Driving impact at scale from automation and AI

February 2019

Digital/McKinsey

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Introduction

Automation, leveraging artificial intelligence (AI) and other technologies, has opened up new possibilities. The pace of adoption has been rapid. Institutions of all sizes globally are leveraging automation to drive value. According to the McKinsey Automation Survey in 2018, 57 percent of 1,300 institutions have already started on this journey, with another 18 percent planning to kick off something within the next year.

When done right, automation has proven to deliver real benefits, including the following:

- **Distinctive insights:** Hundreds of new factors to predict and improve drivers of performance

- **Faster service:** Processing time reduced from days to minutes

- **Increased flexibility and scalability:** Ability to operate 24/7 and scale up or down with demand

- **Improved quality:** From spot-checking to 100 percent quality control through greater traceability

- **Increased savings and productivity:** Labor savings of 20 percent or more

However, success is far from guaranteed. According to our Automation Survey, only 55 percent of institutions believe their automation program has been successful to date. Moreover, a little over half of respondents also say that the program has been much harder to implement than they expected.

In this collection of articles, we explore why automation and AI are so important, how to transform, and what the functional nuances are that can be the difference between success and failure. At a high level, these articles delve into the four most important practices that are strongly correlated with success in automation:

- **Understand the opportunity and move early:** Start taking advantage of automation and AI by assessing the opportunity, identifying the high-impact use cases, and laying out the capability and governance groundwork.

- **Balance quick tactical wins with long-term vision:** Identify quick wins to automate activities with the highest automation potential and radiate out, freeing up capital; in parallel, have a long-term vision for comprehensive transformation, with automation at the core.

- **Redefine processes and manage organizational change:** Since 60 percent of all jobs have at least 30 percent technically automatable activities, redefining jobs and taking an end-to-end process view are necessary to capture the value.

- **Integrate technology into core business functions:** Build AI and other advanced technologies into the operating model to create transformative impact and lasting value, support a culture of collecting and analyzing data to inform decisions, and build the muscle for continuous improvement.

We hope this curated collection will be helpful to you in realizing the full value potential from your own automation transformation.

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We wish to thank Keith Gilson, Vishal Koul, and Christina Yum for their contributions to this collection.

Part

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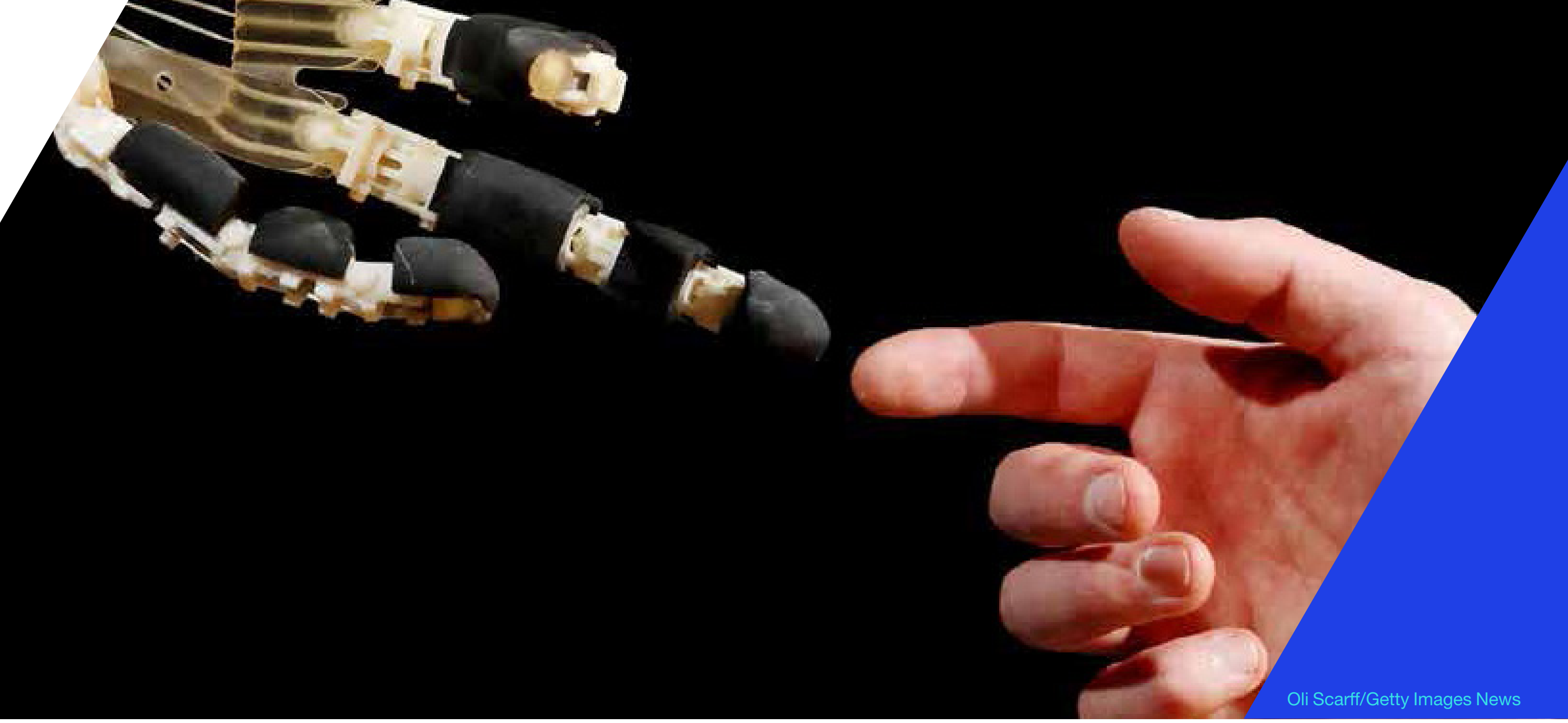
Why automation and AI?


Oli Scarff/Getty Images News

Harnessing automation for a future that works

Jacques Bughin, Michael Chui, Martin Dewhurst, Katy George, James Manyika, Mehdi Miremadi, and Paul Willmott

Automation is happening, and it will bring substantial benefits to businesses and economies worldwide, but it won't arrive overnight. A new McKinsey Global Institute report finds realizing automation's full potential requires people and technology to work hand in hand.

Recent developments in robotics, artificial intelligence, and machine learning have put us on the cusp of a new automation age. Robots and computers can not only perform a range of routine physical work activities better and more cheaply than humans, but they are also increasingly capable of accomplishing activities that include cognitive capabilities once considered too difficult to automate successfully, such as making tacit judgments, sensing emotion, or even driving. Automation will change the daily work activities of everyone, from miners and landscapers to commercial bankers, fashion designers, welders, and CEOs. But how quickly will these automation technologies become a reality in the workplace? And what will their impact be on employment and productivity in the global economy?

The McKinsey Global Institute has been conducting an ongoing research program on automation technologies and their potential effects. A new MGI report, *A future that works: Automation, employment, and productivity*, highlights several key findings.

The automation of activities can enable businesses to improve performance by reducing errors and improving quality and speed, and in some cases achieving outcomes that go beyond human capabilities. Automation also contributes to productivity, as it has done historically. At a time of lackluster productivity growth, this would give a needed boost to economic growth and prosperity. It would also help offset the impact of a declining share of the working-age population in many countries. Based on our scenario modeling, we estimate automation could raise productivity growth globally by 0.8 to 1.4 percent annually.

The right level of detail at which to analyze the potential impact of automation is that of individual activities rather than entire occupations. Every occupation includes multiple types of activity, each of which has different requirements for automation. Given currently demonstrated technologies, very few occupations—less than 5 percent—are candidates for full automation. However, almost every occupation has partial automation potential, as a proportion of its activities could be automated. We estimate that about half of all the activities people are paid to do in the world's workforce could potentially be automated by adapting currently demonstrated technologies. That amounts to almost $15 trillion in wages.

The activities most susceptible to automation are physical ones in highly structured and predictable environments, as well as data collection and processing. In the United States, these activities make up 51 percent of activities in the economy, accounting for almost $2.7 trillion in wages. They are most prevalent in manufacturing, accommodation and food service, and retail trade. And it's not just low-skill, low-wage work that could be automated; middle-skill and high-paying, high-skill occupations, too, have a degree of automation potential. As processes are transformed by the automation of individual activities, people will perform activities that complement the work that machines do, and vice versa.

Still, automation will not happen overnight. Even when the technical potential exists, we estimate it will take years for automation's effect on current work activities to play out fully. The pace of automation, and thus its impact on workers, will vary across different activities, occupations, and wage and skill levels. Factors that will determine the pace and extent of automation include the ongoing development of technological capabilities, the cost of technology, competition with labor including skills and supply and demand dynamics, performance benefits including and beyond labor cost savings, and social and regulatory acceptance. Our scenarios suggest that half of today's work activities could be automated by 2055, but this could happen up to 20 years earlier or later depending on various factors, in addition to other economic conditions.

The effects of automation might be slow at a macro level, within entire sectors or economies, for example, but they could be quite fast at a micro level, for individual workers whose activities are automated or for companies whose industries are disrupted by competitors using automation.

While much of the current debate about automation has focused on the potential for mass unemployment, people will need to continue working alongside machines to produce the growth in per capita GDP to which countries around the world aspire. Thus, our productivity estimates assume that people displaced by automation will find other employment. Many workers will have to change, and we expect business processes to be transformed. However, the scale of shifts in the labor force over many decades that automation technologies can unleash is not without precedent. It is of a similar order of magnitude to the long-term technology-enabled shifts away from agriculture in developed countries' workforces in the 20th century. Those shifts did not result in long-term mass unemployment, because they were accompanied by the creation of new types of work. We cannot definitively say whether things will be different this time. But our analysis shows that humans will still be needed in the workforce: the total productivity gains we estimate will only come about if people work alongside machines. That in turn will fundamentally alter the workplace, requiring a new degree of cooperation between workers and technology. ◆

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AUTOMATION

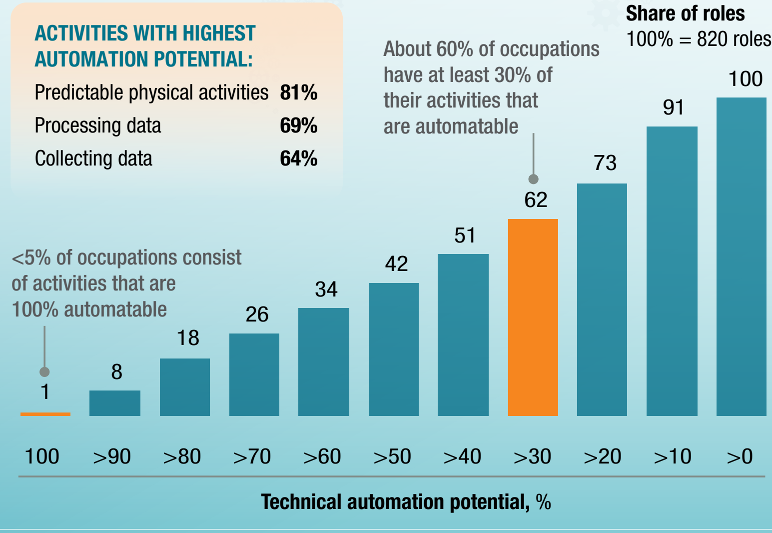
A global force that will transform economies and the workforce

Technical automation potential by adapting currently demonstrated technologies

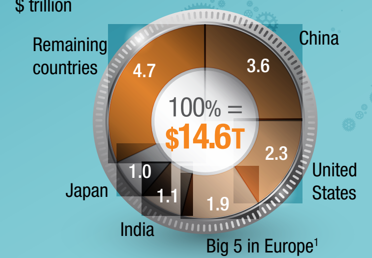
While few occupations are fully automatable, 60 percent of all occupations have at least 30 percent technically automatable activities

ACTIVITIES WITH HIGHEST AUTOMATION POTENTIAL:

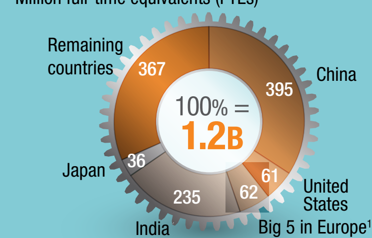
Predictable physical activities	**81%**
Processing data	**69%**
Collecting data	**64%**



Wages associated with technically automatable activities
$ trillion



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



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

Five factors affecting pace and extent of adoption

1 TECHNICAL FEASIBILITY
Technology has to be invented, integrated, and adapted into solutions for specific case use

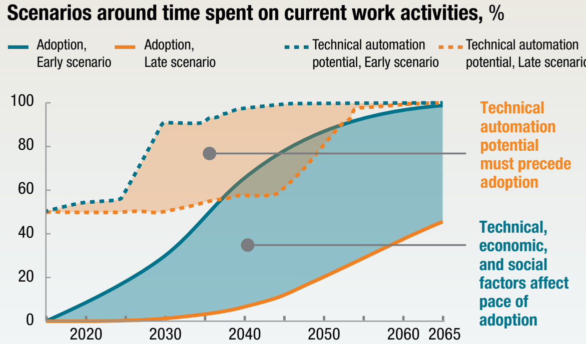
2 COST OF DEVELOPING AND DEPLOYING SOLUTIONS
Hardware and software costs

3 LABOR MARKET DYNAMICS
The supply, demand, and costs of human labor affect which activities will be automated

4 ECONOMIC BENEFITS
Include higher throughput and increased quality, alongside labor cost savings

5 REGULATORY AND SOCIAL ACCEPTANCE
Even when automation makes business sense, adoption can take time

Scenarios around time spent on current work activities, %

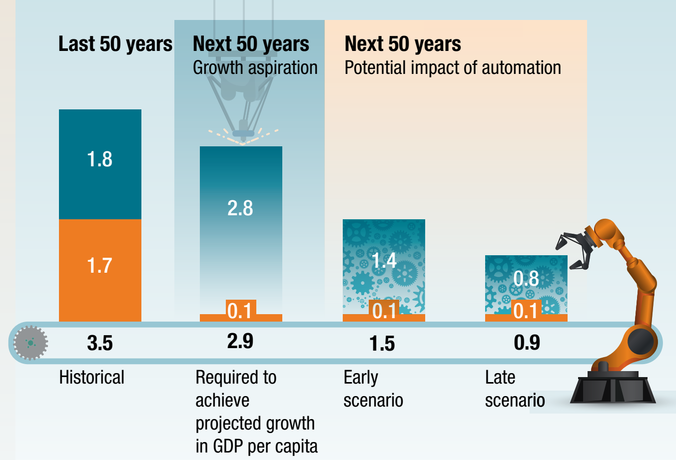


Automation will boost global productivity and raise GDP

G19 plus Nigeria

Productivity growth, %
Automation can help provide some of the productivity needed to achieve future economic growth

Employment growth, %
will slow drastically because of aging



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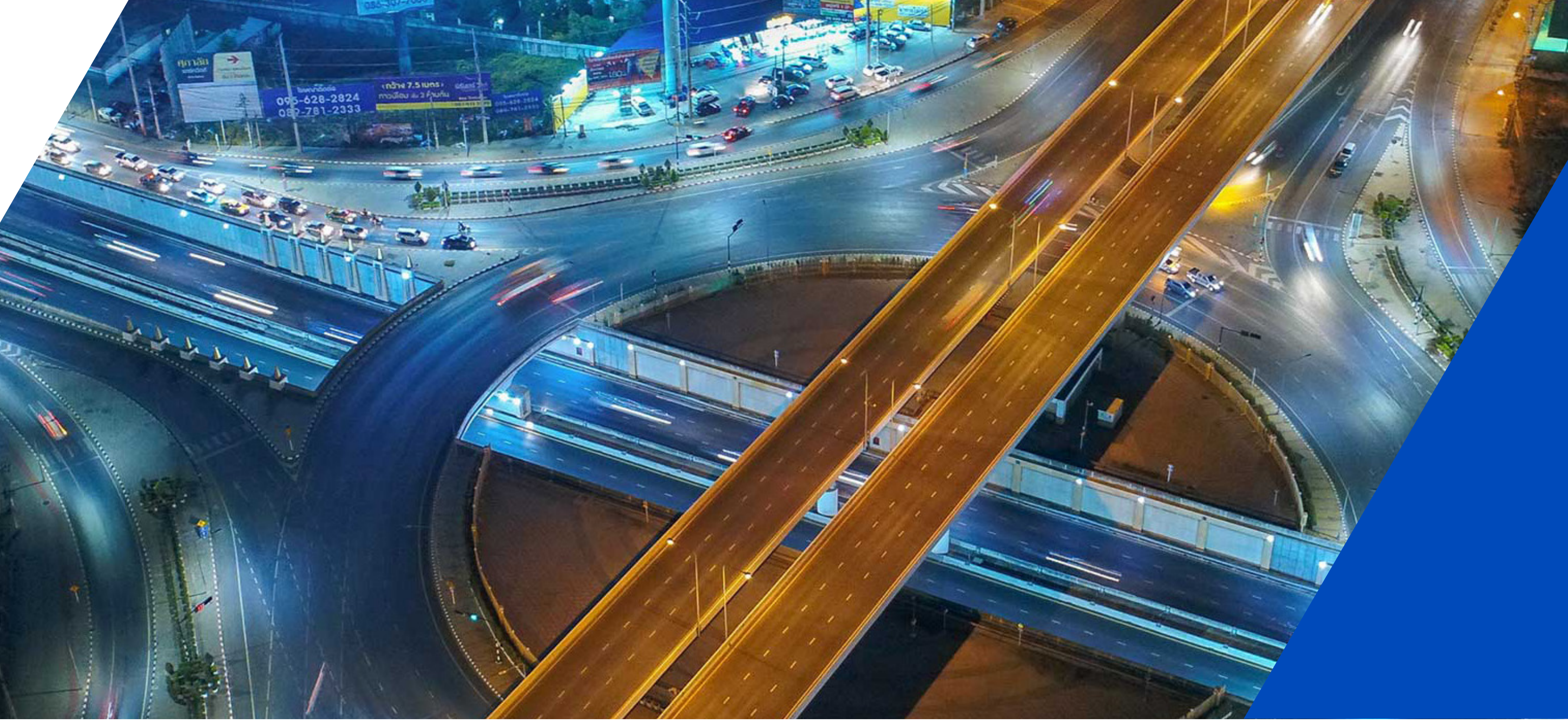


Notes from the AI frontier: Applications and value of deep learning

Michael Chui, Rita Chung, Nicolaus Henke, Sankalp Malhotra, James Manyika, Mehdi Miremadi, and Pieter Nel

An analysis of more than 400 use cases across 19 industries and nine business functions highlights the broad use and significant economic potential of advanced AI techniques.

