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NOTES FROM THE FRONTIER

MODELING THE IMPACT OF AI ON THE WORLD ECONOMY

DISCUSSION PAPER

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IN BRIEF

NOTES FROM THE FRONTIER: MODELING THE IMPACT OF AI ON THE WORLD ECONOMY

WHAT'S INSIDE?

Continuing the McKinsey Global Institute's ongoing exploration of artificial intelligence (AI) and its broader implications, this discussion paper focuses on modeling AI's potential impact on the economy. We take a micro-to-macro and simulation-based approach in which the adoption of AI by firms arises from economic and competition-related incentives, and macro factors have an influence. We consider not only the possible benefits but also the costs related to implementation and disruption.

- **AI has large potential to contribute to global economic activity.** Looking at several broad categories of AI technologies, we model trends in adoption, using early adopters and their performance as a leading indicator of how businesses across the board may (want to) absorb AI. Based on early evidence, our average simulation shows around 70 percent of companies adopting at least one of these types of AI technologies by 2030, and less than half of large companies may be using the full range of AI technologies across their organizations. In the aggregate, and netting out competition effects and transition costs, AI could potentially deliver additional economic output of around $13 trillion by 2030, boosting global GDP by about 1.2 percent a year.
- **The economic impact may emerge gradually and be visible only over time.** Our simulation suggests that the adoption of AI by firms may follow an S-curve pattern—a slow start given the investment associated with learning and deploying the technology, and then acceleration driven by competition and improvements in complementary capabilities. As a result, AI's contribution to growth may be three or more times higher by 2030 than it is over the next five years. Initial investment, ongoing refinement of techniques and applications, and significant transition costs might limit adoption by smaller firms.
- **A key challenge is that adoption of AI could widen gaps between countries, companies, and workers.** AI may widen performance gaps between countries. Those that establish themselves as AI leaders (mostly developed economies) could capture an additional 20 to 25 percent in economic benefits compared with today, while emerging economies may capture only half their upside. There could also be a widening gap between companies, with front-runners potentially doubling their returns by 2030 and companies that delay adoption falling behind. For individual workers, too, demand—and wages—may grow for those with digital and cognitive skills and with expertise in tasks that are hard to automate, but shrink for workers performing repetitive tasks.
- **How companies and countries choose to embrace AI will likely impact outcomes.** The pace of AI adoption and the extent to which companies choose to use AI for innovation rather than efficiency gains alone are likely to have a large impact on economic outcomes. Similarly, how countries choose to embrace these technologies (or not) will likely impact the extent to which their businesses, economies, and societies can benefit. The race is already on among companies and countries. In all cases, there are trade-offs that need to be understood and managed appropriately in order to capture the potential of AI for the world economy.

The results of this modeling build upon, and are generally consistent with, our previous research, but add new results that deepen our understanding of how AI may touch off a competitive race with major implications for firms, labor markets, and broader economies, and reinforce our perception of the imperative for businesses, government, and society to address the challenges that lie ahead for skills and the world of work.

INTRODUCTION

The role of artificial intelligence tools and techniques in business and the global economy is a hot topic. This is not surprising given recent progress, breakthrough results, and demonstrations of AI, as well as the increasingly pervasive products and services already in wide use. All of this has led to speculation that AI may usher in radical—arguably unprecedented—changes in the way people live and work.

This discussion paper is part of MGI's ongoing effort to understand AI, the future of work, and the impact of automation on skills. It largely focuses on the impact of AI on economic growth.[1] Our hope is that this effort helps us to broaden our understanding of how AI may impact economic activity, and potentially touch off a competitive race with major implications for firms, labor markets, and economies. Three key findings emerge:

- **AI has large potential to contribute to global economic activity.** AI is not a single technology but a family of technologies. In this paper, we look at five broad categories of AI technologies: computer vision, natural language, virtual assistants, robotic process automation, and advanced machine learning. Companies will likely use these tools to varying degrees. Some will take an opportunistic approach, testing only one technology and piloting it in a specific function. Others may be bolder, adopting all five and then absorbing them across their entire organization. For the sake of our modeling, we define the first approach as adoption and the second as full absorption.[2] Between these two poles will be many companies at different stages of adoption; the model captures partial impact, too. By 2030, our average simulation shows, some 70 percent of companies may have adopted at least one type of AI technology, but less than half may have fully absorbed the five categories.[3]

  The pattern of adoption and full absorption may be relatively rapid—at the high end of what has been observed with other technologies. However, several barriers may hinder rapid adoption. For instance, late adopters may find it difficult to generate impact from AI because AI opportunities have already been captured by front-runners, and they lag behind in developing capabilities and attracting talent.[4] Nevertheless, at the average level of adoption implied by our simulation, and netting out competition effects and transition costs, AI could potentially deliver additional global economic activity of around $13 trillion

[1] A version of this discussion paper is published in a forthcoming white paper on AI published by the International Telecommunication Union but, as with all MGI research, is independent and has not been commissioned or sponsored in any way. MGI research on the future of work, automation, skills, and AI can be read and downloaded at mckinsey.com/mgi/our-research/technology-and-innovation. Key publications relevant to this paper include *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017; *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017; *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018; and *Skill shift: Automation and the future of the workforce*, McKinsey Global Institute, May 2018. For a data visualization of AI and other analytics, see *Visualizing the uses and potential impact of AI and other analytics*, McKinsey Global Institute, April 2018 (mckinsey.com/featured-insights/artificial-intelligence/visualizing-the-uses-and-potential-impact-of-ai-and-other-analytics).

[2] In this paper, we use the terms "adoption," "diffusion," and "absorption." We define adoption as investment in a technology, diffusion as how adoption spreads—the process by which an innovation is communicated over time among the participants in a social system—and absorption as how technology is used within a firm. "Full absorption" is when a company uses the adopted technology for all operational purposes across its broad workflow system. These definitions align with those in academic literature. See, for instance, Tomaž Turk and Peter Trkman, "Bass model estimates for broadband diffusion in European countries," *Technological Forecasting and Social Change*, 2012, Volume 79, Issue 1; David H. Wong et al., "Predicting the diffusion pattern of internet-based communication applications using bass model parameter estimates for email," *Journal of Internet Business*, 2011, Issue 9; and Kenneth L. Kraemer, Sean Xu, and Kevin Zhuk, "The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business," *Management Science*, October 1, 2006.

[3] These percentages need to be understood not in terms of numbers of firms per se, but in terms of their share of economic activity.

[4] These industry dynamics between front-runners and followers are called the "rank effect" in the literature on technology adoption literature. See Paul Stoneman and John Vickers, "The assessment: The economics of technology policy," *Oxford Review of Economic Policy*, 1988, Volume 4, Issue 4.

globally by 2030, or about 16 percent higher cumulative GDP compared with today. This amounts to about 1.2 percent additional GDP growth per year. If delivered, this impact would compare well with that of other general-purpose technologies through history.[5] Consider, for instance, that the introduction of steam engines during the 1800s boosted labor productivity by an estimated 0.3 percent a year, the impact from robots during the 1990s around 0.4 percent, and the spread of IT during the 2000s 0.6 percent.[6]

- **The economic impact may emerge gradually and be visible only over time.** The impact of AI may not be linear, but may build up at an accelerating pace over time. AI's contribution to growth may be three or more times higher by 2030 than it is over the next five years. An S-curve pattern of AI adoption is likely—a slow start due to substantial costs and investment associated with learning and deploying these technologies, but then an acceleration driven by the cumulative effect of competition and an improvement in complementary capabilities. The fact that it takes time for productivity to unfold may be reminiscent of the Solow Paradox.[7] Complementary management and process innovations will likely be necessary to take full advantage of AI innovations.[8] It would be a misjudgment to interpret this "slow-burn" pattern of impact as proof that the effect of AI will be limited. The size of benefits for those who move into these technologies early will build up in later years at the expense of firms with limited or no adoption.

- **A key challenge is that adoption of AI could widen gaps between countries, companies, and workers.** AI could deliver a boost to economic activity, but the distribution of benefits is likely to be uneven:

  — **Countries.** AI may widen gaps between countries, reinforcing the current digital divide.[9] Countries may need different strategies and responses because AI adoption levels vary. AI leaders (mostly in developed countries) could increase their lead in AI adoption over developing countries. Leading countries could capture an additional 20 to 25 percent in net economic benefits compared with today, while developing countries may capture only about 5 to 15 percent. Many developed countries may have no choice but to push AI to capture higher productivity growth as their GDP growth momentum slows, in many cases partly reflecting the challenges related to aging populations. Moreover, wage rates in these economies are high, which means that there is more incentive than in low-wage, developing countries to substitute labor with machines. Developing countries tend to have other ways to improve their productivity, including catching up with best practices and restructuring their industries, and may therefore have less incentive to push for AI (which, in any case, may offer them a smaller economic benefit than advanced economies). This does not mean that developed economies are set to make the best use of AI and that developing economies are destined to lose the AI race. Countries can choose to strengthen the foundations, enablers, and capabilities needed to reap the potential of AI, and be proactive in accelerating adoption. Some developing countries are already being ambitious in pushing AI. For instance, China, as we have noted, has

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[5] We acknowledge that direct comparison of the impact of AI with that of past technological innovations may not realistically be possible as our quantification of the impact of AI includes a family of technologies. Such comparisons are mainly to indicate a broad sense of magnitude.

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

[7] The Solow Paradox is a phenomenon in which increased investment in IT is not visible in productivity statistics. For an in-depth debate, see Mekala Krishnan, Jan Mischke, and Jaana Remes, "Is the Solow Paradox back?" *McKinsey Quarterly*, June 2018.

[8] *Solving the productivity puzzle: The role of demand and the promise of digitization*, McKinsey Global Institute, February 2018.

[9] Jan A.G.M. van Dijk, "The evolution of the digital divide: The digital divide turns to inequality of skills and usage," in Jacques Bus et al., eds., *Digital Enlightenment Yearbook 2012*, Amsterdam, Netherlands: IOS Press, 2012.

a national strategy in place to become a global leader in the AI supply chain, and is investing heavily.[10]

— **Companies.** AI technologies could lead to a performance gap between front-runners on one side and slow adopters and nonadopters on the other. At one end of the spectrum, front-runners (companies that fully absorb AI tools across their enterprises over the next five to seven years) are likely to benefit disproportionately. By 2030, they could potentially double their cash flow (economic benefit captured minus associated investment and transition costs), which implies additional annual net cash flow growth of about 6 percent for more than the next decade.[11] Front-runners tend to have a strong starting digital base, a higher propensity to invest in AI, and positive views of the business case for AI. Although our simulation treats front-runners as one group, in reality, this category is not homogeneous. Some current AI innovators and creators have big starting endowments of data, computing power, and specialized talent. Other early adopters may not engage in creating these technologies but may be innovative in how they deploy them. At the other end of the spectrum is a long tail of laggards that do not adopt AI technologies at all or that have not fully absorbed them in their enterprises by 2030. This group may experience around a 20 percent decline in their cash flow from today's levels, assuming the same cost and revenue model as today. One important driver of this profit pressure is the existence of strong competitive dynamics among firms, which could shift market share from laggards to front-runners and may prompt debate on the unequal distribution of the benefits of AI.

— **Workers.** A widening gap may also unfold at the level of individual workers. Demand for jobs could shift away from repetitive tasks toward those that are socially and cognitively driven and others that involve activities that are hard to automate and require more digital skills.[12] Job profiles characterized by repetitive tasks and activities that require low digital skills may experience the largest decline as a share of total employment, from some 40 percent to near 30 percent by 2030. The largest gain in share may be in nonrepetitive activities and those that require high digital skills, rising from some 40 percent to more than 50 percent. These shifts in employment would have an impact on wages. We simulate that around 13 percent of the total wage bill could shift to categories requiring nonrepetitive and high digital skills, where incomes could rise, while workers in the repetitive and low digital skills categories may potentially experience stagnation or even a cut in their wages. The share of the total wage bill of the latter group could decline from 33 to 20 percent.[13] Direct consequences of this widening gap in employment and wages would be an intensifying war for people, particularly those skilled in developing and utilizing AI tools, and structural excess supply for a still relatively high portion of people lacking the digital and cognitive skills necessary to work with machines.

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[10] *Artificial intelligence: Implications for China*, McKinsey Global Institute, April 2017.

[11] Large firms have a competitive advantage in adopting and absorbing AI ahead of industry peers. MGI's econometric simulation suggests that they have adoption rates around ten percentage points higher than the average. Similarly, organizations that have a more established digital culture (including elements such as institutionalized user experience design thinking, a nimble organization, scaled and integrated agile ways of working across business and IT domains, and a leadership culture that fosters and enables a network of empowered teams to reach defined goals) are in a better position to accelerate the adoption of AI: their adoption rates are around eight percentage points higher than those of companies that do not have a digital culture. In fact, early corporate adopters will benefit from the exponential impact, potentially gaining three times more economic benefits from AI than followers.

[12] Assessment of the impact of AI on individuals in this research mainly focuses on workers. A more complete view of the impact on individuals would include discussion of the effect of AI on users, citizens, and consumers.

[13] For more detail on the impact of automation on wages, see Daron Acemoglu and Pascual Restrepo, *Low-skill and high-skill automation*, NBER working paper number 24119, December 2017.

Gaps may be widening among firms, workers, and countries, but measures can be taken to manage the transition and steer economies toward higher productivity and job growth. The disruption that comes with AI may lead to some firms leaving the market and some workers losing jobs. There will be major challenges for individuals transitioning to new jobs. However, if they are given the support they need to develop and refresh their skills and return to the labor market, then resources can be redeployed to more productive parts of the economy.

THE AI REVOLUTION IS NOT IN ITS INFANCY, BUT THE MAJORITY OF THE ECONOMIC IMPACT OF AI IS YET TO COME

Substantial progress in many areas has accelerated the development of AI, which has the potential to reshape the competitive landscape of companies, jobs, and the economic development of countries. Over the past few years, there have been many breakthrough results and announcements in natural language processing, machine vision, and games like Go.[14] In addition, many products and services already in wide use employ advances in AI such as personal assistants and facial recognition systems. Much of this progress has been the result of progress in three areas:

1. **Step-change improvements in computing power and capacity.** At the silicon level, there has been continuous progress from central processing units to graphics processing units (GPUs). Today's GPUs can be 40 to 80 times faster than the quickest versions available in 2013. Silicon-level development may put early movers (front-runners in this analysis) at an advantage because they have the resources to drive breakthroughs. Companies such as Google are pushing further with tensor processing units. Many more silicon-level developments are underway. At the cluster level, cloud solutions offer much cheaper computing and storage services on demand. Microsoft offers a hybrid solution combining the public and private cloud that helps companies rapidly ramp up their computing resources and handle spikes in need without large capital outlays.

2. **Explosion of data.** The world creates an unprecedented amount of data every day, feeding algorithms the raw material needed to produce new insights. International Data Corporation estimates that there may be 163 zettabytes (one trillion gigabytes) of data by 2025, or ten times the data generated in 2016.[15] Enormous diversity in the data being generated means that organizing and analyzing these data are extremely challenging, but that there is an unprecedented opportunity to extract value from data that were not available in the past.[16]

3. **Progress in algorithms.** The techniques and algorithms underlying AI have continued to be developed. Recent advances in deep learning techniques are delivering step changes in the accuracy of classification and prediction.[17] Deep learning uses large-scale neural networks (the most common are convolutional and recurrent neural networks) that

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[14] For instance, Eric Horvitz and colleagues at Microsoft Research have demonstrated in-stream supervision in which data can be labeled in the course of natural usage. See Eric Horvitz, "Machine learning, reasoning, and intelligence in daily life: Directions and challenges," *Proceedings of Artificial Intelligence Techniques for Ambient Intelligence*, Hyderabad, India, January 2007. AlphaGo Zero used a new form of reinforcement learning to defeat its predecessor AlphaGo after learning to play the game Go from scratch. See Demis Hassabis et al., *AlphaGo Zero: Learning from scratch*, deepmind.com. DeepMind researchers have had promising results with transfer learning where training is simulated and then transferred to physical robots. See Andre A. Rusu et al., *Sim-to-real robot learning from pixels with progressive nets*, arvix.org, October 2016. For more, see Michael Chui, James Manyika, and Mehdi Miremadi, "What AI can and can't do (yet) for your business," *McKinsey Quarterly*, January 2018.

[15] John Gantz, David Reinsel, and John Rydning, *Data age 2025: The evolution of data to life-critical*, IDC white paper, April 2017.

[16] Behavioral, transactional, environmental, and geospatial data are available from sources including the web, social media, industrial sensors, payment systems, cameras, wearable devices, and human entry, for example. See *The age of analytics: Competing in a data-driven world*, McKinsey Global Institute, December 2016.

[17] Yoshua Bengio, Aaron Courville, and Ian Goodfellow, *Deep Learning*, Cambridge, MA: MIT Press, 2016.

learn through the use of training data and backpropagation algorithms. Also emerging are meta-learning techniques that are attempting to automate the design of machine-learning models and neural networks by classifying images in large-scale data sets. Also notable is the development of reinforcement learning, an unsupervised technique that allows algorithms to learn tasks by trial and error, improving their performance through repetition and, in many cases—the game of Go being one example—surpassing human capabilities.[18] In one-shot learning, an AI model can learn about a topic even where there is only a small number—even one—of real-world examples, reducing the need for large data sets.[19]

While many of the most public breakthroughs have largely been associated with a relatively small group of individuals, companies, and institutions and have mainly, but not exclusively, been US-led, this is changing fast. An increasing number of countries are now starting to put more emphasis on AI initiatives, with China in particular making huge strides (see Box 1, "More countries are taking measures to advance AI").

Most companies currently face significant limitations on their ability to leverage AI (see Box 2, "Current technical limitations to leveraging AI, and some early progress"). However, the AI revolution is certainly no longer in its infancy. These technologies are already widely used in business. MGI analysis of more than 400 cases in which companies and organizations could potentially use AI found that AI is already relatively applicable to real business problems and can have significant impact in areas including marketing and sales, supply chain management, and manufacturing. The research found that three deep learning techniques—feed forward neural networks, recurrent neural networks, and convolutional neural networks—together could enable the creation of between $3.5 trillion and $5.8 trillion in value each year in nine business functions in 19 countries. This is the equivalent of 1 to 9 percent of 2016 sector revenue.[20]

A broad range of companies already use AI tools in a wide variety of ways and functions. As of early 2018, AI was used in supply chains (for instance, Amazon's Kiva robot automation in retail logistics); fixed assets (for example, preventive maintenance of assets by companies such as Neuron Soundware, which uses artificial auditory cortexes to simulate human sound interpretation, and can therefore automate the detection and identification of causes of potential breakdown of equipment); R&D (for instance, Quantum Black's use of AI to streamline R&D in Formula 1 racing); and sales and marketing (for example, AI-powered search by Baidu, and Digiday's AI-based predictive sales target of business-to-business salespeople).[21]

As funding becomes more widely available, the skills to deploy and manage AI are likely to spread to a broader swath of companies and take hold across economies.

[18] Matt Burgess, "DeepMind's latest AI breakthrough is its most significant yet," *Wired*, October 18, 2017.
[19] Yan Duan et al., *One-shot imitation learning*, arxiv.org, December 2017.
[20] *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018.
[21] Jeremy Hsu, "Deep learning AI listens to machines for signs of trouble," *IEEE Spectrum*, December 27, 2016.

Box 1. More countries are taking measures to advance AI

A number of countries have announced initiatives and plans to drive the use of AI in their economies. Here we give just a few examples as of mid-2018:

China. The government is prioritizing AI, including its promotion in, for instance, its 13th Five-Year Plan (which runs from 2016 to 2020), its Internet Plus and AI plans from 2016 to 2018, and a "new generation AI plan." China has stated that it aims to create a domestic AI market of 1 trillion renminbi ($150 billion) by 2020 and become a world-leading AI center by 2030.[1] The private sector is pushing actively for AI, too. Three of China's internet giants—Alibaba, Baidu, and Tencent—as well as iFlytek, a voice recognition specialist, have joined a "national team" to develop AI in in areas such as autonomous vehicles, smart cities, and medical imaging.

Europe. European Union (EU) member states have announced their intention to collaborate on AI more actively across borders to ensure that Europe is competitive in these technologies and that they can tackle their social, economic, ethical, and legal ramifications together.[2] The EU has called for $24 billion to be invested in AI research by 2020.[3] A number of European countries have also been driving national initiatives. The French government has announced an initiative to double the number of people studying and researching AI projects, set new boundaries for data sharing, and invest $1.85 billion to fund research and startups.[4] The United Kingdom has published a comprehensive plan to strengthen the core foundation of AI in an "artificial intelligence sector deal" and has stated its aim to lead in the field of AI ethics.[5]

Asia (outside China). The government of South Korea set up a Presidential Fourth Industrial Revolution Committee in 2017 and announced that it would invest $2 billion by 2022 to strengthen its capabilities in AI R&D.[6] Singapore has launched an AI Singapore national initiative to enhance AI capabilities by forming a partnership of government institutions.[7]

Canada. International research institute CIFAR is leading the government's Pan-Canadian Artificial Intelligence Strategy with three new AI institutes: the Alberta Intelligence Institute in Edmonton, the Vector Institute in Toronto, and MILA in Montreal; these cities are Canada's three major AI centers.[8]

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1 *China to publish guideline on AI development: Minister*, The State Council of the People's Republic of China, March 11, 2018.

2 *EU member states sign up to cooperate on artificial intelligence*, European Commission, April 10, 2018.

3 Aoife White, "EU calls for $24 billion in AI to keep with China, U.S.," *Bloomberg News*, May 1, 2018.

4 Romain Dillet, "France wants to become an artificial intelligence hub," *TechCrunch*, March 29, 2018.

5 *Artificial Intelligence Sector Deal*, HM Government, 2018; and *UK can lead the way on ethical AI, says Lords Committee,* UK Parliament, April 16, 2018.

6 "South Korea aims high on AI, pumps $2 billion into R&D," *SyncedReview*, May 16, 2018.

7 AI Singapore (aisingapore.org/about-ai-singapore/).

8 Pan-Canadian Artificial Intelligence Strategy, CIFAR (cifar.ca/ai/pan-canadian-artificial-intelligence-strategy).

Box 2. Current technical limitations to leveraging AI, and some early progress

Businesses have recorded much progress in making AI applicable to them. However, the following five technical factors are arguably limiting the application of AI:[1]

Labeled training data. In supervised learning, machines do not learn by themselves but need to be taught, which means that humans must label and categorize the underlying training data. However, promising new techniques are emerging to reduce time spent on such efforts, including reinforcement learning and in-stream supervision such as generative adversarial networks, a supervised learning method in which two networks compete with each other to improve their understanding of a concept.[2]

Obtaining sufficiently large data sets. In many business use cases, it can be difficult to create or obtain data sets large enough to train algorithms. One example is the limited pool of the clinical-trial data necessary to predict healthcare treatment outcomes more accurately. Players with access to vast quantities of data may have an advantage. At present, the availability of labeled data is critical since most current AI models are trained through supervised learning, and categorizing data correctly requires a huge amount of human time. This may change as technologies and algorithms develop. One technique that could reduce the need for large data sets is one-shot learning, in which an AI model is pretrained in a set of related data and can then learn even from a small number of real-world examples.

Difficulty explaining results. It is often difficult to explain results from large, complex neural-network-based systems. One development—still at an early stage—that could improve the ease of explaining or transparency of models is local interpretable model agnostic explanations, which attempt to identify which parts of input data a trained model relies on most to make predictions. Another technique that is becoming relatively well established is the application of generalized additive models. They use single-feature models, which limit interactions between features and enable users to interpret each one more easily.

Difficulty generalizing. AI models still have difficulty carrying their experiences from one set of circumstances to another, which leaves companies having to commit resources to training new models even if use cases are relatively similar to previous ones. Transfer learning, in which an AI model is training to apply learning from one task to the next one, is showing promise.[3]

Risk of bias. The first four limitations may be solved as technology advances, but bias—in data in particular, but also in algorithms—has raised broad social concerns and may be challenging to resolve.[4] A great deal of academic, nonprofit, and private-sector research is now underway on this issue.

