly effective "translators" to facilitate this relationship-building process. Silicon Valley outreach efforts by former Defense Secretary Carter were moderately well received in no small part due to his scientific background and ability to "speak the language" with engineers and policymakers alike.[12] Future successful engagements will also depend on including those who can participate or facilitate discussion outside the bounds of formal structures and others who can act as neutral arbiters when tensions are high. Think tanks or academia may be well placed to facilitate bridge building and serve as "mediators" in some circumstances – particularly for longer-term issues.

Likewise, encouraging more mobility between these sectors will be a critical step toward increasing opportunities to cooperate on tough policy challenges over the long term. Whereas "tech tourism…often leads to a less optimal result," as one government official reported, extended cross-sector engagements to acquire skills and connections are more promising. Rethinking government incentives and processes will be essential to recruiting experts from the tech industry and encouraging policymakers to take private-sector positions. For example, under Carter, the Pentagon was exploring programs that would place career officers in technology companies for several months while, at the same time, inviting individuals from technology companies to spend time at the Department of Defense.[13]

In short, creating opportunities to understand the other's issues and positions and being honest about unknowns and misunderstandings will form the foundations for cross-sector dialogue with a purpose and with results. See the next page for a breakdown of our **six lessons for success.**

NEXT STEPS

CNAS and the Copia Institute are going to test these lessons through a few "experiments" with partners in government, the policy community, academia, the technology community, and others. From these efforts we may create some useful case studies for others to mirror, or we may run into the exact same barriers as past efforts – either way, we'll publish and share our findings. Critical elements to our experiments will be relationship building and information sharing ahead of any event, hosts and participants who are able to "translate" effectively for all stakeholders, identification of desired outcomes and a way ahead going into any collaborations, and immersive discussions forcing participants to take different sides.

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12 Tony Capaccio, Brian Womack, and Terry Atlas, "Silicon Valley Wary as Pentagon Chief to Court Innovators," Bloomberg News, August 27, 2015, https://www.bloomberg.com/news/articles/2015-08-27/silicon-valley-wary-as-pentagon-chief-comes-to-court-innovators.
This article can also be found at: https://www.stripes.com/news/us/silicon-valley-wary-as-pentagon-chief-to-court-innovators-1.364983#.WTcKHdy1tiI?

13 Hempell, "DoD Head Ashton Carter Enlists Silicon Valley."

SIX LESSONS FOR SUCCESS

Be transparent – and acknowledge the elephants in the room. At minimum, this means stakeholders from both sectors should be straightforward about their own motives and make an effort to understand the other side's goals and interests before meeting on a potentially sensitive policy topic. Several respondents affirmed that clearing the air was a worthwhile first step. Experts can achieve this by acknowledging the problems and misunderstandings they have experienced in the past or read about in the press.

Own what you don't know and be willing to learn in advance. Homework – and humility about any gaps – will go a long way to making any engagements between these communities worthwhile. This work might be episodic (such as intensive mutual preparation for events and projects) or structural (such as policymaker or legal specialization in technology matters) or a willingness to acknowledge comparative advantages (such as diplomatic familiarity with foreign counterparts or deference to engineering expertise).

Go in with a plan – and a plan for follow-up. Over and over, respondents described potentially positive and fruitful meetings, conferences, phone calls, or other engagements that ultimately resulted in nothing because of a lack of clear objectives, lack of respect for time, and lack of follow-through. Open-ended engagements are clearly not useful, and defining timelines, objectives, and desired outcomes (at least in broad terms) would serve both sectors well.

Use third parties (or: lawyers, keep away!) Third-party participants, translators, and moderators will be useful assets to the technology and international security policy sectors, particularly as hosts and intermediaries for particularly sensitive issues. Third parties make for useful neutral ground, but also as arbiters able to ensure inclusion of the full range of perspectives. This recommendation, affirming an initial hypothesis of our study, also may allow both sectors to avoid some of the internal structural barriers they face, like the legal department's reluctance to bless open dialogue and collaboration.

It's all about relationships. Despite our expectation that demonstrating clear business interest would be the best driver of collaboration, survey respondents strongly encouraged informal encounters in future efforts, as a way to invest in relationships between the sectors, and deemphasized the transactional "what can you do for me" nature of many D.C.–Silicon Valley ventures.

It's not the topic, it's the process. Topics of interest to these sectors will frequently and necessarily be sensitive. Searching for win-win goodwill opportunities for collaboration is a nice idea but likely unrealistic. Survey respondents in particular highlighted that arguing conveners should not discard sensitive topics (like encryption or counterterrorism) on the basis of the topic being difficult or well-trodden. If anything, this is an indication that experts should try new methods of addressing them. More important was a degree of certainty that collaboration will have a direct and positive impact on the issue at hand. Mutual admiration of a problem goes only so far.