Artificial intelligence (AI) stands out as a transformational technology of our digital age—and its practical application throughout the economy is growing apace. In our discussion paper *Notes from the AI frontier: Insights from hundreds of use cases,* we mapped both traditional analytics and newer "deep learning" techniques and the problems they can solve to more than 400 specific use cases in companies and organizations.[1] Drawing on McKinsey Global Institute research and the applied experience with AI of McKinsey Analytics, we assess both the practical applications and the economic potential of advanced AI techniques across industries and

[1] For the full McKinsey Global Institute discussion paper, see "Notes from the AI frontier: Applications and value of deep learning," April 2018, on McKinsey.com.

business functions. Our findings highlight the substantial potential of applying deep learning techniques to use cases across the economy, but we also see some continuing limitations and obstacles—along with future opportunities as the technologies continue their advance. Ultimately, the value of AI is not to be found in the models themselves, but in companies' abilities to harness them.

It is important to highlight that, even as we see economic potential in the use of AI techniques, the use of data must always take into account concerns including data security, privacy, and potential issues of bias.

Mapping AI techniques to problem types

As artificial intelligence technologies advance, so does the definition of which techniques constitute AI.[2] For the purposes of this article, we use AI as shorthand for deep learning techniques that use artificial neural networks. We also examined other machine learning techniques and traditional analytics techniques (Exhibit 1).

Neural networks are a subset of machine learning techniques. Essentially, they are AI systems based on simulating connected "neural units," loosely modeling the way that neurons interact in the brain. Computational models inspired by neural connections have been studied since the 1940s and have returned to prominence as computer processing power has increased and large training data sets have been used to successfully analyze input data such as images, video, and speech. AI practitioners refer to these techniques as "deep learning," since neural networks have many ("deep") layers of simulated interconnected neurons.

We analyzed the applications and value of three neural network techniques:

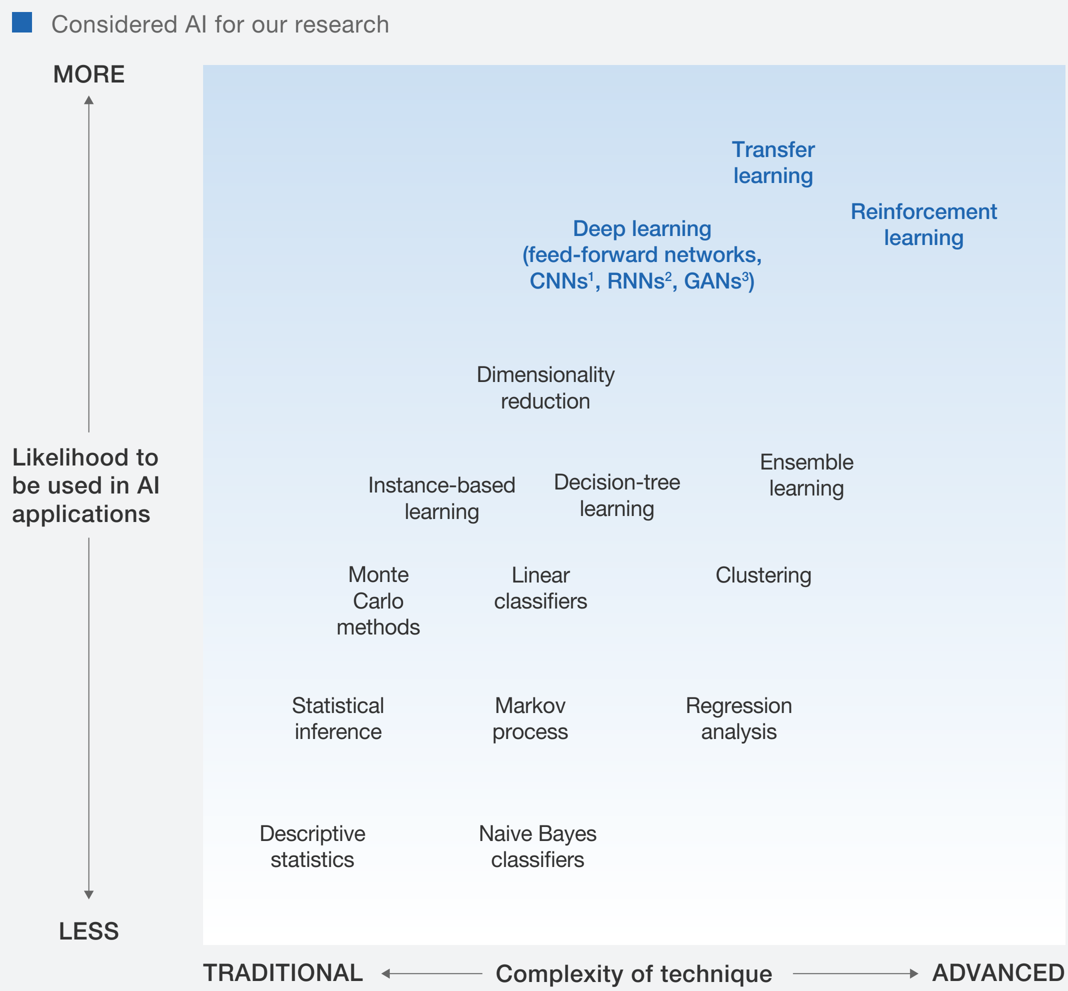
- *Feed-forward neural networks:* The simplest type of artificial neural network. In this architecture, information moves in only one direction, forward, from the input layer, through the "hidden" layers, to the output layer. There are no loops in the network. The first single-neuron network was proposed already in 1958 by AI pioneer Frank Rosenblatt. While the idea is not new, advances in computing power, training algorithms, and available data led to higher levels of performance than previously possible.
- *Recurrent neural networks (RNNs):* Artificial neural networks whose connections between neurons include loops; RNNs are well suited for processing sequences of inputs. In November 2016, Oxford University researchers reported that a system based on recurrent neural networks (and convolutional neural networks) had achieved 95 percent accuracy in reading lips, outperforming experienced human lip readers, who tested at 52 percent accuracy.
- *Convolutional neural networks (CNNs):* Artificial neural networks in which the connections between neural layers are inspired by the organization of the animal visual cortex, the portion of the brain that processes images; CNNs are well suited for perceptual tasks.

For our use cases, we also considered two other techniques—generative adversarial networks and reinforcement learning—but did not include them

[2] For more on AI techniques, including definitions and use cases, see "An executive's guide to AI," February 2018, McKinsey.com.

Exhibit 1

We examined artificial intelligence (AI), machine learning, and other analytics techniques for our research.



[1] Convolutional neural networks.
[2] Recurrent neural networks.
[3] Generative adversarial networks.

Source: McKinsey Global Institute analysis

in our potential value assessment of AI, since they remain nascent techniques that are not yet widely applied:

- *Generative adversarial networks (GANs)* use two neural networks contesting one another in a zero-sum game framework (thus "adversarial"). GANs can learn to mimic various distributions of data (for example, text, speech, and images) and are therefore valuable in generating test data sets when these are not readily available.

- *Reinforcement learning* is a subfield of machine learning in which systems are trained by receiving virtual "rewards" or "punishments," essentially learning by trial and error. Google's DeepMind has used reinforcement learning to develop systems that can play games, including video games and board games such as Go, better than human champions.

In a business setting, these analytic techniques can be applied to solve real-life problems. The most prevalent problem types are classification, continuous estimation, and clustering (see sidebar, "Problem types and their definitions").

Insights from use cases

We collated and analyzed more than 400 use cases across 19 industries and nine business functions. They provided insight into the areas within specific sectors where deep neural networks can potentially create the most value, the incremental lift that these neural networks can generate compared with traditional analytics (Exhibit 2), and the voracious data requirements—in terms of volume, variety, and velocity—that must be met for this potential to be realized. Our library of use cases, while extensive, is not exhaustive and may overstate or understate the potential for certain sectors. We will continue refining and adding to it.

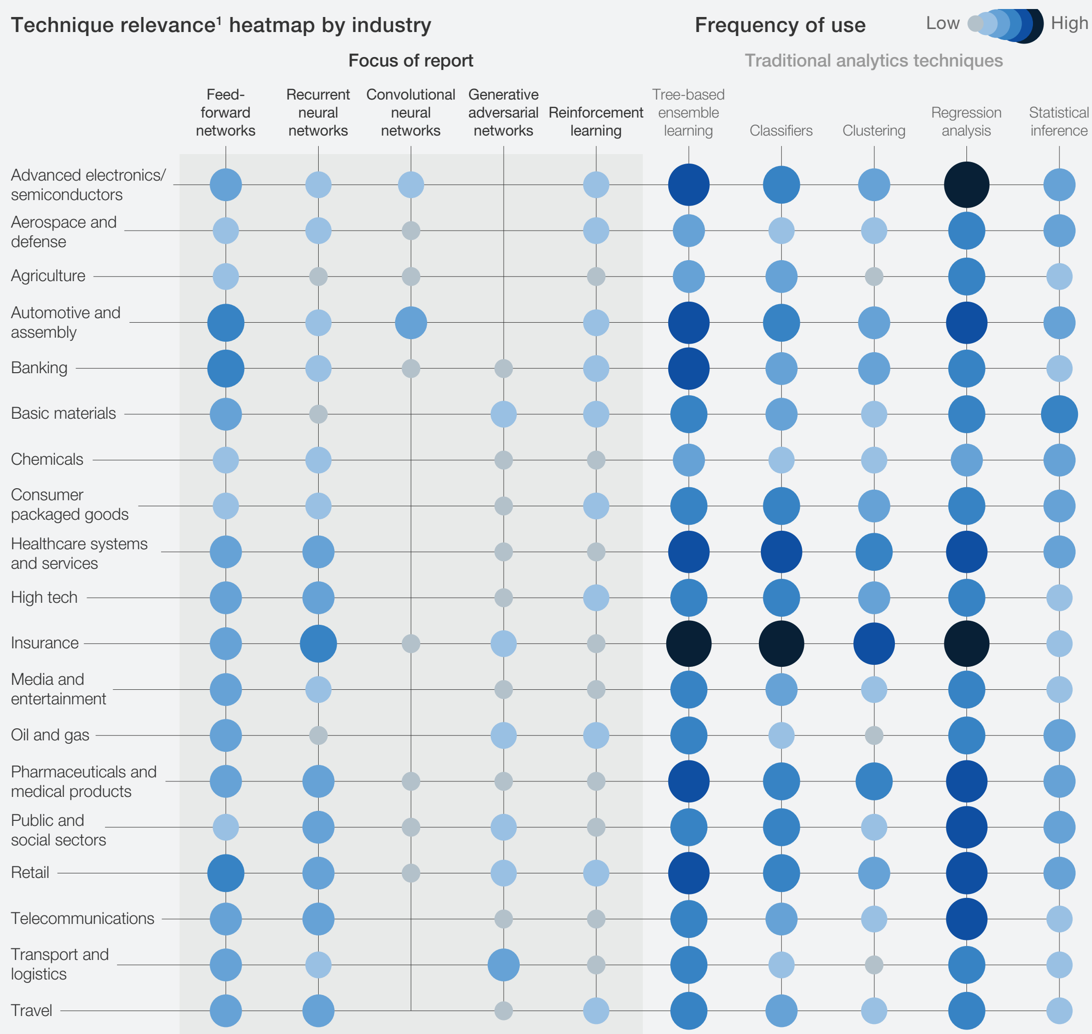
Following are examples of where AI can be used to improve the performance of existing use cases:

- *Predictive maintenance: The power of machine learning to detect anomalies.* Deep learning's capacity to analyze very large amounts of high-dimensional data can take existing preventive maintenance systems to a new level. Layering in additional data, such as audio and image data, from other sensors—including relatively cheap ones such as microphones and cameras—neural networks can enhance and possibly replace more traditional methods. AI's ability to predict failures and allow planned interventions can be used to reduce downtime and operating costs while improving production yield. For example, AI can extend the life of a cargo plane beyond what is possible using traditional analytics techniques by combining plane model data, maintenance history, and Internet of Things (IoT) sensor data such as anomaly detection on engine-vibration data, and images and video of engine condition.

- *AI-driven logistics optimization can reduce costs through real-time forecasts and behavioral coaching.* Application of AI techniques such as continuous estimation to logistics can add substantial value across sectors. AI can optimize routing of delivery traffic, thereby improving fuel efficiency and reducing delivery times. One European trucking company has reduced fuel costs by 15 percent, for example, by using sensors that monitor both vehicle performance and driver behavior; drivers receive real-time coaching, including when to speed up or slow down, optimizing fuel consumption and reducing maintenance costs.

Exhibit 2

Advanced deep learning artificial intelligence techniques can be applied across industries, alongside more traditional analytics.



[1]Relevance refers to frequency of use in our use case library, with the most frequently found cases marked as high relevance and the least frequently found as low relevance. Absence of circles indicates no or statistically insignificant number of use cases.
Note: List of techniques is not exhaustive.

Source: McKinsey Global Institute analysis

Problem types and their definitions

Classification: Based on a set of training data, categorize new inputs as belonging to one of a set of categories. An example of classification is identifying whether an image contains a specific type of object, such as a cat or a dog, or a product of acceptable quality coming from a manufacturing line.

Continuous estimation: Based on a set of training data, estimate the next numeric value in a sequence. This type of problem is sometimes described as "prediction," particularly when it is applied to time-series data. One example of continuous estimation is forecasting the sales demand for a product, based on a set of input data such as previous sales figures, consumer sentiment, and weather.

Clustering: These problems require a system to create a set of categories, for which individual data instances have a set of common or similar characteristics. An example of clustering is creating a set of consumer segments, based on a set of data about individual consumers, including demographics, preferences, and buyer behavior.

All other optimization: These problems require a system to generate a set of outputs that optimize outcomes for a specific objective function (some of the other problem types can be considered types of optimization, so we describe these as "all other" optimization). Generating a route for a vehicle that creates the optimum combination of time and fuel utilization is an example of optimization.

Anomaly detection: Given a training set of data, determine whether specific inputs are out of the ordinary. For instance, a system could be trained on a set of historical vibration data associated with the performance of an operating piece of machinery, and then determine whether a new vibration reading suggests that the machine is not operating normally. Anomaly detection can be considered a subcategory of classification.

Ranking: Ranking algorithms are used most often in information-retrieval problems where the results of a query or request needs to be ordered by some criterion. Recommendation systems suggesting next product to buy use these types of algorithms as a final step, sorting suggestions by relevance, before presenting the results to the user.

Recommendations: These systems provide recommendations based on a set of training data. A common example of recommendations are systems that suggest "next product to buy" for an individual buyer, based on the buying patterns of similar individuals and the observed behavior of the specific person.

Data generation: These problems require a system to generate appropriately novel data based on training data. For instance, a music composition system might be used to generate new pieces of music in a particular style, after having been trained on

- *AI can be a valuable tool for customer service management and personalization challenges.* Improved speech recognition in call center management and call routing as a result of the application of AI techniques allows a more seamless experience for customers—and more efficient processing. The capabilities go beyond words alone. For example, deep learning analysis of audio allows systems to assess a customer's emotional tone; in the event a customer is responding badly to the system, the call can be rerouted automatically to human operators and managers. In other areas of marketing and sales, AI techniques can also have a significant impact. Combining customer demographic and past transaction data with social media monitoring can help generate individualized product recommendations. Next-product-to-buy recommendations that target individual customers—as companies such as Amazon and Netflix have successfully been doing—can lead to a twofold increase in the rate of sales conversions.

Two-thirds of the opportunities to use AI are in improving the performance of existing analytics use cases

In 69 percent of the use cases we studied, deep neural networks can be used to improve performance beyond that provided by other analytics techniques. Cases in which only neural networks can be used, which we refer to here as "greenfield" cases, constituted just 16 percent of the total. For the remaining 15 percent, artificial neural networks provided limited additional performance over other analytics techniques, because, among other reasons, of data limitations that made these cases unsuitable for deep learning (Exhibit 3).

Greenfield AI solutions are prevalent in business areas such as customer-service management, as well as among some industries where the data are rich and voluminous and at times integrate human reactions. Among industries, we found many greenfield use cases in healthcare, in particular. Some of these cases involve disease diagnosis and improved care and rely on rich data sets incorporating image and video inputs, including from MRIs.

On average, our use cases suggest that modern deep learning AI techniques have the potential to provide a boost in additional value above and beyond traditional analytics techniques—ranging from 30 percent to 128 percent, depending on industry.

In many of our use cases, however, traditional analytics and machine learning techniques continue to underpin a large percentage of the value-creation potential in industries including insurance, pharmaceuticals and medical products, and telecommunications, with the potential of AI limited in certain contexts. In part this is due to the way data are used by these industries and to regulatory issues.