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1 "What AI can and can't do (yet) for your business," *McKinsey Quarterly,* January 2018.

2 Eric Horvitz, "Machine learning, reasoning, and intelligence in daily life: Directions and challenges," *Proceedings of Artificial Intelligence Techniques for Ambient Intelligence,* Hyderabad, India, January 2007.

3 See John Guttag, Eric Horvitz, and Jenna Wiens, "A study in transfer learning: Leveraging data from multiple hospitals to enhance hospital-specific predictions," *Journal of the American Medical Informatics Association*, 2014, Volume 21, Number 4.

4 For more, see *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018.

1. AN APPROACH TO ASSESSING THE ECONOMIC IMPACT OF AI

The “new spring” for AI has prompted a great deal of research on the economic impact of AI, and consensus is emerging that it may offer substantial benefits. Thus far, research finds that a broad range of AI technologies could boost productivity levels and elevate GDP growth trajectories. The exact numbers vary because researchers have used different methodologies—for instance, considering a narrow or broad set of drivers of economic impact.[22]

While research to date has provided some early insights, the methodologies deployed have exhibited some shortcomings and limitations. First, estimates have tended to concentrate on developed economies such as Europe and the United States, plus China; outside these three economies, insights have tended to be limited.[23] Second, the channels through which the macroeconomic impact occurs have not been clearly explained or exhaustive. For instance, research has largely focused on new AI investment demand that substitutes hours worked by humans. However, the reality is that a large share of AI use cases relate to retrofitting or replacing old capital investment by, for instance, embedding equipment with smart monitoring and preventive maintenance. Third, the link between microeconomic behavior and the impact of AI has not been made clearly. It is important to consider this link given the fact that the impact of AI depends on the level of its adoption by corporations and government entities, and that this pace of adoption is closely linked to microeconomic factors such as competition and the ability of organizations to deploy new technologies. Last but not least, research has tended to estimate the gross potential of AI, not taking into account the cost of implementation of these technologies into the socioeconomic system or negative externalities such as the impact of major disruptions on economic groups. The latter can be material. Consider, for instance, the cannibalization of old business models through AI-based innovation, or potentially extensive job reallocation due to the adoption of AI. Such negative externalities may be sufficiently large, and affect enough entities, to create the risk of a societal backlash against AI that could limit the full potential anticipated from these technologies.[24]

This research attempts to take a deeper and more detailed view of the impact of AI. (For a brief summary of the scope of the research, drawing on our extensive previous analysis of AI and applying a simulation-based approach, see Box 3, “Modeling approach and limitations.”) We have leveraged our previous research on automation to assess tasks and jobs that are at risk of being replaced by AI and automation technologies.[25] On the issue of new jobs that may be created as AI becomes adopted and absorbed, we rely on early estimates in a set of countries highlighted in December 2017 MGI research.[26] In this paper we mainly focus on the effect of AI on employment, whereas in earlier MGI research we also considered other broad economic effects likely to impact future employment such as the aging of populations and infrastructure investment, for instance. We also use what we learned from analyzing more than 400 AI use cases to assess the potential of AI in analytics, as well as its possible role in reducing costs and enhancing the generation of revenue.[27]

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22 See, for instance, Nicholas Chen et al., *Global economic impacts associated with artificial intelligence*, Analysis Group, February 2016; *Artificial intelligence, automation, and the economy*, Executive Office of the President of the United States, December 2016; and Philippe Aghion, Benjamin F. Jones, and Charles I. Jones, *Artificial intelligence and economic growth*, Stanford Institute for Economic Policy Research working paper number 17-027, October 10, 2017.

23 *Digitally-enabled automation and artificial intelligence: Shaping the future of work in Europe’s digital front-runners*, McKinsey & Company, October 2017.

24 Other social concerns about AI, including those related to privacy and security, could also mitigate against AI adoption and therefore limit its economic impact.

25 See, for instance, *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017.

26 *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

27 *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018.

Box 3. Modeling approach and limitations

This research focuses on AI's potential impact on global economic activity at the country, sector, company, and worker levels, using a simulation. It does not consider other important aspects including ethics and cybersecurity, or the effect of these technologies on sustainability. Nor do we quantify aspects of the consumer surplus that may arise out of using AI technologies, such as saving time or living a healthier life. Some clarifications that may be useful include:

- **Definition of AI used in the economic modeling.** Characterizing AI precisely is difficult because the definition tends to change depending on the specific context of research and application. For the purposes of our modeling, we used several data sources, including previous research on automation, analytics, and corporate surveys.[1] Although the scope of AI technologies covered in various data sets is largely consistent, the data may include some variations at the detailed technical level. In the future of work and automation database, we took an expansive view of AI that included not only natural language processing, machine vision, and deep learning, but also robotics and other automation systems (consistent with many other researchers considering the impact of automation and AI on work). In our analysis of potential AI use cases, we employed a narrower view, focusing on deep learning techniques (especially feed forward neural networks, recurrent neural networks, and convolutional neural networks).[2] The company-level survey used for our modeling of AI adoption and absorption covers five broad sets of AI technologies, namely computer vision, natural language, virtual assistants, robotic process automation, and advanced machine learning.

- **Data sources.** We used both AI-specific and macroeconomic data sets. For AI-specific data, we used three sources. The first combined MGI's regular survey of approximately 3,000 corporations in 14 sectors on digital technologies, undertaken for the VivaTechnology conference in Paris in June 2017, and the McKinsey annual survey on the extent of digitization in corporations worldwide.[3] The second was MGI's proprietary database of 400 potential AI use cases across industries and functions, used in this research to assess the impact on business.[4] The third was MGI's database that analyzes the potential to automate individual jobs—looking at activities rather than entire jobs—in 46 countries; this work assessed 800 existing occupations and around 2,000 activities undertaken within these occupations.[5] For macroeconomic data, we used statistics from external organizations including the United Nations, the World Bank, the Organisation for Economic Co-operation and Development (OECD), and the World Economic Forum.

- **Simulation and econometrics approach.** We used economic modeling and simulation to see how the impact of AI may change in response to certain assumptions and inputs. Rather than forecasting outcomes, based on the best evidence collected so far, the research simulates the likely impact from AI given different contexts at the country, sector, and company levels. For the econometric simulation of firm-level AI adoption and absorption, we used a double blind and multi-sample approach to ensure that our results were solid. MGI's econometrics team and a team from the Free University of Brussels independently analyzed both surveys mentioned above.[6] Both teams estimated and converged on the dynamics of propensity to adopt and absorb technologies. Each team found that consistent dynamics of adoption and absorption were visible in both samples used. Our simulation of economic impact and competitive dynamics also drew

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1 See *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017; and *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

2 *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018.

3 *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017. The online survey was conducted from June 20 to July 10, 2017, and garnered responses from 1,619 C-level executives and senior managers representing the full range of regions, industries, company sizes, and functional specialties. See *How digital reinventors are pulling away from the pack*, McKinsey & Company survey, October 2017.

4 *Notes from the AI frontier: Insights from several hundred use cases*, McKinsey Global Institute, April 2018.

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

6 The results of these surveys have been discussed previously in Jacques Bughin, "Wait-and-see could be a costly AI strategy," *MIT Sloan Management Review*, June 15, 2018; and Jacques Bughin, Tanguy Catlin, Martin Hirt, and Paul Wilmott, "Why digital strategies fail," *McKinsey Quarterly*, January 2018.

on academic literature (for further detail on our econometric approach, see the technical appendix).[7]

- **Approach to AI adoption and full absorption.** The concepts of adoption and full (and partial) absorption have been used in various contexts. In this research, we use an economic entity—notably a company—and its activities as a unit for adoption. Adoption of AI is when that entity chooses to invest in one of the five generic AI technologies (computer vision, natural language, virtual assistants, robotic process automation, and advanced machine learning) either for experimentation or for a narrow functional use.[8] Full absorption means that all five generic AI technologies are adopted and integrated into broad enterprise workflows. Full absorption is the stage at which economic benefits tend to kick in and recur.[9] However, we note that full absorption does not mean that there is a fixed range of technologies. New technologies and applications will continue to emerge. In this report, we use the term "full" as opposed to "partial" to indicate much broader use of AI technologies than is the case in adoption or a pilot.

- **Limitations and sensitivities.** Our firm-level simulation is dependent on the quality of data from the surveys used as inputs, and we acknowledge that this approach has two potential limitations. First, survey answers depend on the knowledge and perceptions of respondents, and their understanding of AI may vary, possibly affecting the quality of the insights and data gathered in this way. Second, the data set from our survey results may be skewed toward early movers. Extrapolating insights from the survey may therefore lead us to overestimate the economic impact because the next wave of companies adopting AI may display different behavior in terms of AI adoption. For these reasons, the result of our simulation should be interpreted as being the upper bound of estimates of AI's economic impact. However, we also note that competitive pressure is a key factor driving up the adoption level. If new companies that are more agile and embrace AI more rapidly join the AI race quicker than expected, this could push up the adoption curve.[10] Notwithstanding, the findings in this research are directionally consistent with our previous research. We also acknowledge that our simulation is highly sensitive to the results of corporate surveys on AI absorption. The adoption and absorption of AI by companies are the foundation of several dimensions of impact we have modeled, including labor augmentation, substitution, and innovation as well as transition costs. We have conducted three annual surveys, and, in general, the results of the simulation have remained broadly similar. However, we acknowledge that, when new data are gathered, the adoption and full absorption curve and the results of the simulation could change.

Note: While simulated figures are given that emerge from the above methods, the numbers presented in this report should not be read as forecasts, but rather are intended to provide a directional perspective on the potential impact of AI.

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7 Aghion and Jones have studied AI's impact on production function. See Philippe Aghion, Benjamin F. Jones, and Charles I. Jones, *Artificial intelligence and economic growth*, October 10, 2017. Korineck and Stiglitz have explored the surplus accruing to innovators, analysis on which we drew in our simulation of impact for front-runners and nonabsorbers. See Anton Korinek and Joseph E. Stiglitz, *Artificial intelligence and its implications for income distribution and unemployment*, NBER working paper number 24174, December 2017. Acemoglu and Restrepo have undertaken various simulations on capital and labor relationships as well as the impact of automation on employment and wages. See Daron Acemoglu and Pascual Restrepo, *Artificial intelligence, automation and work*, NBER working paper number 24196, January 2018; and Daron Acemoglu and Pascual Restrepo, *Modeling automation,* National Bureau of Economic Research (NBER) working paper number 24321, February 2018.

8 This is based on our surveys. Generic AI technologies include machine learning, robotics, and other AI application tools such as virtual assistants, computer vision, and voice recognition.

9 Jacques Bughin, "The diffusion pattern of Enterprise 2.0 technologies: Worldwide estimates of a bass co-diffusion model for the last 10 years," *Journal of Contemporary Management*, December 2016; and Jacques Bughin and Michael Chui, "The rise of the networked enterprise: Web 2.0 finds its payday," *McKinsey Quarterly*, December 2010.

10 Stephen J. Andriole, "Implement first, ask questions later (or not at all)," *MIT Sloan Management Review*, April 13, 2018.

What is new about this latest research is its attempt to gauge the macroeconomic impact of AI globally, and the fact that we have included in our estimate both the cost of implementing AI and the impact of a competitive race for adoption and absorption of these technologies. First, it builds on an understanding of the behavior of firms and the dynamics of various sectors to develop a bottom-up view of how AI technologies are adopted and absorbed (see the description of our seven-step micro-to-macro approach in the technical appendix). Second, the research takes into account the likely disruptions that countries, companies, and workers are likely to experience as they transition to AI. There will probably be costs during this transition period, and they need to be factored into any estimate. We look closely at how economic gains and losses are likely to be distributed among firms, employees, and countries, and how this distribution could potentially hamper the capture of AI benefits. And third, the research examines the dynamics of AI for a wide range of countries—clustered into groups with similar characteristics—with the aim of giving a more global view.

The primary goal of this research is to move the discussion forward by presenting our approach to simulating the economic benefits and challenges that AI creates, rather than producing specific forecasts. We will continue to update our analysis as we learn more about AI technologies and their use on the ground, and accumulate newer data sets. The numbers presented in this discussion paper will inevitably change, and therefore readers should take this analysis not as a conclusion but as a guide to the potential economic impact of AI based on the best knowledge we have at this stage.

2. AI HAS THE POTENTIAL TO BE A SIGNIFICANT DRIVER OF ECONOMIC GROWTH

Predicting the economic impact of AI or any disruptive technology is a highly speculative exercise. This is a world of near-continuous discontinuity. We have already highlighted in our previous work that the scope and pace of automation deployment depend on several variables—some more predictable than others—including technical feasibility, the cost of developing and deploying technologies for specific uses in the workplace, labor-market dynamics including the quality and quantity of labor and associated wages, the benefits of automation beyond labor substitution, and regulatory and social acceptance. Similar factors are likely to determine the pace of AI adoption.[28] In addition to these factors, competitors enabled by digital technologies can burst upon the scene, seemingly from nowhere, putting apparently well-protected and robust incumbent businesses under attack. Vast new markets can rise at a rapid pace. Consider, for instance, that only ten years ago, China accounted for 1 percent of global e-commerce transactions; today, its share is over 40 percent.[29] Technology has accelerated and intensified the natural forces of market competition, and developments are extremely hard to read. It is because of such considerations that we have built scenarios in our previous work, and here extend those through the use of simulations (please refer to Box 3 for methodology and sources).

[28] *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

[29] *Digital China: Powering the economy to global competitiveness*, McKinsey Global Institute, December 2017.

All this said, the results of our simulation of AI's gross and net effect on GDP and labor markets show that AI could add around 16 percent to global output by 2030, or about $13 trillion, compared with today. This would be incremental value created in addition to current global output. This simulation is a combination of a large increase of 26 percent in GDP growth driven by AI, and costs related to the transition to these technologies (for instance, labor displacement) and their implementation (for example, the deployment of AI solutions), as well as negative externalities for the baseline of economic activity (such as loss of consumption during unemployment). Together these elements may produce an annual average net contribution of about 1.2 percent of activity growth between now and 2030.

The impact on economies would be significant if this scenario were to materialize. In the case of steam engines, it has been estimated that, between 1850 and 1910, they enabled productivity growth of 0.3 percent per year. Research has found that the introduction of robots in manufacturing and the introduction of IT accounted for 0.4 percent and 0.6 percent in annual productivity increases, respectively.[30] Recent estimates put the productivity impact of information and communications technology (ICT) and early digital technologies such as broadband at 0.6 percent annually during the 2000s.[31]

WE EXAMINED SEVEN POSSIBLE CHANNELS FOR AI IMPACT

Several factors affect AI-driven productivity growth, including labor automation, innovation, and new competition. Micro factors, such as the pace of adoption of AI, and macro factors such as a country's global connectedness and labor-market structure contribute to the size of the impact. Our simulation examined seven possible channels of impact. The first three relate to the impact of AI adoption on the need for, and mix of, production factors that have direct impact on the productivity of firms. The other four are externalities linked to the adoption of AI and related to the broad economic environment and the transition to AI. We acknowledge that these seven channels are not definitive or necessarily comprehensive, but rather a starting point based on our current understanding and trends currently underway. As AI continues to develop, our approach to understanding the implications of AI will need to continue to evolve.

Production channels

We considered the direct economic impact of AI on three production dimensions. First, we examined additional complementary inputs to improve productivity—what economists call labor and capital "augmentation."[32] The inputs needed to operate new AI capacity include new engineers and big data analysts who will develop and deploy AI solutions. Second, investment in AI technologies will save not only on labor as machines take over tasks that humans currently perform, but also on old capital, for instance by enabling preventative maintenance that increases the life span of assets and thereby reduces the need to invest in new equipment. Third, we looked at more and better innovation associated with AI technologies. In general, process innovation should enable firms to produce the same output with lower inputs, while product and service innovation tends to boost output and the level of inputs such as employment and capital.

[30] See Nicholas Crafts, "Productivity growth in the Industrial Revolution: A new growth accounting perspective," *The Journal of Economic History*, 2004, Volume 63, Issue 2; Nicholas Crafts, "*Steam as a general purpose technology: A growth accounting perspective*," *Economic Journal*, 2004, Volume 114, Issue 495; Mary O'Mahony and Marcel P. Timmer, "Output, input, and productivity measures at the industry level: The EU KLEMS Database," *Economic Journal*, 2009, Volume 119, Issue 538; and George Graetz and Guy Michaels, *Robots at work*, Centre for Economic Performance discussion paper number 1335, March 2015.

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

[32] Daron Acemoglu and Pascual Restrepo, *Artificial intelligence, automation and work*, NBER working paper number 24196, January 2018.

Channel 1: Augmentation

The first dimension relates to increased use of labor and capital. McKinsey surveys in 2016 and 2017 suggest that companies are devoting only 10 to 20 percent of their digital investment budgets to AI tools, but this could increase as they adopt and fully absorb AI technologies. If this were to happen, it could lead to a large increase in annual investment levels. New labor would be deployed and capital invested in economies, potentially leading to higher efficiency.

Investment in AI has complementarities for other factors including jobs. For instance, many jobs are likely to be needed to build the AI infrastructure and monitor its operation to ensure its full use—although most of the time airplanes can be flown automatically, they still have humans on the flight deck. Today, Google has an army of 10,000 "raters" who, among other tasks, look at YouTube videos or test new services. Microsoft operates a Universal Human Relevance System, a crowdsourcing platform that handles micro and administrative tasks. Facebook has announced that it will increase the number of moderators from 4,500 to 7,500.[33]

Between 1980 and 2000 in the United States, about 4 to 9 percent of the workforce were employed in job categories that did not exist 10 to 15 years earlier.[34] Increased capital investment in AI can create demand for jobs—in both existing occupations and new ones—contributing to output growth. For currently demonstrable narrow AI technologies, human beings are needed to manage and transfer insights from one area of narrow AI to another, in contrast to the necessary capabilities of artificial general intelligence.[35] This additional labor complements the increased capital invested in AI.

AI will likely also redefine many existing occupations, augmenting human capabilities and making workers more productive. Our previous research suggested that, on average, 60 percent of occupations have at least 30 percent of activities that theoretically could be automated by adopting and integrating technologies that exist today—numbers that clearly vary from occupation to occupation.[36] As machines take over certain activities, workers are freed up to engage in higher-value tasks using AI tools to be more productive or in other tasks that machines are not yet able to perform, regardless of their value. In call centers, for instance, some processes can be automated entirely while others can be handled by humans much more effectively; AI tools can categorize unaddressed queries accurately, direct callers to the right person to deal with questions, and prepare customized solutions for callers.

Channel 2: Substitution

Technologies that offer better results, cost effectiveness, or both tend to substitute other factors of production. This is the source of much of the current fear about the adoption of AI coming at the expense of labor as basic and repetitive tasks can increasingly be automated.

Our extensive body of research on the impact of automation on work consistently suggests that roughly half of the time spent on various tasks could theoretically be automated

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33 "Artificial intelligence will create new kinds of work," *The Economist*, August 26, 2017.

34 Jeffrey Lin, "Technological adaptation, cities, and new work," *Review of Economics and Statistics*, May 2011, Volume 93, Number 2, pp. 554–574.

35 "Narrow" AI performs one narrow task, while artificial general intelligence seeks to be able to perform any intellectual task that a human can do. Narrow AI is already here, while AGI has yet to arrive. For further discussion, see William Vorhies, "Artificial general intelligence—the Holy Grail of AI," DataScienceCentral.com, February 23, 2016.

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

by adopting existing technology. The picture could, of course, change depending on technological progress.[37]

Simulation in our research found that a midpoint scenario for automation of activities could, on average, substitute around 15 percent of existing time worked globally by 2030. The simulation conducted for our latest research arrived at a directionally similar, but possibly somewhat more aggressive, global result—the midpoint automation potential might be two to three percentage points higher.

The difference in these results is due to the fact that the midpoint scenario in our previous research reflected the median adoption speed of a large set of benchmarked technologies, but it did not explicitly model the pace of AI adoption taking into account factors such as competition and the development of digital capabilities at the firm level, as we have done in this latest analysis. The technology race for AI between firms can create new business models that enable some companies to steal market share from their rivals. Such competitive effects have been well documented elsewhere.[38]

Another reason this latest research may simulate faster adoption and absorption of AI may be that the corporate survey data sets that are one input to the simulation may be skewed toward early movers.

The intensity of substitution depends on the relative costs of inputs.[39] In this research, we modeled the labor-substitution effect—how AI technology automates human activities and effectively substitutes labor with capital, maintaining the output of goods and services but reducing the labor hours required to achieve that output. The substitution also generates additional productivity gains over time as capital becomes more efficient and productive as it "learns."

Channel 3: Product and service innovation and extension

Investment in AI beyond what is needed strictly for labor substitution can produce additional economic output by expanding firms' portfolios, increasing channels for products and services, developing new business models, or some combination of the three. Our research suggests that firms' motivation for adopting and absorbing AI relates as much to a desire to develop new products and services as to a bid to boost efficiency through automation. McKinsey surveys have found that about one-third of companies were investing in AI to improve their sales of current offerings, to expand their offerings of products and services, or both—possibly at the expense of their rivals.[40] To arrive at a sense of the magnitude of this effect, we looked in detail at an extensive set of AI use cases and simulated the relative ratio between the efficiency gained from AI and the magnitude of impact from innovation and market extension.[41]

Innovation often creates new value for an economy as new products and services for underserved markets stimulate consumption. However, in reality, funding for incremental spending needs to come from somewhere. In our modeling, we assumed that the overall economic pie can grow to capture the upside of new value. Nevertheless, innovation may also substitute existing products and services, and innovative firms take share from others; therefore, not all the value that companies create and capture from innovation is

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37 *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017; and *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

38 Lihong Qian and I. Kim Wang, "Keeping up the Red Queen dynamics? Technology competition for generational technologies," *Academy of Management Proceedings*, 2016, Volume 2016, Issue 1.

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

40 *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.

41 *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018.

likely to be "new" to the economy. Anecdotal evidence suggests that a sizable portion of innovation gains come as a result of competition that shifts market share from nonadopters to front-runners. Consider how Uber has substituted incumbent taxi rides, or how AI-based recommendations have tilted sales toward platforms such as Amazon rather than offline channels. Previous surveys we conducted have consistently suggested that a substantial portion of the innovation potential of AI could result in shifting output among firms, with variations according to the industry.[42]

Externality channels

In combination, the augmentation and substitution of inputs and extra innovative output produce new economic activity and productivity gains that researchers tend to take as the measure of the effect of AI on an economy. However, to develop a fuller picture of the economic impact, other factors need to be taken into account. For instance, the use of AI tools and techniques can contribute to global flows between countries and facilitate more efficient cross-border commerce. In this regard, countries that are more connected and participate more in global flows would clearly benefit more from AI. Gains in economic activity can be reinvested and continue to produce growth. However, expanded economic activity can also imply negative externalities arising out of transition costs from implementing AI technologies and more structural costs linked to loss of competitiveness in firms that do not adopt AI or workers being displaced because they lack the skills to operate in an AI-based economy. To draw a more complete picture of the economic impact of AI, we modeled four additional dimensions, both positive and negative.

Channel 4: Economic gains from increased global flows

Economies are not insular; they interact in a global marketplace. Digital data now make up a larger share than in the past of international cross-border flows in the form of knowledge and information exchange, and direct transactions such as cross-border e-commerce.[43] These data flows have already given globally connected, digitally advanced economies a material boost.[44] In previous research, MGI estimated that global data flows boosted global GDP by about 3 percent a year in 2014.[45] This finding implied that digital and data flows could contribute about 7 percent to GDP growth by 2030 compared with today. We simulated that AI could account for up to 20 percent of the contribution of data and digital flows, or an impact of 1.5 percent by 2030 compared with today.