Data requirements for deep learning are substantially greater than for other analytics

Making effective use of neural networks in most applications requires large labeled training data sets alongside access to sufficient computing infrastructure. Furthermore, these deep learning techniques are particularly powerful in extracting patterns from complex, multidimensional data types such as images, video, and audio or speech.

Deep learning methods require thousands of data records for models to become relatively

Exhibit 3

In more than two-thirds of our use cases, artificial intelligence (AI) can improve performance beyond that provided by other analytics techniques.

Source: McKinsey Global Institute analysis

good at classification tasks and, in some cases, millions for them to perform at the level of humans. By one estimate, a supervised deep learning algorithm will generally achieve acceptable performance with around 5,000 labeled examples per category and will match or exceed human-level performance when trained with a data set containing at least ten million labeled examples.[3] In some cases where advanced analytics are currently used, so much data are available—millions or even billions of rows per data set—that AI usage is the most appropriate technique. However, if a threshold of data volume is not reached, AI may not add value to traditional analytics techniques.

These massive data sets can be difficult to obtain or create for many business use cases, and labeling remains a challenge. Most current AI models are trained through "supervised learning," which requires humans to label and categorize the underlying data. However, promising new techniques are emerging to overcome these data bottlenecks, such as reinforcement learning, generative adversarial networks, transfer learning, and "one-shot learning," which allows a trained AI model to learn about a subject based on a small number of real-world demonstrations or examples—and sometimes just one.

Organizations will have to adopt and implement strategies that enable them to collect and integrate data at scale. Even with large data sets, they will have to guard against "overfitting," where a model too tightly matches the "noisy" or random features of the training set, resulting in a corresponding lack of accuracy in future performance, and against "underfitting," where the model fails to capture all of the relevant features. Linking data across customer segments and channels, rather than allowing the data to languish in silos, is especially important to create value.

Realizing AI's full potential requires a diverse range of data types, including images, video, and audio

Neural AI techniques excel at analyzing image, video, and audio data types because of their complex, multidimensional nature, known by practitioners as "high dimensionality." Neural networks are good at dealing with high dimensionality, as multiple layers in a network can learn to represent the many different features present in the data. Thus, for facial recognition, the first layer in the network could focus on raw pixels, the next on edges and lines, another on generic facial features, and the final layer might identify the face. Unlike previous generations of AI, which often required human expertise to do "feature engineering," these neural network techniques are often able to learn to represent these features in their simulated neural networks as part of the training process.

Along with issues around the volume and variety of data, velocity is also a requirement: AI techniques require models to be retrained to match potential changing conditions, so the training data must be refreshed frequently. In one-third of the cases, the model needs to be refreshed at least monthly, and almost one in four cases requires a daily refresh; this is especially the case in marketing and sales and in supply-chain management and manufacturing.

Sizing the potential value of AI

We estimate that the AI techniques we cite in the discussion paper together have the potential to create between $3.5 trillion and $5.8 trillion in value annually across nine business functions in 19 industries. This constitutes about 40 percent of the overall $9.5 trillion to $15.4 trillion annual impact that could potentially be enabled by all analytical techniques (Exhibit 4).

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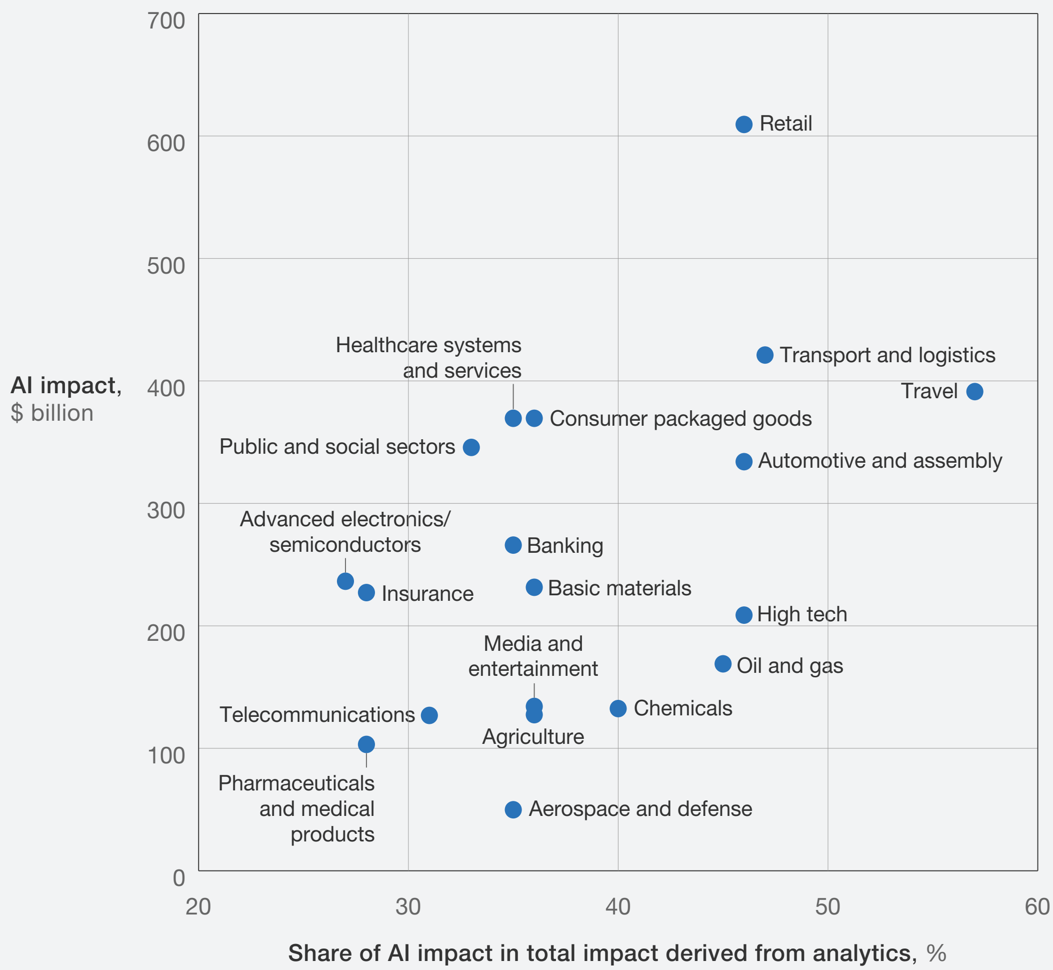
[3] Ian Goodfellow, Yoshua Bengio, and Aaron Courville, *Deep Learning*, Cambridge, MA: MIT Press, 2016.

Exhibit 4

Artificial intelligence (AI) has the potential to create value across sectors.



Source: McKinsey Global Institute analysis

Per industry, we estimate that AI's potential value amounts to between 1 and 9 percent of 2016 revenue. The value as measured by percentage of industry revenue varies significantly among industries, depending on the specific applicable use cases, the availability of abundant and complex data, as well as regulatory and other constraints.

These figures are not forecasts for a particular period, but they are indicative of the considerable potential for the global economy that advanced analytics represents.

From the use cases we have examined, we find that the greatest potential value impact from using AI are both in top-line-oriented functions, such as marketing and sales, and bottom-line-oriented operational functions, including supply-chain management and manufacturing.

Consumer industries such as retail and high tech will tend to see more potential from marketing and sales AI applications because frequent and digital interactions between the business and customers generate larger data sets for AI techniques to tap into. E-commerce platforms, in particular, stand to benefit. This is because of the ease with which these platforms collect customer information such as click data or time spent on a web page. These platforms can then customize promotions, prices, and products for each customer dynamically and in real time.

Here is a snapshot of three sectors where we have seen AI's impact (Exhibit 5):

- In retail, marketing and sales is the area with the most significant potential value from AI, and within that function, pricing and promotion and customer-service management are the main value areas. Our use cases show that using customer data to personalize promotions, for example, including tailoring individual offers every day, can lead to a 1 to 2 percent increase in incremental sales for brick-and-mortar retailers alone.

- In consumer goods, supply-chain management is the key function that could benefit from AI deployment. Among the examples in our use cases, we see how forecasting based on underlying causal drivers of demand rather than prior outcomes can improve forecasting accuracy by 10 to 20 percent, which translates into a potential 5 percent reduction in inventory costs and revenue increases of 2 to 3 percent.

- In banking, particularly retail banking, AI has significant value potential in marketing and sales, much as it does in retail. However, because of the importance of assessing and managing risk in banking—for example, for loan underwriting and fraud detection—AI has much higher value potential to improve performance in risk in the banking sector than in many other industries.

The road to impact and value

Artificial intelligence is attracting growing amounts of corporate investment, and as the technologies develop, the potential value that can be unlocked is likely to grow. So far, however, only about 20 percent of AI-aware companies are currently using one or more of its technologies in a core business process or at scale.[4]

For all their promise, AI technologies have plenty of limitations that will need to be overcome. They include the onerous data requirements listed previously, but also five other limitations:

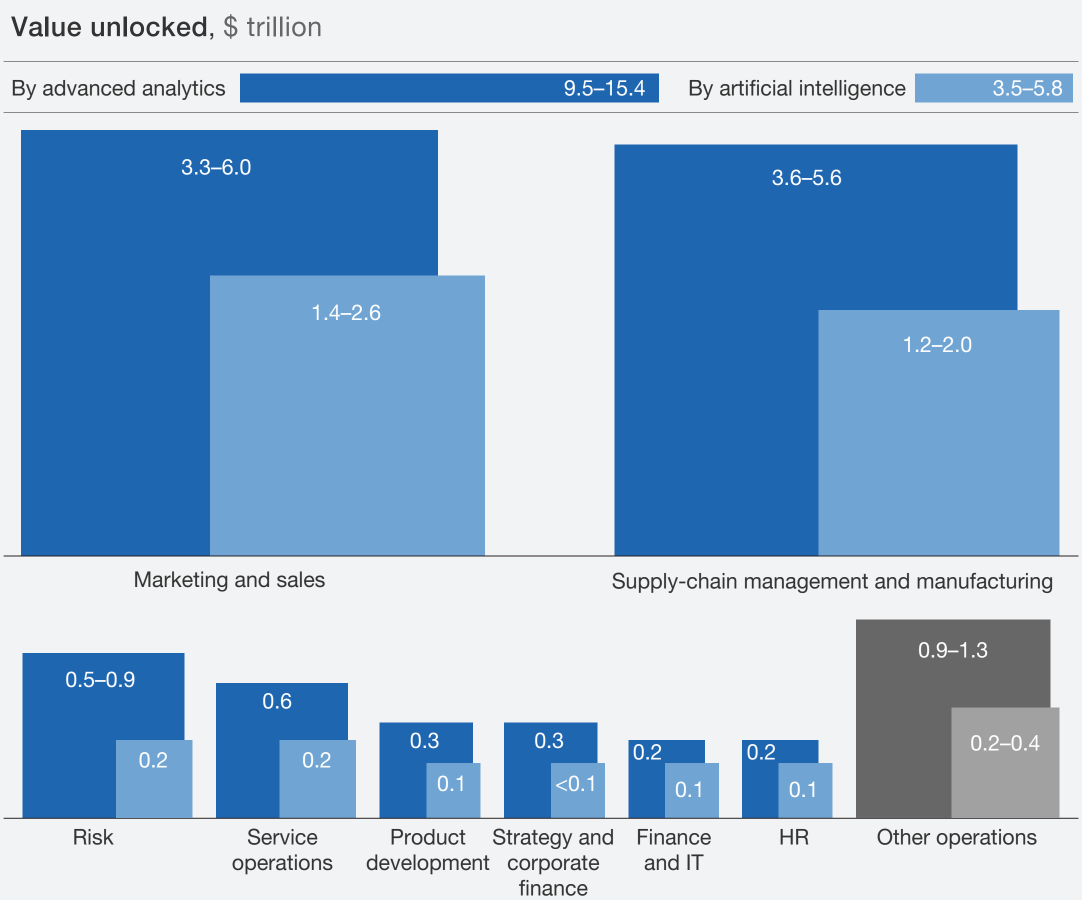
- First is the challenge of labeling training data, which often must be done manually and is necessary for supervised learning. Promising new techniques are emerging to address this challenge, such as reinforcement learning and in-stream supervision, in which data can be labeled in the course of natural usage.

- Second is the difficulty of obtaining data sets that are sufficiently large and comprehensive to be used for training; for many business use cases, creating or obtaining such massive

[4] See "How artificial intelligence can deliver real value to companies," McKinsey Global Institute, June 2017, on McKinsey.com.

Exhibit 5

Artificial intelligence's impact is likely to be most substantial in marketing and sales as well as supply-chain management and manufacturing, based on our use cases.



Note: Figures may not sum to 100%, because of rounding.

Source: McKinsey Global Institute analysis

data sets can be difficult—for example, limited clinical-trial data to predict healthcare treatment outcomes more accurately.

- Third is the difficulty of explaining in human terms results from large and complex models: why was a certain decision reached? Product certifications in healthcare and in the automotive and aerospace industries, for example, can be an obstacle; among other constraints, regulators often want rules and choice criteria to be clearly explainable.

- Fourth is the generalizability of learning: AI models continue to have difficulties in carrying their experiences from one set of circumstances to another. That means that companies must commit resources to train new models even for use cases that are similar to previous ones. Transfer learning—in which an AI model is trained to accomplish a certain task and then quickly applies that learning to a similar but distinct activity—is one promising response to this challenge.

- The fifth limitation concerns the risk of bias in data and algorithms. This issue touches on concerns that are more social in nature and which could require broader steps to resolve, such as understanding how the processes used to collect training data can influence the behavior of the models they are used to train. For example, unintended biases can be introduced when training data is not representative of the larger population to which an AI model is applied. Thus, facial-recognition models trained on a population of faces corresponding to the demographics of AI developers could struggle when applied to populations with more diverse characteristics.[5] A recent report on the malicious use of AI highlights a range of security threats, from sophisticated automation of hacking to hyperpersonalized political disinformation campaigns.[6]

Organizational challenges around technology, processes, and people can slow or impede AI adoption

Organizations planning to adopt significant deep learning efforts will need to consider a spectrum of options about how to do so. The range of options includes building a complete in-house AI capability, outsourcing these capabilities, or leveraging AI-as-a-service offerings.

Based on the use cases they plan to build, companies will need to create a data plan that produces results and predictions that can be fed either into designed interfaces for humans to act on or into transaction systems. Key data engineering challenges include data creation or acquisition, defining data ontology, and building appropriate data "pipes." Given the significant computational requirements of deep learning, some organizations will maintain their own data centers because of regulations or security concerns, but the capital expenditures could be considerable, particularly when using specialized hardware. Cloud vendors offer another option.

Process can also become an impediment to successful adoption unless organizations are digitally mature. On the technical side, organizations will have to develop robust data maintenance and governance processes and implement modern software disciplines such as Agile and DevOps. Even more challenging, in terms of scale, is overcoming the "last mile" problem of making sure the superior insights provided by AI are instantiated in the behavior of the people and processes of an enterprise.

[5] See Joy Buolamwini and Timnit Gebru, "Gender shades: Intersectional accuracy disparities in commercial gender classification," *Proceedings of Machine Learning Research*, 2018, Volume 81, pp. 1–15, proceedings.mlr.press.

[6] Peter Eckersley, "The malicious use of artificial intelligence: Forecasting, prevention, and mitigation," Electronic Frontier Foundation, February 20, 2018, eff.org.

On the people front, much of the construction and optimization of deep neural networks remains something of an art, requiring real experts to deliver step-change performance increases. Demand for these skills far outstrips supply at present; according to some estimates, fewer than 10,000 people have the skills necessary to tackle serious AI problems, and competition for them is fierce among the tech giants.[7]

AI can seem an elusive business case

Where AI techniques and data are available and the value is clearly proven, organizations can already pursue the opportunity. In some areas, the techniques today may be mature and the data available, but the cost and complexity of deploying AI may simply not be worthwhile, given the value that could be generated. For example, an airline could use facial recognition and other biometric scanning technology to streamline aircraft boarding, but the value of doing so may not justify the cost and issues around privacy and personal identification.

Similarly, we can see potential cases where the data and the techniques are maturing, but the value is not yet clear. The most unpredictable scenario is where either the data (both the types and volume) or the techniques are simply too new and untested to know how much value they could unlock. For example, in healthcare, if AI were able to build on the superhuman precision we are already starting to see with X-ray analysis and to broaden that to more accurate diagnoses and even automated medical procedures, the economic value could be very significant. At the same time, the complexities and costs of arriving at this frontier are also daunting. Among other issues, it would require flawless technical execution and resolving issues of malpractice insurance and other legal concerns.

Societal concerns and regulations can also constrain AI use. Regulatory constraints are especially prevalent in use cases related to personally identifiable information. This is particularly relevant at a time of growing public debate about the use and commercialization of individual data on some online platforms. Use and storage of personal information is especially sensitive in sectors such as banking, healthcare, and pharmaceuticals and medical products, as well as in the public and social sector. In addition to addressing these issues, businesses and other users of data for AI will need to continue to evolve business models related to data use in order to address societies' concerns. Furthermore, regulatory requirements and restrictions can differ from country to country, as well from sector to sector.

Implications for stakeholders

As we have seen, it is a company's ability to execute against AI models that creates value, rather than the models themselves. In this final section, we sketch out some of the high-level implications of our study of AI use cases for providers of AI technology, appliers of AI technology, and policy makers, who set the context for both.

- Many companies that develop or provide AI to others have considerable strength in the technology itself and the data scientists needed to make it work, but they can lack a deep understanding of end markets. Understanding the value potential of AI across sectors and functions can help shape the portfolios of these AI technology companies. That said, they shouldn't necessarily prioritize only the areas of highest potential value. Instead, they can combine that data with complementary analyses of the competitor landscape

[7] Cade Metz, "Tech giants are paying huge salaries for scarce AI talent," *New York Times*, October 22, 2017, nytimes.com.

and their own existing strengths, sector or function knowledge, and customer relationships to shape their investment portfolios. On the technical side, the mapping of problem types and techniques to sectors and functions of potential value can guide a company with specific areas of expertise on where to focus.

- Many companies seeking to adopt AI in their operations have started machine learning and AI experiments across their business. Before launching more pilots or testing solutions, it is useful to step back and take a holistic approach to the issue, moving to create a prioritized portfolio of initiatives across the enterprise, including AI and the wider analytics and digital techniques available. For a business leader to create an appropriate portfolio, it is important to develop an understanding about which use cases and domains have the potential to drive the most value for a company, as well as which AI and other analytical techniques will need to be deployed to capture that value. This portfolio ought to be informed not only by where the theoretical value can be captured but also by the question of how the techniques can be deployed at scale across the enterprise. The question of how analytical techniques are scaling is driven less by the techniques themselves and more by a company's skills, capabilities, and data. Companies will need to consider efforts on the "first mile," that is, how to acquire and organize data and efforts, as well as on the "last mile," or how to integrate the output of AI models into frontline workflows, ranging from those of clincial-trial managers and sales-force managers to procurement officers. Previous McKinsey Global Institute research suggests that AI leaders invest heavily in these first- and last-mile efforts.

- Policy makers will need to strike a balance between supporting the development of AI technologies and managing any risks from bad actors. They have an interest in supporting broad adoption, since AI can lead to higher labor productivity, economic growth, and societal prosperity. Their tools include public investments in research and development as well as support for a variety of training programs, which can help nurture AI talent. On the issue of data, governments can spur the development of training data directly through open-data initiatives. Opening up public-sector data can spur private-sector innovation. Setting common data standards can also help. AI is also raising new questions for policy makers to grapple with, for which historical tools and frameworks may not be adequate. Therefore, some policy innovations will likely be needed to cope with these rapidly evolving technologies. But given the scale of the beneficial impact on business, the economy, and society, the goal should not be to constrain the adoption and application of AI but rather to encourage its beneficial and safe use. ◆

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Photo credit: Getty Images

Artificial intelligence is getting ready for business, but are businesses ready for AI?

Terra Allas, Jacques Bughin, Michael Chui, Peter Dahlström, Eric Hazan, Nicolaus Henke, Sree Ramaswamy, and Monica Trench

Companies new to the space can learn a great deal from early adopters who have invested billions in AI and are now beginning to reap a range of benefits.

Claims about the promise and peril of artificial intelligence (AI) are abundant—and growing. AI, which enables machines to exhibit humanlike cognition, can drive our cars or steal our privacy, stoke corporate productivity or empower corporate spies. It can relieve workers of repetitive or dangerous tasks or strip them of their livelihoods. Twice as many articles mentioned AI in 2016 as in 2015, and nearly four times as many as in 2014.[1] Expectations are high.

AI has been here before. Its history abounds with booms and busts, extravagant promises, and frustrating disappointments. Is it different this

[1] Factiva.

time? New analysis suggests yes: AI is finally starting to deliver real-life business benefits. The ingredients for a breakthrough are in place. Computer power is growing significantly, algorithms are becoming more sophisticated, and, perhaps most important of all, the world is generating vast quantities of the fuel that powers AI—data. Billions of gigabytes of it every day.

Companies at the digital frontier—online firms and digital natives such as Google and Baidu—are betting vast amounts of money on AI. We estimate between $20 billion and $30 billion in 2016, including significant M&A activity. Private investors are jumping in, too. We estimate that venture capitalists invested $4 billion to $5 billion in AI in 2016, and private equity firms invested $1 billion to $3 billion. That is more than three times as much as in 2013. An additional $1 billion of investment came from grants and seed funding.

For now, though, most of the news is coming from the suppliers of AI technologies. And many new uses are only in the experimental phase. Few products are on the market or are likely to arrive there soon to drive immediate and widespread adoption. As a result, analysts remain divided as to the potential of AI: some have formed a rosy consensus about AI's potential while others remain cautious about its true economic benefit. This lack of agreement is visible in the large variance of current market forecasts, which range from $644 million to $126 billion by 2025.[2] Given the size of investment being poured into AI, the low estimate would indicate that we are witnessing another phase in a boom-and-bust cycle.

Our business experience with AI suggests that this bust scenario is unlikely. In order to provide a more informed view, we decided to perform our own research into how users are adopting AI technologies. Our research offers a snapshot of the current state of the rapidly changing AI industry. To begin, we examine the investment landscape, including firms' internal investment in R&D and deployment, large corporate M&A, and funding from venture capital (VC) and private equity (PE) firms. We then combine use-case analyses and our AI adoption and use survey of C-level executives at more than 3,000 companies to understand how companies use AI technologies today.

AI generally refers to the ability of machines to exhibit humanlike intelligence—for example, solving a problem without the use of hand-coded software containing detailed instructions. There are several ways to categorize AI technologies, but it is difficult to draft a list that is mutually exclusive and collectively exhaustive, because people often mix and match several technologies to create solutions for individual problems. These creations sometimes are treated as independent technologies, sometimes as subgroups of other technologies, and sometimes as applications. Some frameworks group AI technologies by basic functionality, such as text, speech, or image recognition, and some group them by business applications such as commerce or cybersecurity.[3]

Trying to pin down the term more precisely is fraught for several reasons: AI covers a broad range of technologies and applications, some of which are merely extensions of

[2] Tractica; Transparency Market Research.

[3] Gil Press, "Top 10 hot artificial intelligence (AI) technologies," Forbes.com, January 23, 2017; "AI100: The artificial intelligence start-ups redefining industries," CBinsights.com, January 11, 2017.

earlier techniques and others that are wholly new. Also, there is no generally accepted theory of "intelligence," and the definition of machine "intelligence" changes as people become accustomed to previous advances.[4] Tesler's theorem, attributed to the computer scientist Larry Tesler, asserts that "AI is whatever hasn't been done yet."[5]

The AI technologies we consider in this paper are what is called "narrow" AI, which performs one narrow task, as opposed to artificial general intelligence, or AGI, which seeks to be able to perform any intellectual task that a human can do. We focus on narrow AI because it has near-term business potential, while AGI has yet to arrive.[6]

In this report, we focus on the set of AI technology systems that solve business problems. We have categorized these into five technology systems that are key areas of AI development: robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning, which is based on algorithms that learn from data without relying on rules-based programming in order to draw conclusions or direct an action. Some are related to processing information from the external world, such as computer vision and language (including natural-language processing, text analytics, speech recognition, and semantics technology); some are about learning from information, such as machine learning; and others are related to acting on information, such as robotics, autonomous vehicles, and virtual agents, which are computer programs that can converse with humans. Machine learning and a subfield called deep learning are at the heart of many recent advances in artificial intelligence applications and have attracted a lot of attention and a significant share of the financing that has been pouring into the AI universe—almost 60 percent of all investment from outside the industry in 2016.

Artificial intelligence's roller-coaster ride to today

Artificial intelligence, as an idea, first appeared soon after humans developed the electronic digital computing that makes it possible. And, like digital technology, artificial intelligence, or AI, has ridden waves of hype and gloom—with one exception: AI has not yet experienced wide-scale commercial deployment (see sidebar, "Fits and starts: A history of artificial intelligence").

That may be changing. Machines powered by AI can today perform many tasks—such as recognizing complex patterns, synthesizing information, drawing conclusions, and forecasting—that not long ago were assumed to require human cognition. And as AI's capabilities have dramatically expanded, so has its utility in a growing number of fields. At the same time, it is worth remembering that machine learning has limitations. For example, because the systems are trained on specific data sets, they can be susceptible to bias; to avoid this, users must be sure to train them with comprehensive data sets. Nevertheless, we are seeing significant progress.

[4] Marvin Minsky, "Steps toward artificial intelligence," *Proceedings of the IRE*, volume 49, number 1, January 1961; Edward A. Feigenbaum, *The art of artificial intelligence: Themes and case studies of knowledge engineering*, Stanford University Computer Science Department report number STAN-CS-77–621, August 1977; Allen Newell, "Intellectual issues in the history of artificial intelligence," in *The Study of Information: Interdisciplinary messages*, Fritz Machlup and Una Mansfield, eds., John Wiley and Sons, 1983.

[5] Douglas R. Hofstadter, *Gödel, Escher, Bach: An eternal golden braid*, Basic Books, 1979. Hofstadter writes that he gave the theorem its name after Tesler expressed the idea to him firsthand. However, Tesler writes in his online CV that he actually said, "Intelligence is whatever machines haven't done yet."

[6] William Vorhies, "Artificial general intelligence—the Holy Grail of AI," DataScienceCentral.com, February 23, 2016.

Fits and starts: A history of artificial intelligence

The idea of computer-based artificial intelligence dates to 1950, when Alan Turing proposed what has come to be called the Turing test: Can a computer communicate well enough to persuade a human that it, too, is human?[1] A few months later, Princeton students built the first artificial neural network, using 300 vacuum tubes and a war-surplus gyropilot.[2]

The term "artificial intelligence" was coined in 1955, to describe the first academic conference on the subject, at Dartmouth College. That same year, researchers at the Carnegie Institute of Technology (now Carnegie Mellon University) produced the first AI program, Logic Theorist.[3] Advances followed often through the 1950s: Marvin Lee Minsky founded the Artificial Intelligence Laboratory at MIT, while others worked on semantic networks for machine translation at Cambridge and self-learning software at IBM.[4]

Funding slumped in the 1970s as research backers, primarily the US government, tired of waiting for practical AI applications and cut appropriations for further work.[5] The field was fallow for the better part of a decade.

University researchers' development of "expert systems"—software programs that assess a set of facts using a database of expert knowledge and then offer solutions to problems—revived AI in the 1980s.[6] Around this time, the first computer-controlled autonomous vehicles began to appear.[7] But this burst of interest preceded another AI "winter."

Interest in AI boomed again in the 21st century as advances in fields such as deep learning, underpinned by faster computers and more data, convinced investors and researchers that it was practical—and profitable—to put AI to work.[8]

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1 A. M. Turing, "Computing machinery and intelligence," *Mind*, volume 49, number 236, October 1950.

2 Jeremy Bernstein, "A.I.," *The New Yorker*, December 14, 1981.

3 Leo Gugerty, "Newell and Simon's Logic Theorist: Historical background and impact on cognitive modeling," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* volume 50, issue 9, October 2006.

4 "The IBM 700 Series: Computing comes to business," IBM Icons of Progress, March 24, 2011.

5 Michael Negnevitsky, *Artificial intelligence: A guide to intelligent systems*, Addison-Wesley, 2002.

6 Edward A. Feigenbaum, "Expert systems in the 1980s," working paper, 1980.

7 Hans P. Moravec, "The Stanford Cart and the CMU Rover," *Proceedings of the IEEE*, volume 71, issue 7, July 1983; Tom Vanderbilt, "Autonomous cars through the ages," Wired.com, February 6, 2012.

8 Bruce G. Buchanan, "A (very) brief history of artificial intelligence," *AI Magazine*, volume 26, number 4, Winter 2005.

These advances have allowed machine learning to be scaled up since 2000 and used to drive deep learning algorithms, among other things. The advances have been facilitated by the availability of large and diverse data sets, improved algorithms that find patterns in mountains of data, increased R&D financing, and powerful graphics processing units (GPUs), which have brought new levels of mathematical computing power. GPUs, which are specialized integrated circuits originally developed for video games, can process images 40 to 80 times faster than the fastest versions available in 2013. Advances in the speed of GPUs have enabled the training speed of deep learning systems to improve five- or sixfold in each of the last two years. More data—the world creates about 2.2 exabytes, or 2.2 billion gigabytes, of it every day—translates into more insights and higher accuracy because it exposes algorithms to more examples they can use to identify correct and reject incorrect answers. Machine learning systems enabled by these torrents of data have reduced computer error rates in some applications—for example, in image identification—to about the same as the rate for humans.

AI investment is growing rapidly, but commercial adoption is lagging

Tech giants and digital native companies such as Amazon, Apple, Baidu, and Google are investing billions of dollars in the various technologies known collectively as artificial intelligence. They see that the inputs needed to enable AI to finally live up to expectations—powerful computer hardware, increasingly sophisticated algorithmic models, and a vast and fast-growing inventory of data—are in place. Indeed, internal investment by large corporations dominates: we estimate that this amounted to $18 billion to $27 billion in 2016; external investment (from VCs, PE firms, M&A, grants, and seed funding) was around $8 billion to $12 billion (Exhibit 1).[7]

But for all the recent investment, the scope of AI deployment has been limited so far. That is partly due to the fact that one beneficiary of that investment, internal R&D, is largely focused on improving the firms' own performance. But it is also true that there is only tepid demand for artificial intelligence applications for businesses, partly due to the relatively slow pace of digital and analytics transformation of the economy. Our survey of more than 3,000 businesses around the world found that many business leaders are uncertain about what exactly AI can do for them, where to obtain AI-powered applications, how to integrate them into their companies, and how to assess the return on an investment in the technology.

Most of the investment in AI has consisted of internal spending—R&D and deployment—by large, cash-rich digital native companies. What is the large corporate investment in AI focused on? Bigger companies, such as Apple, Baidu, and Google, are working on suites of technologies internally but vary in the breadth and focus of their AI investment. Amazon is working on robotics and speech recognition, Salesforce on virtual agents and machine learning. BMW, Tesla, and Toyota are among the manufacturers making sizable commitments in robotics and machine learning for use in driverless cars. Toyota, for example, set aside $1 billion to establish a new research institute devoted to AI for robotics and driverless vehicles.[8] Industrial giants such as ABB, Bosch, GE, and Siemens also are investing internally, often in machine learning and robotics, seeking to develop specific technologies related to their core businesses. IBM has pledged to invest

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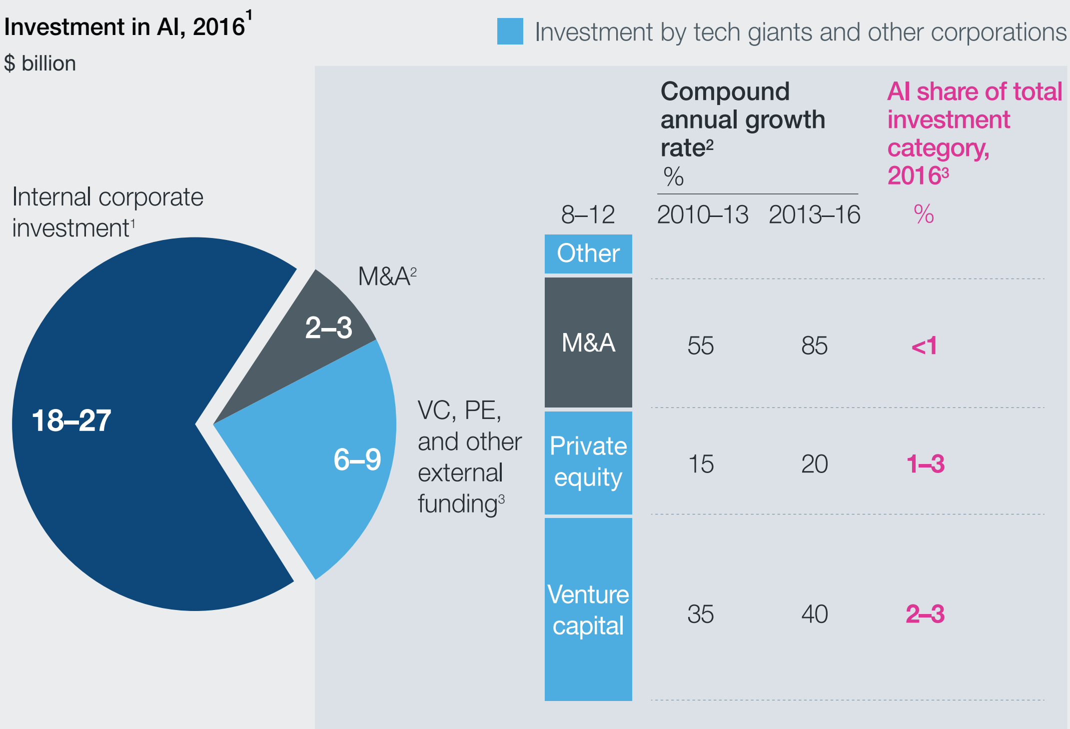
[7] Internal investment includes research and development, talent acquisition, cooperation with scientific institutions, and joint ventures with other companies done by corporations. External investment includes mergers and acquisitions, private equity funding, venture capital financing, and seed funds and other early-stage investing. The estimates of external investment are based on data available in the Capital IQ, PitchBook, and Dealogic databases. Provided values are estimates of annual investment in AI, assuming that all registered deals were completed within the year of transaction. Internal investment is estimated based on the ratio of AI spend to revenue for the top 35 high-tech and advanced manufacturing companies focused on AI technologies.

[8] Craig Trudell and Yuki Hagiwara, "Toyota starts $1 billion center to develop cars that don't crash," Bloomberg.com, November 6, 2015.