AI can contribute to digital flows in two ways. The first is by facilitating more efficient cross-border commerce. We estimate that about one-third of digital data flows are related to cross-border e-commerce, and 30 to 40 percent of digital commerce can potentially be attributable to AI technologies.[46] Some have estimated that AI-based recommendation engines contribute 30 to 40 percent of sales in leading e-commerce players.[47] If we then apply the ratio of firms adopting and absorbing AI—about 50 percent by 2030—AI could perhaps contribute some 5 to 10 percent of the value that digital data flows create, or a boost to GDP growth of about 0.5 percent by 2030 compared with today. AI can also boost global commerce by, for instance, improving supply chain efficiency and reducing complexities associated with global contracts, classification, and trade compliance. Montreal-based 3CE addresses one major source of supply chain friction by deploying natural language processing to automatically identify and correctly classify traded goods according to customs' commodity taxonomies (for example, identifying

[42] *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.
[43] *Digital globalization: The new era of global flows*, McKinsey Global Institute, March 2016.
[44] Jacques Bughin, "Cross-border data flows and growth in Europe," *DigiWorld Economic Journal*, third quarter, Issue 107, 2017.
[45] *Digital globalization: The new era of global flows*, McKinsey Global Institute, March 2016.
[46] *Artificial intelligence set to transform digital commerce marketing*, Gartner, July 2017.
[47] Kumba Sennaar, *Artificial intelligence in ecommerce—comparing the top 5 largest firms*, TechEmergence, February 1, 2018.

that manually labeled “baby food” is the taxonomically correct “homogenized composite food preparation”).[48] Improvements in transparency and supply chain efficiency can help companies secure better trade financing, reducing banks’ concerns about compliance risks. Banks can use AI technologies to review trade documents, sort and label properly, and analyze risks in a much less labor-intensive way. Digital data flows already facilitate cross-border trading, but AI can make that trade even more effective. Take, for instance, global e-commerce platform Wish, which uses machine learning algorithms and connects hundreds of millions of merchants and consumers worldwide with targeted ads.

This had an explosive impact on the volume of goods Sweden imports from China in a very short time—a 65 percent jump in volume in a single year between 2016 and 2017.[49]

The second way that AI generates impact from global flows is by making improved and expanded use of cross-border data in flows other than commerce, which can enhance the performance of AI solutions and, in turn, can improve the productivity of local activities, especially services. We estimated that two-thirds of cross-border digital data flows could be associated with this effect. We then applied AI’s share within these digital data flows—about 35 to 40 percent—using two reference points. The first is MGI’s assessment of 400 potential use cases that estimated that AI accounts for about 40 percent of the total value contribution from analytics.[50] The second is a range of corporate surveys that we draw on to assess AI intensity within digital (AI-related investment out of total digital investment); we find that this may grow from 10 percent today to 35 percent by 2030.[51] We then apply the ratio of firms adopting and absorbing AI (again, about 50 percent by 2030). The result of this analysis is that AI could have an impact of 10 to 15 percent on total digital flows, or about a 1 percent boost to GDP, by 2030.

Huge amounts of data cross borders every day, and an increasing share of these flows can power AI applications.[52] For instance, many large sets of clinical data from hospitals around the world can enhance the accuracy of diagnosing rare cancers. The quality of AI translation engines can be substantially improved when they can be trained using data in different languages. Online travel agencies in one country can offer personalized interaction and services used in another country by analyzing travelers’ information searches as well as their travel patterns. In entertainment, the performance of chatbots, news aggregation engines, and recommendation sites can also benefit from global data flows, and this can encourage more consumption of content. AI could also drive knowledge spillover effects between economies.[53] We are already seeing digital talent platforms accessible across countries that help businesses, especially professional services companies, match their need for expertise with those who have it anywhere in the world. In the early wave of such digital expertise sharing and matching, specialists would manually scan the internet for relevant expert profiles. Analytics and machine learning algorithms are increasingly being used to speed up the process and improve matching; companies doing so include London-based proSapient and New York-based NewtonX, whose services are accessible from multiple countries. The business case for international collaboration among companies using such tools may strengthen.[54]

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[48] Steve Banker, “Global trade is powered by artificial intelligence,” *Forbes*, October 7, 2017.

[49] E-handeln från Kina har exploderat (E-commerce from China has exploded), PostNord, November 16, 2017.

[50] *Notes from the AI frontier: Insights from hundreds of use cases*, McKinsey Global Institute, April 2018.

[51] Various corporate surveys that we conducted suggest that “AI intensity within digital (AI-related investment out of total digital investment)” is around 10 percent today. If this ratio grows in line with the overall pace of AI adoption, it could reach around 35 percent by 2030.

[52] Susan Ariel Aaronson, *Data minefield? How AI is prodding governments to rethink trade in data*, Centre for International Governance Innovation, April 3, 2018.

[53] Avi Goldfarb and Daniel Trefler, AI and international trade, NBER working paper number 24254, January 2018.

[54] Bruce Reed and Matthew Atwell, *The rise of the expert economy: Could sharing wisdom be the next gig?* Civic, May 2018.

Channel 5: Wealth creation and reinvestment

As AI contributes to the higher productivity of economies, the increased output from efficiency gains and innovations can be passed to workers in the form of wages and to entrepreneurs and firms in the form of profits.[55] The generation of wealth induced by AI could create spillover effects that boost economic growth. As workers' incomes rise and they spend more, and firms reinvest their profit into operations, the incremental output can be channeled back into the economy in the form of higher consumption or more productive investment as well as jobs growth. Such secondary effects or spillovers may develop over time; indeed, they have been a major source of sustained growth in the past.

Such benefits will largely have an impact on an economy and its players if they are reinjected into the domestic economy rather than into other countries. Countries with a higher propensity to consume domestically, with resource-allocation systems that enable and encourage reinvestment into the domestic economy, and smaller leakage of capital from the repatriation of corporate profits or outbound capital flows, can maximize the benefit. The AI value chain may grow and boost the ICT sector, making an important economic contribution to an economy. It is important to build a strong AI value chain to maximize the reinjection of additional output into the economy.

Channel 6: Transition and implementation costs

A range of costs are likely to be incurred while executing the transition to AI. Companies are likely to incur cost restructuring their organizations. Some workers may be displaced by new technologies, and companies might need to pay associated costs such as severance. As they adopt new solutions, businesses may need to pay fees to cover the cost of systems, their integration, and associated project and consulting fees. Companies also need to build capabilities to operate new AI tools, hiring new workers and incurring costs such as fees associated with advertising and headhunters. Companies also need to upgrade the skills of their existing workers. As many tasks are automated, employees need to adapt to new types of work, and many workers will need to be trained to use new digital and AI tools for their daily operations. We have detailed the workforce-related transitions in our previous work and draw on that analysis here.[56] Disruptions to society may also incur costs (see Channel 7). We do not claim to have fully sized all such externalities, but we have attempted to model these in our simulation.

Channel 7: Negative externalities

AI could induce major negative distributional externalities affecting workers among others. Many economists argue that technology has caused a decline in the labor share in many economies.[57] As firms adopt and absorb AI, pressure on employment and wages is likely to increase, which may depress the labor share of income and potential economic growth —cyclically through lost consumption during periods when individuals are unemployed or retraining, and structurally through a relative income effect.[58] Other costs may have a direct impact on individuals and an aggregated impact on the economy. Displaced workers may need to take retraining courses supplied and supported by governments and companies if they are to swiftly rejoin the workforce. During the transition, there is likely to be a negative impact on the economy. Those workers who are out of work, and therefore not earning, are likely to cut their consumption (as well as temporarily not contributing to

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55 The exact split of distribution of those rents could lead to a lower labor share of output in the economy.

56 *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017; and *AI, automation, and the future of work: Ten things to solve for*, McKinsey Global Institute, June 2018.

57 Mai Chi Dao et al., *Why is labor receiving a smaller share of global income? Theory and empirical evidence*, IMF working paper number 17/169, July 24, 2017.

58 *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

economic output). Another cost is government support for affected workers in the form of unemployment benefits and other social provision. We also know from historical cases that such externalities can last longer than expected. One example is the so-called Engels' pause, which describes the stagnation of wage growth in Britain in the first half of the 19th century even as output per worker grew; the profit share of national income increased while the labor share of income declined.[59]

OF THE SEVEN CHANNELS OF IMPACT, THREE STAND OUT

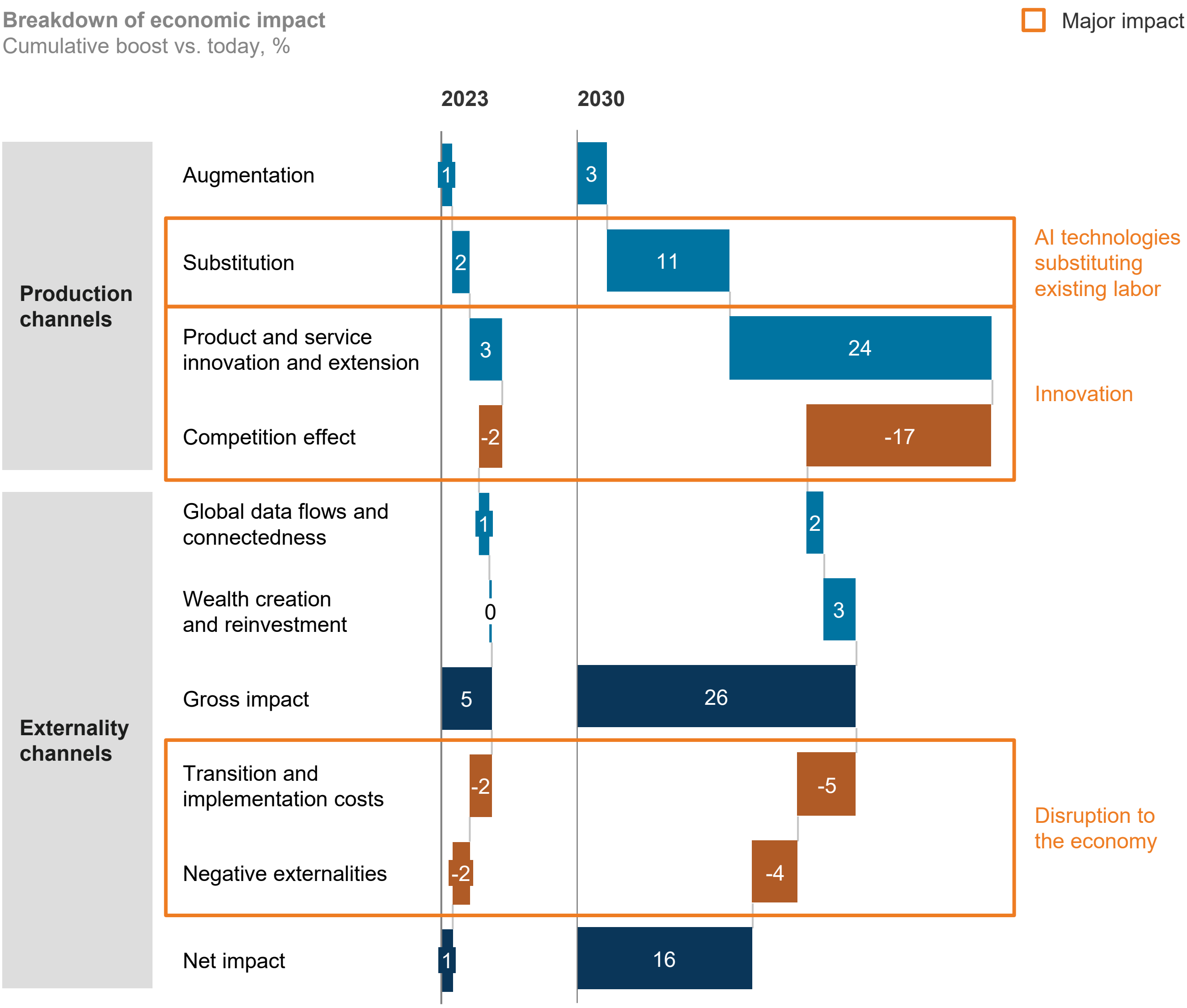
Three of the seven channels stand out: (1) the use of AI-driven automation to substitute existing labor; (2) the application of AI to innovation that creates new and better products and services; and (3) AI-driven competition and the resulting disruption to firms and workers (Exhibit 1).

Exhibit 1

AI's net economic impact has seven dimensions.

SIMULATION

Breakdown of economic impact
Cumulative boost vs. today, %



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts. Figures may not sum to 100% because of rounding.

SOURCE: McKinsey Global Institute analysis

[59] Robert C. Allen, "Engels' pause: Technical change, capital accumulation, and inequality in the British industrial revolution," *Explorations in Economic History*, 2009, Volume 46, Issue 4.

Automation of labor could add up to about 11 percent or around $9 trillion to global GDP by 2030

The substitution of labor by technology is often viewed from the point of view of the supply side of workers, and rarely from the demand side of firms. Yet, firms adopt technology for economic reasons—in the case of AI, the productivity boost available from substituting labor. The impact on people of being displaced by technology is real and important, an issue addressed in previous MGI research.[60]

However, this concern needs to be considered in the context of overall gains in productivity and economic activity. The impact of automation could be as much as $9 trillion, or around 11 percent higher output by 2030 compared with today. This represents growth in value added accumulating over the period to 2030, driven by productivity gains from smart capital and the skills of the labor force, assuming displaced labor can be redeployed elsewhere in the economy. This is not to say that automation is exclusively beneficial for an economy. Yes, it drives the productivity of firms, but it also displaces workers. At an aggregate level, the boost in productivity can lead to greater economic output that is absorbed in the system, creating additional jobs elsewhere, and the overall economy may benefit. At the micro level, however, many workers may come under stress, and they will need support as they transition to an AI-enabled market.

Net gains typically increase over time as the performance of these technologies improves—as we have seen in the case of many general-purpose technologies. For instance, the price of electric motors in Sweden plunged by as much as 70 percent during the 1920s.[61] In the case of AI technologies, costs have fallen quickly even as performance has increased rapidly.[62] Regarding performance, consider computer vision. In the period to 2011, this AI tool typically generated the wrong information from large data pools in one case out of four; five years later, the error rate was only 5 percent, on a par with—and even bettering—the information pattern recognition of an average human being, according to Google Brain.

Innovation in products and services could deliver up to about 7 percent or around $6 trillion of potential GDP by 2030

AI can make an important contribution by boosting innovation that can then be applied to improve current products and services, and create entirely new offerings. Our simulation suggests that innovation can contribute about 7 percent, which could lead to a potential $6 trillion output increase by 2030, incremental to today’s output.

The first reason these AI effects are large is that companies can rapidly improve their top lines by reaching underserved markets more effectively even with existing products and services, while the value of gains from input substitution depends on productivity gains building up over time. The second reason is that, over the longer term, most technologies tend to foster innovation in products and services, boosting nontraditional industries and creating entirely new markets. Think about how the high-pressure compact steam engine moved beyond the factory, leading to a boom in rail and sea travel. The first steam-powered locomotive hit the rails in Britain in early 1800, and the first ship sailed in the United States by 1807. Consider how ICT was the foundation of the internet economy that is now reshaping retail, transportation, and media industries. AI is likely to have such transformative impact, for instance powering a consumer market for genomics and the development of an entirely autonomous road transportation system.

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60 Ibid.

61 Harald Edquist and Magnus Henrekson, “Technological breakthroughs and productivity growth,” in Gregory Clark, Alexander J. Field, and William A. Sundstrom, eds., *Research in Economic History*, Volume 24, Bingley, UK: Emerald Group Publishing Limited, 2006.

62 According to some estimates, the cost of industrial robots will fall by roughly 65 percent by 2025, to levels much lower than most analysts now anticipate. Combined with advances in machine learning and computer vision, this drop in costs should cause an inflection point in demand for robots as they infiltrate new industries with more provocative use cases. See Sam Korus, “Industrial robot cost decline,” *Ark Invest*, August 7, 2017.

There are also competitive effects associated with innovation. Although front-runners can increase their top-line growth, a large portion of gains could be linked to a shift in market share. The implication is a large degree of cannibalization and firms being challenged if they do not redefine their product and service portfolios. To counter this effect and improve cash flow, some firms under competitive pressure are likely to cut investment in R&D, facilities, and the deployment of new technologies, potentially finding themselves in a vicious cycle. The risk is well documented in research related to competitive dynamics in digital markets.[63]

Negative externalities and transition costs could reduce the gross GDP impact by about nine percentage points, or around $7 trillion

The economic benefits of AI-based automation and innovation are secured at a cost, an element that existing research tends to overlook. We find that the deployment of AI will very likely create a shock in labor markets and that there will very probably be costs associated with managing labor-market transitions, especially for workers whose skills are made obsolete or less relevant by AI technologies.

Recent MGI research highlights that up to 14 percent of workers might need to change occupations—and that, while some may change roles within the same company, others may need to move to new sectors and even geographies.[64] The research also found that while most workers will face competition from AI for some tasks, less than 10 percent of occupations are made up of activities all (or more than 90 percent) of which can be fully automated based on currently demonstrated capabilities. Nevertheless, in about 60 percent of occupations, at least one-third of activities could be automated.

This implies significant changes for workers and workplaces.[65] Further, workers may—it is to be hoped—have access to some social security and unemployment benefits to sustain them while they are unemployed and before they reenter the workforce. An obsolete product or service disappears forever except in cases where the product becomes a niche curiosity; workers retrain, upskill, and reenter the workforce.

Our analysis suggests that these changes will incur costs of about $7 trillion by 2030. Negative externalities such as loss of domestic consumption during unemployment could lower the positive impact of AI by four percentage points. Transition and implementation costs could add another five percentage points of cost (Exhibit 2).[66] We note that there are limitations to our modeling, and that readers should use the results of our simulation to get a broad idea of the potential costs that may be incurred. It is difficult to calculate costs exactly because they are likely to be incurred on multiple fronts on the supply and demand sides, and, in many cases, be interrelated. Moreover, transition costs in one part of the value chain may generate new value in another part; therefore, the items of cost listed in our simulation may not be purely additive. We note that our current modeling does not account for detailed value redistribution across the economy. A more complete and robust macroeconomic simulation is needed to assess equilibrium and interconnected loops.

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[63] Jacques Bughin, Laura LaBerge, and Anette Mellbye, "The case for digital reinvention," *McKinsey Quarterly*, February 2017.

[64] For a synthesized view of the labor-market shift, challenges, and potential measures, see *AI, automation, and the future of work: Ten things to solve for*, McKinsey Global Institute, June 2018.

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

[66] These estimates are based on analysis of reskilling per task rather than reskilling individuals. Most people will need to reskill for 2.5 tasks on average, which may imply that costs to support such workers in terms of training and social support may last for six months (a great deal of literature is predicated on the costs being incurred for a single month). For more on this topic, see, for instance, Ljubica Nedelkoska, Frank Neffke, and Simon Wiederhold, *Skill mismatch and the costs of job displacement*, CESifo Area Conference on the Economics of Education, Munich, Germany, September 11–12, 2015; and Benoît Pierre Freyens, "Measures of training costs in Australia," *Management Research News*, August 2006.

Exhibit 2

Substantial transitional costs and negative externalities may accompany the transition to an AI-enabled economy.

SIMULATION

Buildup of transition socioeconomic costs
% of economic value, cumulative 2030

			Example items
Transition and imple-mentation costs	Displaced workforce	-3	Severance pay, accrued paid time off, other compensation
	Implementing solutions	<1	Fees to cover system integration and consulting fees (for a transformation program)
	Hiring of new workers	-1	Advertising, recruiter and referral bonuses, relocation
	Continuous upgrade of skills	-1	Employee AI-development programs
Negative externalities	Skilling and reskilling to reenter the workforce	-1	Training cost by national labor-market program
	Loss of domestic consumption	-1	Unemployed individuals consume less
	Loss of economic contribution	-2	Unemployed individuals do not produce economic output
	Unemployment benefits	<1	Direct and indirect benefits during unemployment
	Total costs	-9 (-4, -5)	

NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts. Figures may not sum to 100% because of rounding.

SOURCE: McKinsey Global Institute analysis

THE IMPACT OF AI BUILDS UP OVER TIME, GATHERING PACE AFTER FIVE TO TEN YEARS

A net productivity effect builds up over time—modest within five years to material by 2030. As a result, AI's contribution to growth may be three or more times higher by 2030 than it is over the next five years. The global net impact of $13 trillion of additional value compared with today's global GDP is likely to develop over a longer period (Exhibit 3). Although we present an annual trend curve here, this is largely for illustrative and simulation purposes. We therefore suggest that readers look at the shape of the curve rather than exact annual figures. As we have noted, our simulation is dependent on the actual level of adoption and absorption by firms, and our current firm-level data set may be skewed toward early adopters. This may mean that the impact shown is an overestimate. In reality, followers may not have organizational capabilities and investment capacity as strong as those of front-runners, and their adoption and absorption might be slower.

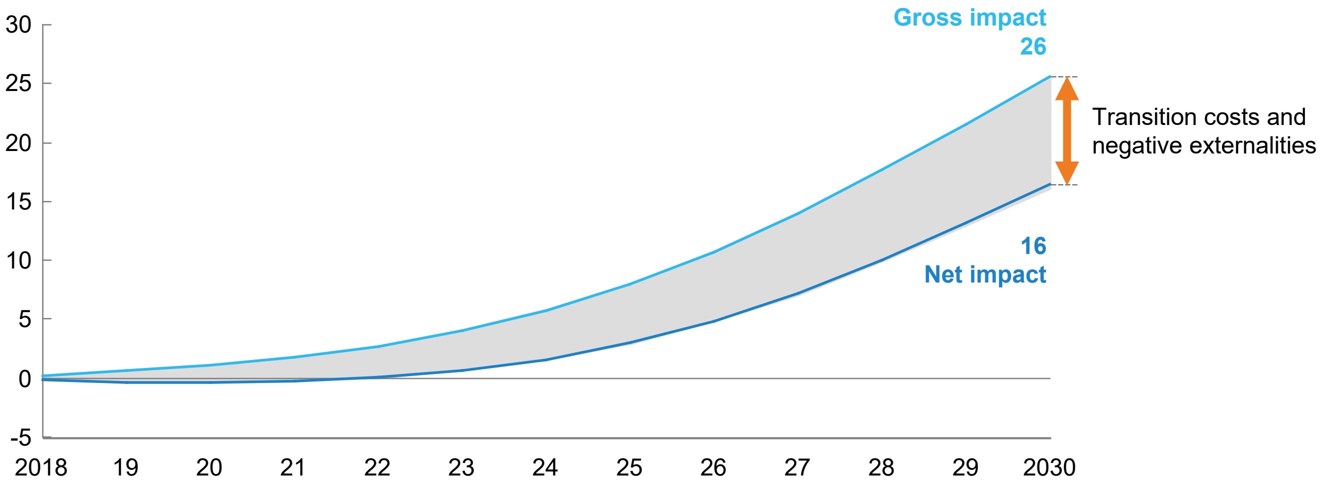
The aggregate net impact of AI may take off after a period of five to ten years. In the near term, there are costs related to the implementation of AI, but subsequently a broader swath of companies adopt and absorb AI throughout their organizations at an accelerating pace over the years as a result of competition and improvement in complementary capabilities to use AI tools. Reminiscent of the Solow Paradox, the small initial impact may persuade some observers that AI is being overhyped, but this could well lead to misjudgment. The benefits to early adopters of these technologies increase sharply in later years at the expense of nonadopters.

Exhibit 3

The economic impact of AI can build up at an accelerating pace.

SIMULATION

Value-added gains of economic output
Cumulative boost vs. today, %



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Global Institute analysis

In aggregate, and over time, the impact of AI is likely to accelerate, boosting productivity growth. Therefore, companies—and countries—with proactive AI strategies will likely need to be committed for the long haul, because the total net impact may become visible only after a few years.[67] We have seen this pattern before with general-purpose technologies such as steam and electricity: a slow start dominated by investment and low productivity, followed (sometimes decades later) by impact in the form of higher productivity. One study found that electricity pervaded businesses and households more generally only after 1915, when machines operated by stand-alone secondary motors diffused, centralized power grids spread, and productivity began to rise.[68] Another found that the accumulation of capital in steam engines was slow. After the patenting of the improved steam engine by James Watt in 1769, it took until 1830 for steam to reach parity with water as a source of power in the British economy. Even as late as 1870, steam power was largely used in mining and cotton textile manufacturing.[69]

[67] Harald Edquist and Magnus Henrekson, "Technological breakthroughs and productivity growth," in Gregory Clark, Alexander J. Field, and William A. Sundstrom, eds., *Research in Economic History*, Volume 24, Bingley, UK: Emerald Group Publishing Limited, 2006.