EXHIBIT 1 **Technology giants dominate investment in AI.**



[1] Estimate of 2016 spend by corporations to develop and deploy AI-based products. Calculated for top 35 high-tech and advanced-manufacturing companies investing in AI. Estimate is based on the ratio of AI spend to total revenue calculated for a subset of the 35 companies.
[2] VC value is an estimate of VC investment in companies primarily focused on AI. PE value is an estimate of PE investment in AI-related companies. M&A value is an estimate of AI deals done by corporations. "Other" refers to grants and seed-fund investments. Includes only disclosed data available in databases and assumes that all registered deals were completed within the year of transaction. Compound annual growth rate values rounded.
[3] M&A and PE deals expressed by volume; VC deals expressed by value.

Source: Capital IQ; PitchBook; Dealogic; S&P; McKinsey Global Institute analysis

$3 billion to make its Watson cognitive computing service a force in the Internet of Things.[9] Baidu has invested $1.5 billion in AI research over the last two and a half years. This is in addition to $200 million it committed to a new in-house venture capital fund, Baidu Venture.[10]

At the same time, big tech companies have been actively buying AI start-ups, not just to acquire technology or clients but to secure qualified talent. The pool of true experts in the field is small, and Alibaba, Amazon, Facebook, Google, and other tech giants have hired many of them. Companies

[9] "IBM invests to lead global Internet of Things market—shows accelerated client adoption," IBM press release, October 3, 2006.

[10] Phoenix Kwong, "Baidu launches $200m venture capital unit focused on artificial intelligence," *South China Morning Post*, September 13, 2016.

have adopted M&A as a way to sign up top talent, a practice known as “acqui-hiring,” for sums that typically work out to $5 million to $10 million per person. The shortage of talent and cost of acquiring it are underlined by a recent report that companies are seeking to fill 10,000 AI-related jobs and have budgeted more than $650 million for salaries.[11]

Overall, corporate M&A is the fastest-growing external source of funding for AI companies, increasing in terms of value at a compound annual growth rate of over 80 percent from 2013 to 2016, based on our estimates. Leading high-tech companies and advanced manufacturers have closed more than 100 M&A deals since 2010. Google completed 24 transactions in that time, including eight in computer vision and seven in language processing. Apple, the second-most-active acquirer, has closed nine, split evenly among computer vision, machine learning, and language processing.

Companies are also expanding their search for talent abroad. Facebook, for instance, is opening an AI lab in Paris that will supplement similar facilities in New York and Silicon Valley—and make it easier for the company to recruit top researchers in Europe.[12] Google recently invested $4.5 million in the Montreal Institute for Learning Algorithms, a research lab at the University of Montreal; Intel donated $1.5 million to establish a machine learning and cybersecurity research center at Georgia Tech; and NVIDIA is working with the National Taiwan University to establish an AI laboratory in Taipei.[13]

The buzz over AI has grown loud enough to encourage venture capital and private equity firms to step up their investment in AI. Other external investors, such as angel funds and seed incubators, also are active. We estimate total annual external investment was $8 billion to $12 billion in 2016.[14]

Machine learning attracted almost 60 percent of that investment, most likely because it is an enabler for so many other technologies and applications, such as robotics and speech recognition (Exhibit 2). In addition, investors are drawn to machine learning because, as has long been the case, it is quicker and easier to install new code than to rebuild a robot or other machine that runs the software. Corporate M&A in this area is also growing fast, with a compound annual growth rate of around 80 percent from 2013 through 2016.

Investment in AI is still in the early stages and relatively small compared with the investment in the digital revolution. Artificial intelligence, for example, attracted 2 to 3 percent of all VC funding by value in 2016, while information technology in general soaked up 60 percent. AI also was a small fraction—1 to 3 percent—of all investment by PE firms in 2016.[15] But AI investment is growing fast.

[11] “U.S. companies raising $1 billion or more to fuel artificial intelligence (AI) development: Looking to staff 10,000+ openings, cites new Paysa research,” Paysa press release, April 18, 2017.

[12] Cade Metz, “Facebook opens a Paris lab as AI research goes global,” Wired.com, June 2, 2015.

[13] Cade Metz, “Google opens Montreal AI lab to snag scarce global talent,” Wired.com, November 12, 2015; “Georgia Tech launches new research on the security of machine-learning systems,” Georgia Institute of Technology press release, October 31, 2016; “NVIDIA collaborates with Taipei Tech to establish Embedded GPU Joint Lab,” National Taipei University of Technology press release, September 4, 2014.

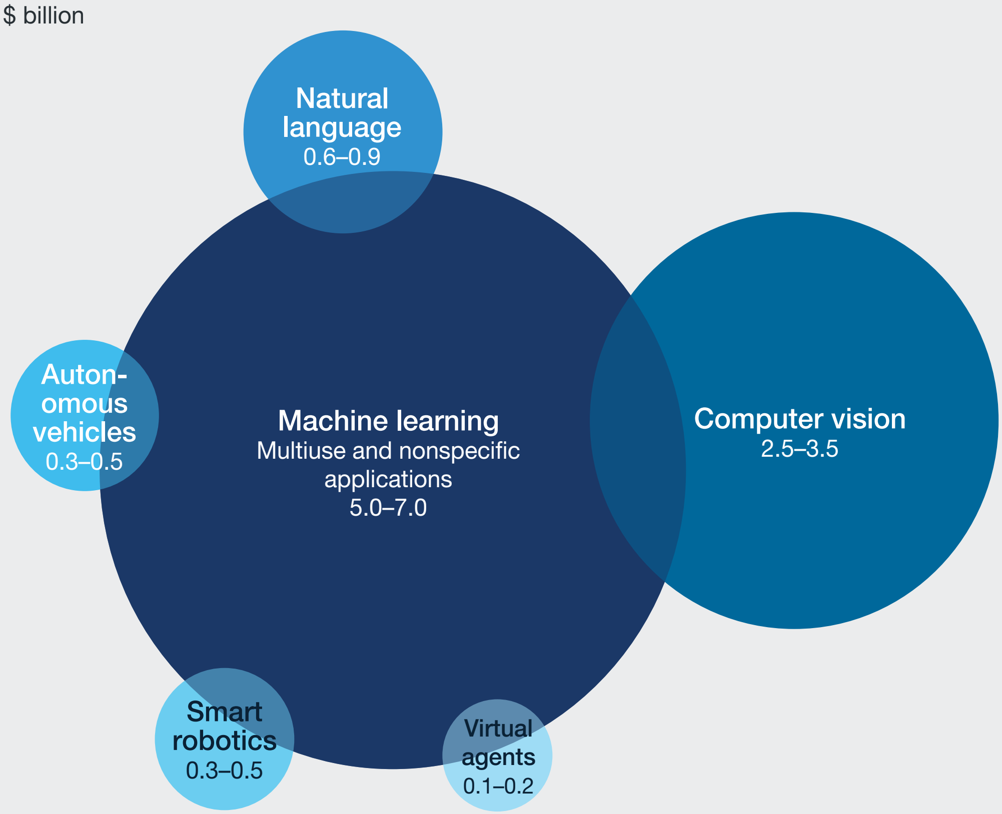
[14] Estimates of external investment in AI vary widely because measurement standards vary. For example, Venture Scanner puts total funding of AI-related start-ups in 2016 at $2.5 billion, while Goldman Sachs estimates that the venture capital sector alone made $13.7 billion of AI-related investment that year.

[15] It is worth noting that VC funds were focusing on AI technology when choosing investments, while PE funds were investing in AI-related companies.

EXHIBIT 2 **Machine learning received the most investment, although boundaries between technologies are not clear-cut.**

External investment in AI-focused companies by technology category, 2016[1]

$ billion



[1] Estimates consist of annual VC investment in AI-focused companies, PE investment in AI-related companies, and M&A by corporations. Includes only disclosed data available in databases and assumes that all registered deals were completed within the year of transaction.

Source: Capital IQ; PitchBook; Dealogic; McKinsey Global Institute analysis

From 2013 through 2016, external investment in AI technologies had a compound annual growth rate of almost 40 percent. That compares with 30 percent from 2010 through 2013. Not only are deals getting bigger and more numerous, but they require fewer participants to complete the financing. This suggests that investors are growing more confident in the sector and may have a better understanding of the technology and its potential.

However, for the most part, investors are still waiting for their investments to pay off. Only 10 percent of start-up companies that consider machine learning to be a core business say they generate revenue, according to PitchBook. Of those, only half report more than $50 million in revenue. Moreover, external investment remains highly concentrated geographically, dominated by a few technology hubs in the United States and China, with Europe lagging far behind.

Firms and industries already on the digital frontier are adopting AI, but others are hesitant to act

Investors are pouring billions of dollars into AI companies based on the hope that a market of AI adopters will develop fairly quickly and will be willing to pay for AI infrastructure, platforms, and services. Clearly, Amazon, Google, and other digital natives are investing for their own applications, such as optimizing searches and personalizing marketing. But getting a sense of how much traditional companies in healthcare, retail, and telecom are spending on AI is not easy. For this reason, we conducted a survey to understand this situation in more depth.

In general, few companies have incorporated AI into their value chains at scale; a majority of companies that had some awareness of AI technologies are still in experimental or pilot phases. In fact, out of the 3,073 respondents, only 20 percent said they had adopted one or more AI-related technology at scale or in a core part of their business.[16] Ten percent reported adopting more than two technologies, and only 9 percent reported adopting machine learning.[17]

Even this may overstate the commercial demand for AI at this point. Our review of more than 160 global use cases across a variety of industries found that only 12 percent had progressed beyond the experimental stage. Commercial considerations can explain why some companies may be reluctant to act. In our survey, poor or uncertain returns were the primary reason for not adopting reported by firms, especially smaller firms. Regulatory concerns have also become much more important.

As with every new wave of technology, we expect to see a pattern of early and late adopters among sectors and firms. We uncover six features of the early pattern of AI adoption, which is broadly in line with the ways companies have been adopting and using the recent cohort of digital technologies. Not coincidentally, the same players who were leaders in that earlier wave of digitization are leading in AI—the next wave.

The first feature is that early AI adopters are from sectors already investing at scale in related technologies, such as cloud services and big data. Those sectors are also at the frontier of digital assets and usage.[18] This is a crucial finding, as it suggests that there is limited evidence of sectors and firms catching up when it comes to digitization, as each new generation of tech builds on the previous one.

Second, independent of sectors, large companies tend to invest in AI faster at scale. This again is typical of digital adoption, in which, for instance, small and midsize businesses have typically lagged behind in their decision to invest in new technologies.

16 Survey results throughout this discussion paper are weighted for firm size; “20 percent of firms” indicates firms representing 20 percent of the workforce.

17 The eight technologies are natural-language processing, natural-language generation, speech recognition, machine learning, decision management, virtual agents, robotic process automation, and computer vision. The five technology systems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

18 *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June 2016; *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015.

Third, early adopters are not specializing in one type of technology. They go broader as they adopt multiple AI tools addressing a number of different use cases at the same time.

Fourth, companies investing at scale do it close to their core business.

Fifth, early adopters that adopt at scale tend to be motivated as much by the upside growth potential of AI as they are by cutting costs. AI is not only about process automation but is also used by companies as part of major product and service innovation. This has been the case for early adopters of digital technologies and suggests that AI-driven innovation will be a new source of productivity and may further expand the growing productivity and income gap between high-performing firms and those left behind.[19]

Finally, strong executive leadership goes hand in hand with stronger AI adoption. Respondents from firms that have successfully deployed an AI technology at scale tended to rate C-suite support nearly twice as high as those from companies that had not adopted any AI technology.

Early-adopting sectors are closer to the digital frontier

Sector-by-sector adoption of AI is highly uneven right now, reflecting many features of digital adoption more broadly. Our survey found that larger companies and industries that adopted digital technologies in the past are more likely to adopt AI. For them, AI is the next wave of digitization.

This pattern in the adoption of technology is not new—we saw similar behavior in firms adopting enterprise social technologies.[20] But this implies that, at least in the near future, AI deployment is likely to accelerate at the digital frontier, expanding the gap between adopters and laggards across companies, industries, and geographic regions.

The leading sectors include some that MGI's Industry Digitization Index found at the digital frontier, namely high tech and telecom and financial services.[21] These are industries with long histories of digital investment. They have been leaders in developing or adopting digital tools, both for their core product offerings and for optimizing their operations. However, even these sectors are far behind in AI adoption when compared with overall digitization (Exhibit 3).

Automotive and assembly is also highly ranked. It was one of the first sectors that implemented advanced robotics at scale for manufacturing and today is also using AI technologies to develop self-driving cars.

In the middle are less digitized industries, including resources and utilities, personal and professional services, and building materials and construction. A combination of factors may account for this. These sectors have been slow to

[19] Rosina Moreno and Jordi Suriñach, "Innovation adoption and productivity growth: Evidence for Europe," working paper, 2014; Jacques Bughin and Nicolas van Zeebroeck, "The right response to digital disruption," *MIT Sloan Management Review*, April 2017.

[20] Jacques Bughin and James Manyika, "How businesses are using web 2.0: A McKinsey global survey," *McKinsey Quarterly*, December 2007; Jacques Bughin and James Manyika, "Bubble or paradigm change? Assessing the global diffusion of enterprise 2.0," in Alex Koohang, Johannes Britz, and Keith Harman, eds., *Knowledge Management: Research and Applications*, Informing Science, 2008.

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

EXHIBIT 3 **Artificial intelligence (AI) adoption is occurring faster in more digitized sectors and across the value chain.**

[1] The MGI Digitization Index is GDP weighted average of Europe and United States.

Source: McKinsey Global Institute AI adoption and use survey; *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June 2016; *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015; McKinsey Global Institute analysis

employ digital tools generally, except for some parts of the professional services industry and large construction companies. They are also industries in which innovation and productivity growth has lagged, potentially in part due to their domestic focus. Some of these sectors have a particularly high number of small firms—an important predictor for AI adoption, as explored following.

Toward the bottom of the pack for now are traditionally less digital fields such as education and healthcare. Despite ample publicity about cutting-edge AI applications in these industries, the reality is that uptake appears to be low so far. Weaker adoption reflects the particular challenges faced in these sectors. In healthcare, for example, practitioners and administrators acknowledge the potential for AI to reduce costs but quickly add that they believe that regulatory concerns and customer acceptance will inhibit adoption.

When it comes to adopting AI, the bigger, the bolder

A stylized fact in IT literature is that large firms usually are early adopters of innovative technology, while smaller firms are more reluctant to be first movers.[22] We find the same digital divide when we look at AI: large firms have much higher rates of adoption and awareness. Across all sectors, larger firms—which we define as those with more than 500 employees—are at least 10 percent more likely than smaller firms to have adopted at least one AI technology at scale or in a core part of their business. In sectors with lower rates of AI uptake, the adoption rate of bigger companies was as much as 300 percent that of smaller companies.

Other digitization indicators reflect this fact, as highlighted in MGI's digitization work. Larger firms typically have access to more and better-structured data and are more likely to have employees with the technical skills needed to understand the business case for AI investment and to successfully engage suppliers. Bigger firms also have an advantage because the kind of fixed-cost investment required for AI tends to generate higher returns when applied to a bigger base of costs and revenue.

Nonetheless, we find success stories among some smaller firms, too. Relative to larger companies, they can benefit from fewer issues with legacy IT systems and lower levels of organizational resistance to change. Smaller firms can also benefit from AI tools provided as a service.

Early AI adopters tend to become serial adopters

We looked at how firms deploy AI across eight different application areas and five technology systems.[23] Our results suggest that early-adopting firms are looking across multiple AI tools when they begin to adopt, rather than focusing on a particular technology. This is consistent with adoption patterns in other digital technologies.[24]

The phenomenon of multitechnology application is persistent at a sector level. Industries with high rates of adopting one technology have higher rates in adopting others. High tech and telecom, for example, report the highest rates of adoption across all five technology groups, while construction is among the lowest among all five.

However, there are anomalies. Education and healthcare are notable for being slow to adopt AI technology. In frontier sectors—those with a

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[22] Kevin Zhu, Kenneth L. Kraemer, and Sean Xu, "The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business," *Management Science*, volume 52, number 10, October 2006; Chris Forman, Avi Goldfarb, and Shane Greenstein, "The geographic dispersion of commercial Internet use," in *Rethinking Rights and Regulations: Institutional Responses to New CommunicationTechnologies*, Lorrie Faith Cranor and Steven S. Wildman, eds., MIT Press, 2003.

[23] The eight technologies are natural-language processing, natural-language generation, speech recognition, machine learning, decision management, virtual agents, robotic process automation, and computer vision. The five technology systems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

[24] Sanjeev Dewan, Dale Ganley, and Kenneth L. Kraemer, "Complementarities in the diffusion of personal computers and the Internet: Implications for the global digital divide," *Information Systems Research*, volume 21, number 5, December 2010.

relatively high percentage of early adopters—two-thirds of firms that had already adopted one of the eight AI technologies had adopted at least two others as well. In healthcare, only one-third had, with language technologies the most likely to be deployed at scale or in a core part of the business.

Users are keeping artificial intelligence close to their core

Functionally, AI technologies are finding applications across the value chain, but with some parts of the value chain getting more attention than others. For example, customer service functions such as sales and marketing, as well as operations and product development, all tend to use the most commonly cited AI applications. General and financial management, by contrast, lag well behind. A similar pattern is found in big data. The literature shows that the most frequent big data applications originate in sales and marketing functions.[25]

In general, firms queried in our survey say they tend to adopt AI technologies affecting the part of their value chain closest to the core. Operations are an important area of adoption in the automotive and assembly and consumer packaged goods sectors, as well as utilities and resources. Operations and customer service are the most important areas for financial services. This is new. Previously, new digital technology tended to remain on the margins, away from the core of the business.

However, in line with trends in technology, we also see sectors going deeper and broader as they increase their degree of AI adoption. Leading sectors are not only more extensively deploying AI in the core parts of their value chain, but they are also deploying it in more parts of their value chain.

Early adopters see AI increasing revenue, while companies experimenting with AI expect lower costs

As companies become more familiar with AI, their perceptions about its benefits change. The results of survey analysis show that early AI adopters are driven to employ AI technologies in order to grow revenue and market share, and the potential for cost reduction is a secondary idea. Firms that we consider more advanced AI adopters were 27 percent more likely to report using AI to grow their market than companies only experimenting with or partially adopting AI and 52 percent more likely to report using it to increase their market share. Experimenters, by contrast, were more focused on costs. They were 23 percent more likely than advanced AI adopters to point to labor cost reductions and 38 percent more likely to mention non-labor cost reductions.

In other words, the more companies use and become familiar with AI, the more potential for growth they see in it. Companies with less experience tend to focus more narrowly on reducing costs.

AI is not only about technical adoption but also about enterprise acceptance

To be successful, AI adoption requires buy-in by the executive suite to generate the momentum needed to overwhelm organizational inertia.

Successful AI adopters, according to our survey, have strong executive leadership support for the new technology. Representatives of firms that have successfully deployed an AI technology at scale tended to rate C-suite support nearly twice as high as those of companies that had not adopted any AI technology. They added that strong support came not only from the CEO and IT executives—that is, chief information officer, chief digital

[25] Jacques Bughin, "Ten big lessons learned from big data analytics," *Applied Marketing Analytics*, volume 2, number 4, 2017.

officer, and chief technology officer—but from all other C-level officers and the board of directors as well. Successful adopters also adjusted their firmwide strategy to become proactive toward AI.

AI's next challenge: Get users to adapt and adopt

IT industry analysts concur that the market size for AI technology will experience strong growth over the next three years. Most of the firms we surveyed expected to increase spending on AI in the coming three years, a finding echoed in other recent surveys. For example, 75 percent of the 203 executives queried in an Economist Intelligence Unit survey said AI would be "actively implemented" in their firms within three years (3 percent said it had already happened).

Expectations of how large this growth will be vary widely. Our survey documented relatively modest growth projections—only one-fifth of firms expected to increase expenditure by more than 10 percent. Industry analysts' forecasts of the compound annual growth rate ranged from just under 20 percent to nearly 63 percent, including both adoption by additional companies and increased spending within companies.[26] The actual growth rate may need to be toward the upper end of that range to meet the expectations of investors piling into the industry.

Growth will hinge on the ability of sectors and firms to overcome technical, commercial, and regulatory challenges. Our survey respondents and outside forecasters expect financial services, retail, healthcare, and advanced manufacturing to be in the AI vanguard. These are the industries where technical feasibility is relatively high (reflected in the case studies on the market today) and the business case for AI is most compelling. They are also the sectors with the highest degree of digital adoption to date—a key foundation for AI (Exhibit 4).

Technical challenges are an important differentiating factor between industries. While big tech and academia are pushing advances in the performance of the underlying technology, engineering solutions need to be worked out for specific use cases, requiring both data and talent. Industries such as financial services, high tech, and telecom have generated and stored large volumes of structured data, but others, including construction and travel, lag far behind.[27]

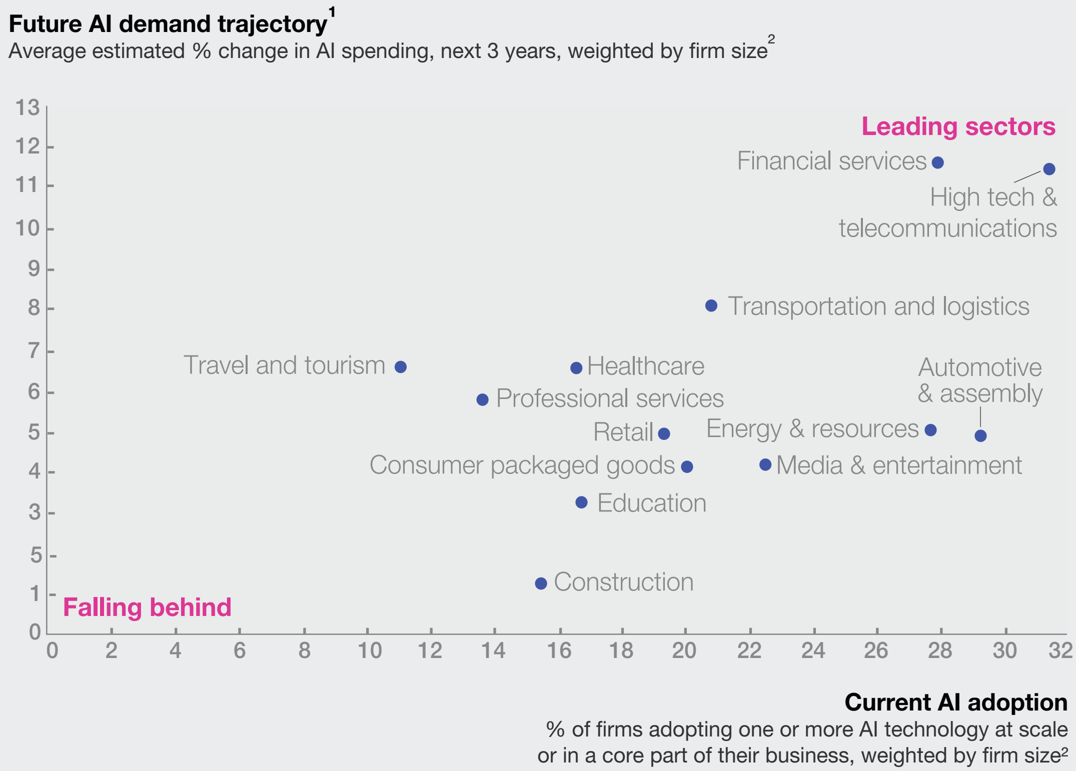
Commercial drivers also differ between sectors. Industries most likely to lead the adoption of AI technologies at scale are those with complex businesses in terms of both operations and geography and whose performance is driven by forecasting, fast and accurate decision making, or personalized customer connections. In financial services, there are clear benefits from improved accuracy and speed in AI-optimized fraud-detection systems, forecast to be a $3 billion market in 2020. In retail, there are compelling benefits from improved inventory forecasts, automated customer operations, and highly personalized marketing campaigns. Similarly, in healthcare, AI-powered diagnosis and treatment systems can both save costs and deliver better outcomes for patients.

Even where compelling commercial use cases have been engineered and are demanded by firms, regulatory and social barriers can raise the cost and slow the rate of adoption. Product liability is one such concern; it is especially troublesome for

[26] The full range of forecasts: BCC Research, 19.7 percent; Transparency Market Research, 36.1 percent; Tractica, 57.6 percent; IDC, 58 percent; and Markets and Markets, 62.9 percent.

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

EXHIBIT 4 **Sectors leading in AI adoption today also intend to grow their investment the most.**



[1] Based on the midpoint of the range selected by the survey respondent.
[2] Results are weighted by firm size.

Source: McKinsey Global Institute AI adoption and use survey; McKinsey Global Institute analysis

automakers and other manufacturers. Privacy considerations restrict access to data and often require it to be anonymized before it can be used in research. Ethical issues such as trained biases and algorithmic transparency remain unresolved. Preferences for a human relationship in settings such as healthcare and education will need to be navigated. Job security concerns could also limit market growth—there are already serious calls for taxes on robots.

These forces will help determine the industries that AI is likely to transform the most. However, if current trends hold, variation of adoption within industries will be even larger than between industries. We expect that large companies with the most digital experience will be the first movers because they can leverage their technical skills, digital expertise, and data resources to develop and smoothly integrate the most appropriate AI solutions.

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After decades of false starts, artificial intelligence is on the verge of a breakthrough, with the latest progress propelled by machine learning. Tech giants and digital natives are investing in and deploying the technology at scale, but widespread adoption among less digitally mature sectors and companies is lagging. However, the current mismatch between AI investment and adoption has not stopped people from imagining a future where AI transforms businesses and entire industries. ◆

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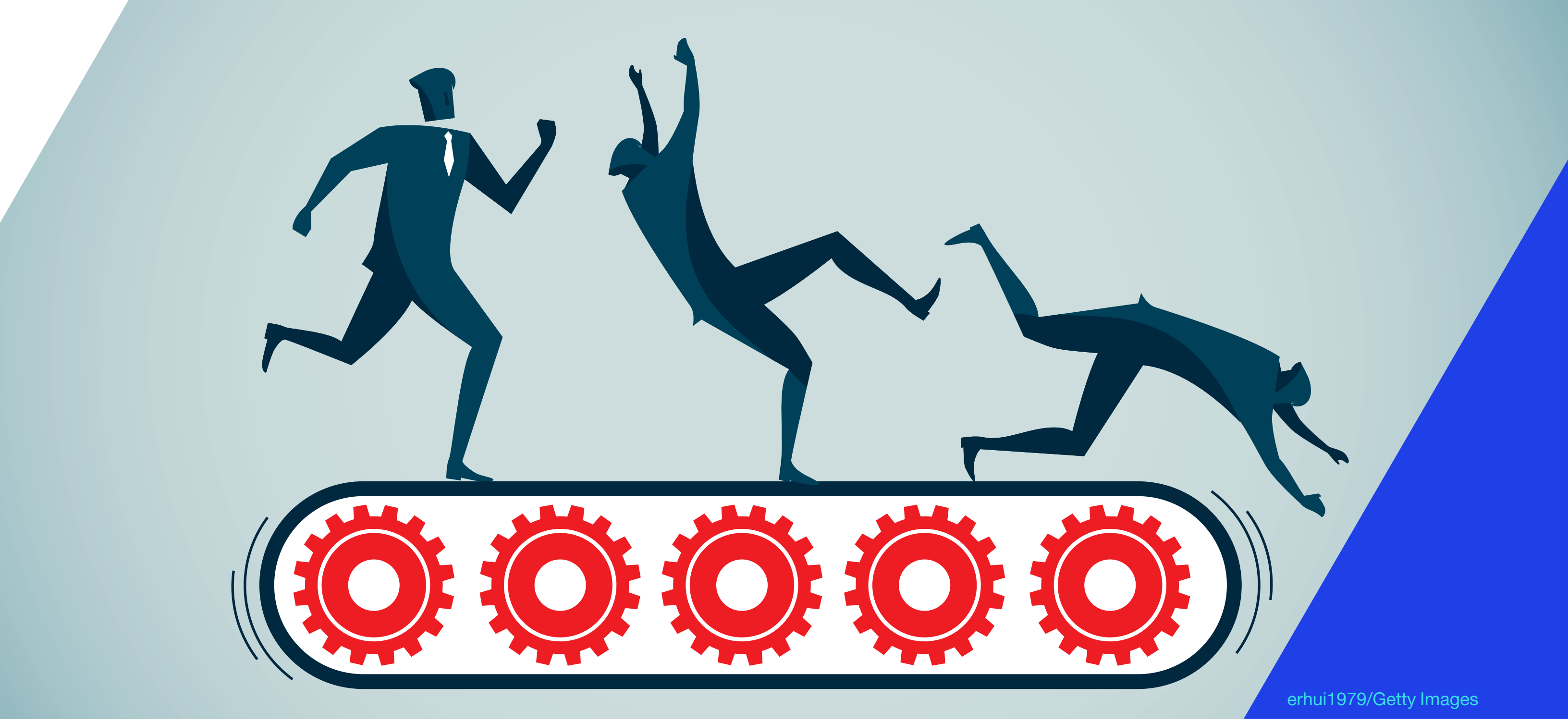
This article was excerpted from the McKinsey Global Institute discussion paper Artificial intelligence: The next digital frontier? *(2017).*

Part

02

How to make transformation successful



Burned by the bots: Why robotic automation is stumbling

Alex Edlich and Vik Sohoni

The realities of bot implementation and maintenance are hampered progress. But there is a path forward.

Over the last several months, we have witnessed the increasing chatter around one of the hottest buzzwords in the digital space: robotics. Robots are a bit like macros in Excel. They execute tasks that are often repetitive. So instead of a human typing in a password and retrieving a piece of data from a program (like someone's salary from a W2 system), the bot will replicate that same task by running a software script that interfaces with those programs. This makes producing the end-of-month compensation report, for example, a lot easier.

A year or so ago, a lot of people around the world got very excited about this. In Europe, we even heard the term "zero FTE back office." The McKinsey Global Institute forecasts that 30 percent of tasks in a majority of occupations can be automated, and robotics is one way to do that. For large back offices with data-entry or other repetitive, low-judgment, high-error-prone, or compliance-needy tasks, this seemed like a panacea. Add in artificial intelligence or machine learning and you could actually get bots to do even more complex tasks, like responding to a customer email inquiry by retrieving some basic data, for example.

Many companies, therefore, rushed to install bot armies, spinning up pilots to configure all sorts of processes and projecting large financial outcomes.

To be sure, there have been several localized successes; at one mining company, the finance function saved 30 human days' worth of work per year by automating the journal posting process. They also saved 60 human days of work per year in the monthly financial-reporting process. A larger business case suggested a double return on investments in robotics.

However, in conversations with dozens of executives, it is clear that the first act in the "robotics evolution" has not been a slam dunk for many, especially when companies try to scale the localized proofs of concept. Specifically:

- Installing thousands of bots has taken a lot longer and is more complex than most had hoped it would be. It might sound simple to pull a salary statement, but what if for that worker the data is in unstructured formats? What if the worker goes on maternity leave and a different set of systems kicks in? What if …? Said differently, a "standard process" can often turn out to have many permutations, and programming bots to cover all of them can be confounding.

- Not unlike humans, thousands of bots need care and attention—in the form of maintenance, upgrades, and cybersecurity protocols, which introduce additional costs and demand ongoing focus for executives.

- The platforms on which the bots interact (or handshake) often change, and the necessary flexibility isn't always configured into the bot. Installing thousands of bots introduces an additional architecture layer into the system, requiring more bespoke governance and oversight by the IT organization, which is often already burdened with maintaining legacy systems.

- Changes upstream and downstream, even during bot configuration, can significantly delay bots being put into production. For example, a new regulation requiring minor changes to an application form could totally throw off months of work in the back office on a bot that's nearing completion.

- The companies providing licenses and platforms for bots may have varying complexities and specializations that may not have been fully considered in deciding which platform to deploy for which process.

- The cultural effects of bots on operators are just being discovered. For example, asking operators to program bots that could take their jobs can understandably create real personnel and morale issues at the front line.

- The economic outcomes often aren't as rosy as originally projected. While it may be possible to automate 30 percent of tasks for the majority of occupations, that doesn't neatly translate into a 30 percent cost reduction. People do many different things, and bots may only address some of them. Unless the process and the organization are reconfigured, savings can prove elusive. Also, bots treat localized pain points. Anyone who's read *The Goal* (or stood in line at a cafeteria) can tell you that fixing one bottleneck may just move the problem elsewhere.

As a result, several robotics programs have been put on hold, or CIOs have flatly refused to install new bots—even those vendors have worked on for months—until solutions have been defined to scale the program effectively.

What's the path forward?

A few companies are resetting their robotics programs. As one CIO said, "We crashed, burned, and are now resurrecting!" Here's what they are learning and doing:

1. A bot is a tool in a toolkit, just like self-serve tools, workflow tools, lean-process maps, or six-sigma methodologies. Companies need

to apply these tools as part of an orchestrated action, not in isolation. For example, it may be more effective to streamline or eliminate fields from an application form instead of tasking a bot with transcribing it to a system. Or it may make more sense to question why someone needs a thick financial report instead of tasking a bot to mindlessly generate one every month. Or deploying a workflow system may simplify information flows and create more timely customer alerts, resulting in a reduction in the calls a bot may have to answer further downstream.

2. Taking an end-to-end view of the outcome needed and measuring that delivered output is better than applying a robotic Band-Aid to a particular pain point. That's not to say that there aren't some pain points that should be immediately addressed, but that, at scale, deploying thousands of bots isn't always the best answer. Better to figure out what the desired goal is and then figure out how bots can (or cannot) help.

   This often means collaboration and coordination with other silos, or creating a corporate business-process management group.

3. Blueprinting the architectural implications before you get into installing bots is crucial. Determining, keeping track of, and updating all the different linkages between systems that bots will develop and rely on is a whole new set of responsibilities. No IT organization appreciates being saddled with responsibility for a whole new technological layer. Clarity around who will undertake this and how the bots will be managed at scale is critical before they proliferate.

4. Treating employees as problem solvers and enabling them to use bots to solve their problems can be culturally very transformational. Delegating authority over the bots to those employees (versus running the bots centrally) can also be a way to ensure continuous improvement and employee participation. This also means that employees need to understand how the bots work, perhaps even learn to configure or code them. All this is similar to some of the other initiatives firms are rolling out (such as agile development or continuous delivery) that are focused on empowering employees.

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These are just some of the ways we foresee companies will have to deal with the issue of scaling the proofs of concept successfully. We expect many C-suite executives will soon go through a process of resetting the bot wave. And that delicate managerial process is not something a bot will be able to automate away. ◆

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Photo credit: Getty Images

Ten red flags signaling your analytics program will fail

Oliver Fleming, Tim Fountaine, Nicolaus Henke, and Tamim Saleh

Struggling to become analytics-driven? One or more of these issues is likely what's holding your organization back.

How confident are you that your analytics initiative is delivering the value it's supposed to?

These days, it's the rare CEO who doesn't know that businesses must become analytics-driven. Many business leaders have, to their credit, been charging ahead with bold investments in analytics resources and artificial intelligence (AI). Many CEOs have dedicated a lot of their own time to implementing analytics programs, appointed chief analytics officers (CAOs) or chief data officers (CDOs), and hired all sorts of data specialists.