[68] Paul A. David, "Computer and dynamo: The modern productivity paradox in a not-too-distant mirror," in *Technology and productivity: The challenge for economic policy*, OECD, 1991.

[69] Nicholas Crafts, *Steam as a general purpose technology: A growth accounting perspective*, May 2003.

MICRO AND MACRO FACTORS EACH CONTRIBUTE TO THE IMPACT OF AI

Micro and macro factors underpin the impact of AI on global economic activity to broadly the same extent. The most material micro factors relate to influences on the dynamics of firms' adoption and absorption of AI. The key macro factors include AI investment and research capabilities as well as key enablers such as digital absorption, human capital, connectedness to global flows, and labor-market structures and flexibility.

Micro factors influence AI adoption and absorption

The economic impact of AI depends on the rate at which these technologies are adopted by economic entities and absorbed throughout their organizations. Decisions to invest in these technologies do not occur in a vacuum, but depend on several important variables that determine the economic and competitive case for adoption and absorption.

Total absorption level of AI by companies might reach about 50 percent by 2030

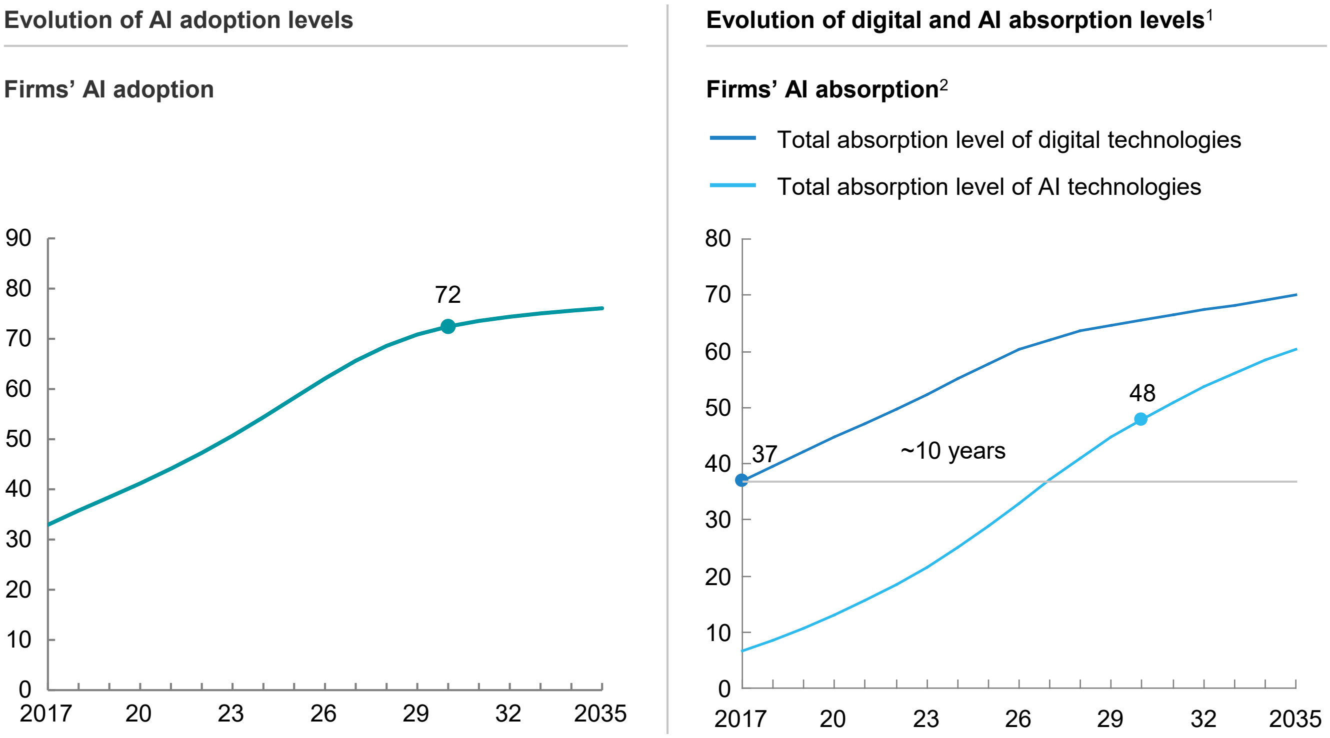
Using econometric analysis and proprietary data along with early evidence from surveys on how companies are adopting AI, we estimate that about 70 percent of companies might adopt some AI technologies by 2030, up from today's 33 percent, and about 35 percent of companies might have fully absorbed AI, compared with 3 percent today. Companies that partially absorb AI technologies are likely to capture partial benefits from AI. In our modeling, we factored in different degrees of absorption and calculated "total" absorption by adding "partial" and "full" absorption; it could reach about 50 percent by 2030 (Exhibit 4).

Exhibit 4

AI absorption by firms may reach about 50 percent by 2030—taking ten years to match today's level of digital technologies.

SIMULATION

Share of firms
%



1 Digital technologies for this purpose are big data, cloud, mobile, and web technologies.
2 Total absorption includes the weighted share of firms that have both partially and fully absorbed AI.
NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Global Institute analysis

One way to put these estimates into context is to compare them to the absorption of digital technologies such as web, mobile, cloud, and big data. Those technologies started to be used about ten to 25 years ago. The average level of absorption of this previous generation of digital technologies was about 37 percent in 2017 and may reach 70 percent by 2035. In comparison, absorption of AI might reach today's level of digital absorption by 2027—in roughly ten years.

Early digitization and the competitive race are important determinants of the pace of AI adoption and absorption

Full absorption takes time, as we have seen in the case of the previous generation of digital technologies. AI may be adopted and fully absorbed slightly faster—at the high end of benchmarks of the speed at which technologies percolate. AI adoption and absorption could be more rapid because of the breadth of ways in which it is used, including in domains where digitization is still underpenetrated, such as the automation of services and smart automation of manufacturing processes. Another reason that AI may be adopted and absorbed more quickly than previous technologies is that its returns tend to be large and to come with significant cannibalization and substitution that create an imperative to respond to, and attempt to move ahead of, the competition. Nevertheless, the adoption and absorption of AI may be bounded by its dependence on the technical infrastructure needed for its effective use. Two aspects worth highlighting are digitization and competition.

- **Digitization.** An important factor in the adoption of AI is whether previous digital technologies are in place, because these are the technical backbone for its effective rollout.[70] Machine learning underpins a large share of AI technologies. Most algorithms require big data and a digital architecture (however it is provided; for example, via the cloud or on premises). Superior insight from AI does not translate into increases in corporate performance unless many activities change—for instance, many salespeople need to change the way they sell. Even when the technological backbone is present, companies cannot generate value from AI without the skilled labor and experience necessary to tap into its opportunities and mobilize change within organizations.

  The way the absorption of previous generations of digital technologies affects the deployment of AI has been demonstrated. Correlating the absorption of AI with the digital maturity of a firm reveals that companies that are more digitally mature have annual AI adoption and absorption up to 12 percentage points higher than firms that are less digitally mature (Exhibit 5).

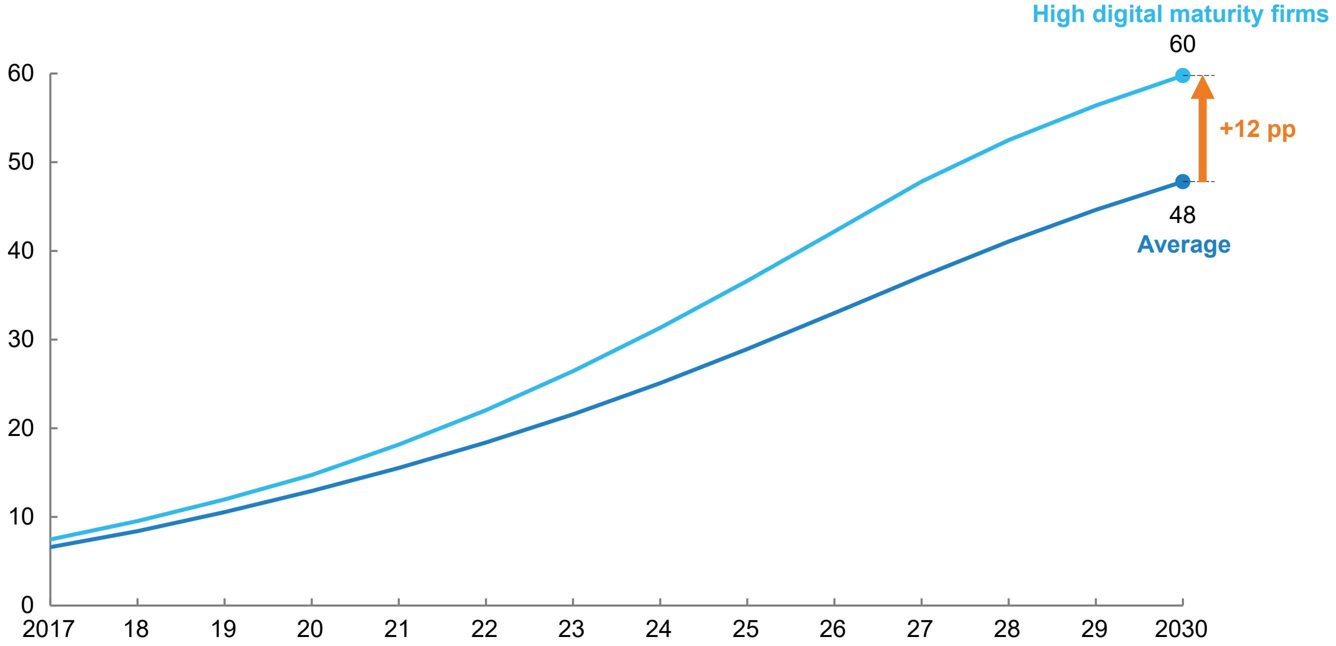
[70] Jacques Bughin and Nicolas van Zeebroeck, "Artificial intelligence: Why a digital base is critical," *McKinsey Quarterly*, July 2018.

Exhibit 5

High digital maturity can accelerate AI adoption and absorption.

SIMULATION

Evolution of total absorption levels of firms with high digital maturity vs average[1]
Share of firms
%



1 Constitutes companies that have absorbed web, cloud, mobile, and big data technologies.
NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Digital Survey; McKinsey Global Institute analysis

- **Competitive pressure.** Economists have long been interested in how technological innovation and technology interact with competition. According to both Schumpeterian and disruptive theory views, the adoption of technology is typically driven by competition and may build a first-to-market advantage if the performance of the technology is strong enough to compensate for all the uncertainty surrounding its introduction.[71] Some economists have shown that competition was the most important driver of PC adoption, for instance.[72]

  Some companies adopt AI in a preemptive move against perceived fear of disruption from competitors or as a direct response to a new competitor, while others react more slowly. MGI's econometric analysis and our corporate survey have consistently suggested that, for each type of AI technology analyzed, the presence of rivals investing in AI plays a significant role in any decision by a company to invest.

71 Heidrun C. Hoppe, "The timing of new technology adoption: Theoretical models and empirical evidence," *The Manchester School*, 2002, Volume 70, Issue 1.
72 Adam Copeland and Adam Hale Shapiro, *The impact of competition on technology adoption: An Apples-to-PCs analysis*, Federal Reserve Bank of New York staff report number 462, August 4, 2010.

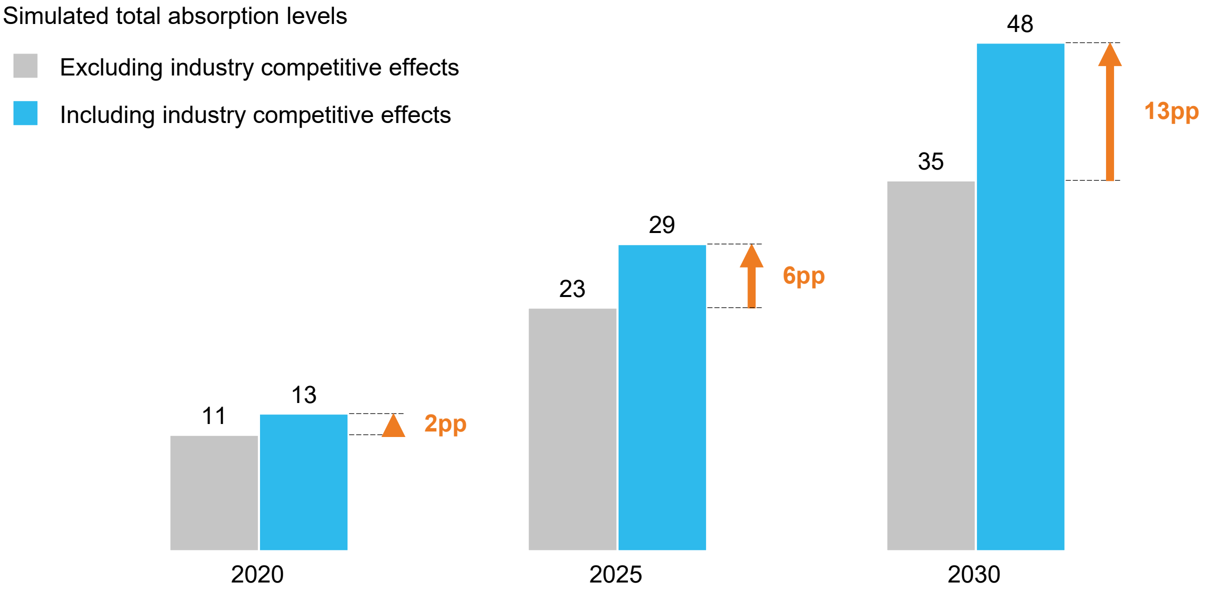
In this research, taking our corporate survey as an input, the model simulates the extent to which companies are considering deploying AI technologies in specific functions or across their broader organization in response to competitive moves made by other firms in the same industry and geography. We also examined other determinants such as the impact of AI on profitability and whether tangible use cases are available. Extrapolating from this microeconomic effect, we find that competitive pressure can increase the absorption level by about 13 percentage points in 2030 (Exhibit 6).

Exhibit 6

Competitive pressure can accelerate the pace of AI absorption.

SIMULATION

Impact of competitive dynamics on firms to absorb AI technologies[1]
% of firms



1 McKinsey's survey gathered data from C-level executives on whether, and to what extent, they would adopt AI technologies if a competitor or peer did so. MGI used econometrics to study the effect on adoption and absorption levels with and without this effect to understand the degree to which significant competition drives adoption and absorption levels.
NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Digital Survey; McKinsey Global Institute analysis

Macro drivers can affect the adoption, absorption, and economic impact of AI, and potentially lead to a new AI divide

Other important macro drivers can affect the adoption, absorption, and economic impact of AI technologies by firms and countries. In general, these drivers tend to favor developed countries more than developing ones. We largely looked at two major categories: (1) indicators that are directly related to investment and research in AI and the automation potential of economies; and (2) enablers that are the foundations or preconditions for AI's potential to be unleashed. We compiled multiple indicators in eight dimensions for 41 countries to gauge the readiness of countries to adopt and absorb AI. These indicators are by no means exhaustive, but they are useful for gauging the relative positions of countries. The data set we used has limitations and may not capture the full picture of each dimension. We intend to continue to refine and update the data we use for this analysis and will improve the accuracy of our findings as data become available.

AI-related indicators

We assessed the following three types of AI-related indicators:

- **AI investment.** The economic impact of AI depends on whether there is sufficient investment to fund new AI companies and research, and enable greater corporate investment. Investment in AI is growing rapidly but is still largely concentrated in the United States and China. Tech giants such as Google and Baidu spent an estimated $20 billion to $30 billion on AI in 2016.[73] In 2017, according to CBInsights, $15.2 billion was invested in AI startups around the world, and nearly half (48 percent) of that total went to China; 38 percent was invested in the United States. The United States still has more AI startups than China, but China is making considerable headway in striking equity deals in the AI sphere. In 2013, the United States accounted for 77 percent of such deals, but that share fell to 50 percent in 2017.[74] We compiled AI-related investment data from Dealogic, S&P, and Capital IQ. Investment figures include sources of funding such as seed, grant, mergers and acquisitions, private equity, and venture capital. We note, however, that we tracked "external" investments (investment from one firm to another), a metric that does not capture in-house investment, which could be sizable in some economies.

- **AI research activities.** We have noted that AI could have a large gross impact if companies use it to create new products and services (beyond simple labor substitution). We analyzed AI-related research activities using data on AI-related patents from the World Intellectual Property Organization, and AI research using AI publications and citations from Scimago Journal Rank. We note that these sources do not cover the full range of work being undertaken by companies, because many corporate research laboratories may not fully publish the scope and extent of their research given competitive dynamics. Having said that, it's important to note that many corporate labs are now among the top contributors of AI knowledge for key conferences, including the Conference on Neural Information Processing Systems (NIPS) and the International Conference on Machine Learning (ICML).[75]

- **Potential productivity boost from AI and automation.** Previous MGI research has found that the potential to automate and for AI to be deployed can be driven by the relative costs of machines and wages. Because wages are relatively low in developing countries, the potential to automate is lower. However, in most developed economies, higher wages will likely lead to more AI adoption and absorption when it substitutes for human labor.[76] Although we did not explicitly model the impact here, companies that substitute AI for labor may be motivated not only by cost savings, but also by AI's ability to outperform humans in some functions. Depending on the wage level, economics, and social acceptance, the automation potential, and therefore the substitution effect, may differ. This research used MGI's future of work database to assess different degrees of potential. Developed economies tend to have high automation potential, because the business case for AI solutions is easy to justify. The high index reading should be interpreted as high potential to substitute labor rather than a country's strength.

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73 *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.

74 *Top AI trends to watch in 2017*, CBInsights, February 2018.

75 See Robbie Allen, NIPS accepted papers stats, *Machine Learning in Practice*, December 5, 2017; and Robbie Allen, ICML 2018 accepted papers stats, *Machine Learning in Practice*, July 9, 2018.

76 *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017; and *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

AI enablers

The other five dimensions we looked at are enablers. They are the foundations for adoption and absorption of AI (as well as other emerging technologies), and some are likely to correlate with AI-related indicators (and therefore these dimensions may not be orthogonal):

- **Digital absorption.** Conventional measures of digital readiness, maturity, or competitiveness of countries tend to focus on digital infrastructure: internet penetration, broadband speed, and affordability for households, for example. There is a wide variety of data on these measures.[77] However, how companies are developing digital assets and using them across their organization is perhaps the more important precondition of AI. Our previous work on digitization in China, Europe, and the United States demonstrated wide variances among sectors and countries. In general, the United States leads, closely followed by a few European countries such as the United Kingdom and Scandinavian economies, with China still some distance behind.[78] Because our assessment was based on bottom-up sector-level data, we have limited samples for broad cross-country comparison on a global basis. We therefore used alternative sources from the Global Talent Competitiveness Index report. We drew on the technology utilization index, which measures how corporations are using the latest (digital) technologies in each country as a proxy for the ability of companies to absorb digitization.

- **Innovation foundation.** The degree of innovation can determine whether a country is able to develop and commercialize powerful AI solutions. This research assessed overall innovation capacity using data on R&D investment from the OECD and evaluated industry dynamism using data on ICT and business-model creation and ICT organizational model creation from the Global Innovation Index 2017 report by INSEAD and the World Intellectual Property Organization. For our modeling, we focused more on differences among companies in terms of whether they can use the technologies and create new business models, and whether companies can improve their organizational models in order to absorb technologies.

- **Human capital.** Economies need to ensure that they update the skills available not only to ensure that there are sufficient AI specialists, but also to enable large numbers of individuals to work alongside machines.[79] Human capital is critical to the absorption of new knowledge and its real-world applications. This research looked at problem-solving skills using scores from the OECD's Programme for International Student Assessment (PISA); the availability of scientists and engineers as well as employment in knowledge-intensive sectors from INSEAD; the overall quality of human capital from the World Economic Forum's Global Human Capital Index; and the availability of talent using data on science, technology, engineering, and math (STEM) graduates from UNESCO and Eurostat.

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[77] For example, the International Telecommunication Union's ICT Development Index; penetration using ITU data on internet penetration among individuals; quality using ITU statistics on broadband speed; and affordability from the derived ratio of cost to per capita GDP from BDRC Continental and Cable.co.uk.

[78] In previous MGI research, we have looked at the extent to which sectors in countries and countries are digitized. While we believe this work to be more in-depth (including detailed sector-level views) than the metrics used here, this previous analysis did not fully cover all the countries we wanted to include in the assessments undertaken for this discussion paper, which therefore uses broad digital-related statistics that we can compare across a larger number of countries. For more, see *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015; *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June 2016; and *Digital China: Powering the economy to global competitiveness*, McKinsey Global Institute, December 2017.

[79] *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015.

- **Connectedness.** Countries with stronger connections to the world may have better foundations for innovation and are most likely to have increased potential to reap the benefits of AI. Connectedness can help countries use cross-border data flows to enhance the performance of AI applications and participate in global value chains, as we have noted. In previous research, MGI looked at global flows and connectedness in detail, and this analysis builds on that work. We used MGI's Connectedness Index, which ranks countries on their flows of goods, services, capital, people, and data. Data sources behind this index include the United Nations, ITC Trade Map, and TeleGeography.

- **Labor-market structure and flexibility.** Widespread penetration of AI will almost certainly displace many existing working tasks. Minimizing the risk of societal backlash will require as smooth as possible a transition to AI by putting in place mechanisms such as transitional support and training for displaced workers.[80] Countries that have robust social support and extensive provision of training may be less likely to run into popular opposition to AI that could add cost to its implementation. We compiled scores on aspects including collaboration between workers and employers, active labor-market policies, development of employees, and environmental performance from the Global Competitive Talent Index report published by INSEAD. We also referred to redundancy cost (costs related to advanced notice and severance payments when terminating workers) from the World Bank.

Other factors may also play a role, including various legal frameworks governing the use of data in certain geographies. Examples include the EU's General Data Protection Regulation and the California Consumer Privacy Act of 2018, US sector-based regulation such as the Health Insurance Portability and Accountability Act, and the Gramm-Leach-Bliley Act in finance. While we acknowledge that regulation and other factors may affect outcomes, we have limited our model to those factors that we can attempt to quantify.

3. ALONG WITH LARGE ECONOMIC GAINS, AI MAY BRING WIDER GAPS

While the potential benefits of AI may be large, they are not likely to be distributed equally. Our simulated estimate of the impact of AI on the world economy is an average of the effect on different countries, sectors, and firms. There could be widening gaps among countries, sectors, firms, and workers. This possibility needs to be managed if the potential impact of AI on the world economy is to be captured in a sustainable way—and even to avoid a backlash against these technologies that could limit their economic impact.

IN TERMS OF READINESS FOR AI, COUNTRIES APPEAR TO FALL INTO FOUR GROUPS

Using various indicators for the macro dimensions we have described, we analyzed 41 countries to assess where they stand relative to each other. We calculated a global average and then measured standard deviation. We categorized countries one standard deviation above the average as "above threshold," and those one standard deviation below the average as "below threshold"; we categorized the rest as "within the threshold" (Exhibit 7).[81]

This analysis found that there may be four groups of countries that share relatively similar degrees of preparedness, based on currently available data. We note that the economic impact of AI is not guaranteed by being in a particular group of countries that look promising in terms of readiness—passivity will mean that even if the factors appear to be in place for the rapid adoption of AI, the economic benefits are unlikely to materialize. In addition, the

[80] *AI, automation, and the future of work: Ten things to solve for*, McKinsey Global Institute, June 2018.

[81] For certain dimensions where values for leading countries are far higher than the average (AI research activities, for example), we lowered the threshold to show relative differences clearly.

groups are not fixed; countries could move from one to another over time depending on the choices they make and the actions they take. In fact, developing economies could potentially leapfrog advanced ones if they were to strengthen core enablers. An absence of legacy, inefficiencies in various parts of the economy, and the role of smart capital in overcoming skills issues may present attractive opportunities for the commercialization of AI use.