However, too many executives have assumed that because they've made such big moves, the main challenges to becoming analytics-driven are behind them. But frustrations are beginning to surface; it's starting to dawn on company executives that they've failed to convert their analytics pilots into scalable solutions. (A recent McKinsey survey found that only 8 percent of 1,000 respondents with analytics initiatives engaged in effective scaling practices.) More boards and shareholders are pressing for answers about the scant returns on many early and expensive analytics programs. Overall, McKinsey has observed that only a small fraction of the value that could be unlocked by advanced-analytics approaches has been unlocked—as little as 10 percent in some sectors.[1] And McKinsey's AI Index

[1] See "The age of analytics: Competing in a data-driven world," McKinsey Global Institute, December 2016, on McKinsey.com.

reveals that the gap between leaders and laggards in successful AI and analytics adoption, within as well as among industry sectors, is growing.

That said, there's one upside to the growing list of misfires and shortfalls in companies' big bets on analytics and AI. Collectively, they begin to reveal the failure patterns across organizations of all types, industries, and sizes. We've detected what we consider to be the ten red flags that signal an analytics program is in danger of failure. In our experience, business leaders who act on these alerts will dramatically improve their companies' chances of success in as little as two or three years.

1. The executive team doesn't have a clear vision for its advanced-analytics programs.

In our experience, this often stems from executives lacking a solid understanding of the difference between traditional analytics (that is, business intelligence and reporting) and advanced analytics (powerful predictive and prescriptive tools such as machine learning).

To illustrate, one organization had built a centralized capability in advanced analytics, with heavy investment in data scientists, data engineers, and other key digital roles. The CEO regularly mentioned that the company was using AI techniques, but never with any specificity.

In practice, the company ran a lot of pilot AI programs, but not a single one was adopted by the business at scale. The fundamental reason? Top management didn't really grasp the concept of advanced analytics. They struggled to define valuable problems for the analytics team to solve, and they failed to invest in building the right skills. As a result, they failed to get traction with their AI pilots. The analytics team they had assembled wasn't working on the right problems and wasn't able to use the latest tools and techniques. The company halted the initiative after a year as skepticism grew.

First response: The CEO, CAO, or CDO—or whoever is tasked with leading the company's analytics initiatives—should set up a series of workshops for the executive team to coach its members in the key tenets of advanced analytics and to undo any lingering misconceptions. These workshops can form the foundation of in-house "academies" that can continually teach key analytics concepts to a broader management audience.

2. No one has determined the value that the initial use cases can deliver in the first year.

Too often, the enthusiastic inclination is to apply analytics tools and methods like wallpaper—as something that hopefully will benefit every corner of the organization to which it is applied. But such imprecision leads only to large-scale waste, slower results (if any), and less confidence, from shareholders and employees alike, that analytics initiatives can add value.

That was the story at a large conglomerate. The company identified a handful of use cases and began to put analytics resources against them. But the company did not precisely assess the feasibility or calculate the business value that these use cases could generate, and, lo and behold, the ones it chose produced little value.

First response: Companies in the early stages of scaling analytics use cases must think through, in detail, the top three to five feasible use cases that can create the greatest value quickly—ideally within the first year. This will generate momentum and encourage buy-in for future analytics investments. These decisions should take into account impact, first and foremost. A helpful way to do this is to analyze the entire value chain of the business, from supplier to purchase to after-sales service, to pinpoint the highest-value use cases (Exhibit 1).

To consider feasibility, think through the following:

- Is the data needed for the use case accessible and of sufficient quality and time horizon?
- What specific process steps would need to change for a particular use case?
- Would the team involved in that process have to change?
- What could be changed with minimal disruption, and what would require parallel processes until the new analytics approach was proven?

3. There's no analytics strategy beyond a few use cases.

In one example, the senior executives of a large manufacturer were excited about advanced analytics; they had identified several potential cases where they were sure the technology could add value. However, there was no strategy for how to generate value with analytics beyond those specific situations.

Meanwhile, a competitor began using advanced analytics to build a digital platform, partnering with other manufacturers in a broad ecosystem that enabled entirely new product and service categories. By tackling the company's analytics opportunities in an unstructured way, the CEO achieved some returns but missed a chance to capitalize on this

EXHIBIT 1 **Analytics use cases should be prioritized based on feasibility and impact.**

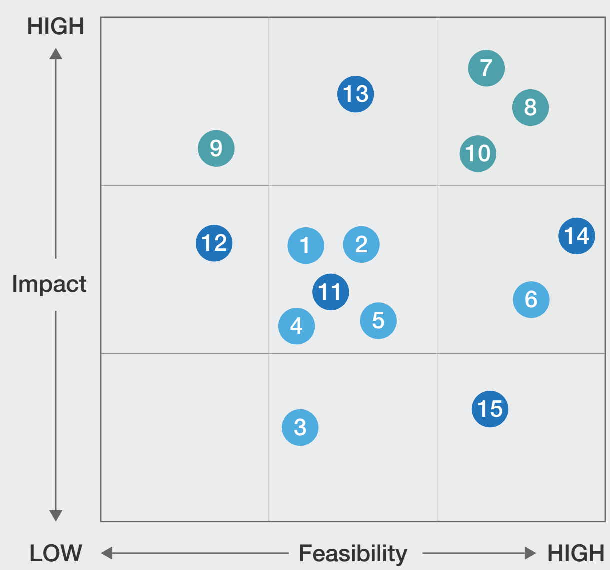
Step 1: Create a list of use cases.
Sample list for consumer-packaged-goods company

Sales/customer relationship management (CRM)
1. Overall brand management
2. Overall campaign management
3. 360° view of shopper
4. Targeted acquisition campaigns
5. Real-time image advertising (awareness)
6. Retargeting campaign

Marketing
7. Optimization of spend across media
8. Optimization of spend within digital media
9. Digital attribution modeling
10. Performance advertising (sales)

Innovation
11. Consumer insights (social listening/sentiment analysis)
12. New product success (predictive behavior model)
13. Product customization at scale
14. Open innovation on promotion mechanisms
15. New digital sales models

Step 2: Prioritize them.
Sample impact vs feasibility matrix



much bigger opportunity. Worse yet, the missed opportunity will now make it much more difficult to energize the company's workforce to imagine what transformational opportunities lie ahead.

As with any major business initiative, analytics should have its own strategic direction.

First response: There are three crucial questions the CDO or CAO must ask the company's business leaders:

- What threats do technologies such as AI and advanced analytics pose for the company?
- What are the opportunities to use such technologies to improve existing businesses?
- How can we use data and analytics to create new opportunities?

4. Analytics roles—present and future—are poorly defined.

Few executives can describe in detail what analytics talent their organizations have, let alone where that talent is located, how it's organized, and whether they have the right skills and titles.

In one large financial-services firm, the CEO was an enthusiastic supporter of advanced analytics. He was especially proud that his firm had hired 1,000 data scientists, each at an average loaded cost of $250,000 a year. Later, after it became apparent that the new hires were not delivering what was expected, it was discovered that they were not, by strict definition, data scientists at all. In practice, 100 true data scientists, properly assigned in the right roles in the appropriate organization, would have sufficed. Neither the CEO nor the firm's human-resources group had a clear understanding of the data-scientist role—nor of other data-centric roles, for that matter.

First response: The right way to approach the talent issue is to think about analytics talent as a tapestry of skill sets and roles (Exhibit 2). Naturally, many of these capabilities and roles overlap—some regularly, others depending on the project. Each thread of that tapestry must have its own carefully crafted definition, from detailed job descriptions to organizational interactions. The CDO and chief human resources officer (CHRO) should lead an effort to detail job descriptions for all the analytics roles needed in the years ahead. An immediate next step is to inventory all of those currently with the organization who could meet those job specifications. And then the next step is to fill the remaining roles by hiring externally.

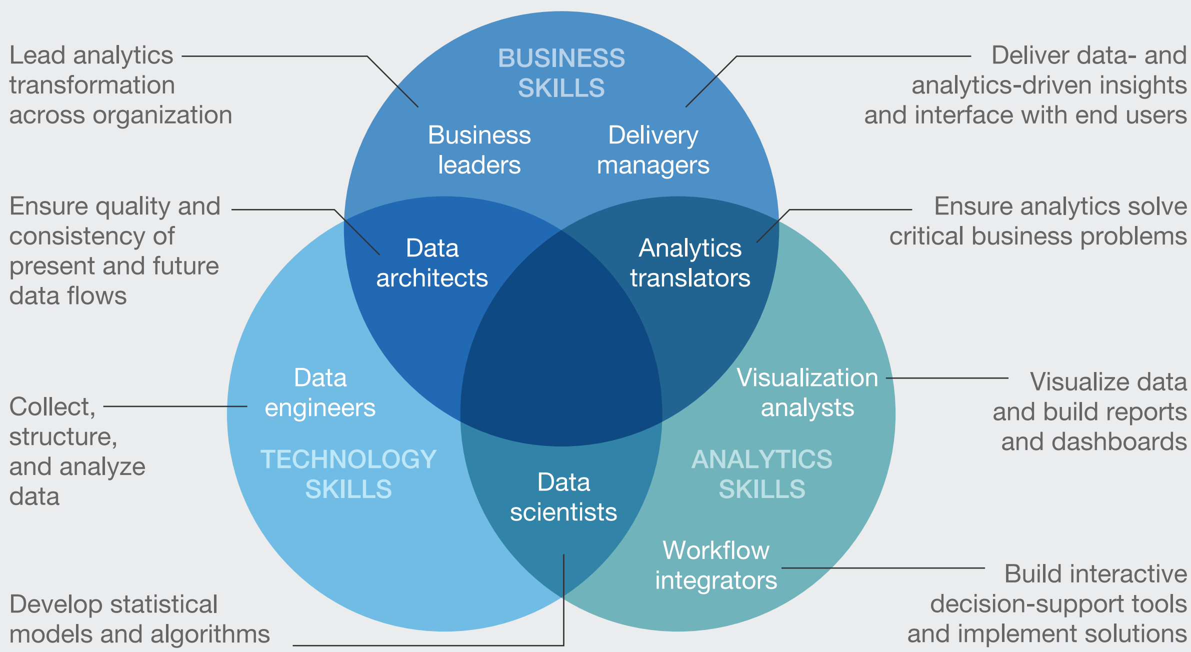
5. The organization lacks analytics translators.

If there's one analytics role that can do the most to start unlocking value, it is the analytics translator. This sometimes overlooked but critical role is best filled by someone on the business side who can help leaders identify high-impact analytics use cases and then "translate" the business needs to data scientists, data engineers, and other tech experts so they can build an actionable analytics solution. Translators are also expected to be actively involved in scaling the solution across the organization and generating buy-in with business users. They possess a unique skill set to help them succeed in their role—a mix of business knowledge, general technical fluency, and project-management excellence.

First response: Hire or train translators right away. Hiring externally might seem like the quickest fix. However, new hires lack the most important quality of a successful translator: deep company knowledge. The right internal candidates have extensive company knowledge and business acumen and also the education to understand mathematical models and to work with data scientists to bring out valuable insights. As this unique combination of skills is hard to find, many companies have created their own translator academies to train these candidates. One global steel company, for example, is training

EXHIBIT 2 **Organizations need a variety of analytics talent with well-defined roles.**

Analytics roles and responsibilities



300 translators in a one-year learning program. At McKinsey, we've created our own academy, training 1,000 translators in the past few years.

6. Analytics capabilities are isolated from the business, resulting in an ineffective analytics organization structure.

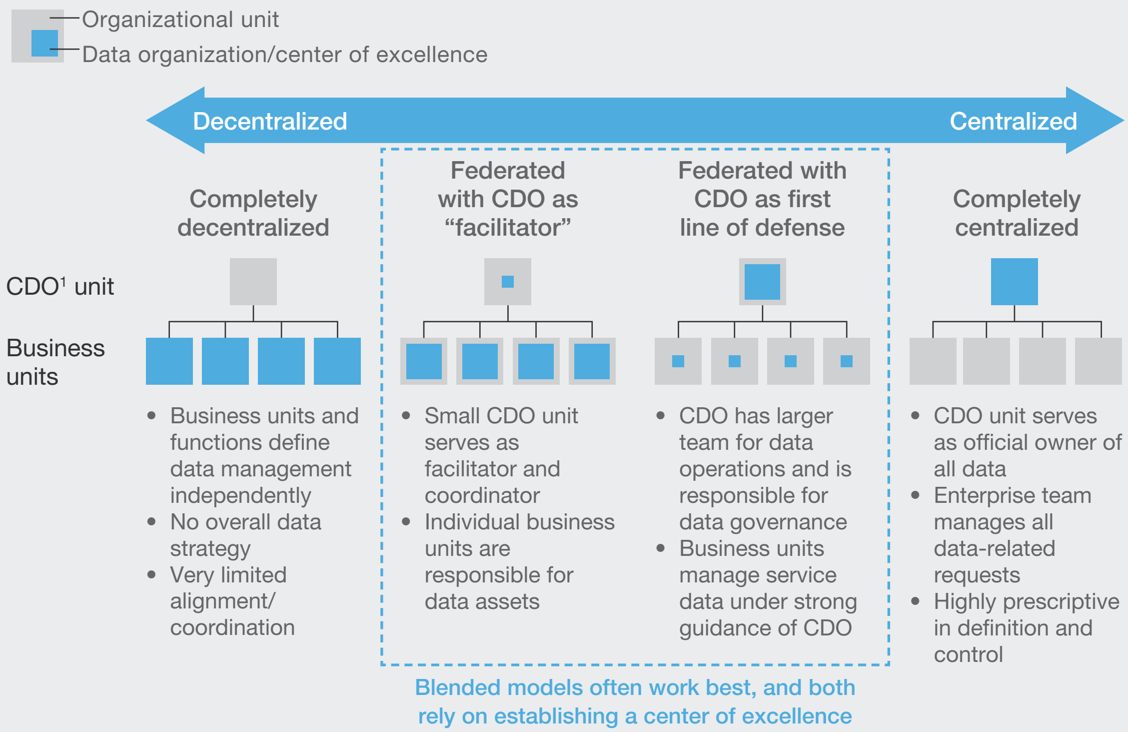
We have observed that organizations with successful analytics initiatives embed analytics capabilities into their core businesses. Those organizations struggling to create value through analytics tend to develop analytics capabilities in isolation, either centralized and far removed from the business or in sporadic pockets of poorly coordinated silos. Neither organizational model is effective. Overcentralization creates bottlenecks and leads to a lack of business buy-in. And decentralization brings with it the risk of different data models that don't connect (Exhibit 3).

A definite red flag that the current organizational model is not working is the complaint from a data scientist that his or her work has little or no impact and that the business keeps doing what it has been doing. Executives must keep an ear to the ground for those kinds of complaints.

First response: The C-suite should consider a hybrid organizational model in which agile teams combine talented professionals from both the business side and the analytics side. A hybrid model will retain some centralized capability and decision rights (particularly around data governance and

EXHIBIT 3 **Hybrid organizational models often work best for broadscale analytics initiatives.**

Organizational types



[1]Chief data officer.

other standards), but the analytics teams are still embedded in the business and accountable for delivering impact.

For many companies, the degree of centralization may change over time. Early in a company's analytics journey, it might make sense to work more centrally, since it's easier to build and run a central team and ensure the quality of the team's outputs. But over time, as the business becomes more proficient, it may be possible for the center to step back to more of a facilitation role, allowing the businesses more autonomy.

7. Costly data-cleansing efforts are started en masse.

There's a tendency for business leaders to think that all available data should be scrubbed clean before analytics initiatives can begin in earnest. Not so.

McKinsey estimates that companies may be squandering as much as 70 percent of their data-cleansing efforts. Not long ago, a large organization spent hundreds of millions of dollars and more than two years on a company-wide data-cleansing and data-lake-development initiative. The objective was to have one data meta-model—essentially one source of truth and a common place for data management. The effort was a waste. The firm did not track the data properly and had little sense of which data might work best for which use cases. And even when it had cleansed the data, there were myriad other issues, such as the inability to fully track the data or understand their context.

First response: Contrary to what might be seen as the CDO's core remit, he or she must not think or act "data first" when evaluating data-cleansing initiatives. In conjunction with the company's line-of-business leads and its IT executives, the CDO should orchestrate data cleansing on the data that fuel the most valuable use cases. In parallel, he or she should work to create an enterprise data ontology and master data model as use cases become fully operational.

8. Analytics platforms aren't built to purpose.

Some companies know they need a modern architecture as a foundation for their digital transformations. A common mistake is thinking that legacy IT systems have to be integrated first. Another mistake is building a data lake before figuring out the best ways to fill it and structure it; often, companies design the data lake as one entity, not understanding that it should be partitioned to address different types of use cases.

In many instances, the costs for such investments can be enormous, often millions of dollars, and they may produce meager benefits, in the single-digit millions. We have found that more than half of all data lakes are not fit for purpose. Significant design changes are often needed. In the worst cases, the data-lake initiatives must be abandoned.

That was the case with one large financial-services firm. The company tried to integrate its legacy data warehouses and simplify its legacy IT landscape without a clear business case for the analytics the data would fuel. After two years, the business began to push back as costs escalated, with no signs of value being delivered. After much debate, and after about 80 percent of the investment budget had been spent, the program screeched to a halt.

First response: In practice, a new data platform can exist in parallel with legacy systems. With appropriate input from the chief information officer (CIO), the CDO must ensure that, use case by use case, data ingestion can happen from multiple sources and that data cleansing can be performed and analytics conducted on the platform—all while the legacy IT systems continue to service the organization's transactional data needs.

9. Nobody knows the quantitative impact that analytics is providing.

It is surprising how many companies are spending millions of dollars on advanced analytics and other digital investments but are unable to attribute any bottom-line impact to these investments.