The four country groups are:

- **Active global leaders (China and the United States).** These two countries are currently leading the race to supply AI, and they have unique strengths that set them apart from all others. Scale effects enable more significant investment, and network effects enable these economies to attract the talent needed to make the most of AI. Together, they are responsible for the vast majority of AI-related research activities. They are a long way ahead of other countries on AI-related patents, publications, and citations. They also make substantial investment in AI. In terms of external investment (investment from one firm to another), including venture capital, private equity, and M&A, the United States accounted for 66 percent, while China was a distant second with 17 percent in 2016. However, China's share is growing rapidly.[82] These countries also have solid enablers. In 2016, they invested about 2 to 3 percent of GDP in overall R&D. Depending on national priorities and business opportunities, these huge R&D investment capacities could be channeled into AI. Although China's capacity to innovate is increasing, the economy is digitizing quickly, and investment in AI is substantial.[83] China and the United States are also the large contributors to global trade (in terms of both exports and imports), responsible for more than 20 percent of all the value being traded globally.

- **Economies with strong comparative strengths.** A wide range of countries belongs to this group, including, for instance, Canada, France, South Korea, and Sweden. They are relatively well positioned to capture the benefits of AI given their generally robust foundation of enablers. Many of these economies are highly motivated to embrace AI because they have been experiencing slowing productivity growth.[84] Another incentive is the fact that labor costs tend to be high in these economies, especially advanced ones. Several large economies belong to this group—including Germany, Japan, and the United Kingdom—that have the capacity to drive innovation on a major scale and to accelerate the commercialization of AI solutions. Smaller, globally connected economies such as Finland, Singapore, South Korea, and Sweden typically score highly on their ability to foster productive environments where novel business models can thrive.

- **Economies with moderate foundations.** This group, which includes India, Italy, and Malaysia, has a moderate ability to capture economic benefits from AI. While the potential for economic gains is broadly positive, these countries are in a weaker starting position than those in the first two groups, but they exhibit comparative strengths in specific areas on which they may be able to build. India, for instance, has somewhat underdeveloped digital infrastructure and currently has a relatively low automation potential, but it produces around 1.7 million graduates a year with STEM degrees—more than the total of STEM graduates produced by all G-7 countries. Moreover, a high share of India's exports is ICT-related.

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82 *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017; and *Digital China: Powering the economy to global competitiveness*, McKinsey Global Institute, December 2017.

83 For further discussion, see *The China effect on global innovation*, McKinsey Global Institute, October 2015; and *Digital China: Powering the economy to global competitiveness*, McKinsey Global Institute, December 2017.

84 In Germany, for instance, total economy productivity growth decelerated by 0.7 percent in 2010–14 versus 2000–04. In the United States, the decline in private business sector productivity between these two periods was 3.8 percent. See *Solving the productivity puzzle: The role of demand and the promise of digitization*, McKinsey Global Institute, February 2018.

Exhibit 7

Varying conditions among countries imply different degrees of AI adoption and absorption, and therefore economic impact.

Above threshold[1] Within threshold[1] Below threshold[1]

Group		AI-related			Enablers					Total score[5]
	Readiness areas	AI invest-ment	AI research activities	Producti-vity boost from auto-mation	Digital absorption	Innovation foundation	Human capital	Connect-edness	Labor-market structure	
	Examples of indicators included	VC, PE, M&A, seed, grant[2]	Patents, publica-tions, citations	Automa-tion potential of activities	Techno-logy utilization	R&D invest-ment, business-model creation	PISA score, STEM graduates, GHCI[3]	MGI Connect-edness Index	Redun-dancy costs, indexes on worker-employer collabora-tion	
	Data sources	Dealogic, S&P, Capital IQ	WIPO, Scimago Journal Rank	MGI	GTCI[4] (INSEAD)	OECD, INSEAD, WIPO	INSEAD, WEF, UNESCO, Eurostat	MGI	World Bank, INSEAD	
1	China									
	United States									
2	Australia	n/a								
	Belgium	n/a								
	Canada									
	Estonia	n/a								
	Finland	n/a								
	France									
	Germany									
	Iceland	n/a								
	Israel	n/a								
	Japan									
	Netherlands	n/a								
	New Zealand	n/a								
	Norway	n/a								
	Singapore	n/a								
	South Korea									
	Sweden									
	United Kingdom									

1 For the threshold, we calculated a global average and then measured standard deviation. If countries are generally one standard deviation above the average, we categorized them as "above" and one standard deviation below average as "below"; we categorized the rest as being "within." For certain dimensions where values for leading countries are far higher than the average, we lowered the threshold to show relative differences clearly.
2 VC = venture capital; PE = private equity; M&A = mergers and acquisitions.
3 PISA = Programme for International Student Assessment, OECD; STEM = science, technology, engineering, and math; GHCI = Global Human Capital Index; WEF = World Economic Forum.
4 GTCI = Global Talent Competitiveness Index.
5 The score is calculated based on a weighted average of each area that can have a different degree of impact on GDP growth per their elasticity.
NOTE: The contents of this table are indicative. Countries in each group are listed in alphabetical order.

SOURCE: World Bank; UNdata; ILO; Global Innovation Index 2017; World investment report, UNCTAD; McKinsey Global Institute analysis

Exhibit 7 (continued)

Varying conditions among countries imply different degrees of AI adoption and absorption, and therefore economic impact (continued).

Above threshold[1] Within threshold[1] Below threshold[1]

Group		AI-related			Enablers					Total score[5]
	Readiness areas	AI investment	AI research activities	Productivity boost from automation	Digital absorption	Innovation foundation	Human capital	Connectedness	Labor-market structure	
	Examples of indicators included	VC, PE, M&A, seed, grant[2]	Patents, publications, citations	Automation potential of activities	Technology utilization	R&D investment, business-model creation	PISA score, STEM graduates, GHCI[3]	MGI Connectedness Index	Redundancy costs, indexes on worker-employer collaboration	
	Data sources	Dealogic, S&P, Capital IQ	WIPO, Scimago Journal Rank	MGI	GTCI[4] (INSEAD)	OECD, INSEAD, WIPO	INSEAD, WEF, UNESCO, Eurostat	MGI	World Bank, INSEAD	
3	Chile	n/a								
	Costa Rica	n/a								
	Czech Republic	n/a								
	India	n/a								
	Italy	n/a								
	Lithuania	n/a								
	Malaysia	n/a								
	South Africa	n/a								
	Spain									
	Thailand	n/a								
	Turkey	n/a								
4	Brazil	n/a								
	Bulgaria	n/a								
	Cambodia	n/a								
	Colombia	n/a								
	Greece	n/a								
	Indonesia	n/a								
	Pakistan	n/a								
	Peru	n/a								
	Tunisia	n/a								
	Uruguay	n/a								
	Zambia	n/a								

1 For the threshold, we calculated a global average and then measured standard deviation. If countries are generally one standard deviation above the average, we categorized them as "above" and one standard deviation below average as "below"; we categorized the rest as being "within." For certain dimensions where values for leading countries are far higher than the average, we lowered the threshold to show relative differences clearly.
2 VC = venture capital; PE = private equity; M&A = mergers and acquisitions.
3 PISA = Programme for International Student Assessment, OECD; STEM = science, technology, engineering, and math; GHCI = Global Human Capital Index; WEF = World Economic Forum.
4 GTCI = Global Talent Competitiveness Index.
5 The score is calculated based on a weighted average of each area that can have a different degree of impact on GDP growth per their elasticity.
NOTE: The contents of this table are indicative. Countries in each group are listed in alphabetical order.

SOURCE: World Bank; UNdata; ILO; Global Innovation Index 2017; World investment report, UNCTAD; McKinsey Global Institute analysis

- **Economies that need to strengthen foundations.** These countries are relatively challenged in their ability to capture the economic benefits of AI. They have somewhat limited automation potential because wages tend to be rather low, and therefore the incentive to substitute labor to boost productivity is weak. They also have relatively underdeveloped digital infrastructure, innovation and investment capacity, and digital skills, and are comparatively isolated from global trade and data flows. These economies tend to prioritize stimulating economic growth, reducing poverty, and developing away from agriculture into basic, and then more advanced, manufacturing and services. Initiatives to catch up with best practices may generate the higher return on investment rather than making substantial investment in advanced technologies that are currently beyond their reach. However, the risk is that they may fall behind as other countries embrace AI.

It is important to note that these groups are not static—countries may move from one to another courtesy of the choices they make. It is not inevitable that developed countries will always be at the forefront of AI adoption and impact, and that developing countries will lag behind. Countries that take active steps to strengthen their AI foundations, capabilities, and enablers can change their AI-adoption trajectories. Indeed, our simulation indicates that the potential economic impact of AI can be sensitive to the pace of AI adoption, AI-related investment, and innovation capacity.

THE GAP BETWEEN LEADING AND LAGGING COUNTRY GROUPS IS SIGNIFICANT AND MAY GROW FURTHER

Levels of AI absorption vary significantly between the country groups with the most and the least absorption (Exhibit 8). According to our simulation, economies with higher readiness to benefit from AI may achieve absorption levels about 11 percentage points higher than those of slow adopters by 2023, and this gap looks set to widen to about 23 percentage points by 2030. This indicates that like the digital divide, an AI divide may emerge between advanced and developing economies.[85]

As absorption rates diverge, so does the potential economic impact of AI. Because economic gains combine and compound over time, the simulated gap in net economic impact between the country groups with the highest economic gains and those with the least is likely to become larger. Country simulations suggest that there could be a large gap in economic impact between the leading and the lagging—between Sweden and Zambia, for example. That gap could widen from three percentage points in 2025 to 19 percentage points in 2030 in terms of net GDP impact (Exhibit 9).

Our simulation suggests that AI-enabled growth, especially in some advanced countries such as Sweden, the United Kingdom, and the United States, may become as large as consensus growth projections (Exhibit 10).

The economic drivers of AI impact we have discussed generally favor those groups that are the most ready for these technologies. However, there are differences in the degree to which these drivers work to benefit individual countries (Exhibit 11). For instance, productivity gains from substituting labor are most likely to accrue to countries with high automation potential. This research finds that advanced economies could gain about 10 to 15 percent of impact from labor substitution, compared with an impact of 5 to 10 percent in developing economies.

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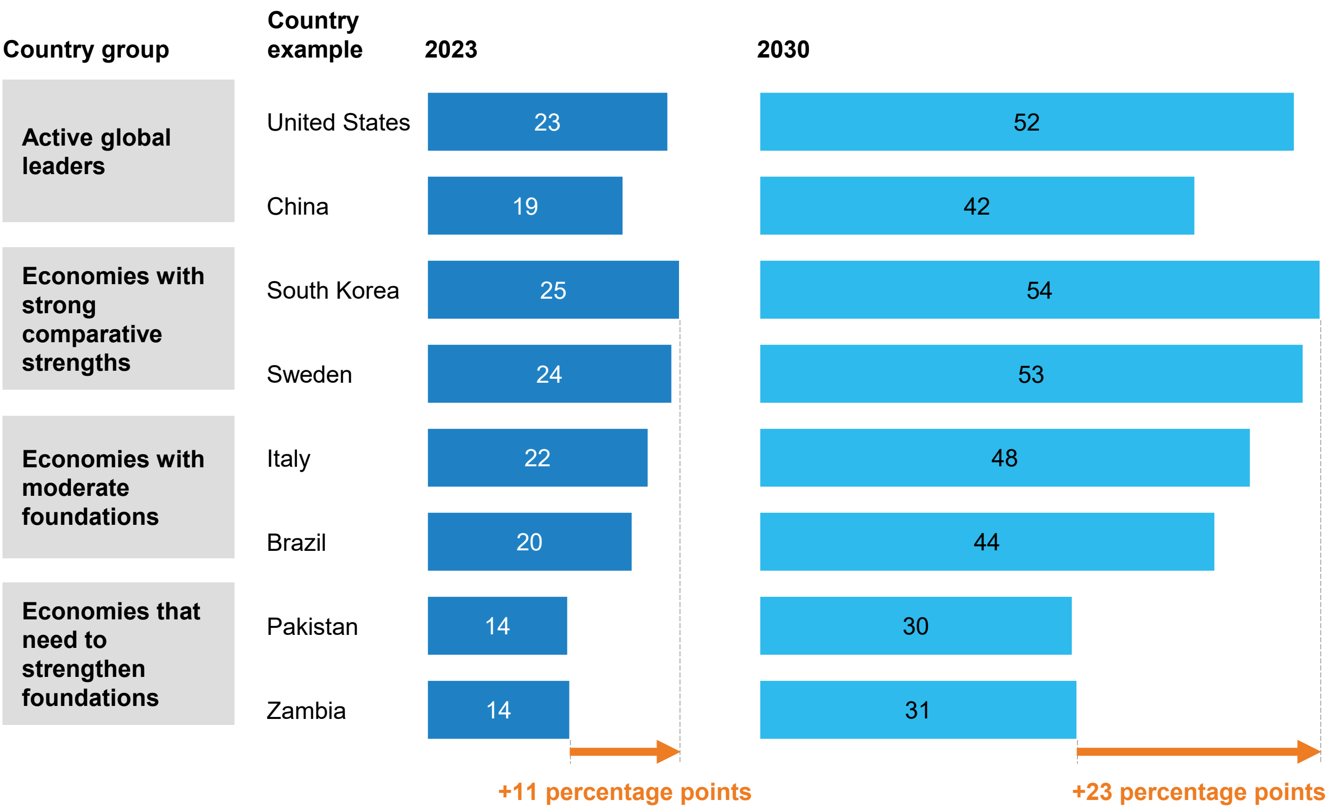
[85] Diego Comín and Bart Hobij, *Cross-country technology adoption: Making the theories face the facts*, Federal Reserve Bank of New York staff report number 169, June 2003.

Exhibit 8

Gaps in AI absorption levels between groups may increase over time.

SIMULATION

Simulated AI absorption levels per country group
Share of firms, %



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

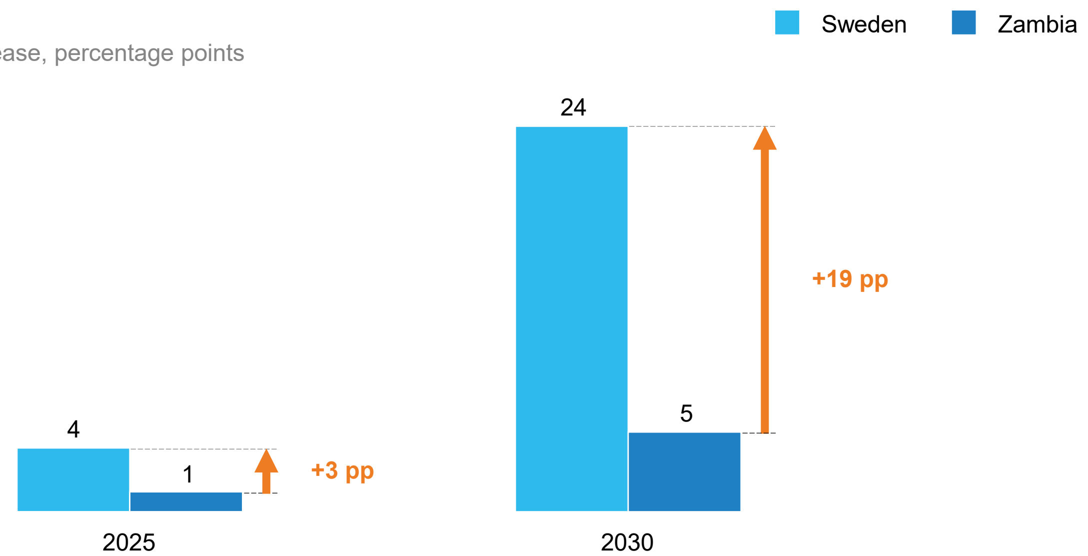
SOURCE: McKinsey Global Institute analysis

Exhibit 9

The economic impact of AI is likely to be much larger in developed economies.

SIMULATION

Net GDP impact
Cumulative GDP increase, percentage points



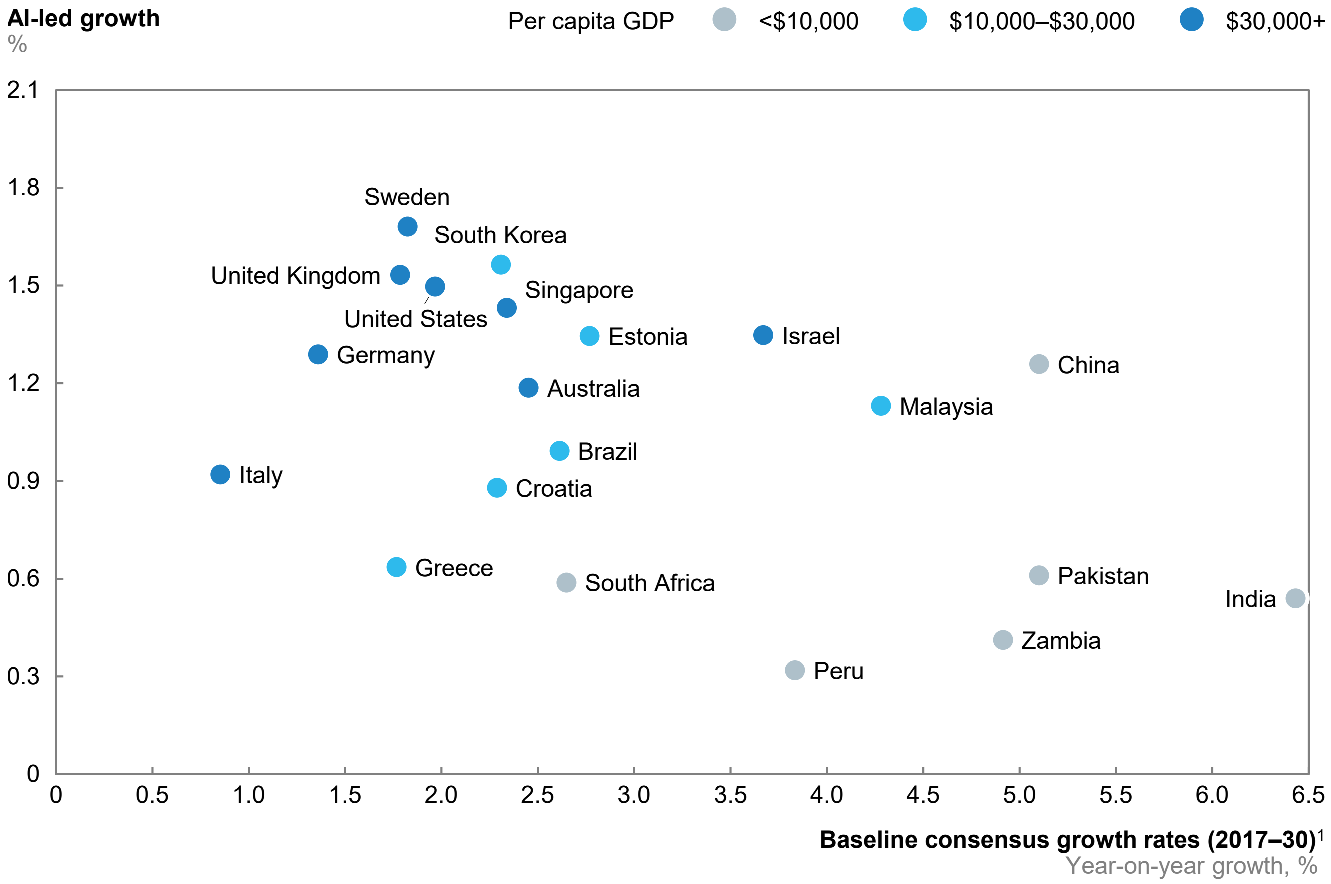
NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Global Institute analysis

Exhibit 10

AI adoption and absorption could make a large contribution to growth in slow-growing developed economies.

SIMULATION



1 Consensus based on IHS Markit, Economist Intelligence Unit, and Oxford Economics.
NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: IHS Markit; Economist Intelligence Unit; Oxford Economics; McKinsey Global Institute analysis

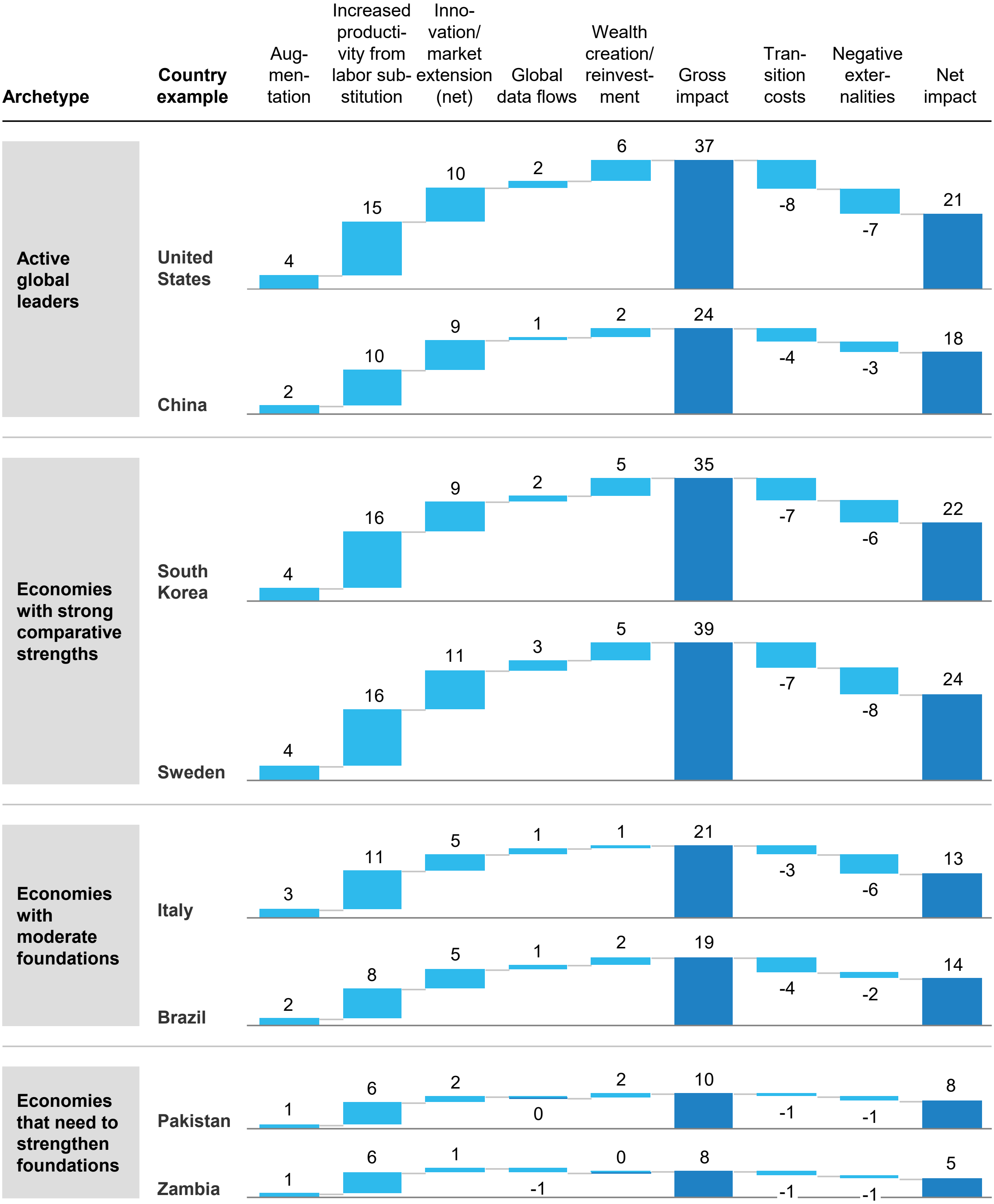
In the case of innovation gains from developing new products and services, countries with strong capacity to innovate could potentially generate about 10 percent; for members of country groups that are less ready, the potential impact could be lower, at 1 to 5 percent. Globally connected economies could also benefit from global data flows and trade, which could contribute impact of 1 to 3 percent in comparison with an impact of less than 1 percent—or even a negative impact—in the case of the least developed country group. This differential also reflects the fact that more connected economies with strong AI foundations and the human capital to drive innovation are also likely to be global suppliers of AI technologies. Countries with a high propensity to consume and substantial investment capacity could create an impact of about 5 percent from spillovers into their domestic economies, compared with 1 to 2 percent in the case of the least ready country group. In terms of negative externalities, the impact will vary among countries depending on their pace of AI adoption and their labor-market structures.

Exhibit 11

The impact of AI adoption and absorption can vary among country groups.

SIMULATION

Breakdown of economic drivers by country group
Incremental GDP increase, percentage points



NOTE. Numbers are simulated figures to provide directional perspectives rather than forecasts. Figures may not sum to 100% because of rounding.

SOURCE: McKinsey Global Institute analysis

MORE DIGITALLY SAVVY, DYNAMIC SECTORS MAY EXPERIENCE GREATER IMPACT FROM AI

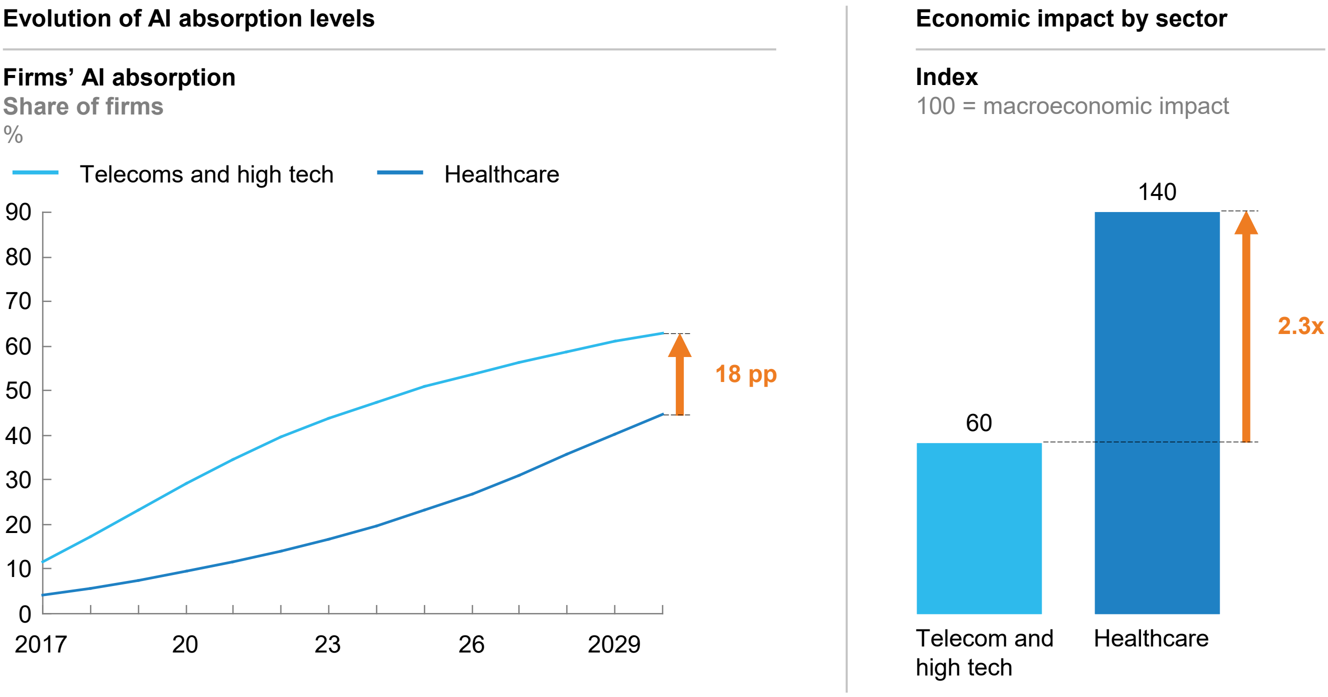
Sectors also have very different dynamics in terms of adopting and absorbing AI and therefore economic impact.[86] In previous MGI research, we found that the digital maturity of the sectors correlates positively with the state of AI adoption and absorption of the sectors.[87] The share of full-time-equivalent positions likely to be substituted by automation and AI technologies partly depends on job activities and specific industry processes.[88]

In order to gauge sector-level differences, we chose two sectors as indicative examples: (1) the telecom and high-tech sector that is adopting AI relatively rapidly; and (2) healthcare, which is adopting AI slowly. We then simulated potential differences between them in the economic impact of AI. Using our firm-level survey, we simulated these sectors' different pace of adoption and absorption, and the impact of AI on economic activity.[89] Our preliminary simulation shows that the economic impact in the telecom and high-tech sector could be more than double that of healthcare in 2030. If the national average of macroeconomic impact is 100, healthcare might experience 40 percent lower impact while the telecom and high-tech sector could experience 40 percent higher impact than the national average (Exhibit 12).

Exhibit 12

AI absorption curves can vary by sector, leading to different levels of economic impact.

SIMULATION



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Digital Survey; McKinsey Global Institute analysis

[86] While our current modeling and treatment of survey data are based on a traditional sectoral view, we also note that traditional sector definitions may lose some relevance over time as companies increasingly blur these boundaries. Particular sectors could play the role of platforms for others given their strengths in data, computing power, and innovation capacity.

[87] *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.

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

[89] The sector-level simulation is based on firms headquartered in the United States and Western Europe.

We will continue to attempt to deepen our analysis of AI adoption by sector as we accumulate more firm- and sector-level data and insights, but our early findings show that the impact of AI is likely to vary significantly among sectors. The differences in economic impact are due to a variety of factors. The extent of competition for market share and new demand are relatively higher in high tech, which leads to fast adoption and absorption of AI. Competition in this sector may persuade firms to focus more on innovating than on aiming for pure cost efficiency. The nature of tasks and the sector's economics may make a stronger case for telecom and high-tech companies to substitute labor with AI solutions. In addition, varying degrees of connectedness to global flows and value chains may also contribute to differences.

AMONG FIRMS, PERFORMANCE GAPS BETWEEN FRONT-RUNNERS AND NONDIFFUSERS MAY WIDEN

We simulated the economic impact of AI for three groups of companies: "front-runners," "followers," and "laggards." [90] The first group experiences the largest benefits from AI, and the last group the lowest (Exhibit 13).

Front-runners are defined as companies that adopt a broad set of AI technologies and absorb the application of technologies across their organizations over the next five to seven years. In our simulation, we assumed that this group comprises about 10 percent of companies whose AI-facilitated growth profile is similar to that of the top quartile of high-growth performing firms.[91] This segment is similar in spirit and size to the early adopters observed in the theory of technology diffusion laid out by Everett M. Rogers, among others.[92] There may be two types of front-runner. The first type is the "producer-user" front-runner that develops and provides AI technologies. Such companies have substantial advantages in securing critical resources such as talent, computing power, massive data sets, and more accurate algorithms. The second type is the "user-only" front-runner that largely employs AI technologies supplied by the first type. These companies tend to adopt AI much faster and more effectively than others, and therefore can enhance their competitive advantage over companies that move later (or not at all). Although we didn't model these two types separately, it might be worth exploring how they capture value differently, what determines which type of front-runner a company is, and how the constraints associated with being a certain type of front-runner change over time.

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90 This segmentation is arbitrary and has no effect on the total economic impact on companies. Redefining these groups simply redistributes total economic gains and losses between the segments we have defined.

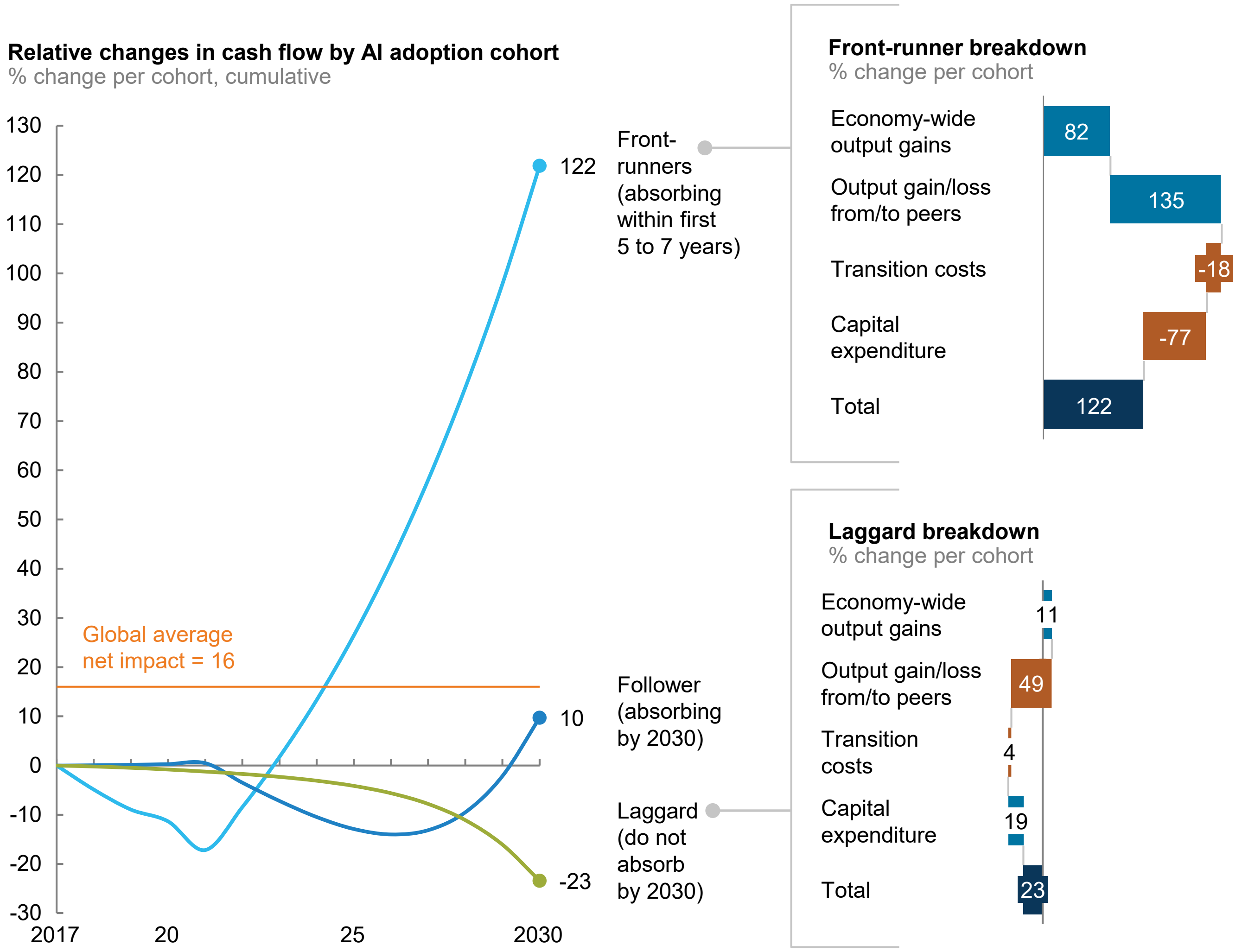
91 Bing Cao, Bin Jiang, and Tim Koller, "Sustaining top-line growth: The real picture," *McKinsey Quarterly*, May 2011.

92 Rogers' diffusion of innovations theory contends that diffusion is the process by which an innovation is communicated over time among the participants in a social system. Four main elements influence the spread of a new idea or technology: the innovation itself; communication channels; time; and a social system. Rogers identifies six segments and posits that 50 percent of the early population is split between innovators (2.5 percent), early adopters (the next 13.5 percent), and the early majority (34 percent). See Everett M. Rogers, Diffusion of Innovations, New York, NY: The Free Press, 1983. Also see Barbara Wejnert, "Integrating models of diffusion of innovations: A conceptual framework," 2002, Annual Review of Sociology, Volume 28.

Exhibit 13

Faster adoption and absorption by front-runners can create larger economic gains for these companies.

SIMULATION



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Global Institute analysis

The simulation finds that front-runners could increase economic value (economic output minus AI-related investments and transition costs) by 122 percent by 2030, or an implicit additional growth rate of cash generation of about 6 percent a year for the next 12 years. Achieving and sustaining this rate of growth over such a long period would be remarkable, as it conflicts with Gibrat's Law that a firm's growth rate is independent of its size.[93] The analysis suggests that cash generation is likely to accelerate after a five-year period in which front-runners could experience cash outflows as they invest in, and scale up, AI. Front-runners tend to slowly concentrate the profit pool of their industry in a winner-takes-all phenomenon. This may lead to the phenomenon of increasing concentration and the rise of "superstar" firms. Some researchers argue that technology could enable superstars to pull away from the pack, but also that a slowdown in the diffusion of technology could

[93] Yoshi Fujiwara et al., "Do Pareto-Zipf and Gibrat laws hold true? An analysis with European firms," *Physica A: Statistical Mechanics and Its Applications*, 2004, Volume 335, Issue 1.

then prevent laggards from catching up.[94] Indeed, the fact that benefits from AI come after a delay implies a very low discounted return on investment, especially for the latecomers. However, we also note that there are various approaches to analyzing and explaining the superstar phenomenon—why and where it happens, and how to measure it—that need further study.[95]

The second group, the followers, consists of firms that are joining the AI party, but cautiously. They are starting to adopt and absorb AI technologies, having seen the tangible impact enjoyed by front-runners and having realized the competitive threat of not adopting and absorbing. We simulated that 20 to 30 percent of firms would be in this group by 2030. For these companies, the pace and degree of change in cash flow are likely to be more moderate. On the one hand, front-runners have already triggered some spillover effects that spread some benefits to followers; on the other hand, followers are cannibalized by front-runners (although later on, followers do the same to laggards).

The final group comprises laggards (a group that includes nonadopters) that are not investing in AI seriously or at all. Laggards account for 60 to 70 percent of firms globally in our simulation. They could lose around 23 percent of cash flow compared with today, according to our simulation.[96] When laggards don't exercise the option of fully investing in AI, adopting has limited returns because these companies are moving too late. Laggards may have major capability issues that prevent them from joining the AI race, and therefore they may need to respond in other ways such as limiting costs and cutting investment. The latter is a common response observed in industries faced with similar situations—companies argue that they are cutting costs to get themselves out of a crunch and preparing for future growth. A McKinsey survey finds that late adopters and nonadopters of AI reduce their employment and investment more than other peers.[97] This behavior may seem typical of how companies behave in the face of difficult economic conditions, but in this case, we are seeing more of a life-cycle phase in which firms adjust to the risk of exiting the market.

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94 David Autor et al., *The fall of the labor share and the rise of superstar firms*, May 1, 2017. The authors find that the rising industry concentration is positively and significantly correlated with the growth of patenting intensity and total factor productivity, suggesting that concentration is associated with faster technological progress. They cite a 2015 OECD paper that found widening productivity differences between the top 5 percent of firms and the rest, which was attributed to a slowdown in technological diffusion between frontier firms and the laggards that reflected leading firms' ability to protect their advantages, contributing to a slowdown in aggregate productivity growth. Consistent with the OECD findings, they found that in industries where the speed of diffusion had slowed (indicated by a drop in the pace of citations), concentration had risen by more and labor shares had fallen by more. For instance, in industries where the proportion of total citations received in the first five years was ten percentage points lower, concentration rose by an extra 3.3 percentage points. See Dan Andrews, Chiara Criscuolo, and Peter N. Gal, *Frontier firms, technology diffusion and public policy: Micro evidence from OECD countries*, OECD future of productivity background paper, 2015.

95 For a summary of literature on concentration, see *Market concentration*, OECD Directorate for Financial and Enterprise Affairs Competition Committee issues paper, June 2018. In summary, the OECD's review of academic literature finds that there has been a moderate increase in broad measures of concentration in Japan and the United States (but not in Europe), but that the imprecision of these measures tells us little about whether competitive intensity has changed.

96 We see similar divergence between early movers and laggards in the case of digitization. One study found that, on average, bold, at-scale responses pay off twice as much as semi-bold reactions and three times as much as medium reactions. There is some variation by industry, but it is not dramatic. In telecom and high tech, for instance, bold, at-scale reactions have 2.5 times greater payoff than medium reactions. In manufacturing, it is 2.2 times greater, and in retail and media, 1.9 times greater. The study estimates that a medium reaction is worth 1.5 points of earnings before interest and taxation (EBIT) growth a year and about 2 points in revenue growth per year, and the effect of a successful bold, at-scale move is roughly 4.5 points in EBIT and 6 points in revenue. See Jacques Bughin and Nicolas van Zeebroeck, "The best response to digital disruption," *MIT Sloan Management Review*, April 6, 2017.

97 *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.

THERE MAY BE LARGE SHIFTS IN DEMAND FOR CERTAIN SKILLS, POTENTIALLY WIDENING GAPS BETWEEN WORKERS

Previous MGI research estimated that up to 375 million workers, or 14 percent of the global workforce, may need to change occupations—and virtually all workers may need to adapt to work alongside machines in new ways.[98] MGI has analyzed 2,000 job activities and simulated how likely they are to be automated. We identified seven high-level categories of work activity. Each of these categories has different potential for automation. Three categories have the highest technical potential for automation at about 60 to 80 percent: performing physical activity and operating machinery in predictable environments, processing data, and collecting data. The other four high-level categories have considerably lower potential to be automated at around 10 to 25 percent: performing physical activities and operating machinery in unpredictable environments; interfacing with stakeholders; applying expertise to decision making, planning, and creative tasks; and, least susceptible to automation, managing and developing people.

Overall, the picture that emerges is one of rising wage and employment opportunity inequality, broadly consistent with recent academic literature that points to rising wage inequality when jobs start to be created following a technological disruption.[99] Among different cohorts of workers, we may observe patterns similar to those we have simulated for firms: groups with superior skill sets may capture a disproportionate share of gains. Workers engaged in nonrepetitive activities requiring high digital skills could increase the wages they command because their skills are in short supply, while raising the productivity they contribute to their employers. In contrast, workers in repetitive tasks are likely to be squeezed as their skill sets are increasingly irrelevant and their power to negotiate higher wages is likely to decline. In other words, some workers are at risk of being replaced by machines, while there could be shortages of workers who can complement what machines do (see Box 4, “Categorizing skill shifts”).

Some noteworthy patterns emerge from our simulation (Exhibit 14):

- **AI is likely to shift the jobs mix toward tasks requiring high digital skills and those involving nonrepetitive tasks.** A large shift could occur in the category with low digital skills and repetitive tasks, declining from 43 percent of jobs in the global economy currently to 32 percent by 2030. The share of jobs requiring high digital and nonrepetitive tasks might increase from 42 to 53 percent during the same period.[100] All stakeholders in the economy—policy makers, companies, other institutions, and individuals—will need to make a substantial effort to manage this shift. More retraining, job matching, and mobility programs will be required. Because social and emotional skills cannot be easily replaced by AI applications, demand for nondigital and nonrepetitive tasks such as healthcare work could moderately increase, too.

- **Uneven wage bill distribution may emerge from AI.** Our simulation suggests that while the share of employment with repetitive activities and requiring low digital skills could be reduced by 25 percent, total wages associated with these jobs may shrink by 39 percent as employment declines and wages potentially remain stagnant. In contrast, employment requiring high digital skills and nonroutine tasks may increase, and wages may go up by more than ten percentage points in 2030, driven by demand and higher

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[98] *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

[99] See, for instance, Anton Korinek and Joseph E. Stiglitz, *Artificial intelligence and its implications for income distribution and unemployment*, NBER working paper number 24174, December 2017; and Philippe Aghion and Peter Howitt, “On the macroeconomic effects of major technological change,” in *The Economics and Econometrics of Innovation*, David Encaoua et al., eds., Boston, MA: Kluwer Academic Publishers, 2000.

[100] This finding aligns with other research. See, for instance, Vincenzo Spiezia, *Measuring the demand for skills in the digital economy*, OECD, 2016.

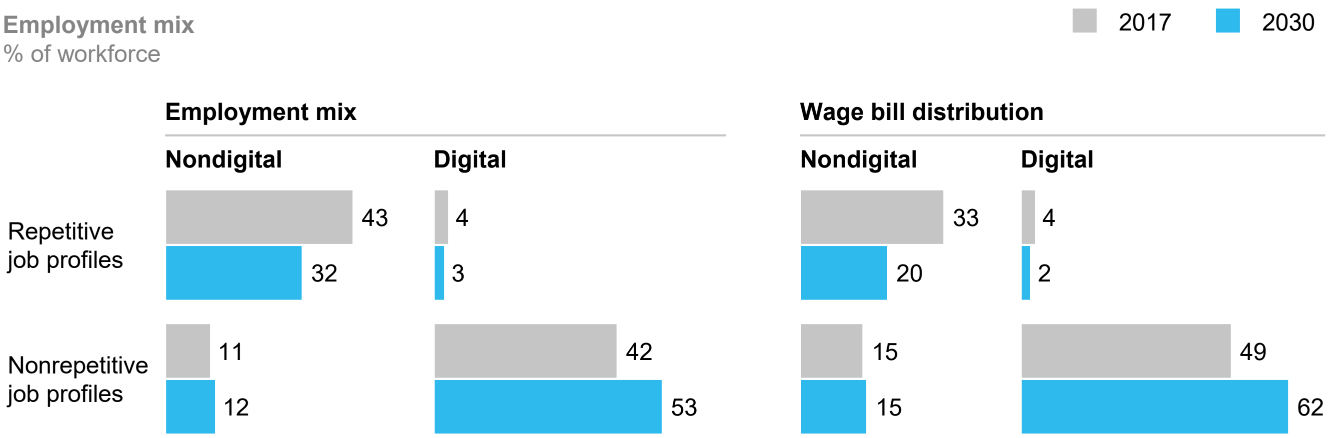
productivity.[101] Previous MGI research has highlighted two reasons for this. First, there are changes in the mix of occupations and the wages associated with them. Second, some forms of automation will be skills-biased—raising the productivity of highly skilled workers but reducing demand for lower-skill, routine occupations.[102] We note that the findings in this paper are based on indicative scenarios and simulation, and that more thorough modeling of labor markets will be needed. For example, the outcome of simulation can be sensitive to the evolution of the labor share of income versus capital, which is determined by a variety of complex economic factors.

- **The effect on skills and wages will vary depending on the company.** Changes in the returns on various skills become even more obvious when we consider jobs at companies at different stages of AI adoption. In front-runners, the mix of jobs is likely to evolve quickly toward nonrepetitive activities and activities requiring high digital skills, accelerating the displacement of workers who perform repetitive tasks. However, this group of companies can further expand output and employment, using the first-mover advantage of being able to tap into the best talent, and likely paying a premium to secure it. Front-runners may thus be characterized by their creation of employment (although some will create huge shocks in traditional industries they disrupt), a higher mix of nonrepetitive jobs and jobs requiring digital skills, a likely pay premium for higher skills, and stable employment. Such dynamics are already emerging. Analysis of US company data suggests that the average wage of workers at top-percentile firms has been increasing fast, while that of lower-percentile firms has largely been stagnant.[103] In laggards, workers may feel more secure in the next few years because limited skill shifts will be required. However, as revenue and market shares start to wane, these companies are likely to be under pressure to cut headcount. Additional pressure on margins will likely lead to downward pressure on wages, too, and workers for such companies would then be faced with lower wages or higher risk of losing their job. According to the OECD, a 10 percent higher risk of automation corresponds to a 4.3 percent decline in hourly earnings.[104]

Exhibit 14

AI adoption and absorption can change the employment mix and distribution of wages.

SIMULATION



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts. Figures may not sum to 100% because of rounding.

SOURCE: McKinsey Global Institute analysis

[101] We simulated how the changing nature of tasks and skill requirements can impact employment and wages. Also see Daron Acemoglu and Pascual Restrepo, *Modeling automation*, NBER working paper number 24321, February 2018.

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

[103] Jacques Bughin, "Why AI isn't the death of jobs," *MIT Sloan Management Review*, May 24, 2018; and Nicholas Bloom, "Corporations in the age of inequality," *Harvard Business Review*, April 2014.

[104] *Putting faces to the jobs at risk of automation*, OECD policy brief on the future of work, March 2018.

Box 4. Categorizing skill shifts

For the sake of simplicity, we have categorized activities that are highly automatable as "repetitive" and activities that are difficult to automate as "nonrepetitive," and then simulated likely trends in these two categories. We also added another dimension to take account of skills requirements—digital versus nondigital—that could be a precondition or foundation of applying AI. In reality, the change in skill mix will be much more complex. However, even this simple categorization has the merit of providing some idea of the magnitude of the shift away from the repetitive, nondigital paradigm that dominated the previous version of industrial production.

Jobs characterized by degree of repetitive versus nonrepetitive tasks. Routine and repetitive tasks are the most likely to be substituted by automation, while new jobs created are likely to require advanced digital skills or associated with high-value-added functions such as design. We find that demand for basic cognitive skills, including simple data inputting and processing, is likely to decline from 18 percent of hours worked in 2016 to 14 percent by 2030. In contrast, demand for technological skills—the smallest category today—may rise from 11 percent of hours worked in 2016 to 16 percent by 2030.[1] We used MGI's automation database to categorize repetitive and nonrepetitive jobs, and simulated how the mix of these would shift as AI is adopted and absorbed. Although nonrepetitive jobs are not immune to the impact of automation and AI, the displacement impact on repetitive jobs is likely to be much bigger.

Jobs characterized by degree of digital versus nondigital skill requirements. Increasingly, jobs are likely to need more ICT and digital skills. The OECD has pointed to future need for technical and professional skills, including specialist ICT skills for workers who drive innovation, and the skills necessary to support digital infrastructure; generic ICT skills for workers and citizens who need to be able to use these technologies; and soft skills that complement ICT, including leadership, communication, and teamwork skills.[2] Changing requirements are already evident in labor markets. In the United States, for instance, the share of jobs requiring AI skills has grown 4.5 times since 2013.[3]

1 *Skill shift: Automation and the future of the workforce*, McKinsey Global Institute, May 2018.
2 *Skills for a digital world*, OECD policy brief, December 2016.
3 *Artificial intelligence index, 2017 annual report*, November 2017.

AI IS LIKELY TO DISRUPT LABOR MARKETS BUT MAY HAVE A NEUTRAL TO MODESTLY NEGATIVE IMPACT ON LONG-TERM EMPLOYMENT OVERALL

There has been a great deal of discussion about the displacement impact of automation in general, and AI in particular.[105] A persistent view holds that AI will lead to the loss of existing jobs to machines, and policy conversations have focused on how to support individuals through basic income programs, tax reforms, and other redistribution mechanisms that transfer wealth generated by machines to a permanently displaced workforce. However, there has been less exploration of the employment opportunities that AI may create through the expansion of products and services, and of productivity gains that ultimately may be reinvested in economies, creating jobs.[106] Overall, the adoption of AI may not have a significant impact on net employment in the long term.

In our previous research on the future of work, we found that around half of all work activities could be automated, adapting currently available technologies, but the proportion of work displaced by 2030 is likely to be lower because of a range of technical, economic, and social factors. Our scenarios covering 46 countries suggest that between zero and one-third of work activities could be displaced during this period, with a midpoint of 15 percent. This proportion varies widely among countries.[107] As noted, the firm-level simulation in this

105 On the general impact of automation, see, for instance, John Maynard Keynes, "The economic possibilities for our grandchildren," *Essays in persuasion*, London, UK: Macmillan, 1931. On the specific impact of AI, see, for instance, Melanie Arntz, Terry Gregory, and Ulrich Zierahn, *The risk of automation for jobs in OECD countries: A comparative analysis*, OECD Social, Employment and Migration working papers number 189, 2016; and Daron Acemoglu and Pascual Restrepo, *Robots and jobs: Evidence from US labor markets*, NBER working paper number 23285, March 2017.
106 Jacques Bughin, "Why AI isn't the death of jobs," *MIT Sloan Management Review*, May 24, 2018.
107 *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

research is generally consistent with these findings but is slightly more aggressive than the midpoint scenario on a global basis. This reflects, among other factors, the competitive race among firms highlighted in our survey data.

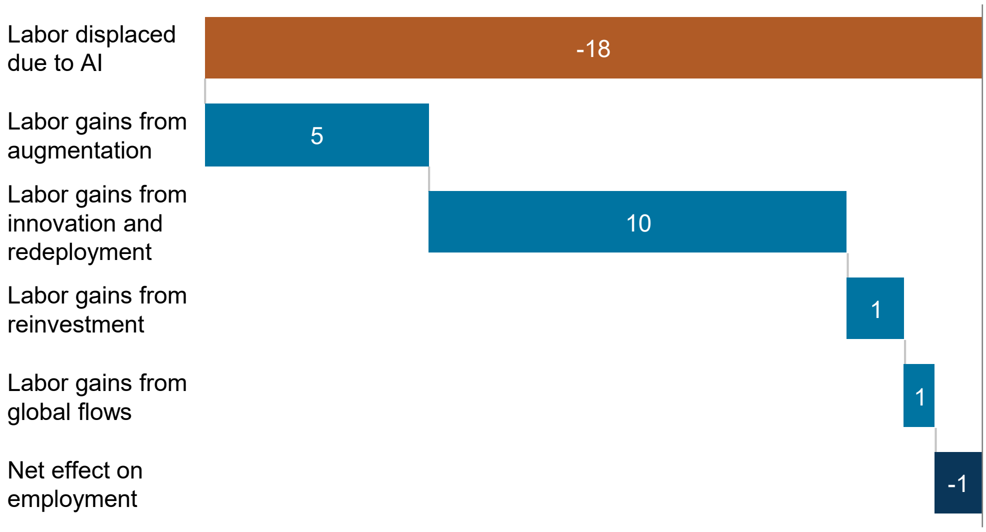
Considering all the different forces playing out, there is likely to be more rather than less pressure on full-time employment demand, but the total pressure in the aggregate may be more limited than many fear. Our average global scenario suggests that total full-time-equivalent employment demand may remain flat at best compared with today.[108] In the long term, total employment demand may be positive if one considers the fact that number of hours worked per employment unit may continue the downward trend observed over the past decade. In practice, the dynamics of employment will depend on the interplay of the five factors illustrated in Exhibit 15.

Exhibit 15

AI adoption and absorption can affect employment in five key ways.

SIMULATION

Impact on employment by 2030, cumulative
% change, FTEs



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts. Figures may not sum to 100% because of rounding.

SOURCE: McKinsey Global Institute analysis

There will be job losses and gains as AI penetrates. Throughout history, technologies have displaced existing workers. The horse and carriage was replaced by the car, which was much faster. As cars became the preferred means of transport, a range of jobs were displaced, including manufacturers of wagons, carriages, harnesses, and saddles, and horse breeders, but ten times as many jobs were created in a range of new occupations including in auto manufacturing, auto dealerships, gas stations, and transportation and logistics.[109]

History also tells us that technological innovation creates jobs in the long term. For instance, the transformative shift from agriculture to industry and then services did not lead to mass unemployment, but to new types of jobs. One recent study found that up to 9 percent of

[108] Globally, the working-age population is growing, which could pose additional challenges to the labor supply and to demand dynamics.

[109] *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

US workers in 1980 to 2000 were employed in categories that did not exist 10 to 15 years previously, as we noted earlier.[110]

Using historical trends of new jobs created to old jobs, and adjusting for a lower labor-output ratio that considers the likely labor-saving nature of AI technologies via smart automation, new jobs driven by investment in AI could contribute about 5 percent to employment by 2030. The boost to employment also comes from AI expanding economic activity through innovation in products and services, higher participation in global flows, and thus increased demand for labor. Moreover, additional wealth created in the economy creates spillover effects, boosting labor demand. These could have a positive contribution to employment of about 12 percent.

Most jobs created by technology can be outside the technology-producing sector itself. For instance, MGI estimates that the advent of the personal computer has enabled the creation of 15.8 million net new jobs in the United States since 1980—90 percent of them in nontechnology sectors.[111] We cannot be sure that this will happen with the advent of AI, but historical precedent together with the findings of our executive survey suggest that we can be optimistic. As noted, competitive pressure is likely to drive corporate investment in AI that goes beyond what is needed simply to substitute labor, and this investment can create jobs. Of course, investment in AI needs to be managed to be effective for businesses. AI solutions need to be modeled and developed by data scientists, and workers then need to be trained to use them. Other types of AI-related jobs are already emerging, including business intelligence developers and computer vision engineers.

4. CONSIDERING KEY QUESTIONS CAN HELP ECONOMIC ENTITIES DECIDE HOW TO OPTIMIZE FOR AI

The opportunity of AI is significant, but there is no doubt that its penetration may cause disruption. The productivity dividend of AI probably will not materialize immediately—its impact is likely to build up at an accelerated pace over time, and therefore the benefits of initial investment may not be visible in the short term. Patience and long-term strategic thinking will be required. Policy makers will need to show bold leadership to overcome understandable discomfort among citizens about the perceived threat to their jobs as automation takes hold. Companies will also be important actors in searching for solutions on the mammoth task of skilling and reskilling people to work with AI. Individuals need to adjust to a new world in which job turnover may be more frequent, they may have to transition to new types of employment, and they are likely to need to continually refresh and update their skills to match the needs of a dynamically changing jobs market.[112]

In simplified terms, countries can make two broad types of choice. First, they can opt to adopt AI rapidly or slowly. Second, they can elect to handle labor-market transitions in such a way as to generate high or low demand for jobs (many of them new) in the economy. Depending on the choices countries make on these fronts, different scenarios might unfold. Policy makers and business executives may influence—and need to strive to secure—the best possible outcome: job growth together with higher productivity. To capture these twin benefits may require them to embrace AI technologies enthusiastically while addressing transition issues, especially the workforce-related issues we have detailed, to ensure that productivity gains lead to a virtuous cycle of income growth and higher demand that can

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[110] Jeffrey Lin, "Technological adaptation, cities, and new work," *Review of Economics and Statistics*, 2011, Volume 93, Number 2.

[111] *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

[112] *AI, automation, and the future of work: Ten things to solve for*, McKinsey Global Institute, June 2018.

create more jobs.[113] However, it is possible for economies to experience secular stagnation in which neither productivity nor jobs grow. A country that adopts AI at a slow pace may lose global competitiveness, fail to raise productivity and experience pressure on growth and difficulties in creating jobs. This would leave such a country in a position of not being able to deploy displaced workers even if it were to step up its adoption of automation and AI, leading to a vicious cycle.

To secure the best outcome for their economies, major economic entities—governments, companies, and individuals—will need to address many questions and challenges during the transition. In this section, we pose some questions that could help them to think about how to optimize the economic impact of AI. The first set of questions is designed to help point the way for countries seeking to capitalize on the potential of AI. The second set relates to how AI could change the basis of competition among firms and sectors. Finally, we offer questions related to the transition of the individual workers associated with AI.

How countries can capitalize on AI

- How can countries step up investments that are beneficial in their own right but will also contribute to demand for work?

- How can policy makers evolve education systems and learning with a new emphasis on creativity, critical thinking, and adaptive and lifelong learning? How can countries increase investment in human capital, reversing the trend of low—and, in some countries, declining—public investment in worker training?

- How can policy makers improve the dynamism of labor markets, facilitate improved and faster matching of workers and jobs, enable a wider range of ways of working such as the gig economy, and solve such issues as portability of benefits, worker classification, and wage variability?

- How can countries embrace AI and automation safely, addressing issues including data security, privacy, malicious use, and potential issues of bias?

- How can countries rethink policy related to incomes to minimize disruption in case of a significant reduction in employment, greater pressure on wages, or both? Should they consider testing ideas such as conditional transfers, support for mobility, universal basic income, or some combination of the three? How can they best offer transition support and safety nets for workers affected? How can countries also forge a new social contract that garners support from all stakeholders including labor unions?

How AI will change the basis of competition among sectors and firms

- How are computing power and capacity, data, algorithms, and the availability of talent likely to evolve? How will developments in each of these affect individual firms? Which could benefit, and which might lose out?

- How can healthy competition be encouraged, maintaining an optimal balance in which front-runners are rewarded while minimizing the downside that could be imposed by winner-takes-all dynamics on later movers?

- How are industry structures likely to evolve, and how will sectors be redefined? For example, what role will be played by technology platforms that are most likely to be creator front-runners?

- What are the potential effects of widening gaps between front-runners and laggards, and how could these gaps play out in different sectors?

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[113] Ibid.

- How can companies redesign workflows to help workers adapt to working more closely with machines and fully absorb AI technologies across organizations? How can they create more collaborative, agile, and nonhierarchical organizations and cultures?

How individuals should be prepared for the AI-led transition

- How can individuals develop the skills that will be needed to power the AI economy and embrace a culture of lifelong learning?

- How can individuals leverage new ways of working, including participating in the gig economy and searching for jobs digitally?

•••

The economic impact of AI is likely to be large, comparing well with other general-purpose technology in history. At the same time, there is a risk that a widening AI divide could open up between those who move quickly to embrace these technologies and those who do not adopt them, and between workers who have the skills that match demand in the AI era and those who don't. The benefits of AI are likely to be distributed unequally, and if the development and deployment of these technologies are not handled effectively, inequality could deepen, fueling conflict within societies. This research is our attempt to simulate how the transition to AI might unfold. We will continue to refine our analysis as new data become available and as we learn more about how the shift to AI is progressing on the ground. Our hope is that this research can help inform the ongoing discussion about AI and its potential impact on the global economy.

TECHNICAL APPENDIX

This research models a set of critical channels through which AI can affect the performance of firms, how this creates spillovers to other economic entities, and therefore the aggregate performance of sectors and economies.

This modeling and simulation relies on two important features. The first is the quality of data that provide us with the range of estimates of how AI is perceived by companies and of how they use these technologies economically and strategically. We use two unique data sets and surveys to ensure that our modeling has appropriate input. The results of the modeling and simulation will change as more versatile data sets are created, and therefore the results presented in this paper may evolve. The second feature of this research is its inclusion of micro-estimates of the pace of adoption and full absorption of AI technologies. This adds new insights compared with previous MGI work on AI and the future of work that largely leveraged a set of benchmarks of how previous technologies diffused in economies. The approach taken in this analysis is based on the premise that AI should be treated as a disruptive innovation that has a strong competitive and strategic rationale for companies.[114]

OUR MICRO-TO-MACRO APPROACH

Our simulation of the economic impact of AI takes a micro-to-macro approach with the following seven steps:

1. **Integrate relevant data sources.** The research uses a range of data sources including two independent corporate surveys that gauge companies' appetite to invest in AI. Complementing these data sets is MGI's proprietary database of 400 existing AI use cases across industries and functions that we used to confirm the order of magnitude of AI's potential impact on profits with related cost and revenue drivers.[115] Further, to gauge the impact on labor specifically, the analysis drew on a database developed in MGI's future of work research that analyzes the potential to automate individual jobs—looking at activities rather than entire jobs—in 46 countries; this work assessed 800 existing occupations and around 2,000 activities undertaken within these occupations, and the amount of effort and types of capabilities these activities require.[116]

2. **Prepare a foundational data set from econometrics.** Using the survey data detailed in Step 1, the research derives a corporate adoption econometric model that links firms' decision to invest to a set of factors from literature on the diffusion of innovation. This econometric model therefore endogenizes corporate adoption based on the explicit competitive and strategic value of AI, rather than taking a set of older technology adoption curve benchmarks as we did in previous MGI research.[117] The rate of adoption and absorption that results from the econometrics of this research is typically faster that the average of the technology diffusion rate benchmarks collected in previous MGI research. This result is consistent with the idea that AI is strongly disruptive.[118] For details, see the section on econometric modeling.

3. **Simulate "gross" GDP impact.** In addition to estimating corporate adoption and absorption of AI, the research models macroeconomic factors expected to be influenced by AI, namely labor augmentation, labor substitution, product and service innovation, the

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[114] See, for example, William J. Abernathy and James M. Utterback, "Patterns of industrial innovation," *Technology Review*, 1978, Volume 80, Number 7.

[115] Notes from the AI frontier: Insights from several hundred use cases, McKinsey Global Institute, April 2018.

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

[117] For example, in *Jobs lost, jobs gained: Workforce transitions in a time of automation*, McKinsey Global Institute, December 2017.

[118] Notes from the AI frontier: Insights from several hundred use cases, McKinsey Global Institute, April 2018.

impact of the global value chain, and the feedback loop in the macroeconomy (that is, improved productivity leads to additional reinvestment of consumption in the economy). For the impact of AI on the global value chain, the research factors in the contribution from increased flows of data, an adjustment in foreign direct investment for the reinvestment capacity of profit flows, and a trade adjustment in the effect on competition (for example, companies in a given economy will become more or less competitive depending on their openness to trade and relative AI absorption).

4. **Simulate "net" GDP impact.** Most existing research on the impact of AI tends to focus on the gross figure. This research models the net impact by taking into account a range of costs related to the implementation of AI, including investment in the deployment of systems and transition costs associated with labor, for instance the cost of labor displacement, retraining, and rehiring. We also assess negative externalities such as loss of consumption during unemployment as well as social costs incurred by paying benefits to those who are unemployed during the transition.

5. **Simulate the impact on labor markets.** The next step was linking the economic impact with the effect on labor markets, taking into account different skill and wage levels. Various segments of workers and the tasks they perform (that is, routine versus nonroutine, and digital versus nondigital) will experience different shifts in employment and wages.

6. **Model country variances.** After building a foundational model based on the global average, the research modeled variances for individual countries. The research identifies enablers that correlate strongly to factors driving adoption of AI, such as innovation capacity, human capital, and connectedness to the world. It also modeled specifics such as digital infrastructure, automation potential, and other macroeconomic factors including foreign direct investment intensity and unemployment benefits for each country.

7. **Undertake sensitivity analysis.** Finally, the results presented in the main body of the research are the average results for a multiple set of simulations. In order to gauge the degree of changing impact by key variables, the research includes a sensitivity analysis of selected variables.

SURVEY DATA

The research draws on two independent corporate surveys conducted by MGI and McKinsey.

Two independent surveys conducted in 2017

The first is McKinsey's regular digital survey of around 1,600 business executives across industries worldwide on digital technologies and AI to ascertain the causes of economic impact and the likely pace of that impact.[119] It is part of a series of global surveys on economic matters administered independently by a global research firm. Respondents are typically executives who receive detailed survey insights as an incentive to respond to the questionnaire. The questionnaire is typically cross-checked for systematic correlated bias of answers in order to ensure its scientific validity. The survey universe is 12,000 firms across sectors and geographies that mimic the world economy. The typical response rate is 10

[119] The online survey was conducted from June 20 to July 10, 2017, and garnered responses from 1,619 C-level executives and senior managers representing the full range of regions, industries, company sizes, and functional specialties. See *How digital reinventors are pulling away from the pack*, McKinsey & Company survey, October 2017.

to 15 percent, which is in the high range for surveys. The digital survey received more than 1,600 valid responses, matching other surveys.

The second survey was conducted in 2017 and collected answers from more than 3,000 corporations in 14 sectors in ten countries.[120] The MGI survey was also commissioned externally from a major research firm (a different firm from the one used for McKinsey's digital survey). In total, there were about 25 questions with an average total answer time of less than 20 minutes in order to maximize take-up rates and adequate responses. The survey was administered online. The ten countries were Canada, China, France, Germany, Italy, Japan, South Korea, Sweden, the United Kingdom, and the United States. These countries were chosen because they are the largest contributors to world GDP, are all digitally advanced, and have all recently scaled up their investment in AI. The largest portion of answers came from the United Kingdom (12 percent), followed by the United States. The country with the fewest answers was Sweden (5 percent). Twenty-seven percent of respondents came from very small firms with fewer than ten employees, while 7 percent came from large firms with more than 10,000 employees. The sample covers service, agriculture, and industrial sectors.

The MGI questionnaire largely overlaps with the McKinsey Digital Survey, and we can therefore compare responses. One test of consistency between the two surveys is the fact that the adoption rate for each set of AI technology is not significantly different for the ten countries that the two surveys have in common.

The MGI survey has the more relevant data for our attempt to model the impact of AI. For instance, the survey delves deep in an attempt to understand firms' objectives for investing in AI—whether pure automation of processes and labor or capital expenditure enhancement or new product and service innovations. This is the reference sample we used for our final simulation, but we used both survey samples to estimate adoption curves and to ensure that results converge.

Testing sample validity

We performed a set of initial tests on the sample in order to ensure its relevance. While the tests are only indicative, they suggest that our base of work is relatively solid as a starting point for estimating the impact of AI on economies.

We note two key tests. The first was to test for answer bias. The second was to confirm that some robust economic relationships established in economic literature emerged in our data, too. Specifically, we tested whether there were any differences in our sample of answers from the original target of firms per sector and country, and in terms of the mean difference in key financial metrics (revenue, revenue growth, profit, and profit growth) of respondents and nonrespondents. We used a simple one-way test per financial metric, as well as a multivariate logit model of a firm answering or not answering, linked to all the financial metrics. We could not find statistical differences in answer rates. Finally, we tested for some self-reported biases. We randomized the order of questions for half of the sample and did not find any bias in types of responses. We checked for systematic responding (either extreme, or only middle answers). We spotted 122 answers, or 4 percent, where there were very low differences between answers in all categories of the questionnaire (AI awareness, AI impact on profit, AI impact on employment, and AI impact on employment mix); we define very low as being in the bottom 5 percent in terms of differences in answers across all categories). However, the econometric results are not sensitive to whether these responses were included, so we kept our full sample as the basis for our simulations.

[120] *Artificial intelligence: The next digital frontier?* McKinsey Global Institute, June 2017.

We further tested a few important regularities uncovered in the technology innovation literature to ensure that they also emerged from our data set. For instance, there is a size bias (size of firms) in AI adoption.[121] We therefore built two indexes—one for digital absorption and one for AI absorption in which absorption is the proportion of digital technologies and AI used at scale by each corporation. We then ran a cross-section correlation with firm revenue and employee size. The size-absorption correlation effect is especially strong for large companies with more than 10,000 employees (the coefficient of correlation with employee was r = 0.56 for digital and 0.63 for AI).

ECONOMETRICS OF FIRMS' ABSORPTION OF AI AND THE IMPACT ON THEIR PROFIT GROWTH

Variety of models

In order to derive AI adoption and absorption curves, we used a three-step process. The first two steps link firms' adoption of AI to competition and the benefits of AI, demonstrating a strong stock/dynamic effect in which the propensity to adopt at a certain time (t) is the result, among others, of the number of competitors already vested and the stock of other technologies already absorbed. The third step forecasts adoption and absorption at an aggregate level based on the econometric results and the stock effect, which conditions the dynamics at time t+1:

- **Step 1.** The first step was estimating a series of models and relationships at the firm level related to the adoption of AI and its absorption within workflows for four clusters of AI technologies (advanced machine learning, robotics and robotic process automation, virtual assistants, and other tools such as computer vision and language processing). The model is a logit model where the dependent variable is a binary (yes/no) variable regarding the state of adoption and absorption, and the set of independent variables includes a set of factors, notably including: *capabilities and learning effects* (current stock of AI technology already invested and current use of previous digital technologies such as cloud, mobile, and web); *uncertainty of use ca*se (as measured by firms' perception of the business case of investing in AI, and negatively linked to the perceived importance of the technology); *state of competition* (adoption and absorption of AI technology by rivals); and *complementary effects* (for instance, adoption in other AI technologies). In general, this approach results in statistically robust relationships. The final model relationship retained was the one with the best fit (adjusted by degrees of freedom). The details of the results discussed in this appendix suggest strong competitive, stock, and scope effects.

- **Step 2:** The second step was to estimate a simultaneous model of profit growth and AI adoption and absorption, using the logic that if faster adoption relative to rivals brings more profit potential, then the promise of higher profit may improve the business case for AI, and therefore further push a firm to adopt. This extra step analysis uses instrumental techniques, with industry and country effects as well as past profitability as instruments. The profit growth equation is profit expectations over the next three years based on profit growth of the past three years (reflecting the fact that profit dynamics are typically path-dependent), as well as on AI adoption and absorption, and growth in AI investment. The analysis confirms that profit growth is path dependent, that is, that one percentage point of profit growth in the past three years induces 0.6 percentage point of profit-growth expectation in the next three years. We also find a two-way relationship between AI adoption and absorption, and profit; there is a 15 to 20 percent uplift for early adopters

[121] This is a typical stylized fact regarding technology adoption—see, for instance, a synthesis in Stefanie A. Haller and Iulia Siedschlag, "Determinants of ICT adoption: Evidence from firm-level data," *Applied Economics*, 2011, Volume 43, Issue 26, pp. 3775–3788.

versus the average, and this profit expectation further boosts adoption, but only by a marginal 3 to 5 percent, depending on the type of AI technology.

- **Step 3.** Based on a dynamic relationship between stock and diffusion, we used the econometric equation to simulate how adoption may spread across years. First, we considered the current stock of AI adoption and absorption at t. For t+1, we used the digital survey to estimate how digital technologies have been adopted and absorbed over time, while we used the regression results for each cluster of AI technology to estimate the marginal portion of companies to adopt AI at time t+1, based on the portion of companies already vested, the scope effect among clusters of AI technology, and the stock effect of digital technology. The process is recursive for time t+é. One caveat we note is that the adoption relationship uncovered by the econometrics is assumed to remain stable. Because this relationship essentially covers the early stage of AI, one cannot assume that this relationship will hold later. For instance, one may assume that the competitive effect is not necessarily constant and may decrease with time, as the strategic value of first-mover advantage has largely disappeared. Thus, our calibration of Step 3 may be seen as an upper bound.

Econometric model

The process of new technology adoption has been widely studied and debated in economic literature over the past 20 years. Applying this literature to the practice of AI adoption, the process suggests that AI is a function of a set of key predictors, outside of control effects which we note in equation 1.

Pr(AIij)= f (rivalry, digital capabilities, AI complements, expected profitability,…) (1)

Where Pr denotes the probability by the ith-firm to adopt the cluster j of AI technology, and the probability is a function to be estimated of a vector (.,.), ultimately composed of the following four key predictors assumed to affect the probability to adopt:

- **Rivalry.** The large body of literature on game theory suggests that the marginal propensity to adopt depends on the extent of rivalry, or the portion of rivals that has already decided to adopt the technology. However, the effect of competition is not known a priori. If one assumes that the benefit to the marginal adopter from acquiring a new technology decreases with an increase in the number of previous adopters—which is the case with strong first-mover advantage and fixed market potential—then the effect of rivals' adoption may decrease marginal incentives to adopt.[122] However, the diffusion of new technology often creates new markets. Furthermore, there are many more reasons that the effect of rivalry should have the reverse—positive—effect on the marginal propensity to adopt. One case in point is when network externalities are positively related to the number of users of the new technology in the industry. Being part of a network increases the awareness of the new technology and reduces the risks associated with adopting and using it.[123] Another case is when competition is of the oligopoly type, with strategic interactions among firms. If the stealing of market share is enhanced by technology adoption, it should oblige other firms to follow.[124] In general, the literature suggests that the rivalry is usually strongly visible and induces epidemic adoption when it comes to technology diffusion associated with disruption.[125] We posit

[122] Massoud Karshenas and Paul Stoneman, "Technological diffusion," in Paul Stoneman, ed., *Handbook of the economics of innovation and technological change*, Oxford, UK: Wiley-Blackwell, 1995.

[123] Michael Katz and Carl Shapiro, "Technology adoption in the presence of network externalities," *Journal of Political Economy*, 1986, Volume 94, Issue 4.

[124] John P. Weyant and Kevin Zhu, "Strategic decisions of new technology adoption under asymmetric information: A game-theoretic model," *Decision Sciences*, 2003, Volume 34, Issue 4.

[125] Giuliana Battisti et al., "Inter and intra firm diffusion of ICT in the United Kingdom (UK) and Switzerland (CH): An internationally comparative study based on firm-level data," *Economics of Innovation and New Technology*, 2007, Volume 16, Issue 8.

the same here, as we further control for expected profitability as another factor mediating the effects of rivalry of adoption patterns in our vector of predictors.

- **Digital capabilities.** It is generally assumed in the literature on the diffusion of technology that potential users of a new technology differ from one another on important dimensions so that some firms adopt more (or faster) than others. This heterogeneity is called the rank effect.[126] One group of rank factors refers to general characteristics of firms such as location, size, and industry: larger firms tend to adopt faster, or firms exposed to international competition are more inclined to innovate and adopt new technologies. In addition to the variables in our vector above, we control in our regression for the location of company headquarters, global presence, size, and the main industry in which the company operates. One other rank factor relevant for our purposes is linked to the digital maturity of the firm. Informally, in our survey, companies report that prior investment in digital technologies is critical to investment in AI as it brings a new set of technical and operating complementarity capabilities. Likewise, we know that AI benefits may rely on the degree of access to big data and architecture, for instance, because most AI-based algorithms rely to an extent on identifying powerful hidden networks of relationships among data that are discoverable only with the right big data investment.[127] In particular, we use two types of complementary digital technologies. The first is early-access technology such as web and mobile, and the second is advanced technologies such as cloud, big data, and advanced analytics.

- **AI complementarities.** As discussed, AI encompasses a multiple set of technologies, which we have grouped in several clusters in this research. There is clearly a point where each cluster acts as a complement to another. For example, when a firm uses AI to automate a process, it will likely combine both advanced robotics and artificial visualization (so that robots can interface with each other). This complementarity in technology diffusion has been shown as being large in the case of digital technologies.

- **Expected profitability.** Any investment decision in a new technology relies on a business case. We have discussed this loop effect above.

Equation 1 was estimated as a single logit or OLS model or as a system of two equations with, first, expected profitability, and then Equation 1 with expected profitability instrumented as described above. Equation 1 was estimated for both adoption and absorption, with the final model chosen being the one with the best fit, with removal of multicolinearity, and all misspecification tests (see Exhibit A1 for a summary of the significant effects for adoption and, for a more concrete synthesis of the results, reporting only statistically significant coefficients, Exhibit A2).

Their magnitude of impact on adoption and absorption is qualified as high, medium, or low depending on their odd ratio effect on adoption propensity. In general, the effects are marginally more significant for decisions to adopt than to absorb. Further, AI complementarities are relatively strong: companies tend to invest in the broad set of technologies; expected profitability plays a stimulating role, but the effects are lower than any other predictors. Rivalry is a pervasive effect, but it is especially visible when it concerns the adoption and absorption of advanced machine learning techniques.

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126 Massoud Karshenas and Paul Stoneman, "Rank, stock, order, and epidemic effects in the diffusion of new process technologies," 1993, *RAND Journal of Economics*, Volume 24, Issue 4.

127 This is in line with research by Harrison and O'Neill, who state, "Companies that rush into sophisticated AI before reaching a critical mass of automated processes and structured analytics can end up paralyzed." We expect complementary technologies such as big data and advanced analytics to have a positive effect on AI technology adoption. See Nick Harrison and Deborah O'Neill, "If your company isn't good at analytics, it's not ready for AI," *Harvard Business Review*, 2017.

Exhibit A1

Regression results for AI technology cluster corporate absorption.

%

			Estimate	Standard error	Significance
Adoption of advanced machine learning	Key predictors	Rivalry	5.01	0.79	0.00
		Digital capabilities	2.88	0.40	0.00
		AI complementarities	3.31	0.23	0.00
		Expected profitability	0.02	0.01	0.09
	Controls	Region: Asia–Pacific	-0.54	0.27	0.04
		Region: Europe	-0.39	0.20	0.05
		Revenue above $1 billion	0.46	0.17	0.01
		Industry: Services	0.87	0.23	0.00
		Industry: Retail	0.39	0.35	0.27
		Constant	-6.95	0.55	0.00
Advanced robotics and robotic process automation	Key predictors	Rivalry	-5.53	1.15	0.00
		Digital capabilities	0.55	0.30	0.07
		AI complementarities	2.54	0.20	0.00
		Revenue above $1 billion	0.98	0.16	0.00
	Controls	Region: Asia–Pacific	0.32	0.22	0.14
		Region: Europe	0.53	0.16	0.00
		Industry: Advanced electronics	3.25	1.19	0.01
		Industry: Automotive and assembly	1.06	0.34	0.00
		Industry: Services	-0.49	0.22	0.03
		Industry: Chemicals	1.55	0.42	0.00
		Industry: Financial services	1.06	0.31	0.00
		Industry: High tech	0.61	0.33	0.06
		Industry: Media and entertainment	-1.42	0.38	0.00
		Industry: Metals and mining	1.14	0.44	0.01
		Industry: Paper and forest products	2.49	1.20	0.04
Natural language and computer vision	Key predictors	Rivalry	1.49	0.73	0.04
		Digital capabilities	1.31	0.30	0.00
		AI complementarities	3.30	0.23	0.00
		Revenue above $1 billion	0.21	0.08	0.09
	Controls	Industry: Chemicals	-0.99	0.47	0.03
		Industry: Electric power and natural gas	1.16	0.45	0.01
		Industry: Financial services	-0.40	0.22	0.07
		Industry: Media and entertainment	0.69	0.32	0.03
		Constant	-4.32	0.44	0.00

SOURCE: McKinsey Global Institute analysis

Exhibit A1 (continued)

Regression results for AI technology cluster corporate adoption (continued).

%

			Estimate	Standard error	Significance
Virtual assistants and other AI tools	Key predictors	Rivalry	0.62	0.21	0.09
		Digital capabilities	1.04	0.30	0.00
		AI complementarities	3.79	0.25	0.00
		Revenue above $1 billion	0.01	0.00	0.00
	Controls	Region: Latin America	-0.71	0.35	0.04
		Industry: Chemicals	-1.44	0.49	0.00
		Industry: Electric power and natural gas	-0.67	0.43	0.12
		Industry: Infrastructure	-0.87	0.42	0.04
		Industry: Pharmaceuticals and medical products	-0.69	0.40	0.09
		Industry: Retail	-0.71	0.34	0.04
		Constant	-3.15	0.35	0.00

SOURCE: McKinsey Global Institute analysis

Exhibit A2

Heat map of influence of AI technologies on corporate absorption.

Impact on AI uptake[1] ● High[1] ◉ Medium[1] ○ Low[1]

	Advanced machine learning		Advanced robotics		Computer vision and language processing		Virtual assistants	
Dimensions	Adoption[2]	Absorption[3]	Adoption[2]	Absorption[3]	Adoption[2]	Absorption[3]	Adoption[2]	Absorption[3]
Digital capabilities								
▪ Absorption cloud and big data	●				◉		○	
▪ Absorption mobile, internet, and web		○	○		◉		○	
AI complementarities	●	●	●		●	●	●	◉
Rivalry	●	●	●		◉		○	○
AI expected profitability	○	○	○	○	○	○	○	○
Average uptake %	40	15	31	10	43	7	41	10

1 High = odd ratio > 10; medium = odd ratio > 3; low = odd ratio > 1.
2 Adoption includes both pilot, use cases not at scale, and all their cases of absorption at scale, either functional or across the whole enterprise; absorption is only adoption at scale across the whole enterprise.
3 Absorption intensity, or the ratio of absorption to adoption rate, as a measure of how adoption is scaled.

SOURCE: McKinsey Global Institute analysis

SOURCES FOR COUNTRY HEAT MAP

In order to assess readiness for AI, we examined more than 25 indicators. Some of the public sources that we used in this analysis were:

International Telecommunication Union development index: ITU (http://www.itu.int/net4/ITU-D/idi/2017/)

Internet penetration: ITU (https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx)

R&D expenditure: World Bank (https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?view=map)

Gross savings: World Bank (https://data.worldbank.org/indicator/NY.GNS.ICTR.ZS)

ITU ICT business model creation, ITU ICT organizational model creation, ITU ICT use: World Intellectual Property Organization (http://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2017.pdf)

AI patents: WIPO Patentscope (https://patentscope.wipo.int/search/en/search.jsf)

Scimago Journal and Country Rank (https://www.scimagojr.com/)

Global Talent Competitiveness Index: INSEAD (https://gtcistudy.com/gtci-2018-report/)

Redundancy costs: World Bank (https://tcdata360.worldbank.org/indicators/redun.cost?indicator=659&viz=line_chart&years=2007,2017)

Availability of scientists and engineers; workforce with secondary education: INSEAD GTCI (https://www.insead.edu/sites/default/files/assets/dept/globalindices/docs/GTCI-2018-report.pdf)

PISA problem solving: OECD (http://www.oecd.org/pisa/)

The Global Human Capital Index: World Economic Forum (https://www.weforum.org/reports/the-global-human-capital-report-2017)

Global Innovation Index: INSEAD (https://www.globalinnovationindex.org/Home)

Trade: UNCTAD, ICT Trade Map (https://www.trademap.org/Index.aspx)

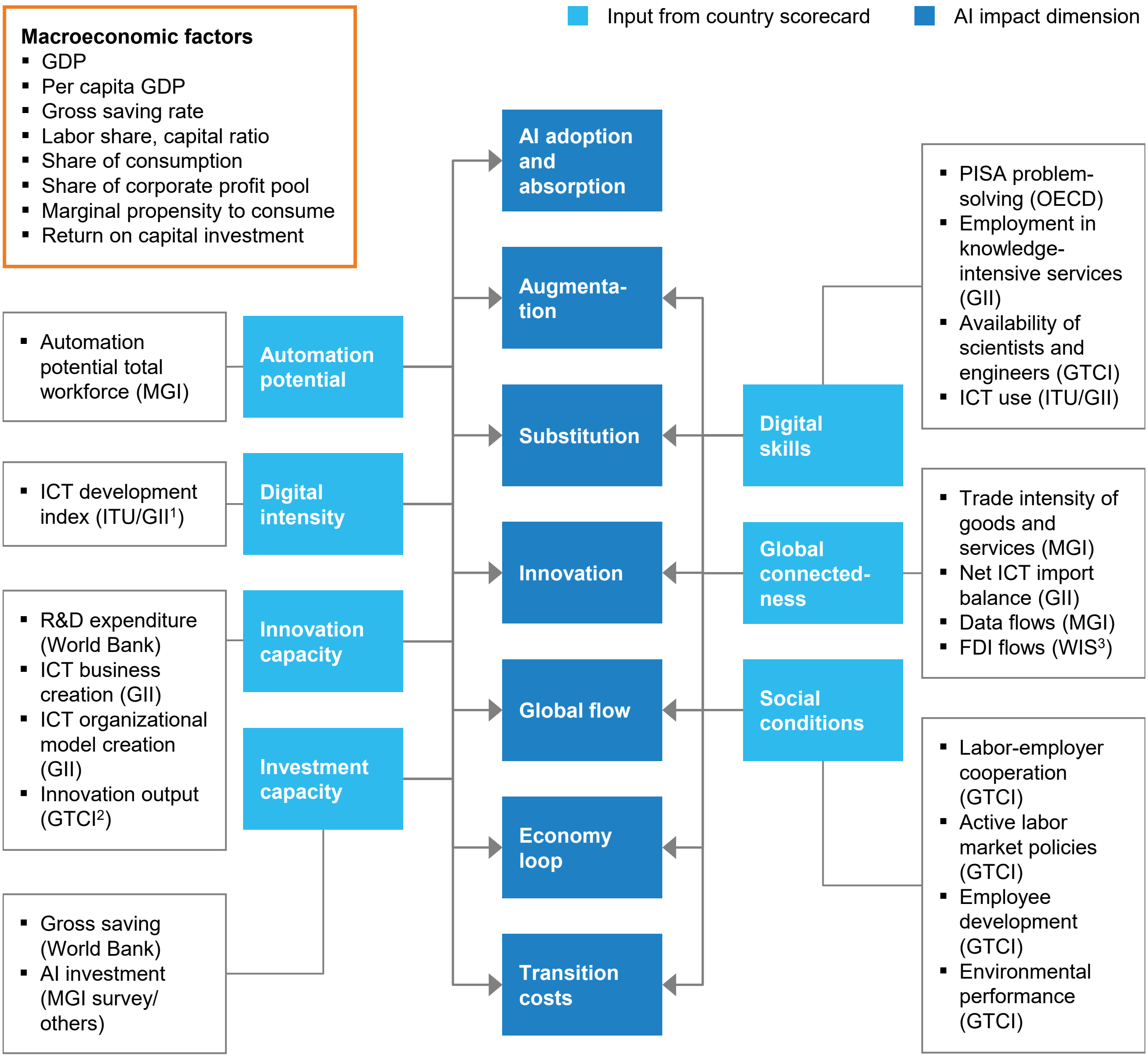
Macroeconomic indicators: World Bank (https://data.worldbank.org/products/wdi)

SIMULATING COUNTRY-LEVEL ECONOMIC IMPACT

We used multiple data sets to simulate the impact of AI on individual countries. First, we used macroeconomic data for each country as the basis for capturing differences in the stage of development and economic structure of individual countries. Each country has a different profile in terms of GDP, share of consumption, and labor share of economic activity, for example. Second, we took a subset of AI-related indicators for each country that are linked to different dimensions of economic impact. We modeled different degrees of variance by country for each variable, producing a different level of impact for each country. For example, differences in skill levels by country can have an impact on augmentation, innovation, and spillovers. Differences in R&D expenditure (an indicator of input into innovation systems), ICT business creation (an indicator that measures economic activity enabled by innovation, in particular in startups and small and medium-size enterprises), and ICT organizational model creation (an indicator to check innovative activity within firms, in particular large ones) will impact the output of innovation. Social indicators such as labor-employer cooperation can have an effect on transition costs (Exhibit A3).

Exhibit A3

Factors considered for country simulation.



1 Global Innovation Index 2017.
2 Global Talent Competitiveness Index 2018.
3 World Investment Summit Report 2017.

SOURCE: ITU; World Bank; OECD; INSEAD; WIPO; UNCTAD; Dealogic; S&P; Capital IQ; McKinsey Global Institute analysis

STRESS TESTING THE ECONOMIC IMPACT OF AI

We simulated several questions to assess the sensitivities of economic impact to different variables (Exhibit A4). We tested six key areas. Of these, the rate of AI absorption and innovation gains tended to be the most sensitive to a ten-percentage-point change to baseline assumptions (a 1.1-to 3.6-percentage-point average cumulative impact on GDP by 2030); other areas tended to change moderately (0.2 to one percentage point):

1. **AI adoption and absorption levels.** It is important to gauge sensitivities of this kind so that countries can understand the impact on their economies of enabling or hampering AI adoption and absorption. We simulated a 10 percent change in adoption and absorption rates for each country by 2030—from the 48 percent current global average to 53 percent, for instance. Globally, increasing the adoption and absorption rate by this amount yields an additional 1.4 percentage points of cumulative value added by 2030.

2. **Investment in AI.** AI investment can be used not only to substitute laborious tasks, but also to develop new business models, products, and services. However, achieving a healthy return on that investment depends on a number of factors including the country's economic context, regulatory policies, infrastructure available for incubating startups, and appropriate social safety nets (for example, providing the right support environments for startups). We simulated a 10 percent change in AI investment. Globally, this could generate an additional 0.7 percentage point of net GDP impact by 2030.

3. **Innovation capacity.** Each country has different capacity and capabilities for innovation. We simulated the impact of product and service gains and extension, specifically a 10 percent increase in the effectiveness ratio (the ratio of innovation gains to labor-force efficiency improvement). Globally, this could lead to a 0.9-percentage-point increase in GDP by 2030.

4. **Global data flows and connectedness.** The economic potential of AI also depends on the economy's participation in global cross-border data and trade flows. We simulated each country's position on global connectedness, and a 10 percent increase in data flows. On a global level, the simulation yields a 0.2-percentage-point change; this could have a different impact on countries depending on their current position in global connectedness.

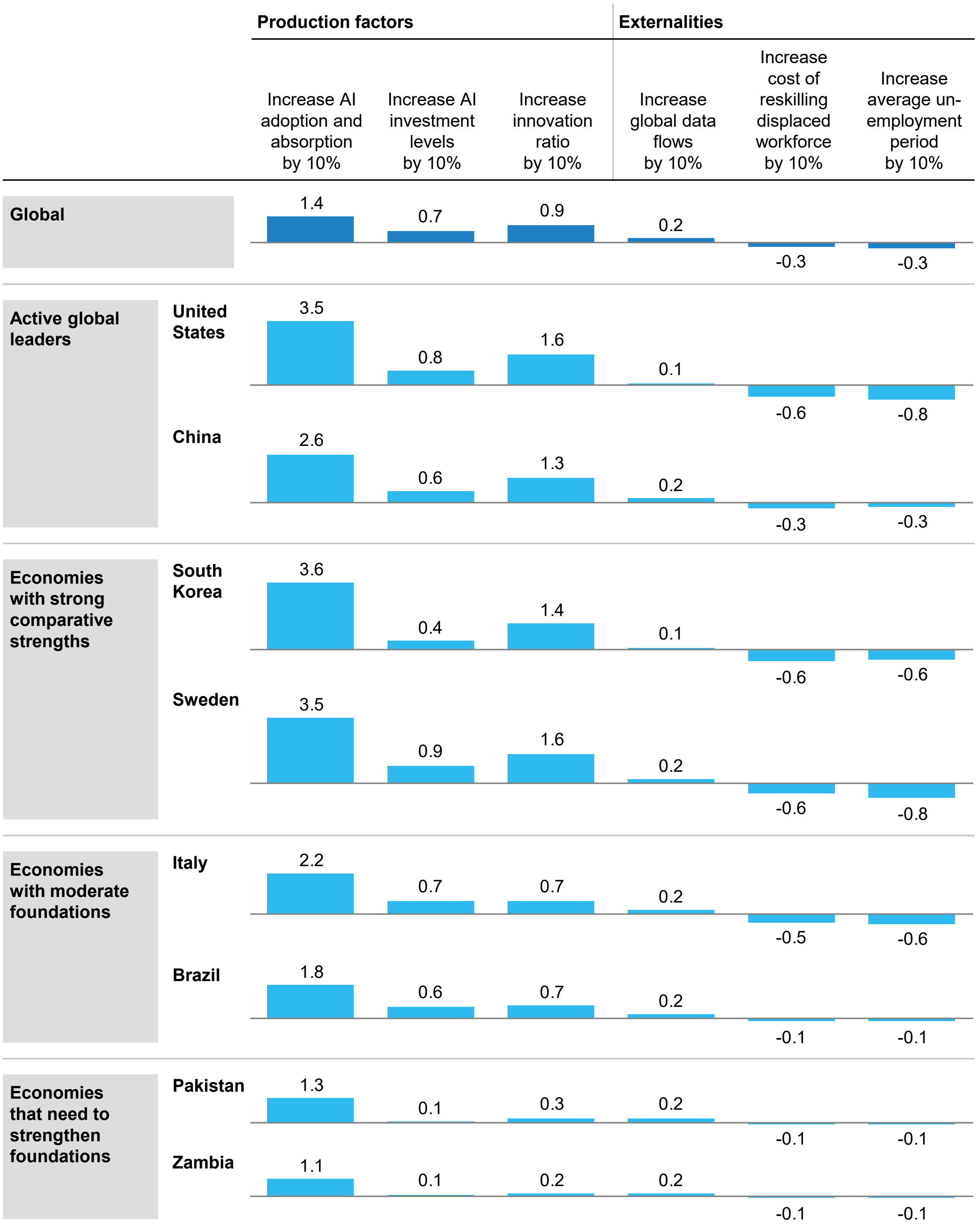
5. **Transition costs.** Economies can avoid certain costs associated with the displacement of people if they redeploy them rather than let them go, enabling them to shift to other roles by giving them the appropriate skills. The cost of reskilling depends on how effective the program is. Effective programs retrain individuals and get them back into the workforce more quickly, cutting economic cost. We simulated reskilling taking a 10 percent higher cost that could reduce the GDP impact by 0.3 percentage point globally.

6. **Negative externalities due to increased unemployment duration.** The duration of unemployment has significant implications for economic costs. The longer a person displaced by AI is unemployed, the longer that individual is not consuming, and any unemployment benefits also incur an economic cost. We simulated a 10 percent increase in unemployment period for each country. This would produce a negative impact on the economic potential of AI of 0.3 percentage point.

Exhibit A4

Countries have different degrees of sensitivity.

Percentage points



NOTE: Numbers are simulated figures to provide directional perspectives rather than forecasts.

SOURCE: McKinsey Global Institute analysis

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