The companies that have learned how to do this typically create a performance-management framework for their analytics initiatives. At a minimum, this calls for carefully developed metrics that track most directly to the initiatives. These might be second-order metrics instead of high-level profitability metrics. For example, analytics applied to an inventory-management system could uncover the drivers of overstock for a quarter. To determine the impact of analytics in this instance, the metric to apply would be the percentage by which overstock was reduced once the problem with the identified driver was corrected.

Precisely aligning metrics in this manner gives companies the ability to alter course if required, moving resources from unsuccessful use cases to others that are delivering value.

First response: The business leads, in conjunction with translators, must be the first responders; it's their job to identify specific use cases that can deliver value. Then they should commit to measuring the financial impact of those use cases, perhaps every fiscal quarter. Finance may help develop appropriate metrics; the function also acts as the independent arbiter of the performance of the use cases. Beyond that, some leading companies are moving toward automated systems for monitoring use-case performance, including ongoing model validation and upgrades.

10. No one is hyperfocused on identifying potential ethical, social, and regulatory implications of analytics initiatives.

It is important to be able to anticipate how digital use cases will acquire and consume data and to understand whether there are any compromises to the regulatory requirements or any ethical issues.

One large industrial manufacturer ran afoul of regulators when it developed an algorithm to predict absenteeism. The company meant well; it sought to understand the correlation between job conditions and absenteeism so it could rethink the work processes that were apt to lead to injuries or illnesses. Unfortunately, the algorithms were able to cluster employees based on their ethnicity, region, and gender, even though such data fields were switched off, and it flagged correlations between race and absenteeism.

Luckily, the company was able to pinpoint and preempt the problem before it affected employee relations and led to a significant regulatory fine. The takeaway: working with data, particularly personnel data, introduces a host of risks from algorithmic bias. Significant supervision, risk management, and mitigation efforts are required to apply the appropriate human judgment to the analytics realm.

First response: As part of a well-run broader risk-management program, the CDO should take the lead, working with the CHRO and the company's business-ethics experts and legal counsel to set up resiliency testing services that can quickly expose and interpret the secondary effects of the company's analytics programs. Translators will also be crucial to this effort.

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There is no time to waste. It is imperative that businesses get analytics right. The upside is too significant for it to be discretionary. Many companies, caught up in the hype, have rushed headlong into initiatives that have cost vast amounts of money and time and returned very little.

By identifying and addressing the ten red flags presented here, these companies have a second chance to get on track. ◆

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The automation imperative

As many organizations move to build their automation capabilities, recent survey results suggest that certain best practices will differentiate successful efforts from others.

Organizations in every region and industry are automating at least some business processes, yet only a slight majority have succeeded at meeting their targets, according to a new McKinsey Global Survey on the topic.[1] As advances in artificial intelligence, software robotics, machine learning, and innovative technology platforms enable businesses to redefine processes, workplace automation is expected to provide a significant opportunity for improvements in performance and efficiency.[2] Indeed, three-quarters of all respondents say their companies have already begun to automate business processes or plan to do so within the next year. The results also suggest which practices best support a successful automation effort: making automation a strategic priority, deploying technologies systematically, decentralizing governance, ensuring the IT function's involvement, internalizing automation's

[1] The online survey was in the field from January 16 to January 26, 2018, and garnered responses from 1,303 participants representing a full range of regions, industries, company sizes, functional specialties, and tenures. Of these respondents, 764 work at organizations that have piloted the automation of, or that have fully automated, business processes in at least one function or business unit. To adjust for differences in response rates, the data are weighted by the contribution of each respondent's nation to global GDP.

[2] For more, see the McKinsey Global Institute articles, "Harnessing automation for a future that works," January 2017, and "What's now and next in analytics, AI, and automation," May 2017, both available on McKinsey.com.

costs and benefits, and prioritizing workforce management.

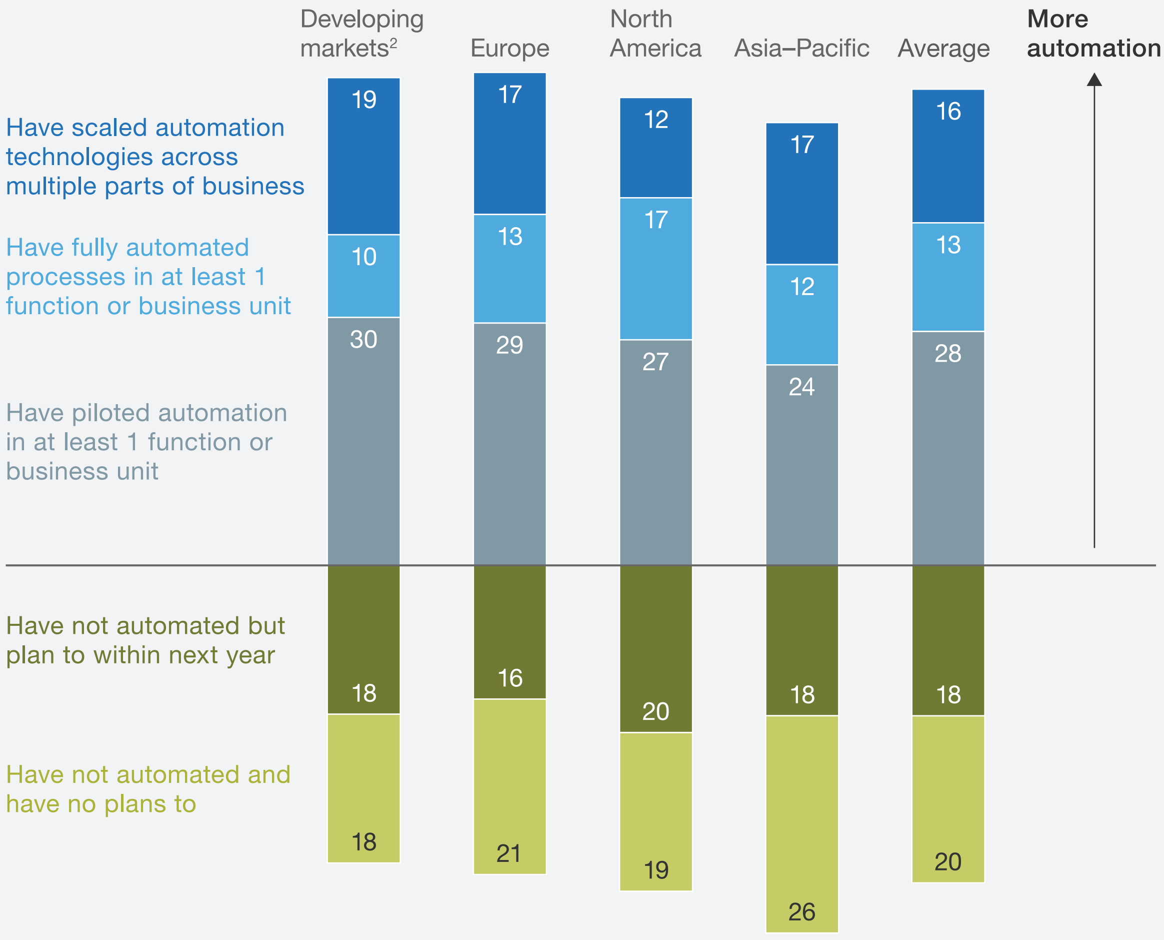
Automation, a global phenomenon

Across regions and industries, the survey results suggest that automating businesses is a global phenomenon (Exhibit 1). A majority of all respondents (57 percent) say their organizations are at least piloting the automation of processes in one or more business units or functions. Another 38 percent say their organizations have not begun to automate business processes, but nearly half of them say their organizations plan to do so within the

EXHIBIT 1

Automation is a global phenomenon.

Steps organizations have taken to automate business processes, by office location, % of respondents[1]



[1]Respondents who answered "don't know" are not shown. Total n = 1,303; in developing markets, n = 373; in Europe, n = 479; in North America, n = 281; and in Asia–Pacific, n = 170.
[2]Includes respondents in China, India, Latin America, Middle East, and North Africa.

next year.[3] Across regions, respondents in developing markets are just as likely as their peers to report automation activity.

Not surprisingly, the high-tech and telecom industries are leading the way on automation. Three-quarters of respondents in those sectors say they are at least piloting automation in one or more business units or functions. Nonetheless, the results suggest that all industries have been or expect to be deploying automation technologies. At least half of respondents in all other industries say their companies have already begun to pilot or adopt automation.

The results also suggest that larger organizations are leading smaller ones in pursuing automation.[4] Among respondents at large companies, 40 percent say theirs are using automation across the organization or have fully automated processes in at least one function or business unit. At smaller organizations, just 25 percent say the same.

The factors in automation success

Although automation has become commonplace, the results indicate that success is by no means assured. We looked closely at the responses from larger organizations, where automation is more prevalent. Across industries, more than half of large-company respondents say their organizations have seen success to date (that is, their automation efforts have been successful or very successful at meeting targets). The results also point to six practices that the most successful companies tend to employ.

Make automation a strategic priority

According to respondents, organizations with successful automation efforts are more likely than others to designate automation as a strategic priority. When asked about their companies' primary reasons for adopting automation technologies, these respondents are more likely than others to say automation was defined as a priority during the strategic-planning processes or is required to keep pace with competitors (Exhibit 2).

Deploy automation technologies systematically

While automation success is possible through either traditional top-down (waterfall) deployment or more-flexible agile methods, a systematic approach is key. Only 5 percent of respondents at successful companies say their deployment methods have been ad hoc, compared with 19 percent of peers not reporting success (Exhibit 3).

What's more, successful organizations are implementing different automation technologies from the ones other organizations are adopting. Respondents with successful automation efforts are more than twice as likely as others to say their organizations are deploying machine learning (Exhibit 4). They are also more likely to cite the use of other cognitive-based automation capabilities, such as cognitive agents and natural-language processing.[5] At respondents' organizations overall, the most commonly adopted automation technology is robotic process automation, which respondents say is deployed in equal shares of successful and other organizations.

Decentralize governance

Another differentiator of automation success, the results suggest, is the way programs are organized. The results favor decentralization. Respondents at successful organizations are more likely than their

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[3] All other respondents (4 percent) say they don't know what actions their organizations have taken to automate business processes. They were not asked the remaining questions in the survey.

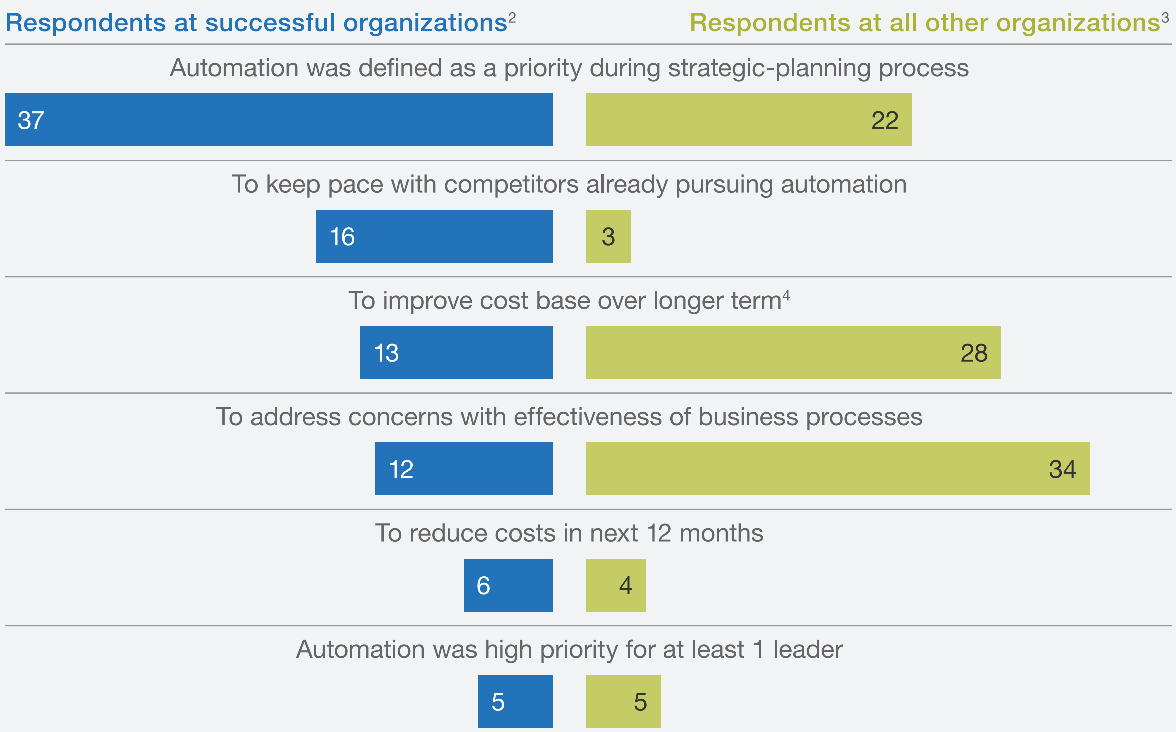
[4] "Large companies" are defined as those with annual revenues of $1 billion or more, according to respondents. Those with annual revenues of less than $1 billion are classified as "small companies."

[5] For more on the changing demand for cognitive work, see "Skill shift: Automation and the future of the workforce," McKinsey Global Institute, May 2018, on McKinsey.com.

EXHIBIT 2

Organizations with successful automation efforts are more likely than others to designate automation a strategic priority.

Primary reason for pursuit of automation, % of respondents at large organizations[1]



[1]Respondents working at organizations with annual revenue of $1 billion or more, n = 162. Respondents who answered "other" or "don't know" are not shown.
[2]Respondents who say their companies have been successful or very successful at meeting targets for automation efforts.
[3]Respondents who say their companies have been unsuccessful, very unsuccessful, or neither successful nor unsuccessful at meeting targets for automation efforts.
[4]That is, next 2–3 years.

peers to say their functions or business units are accountable for delivering automation efforts, with or without support from a central team. Conversely, respondents at less successful organizations are more than twice as likely as those at successful ones to say a central team is solely responsible for automation delivery across the organization.

Ensure the IT function's involvement

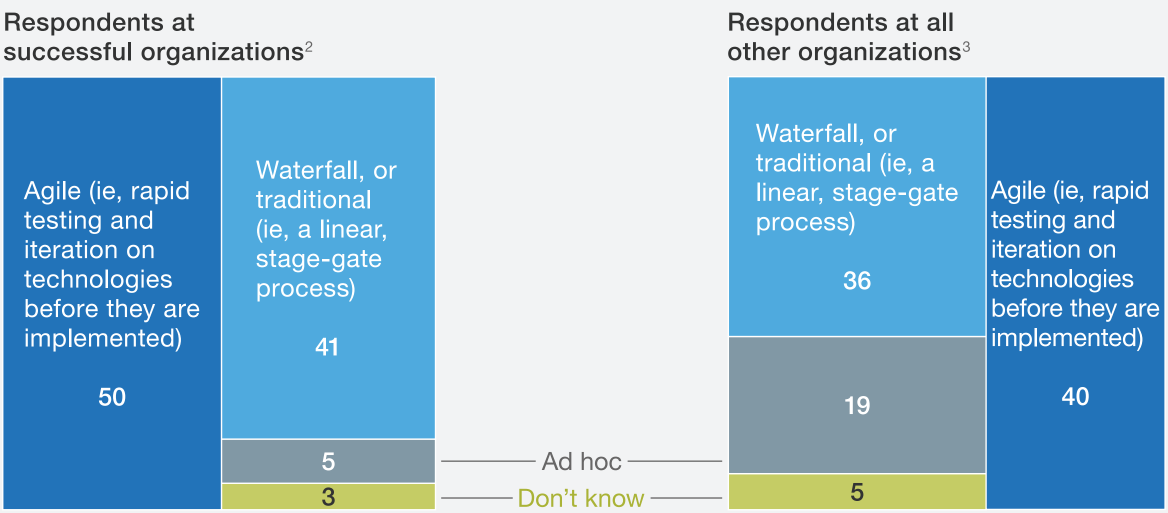
The success of automation programs also relies on the early engagement of the IT function, according to respondents from organizations with successful efforts. First, these organizations' IT teams are more likely to have automated their own processes.[6] Furthermore, IT's involvement in the automation

[6] Among large companies, 75 percent of respondents who report successful automation efforts say their IT functions have automated at least one business process, compared with 56 percent of all others.

EXHIBIT 3

Success with automation is most often achieved with a systematic approach to deploying technologies.

Organizations' process for deploying automation technologies,
% of respondents at large organizations[1]



[1]Respondents working at organizations with annual revenue of $1 billion or more, n = 162. Figures may not sum to 100%, because of rounding.
[2]Respondents who say their organizations have been successful or very successful at meeting targets for automation efforts.
[3]Respondents who say their companies have been unsuccessful, very unsuccessful, or neither successful nor unsuccessful at meeting targets for automation efforts.

effort also is a differentiator of success. More than 75 percent of respondents from successful organizations say IT was involved in initial discussions of automation projects, compared with 58 percent of all other respondents (Exhibit 5). By contrast, just 13 percent of respondents who consider their automation efforts successful say IT was not brought onboard until pilots were already under way.

Internalize both costs and benefits

Successful and less successful automation efforts also diverge in regard to management's understanding of the total cost of ownership (TCO).[7] Half of respondents with successful automation efforts say their leaders understand very well the TCO for automation projects. Only 7 percent of peers at other organizations say the same. That said, respondents report similar benefits from their automation efforts, regardless of their success to date at meeting targets. The most common benefit reported is reduced costs, identified by about one-third of all respondents.

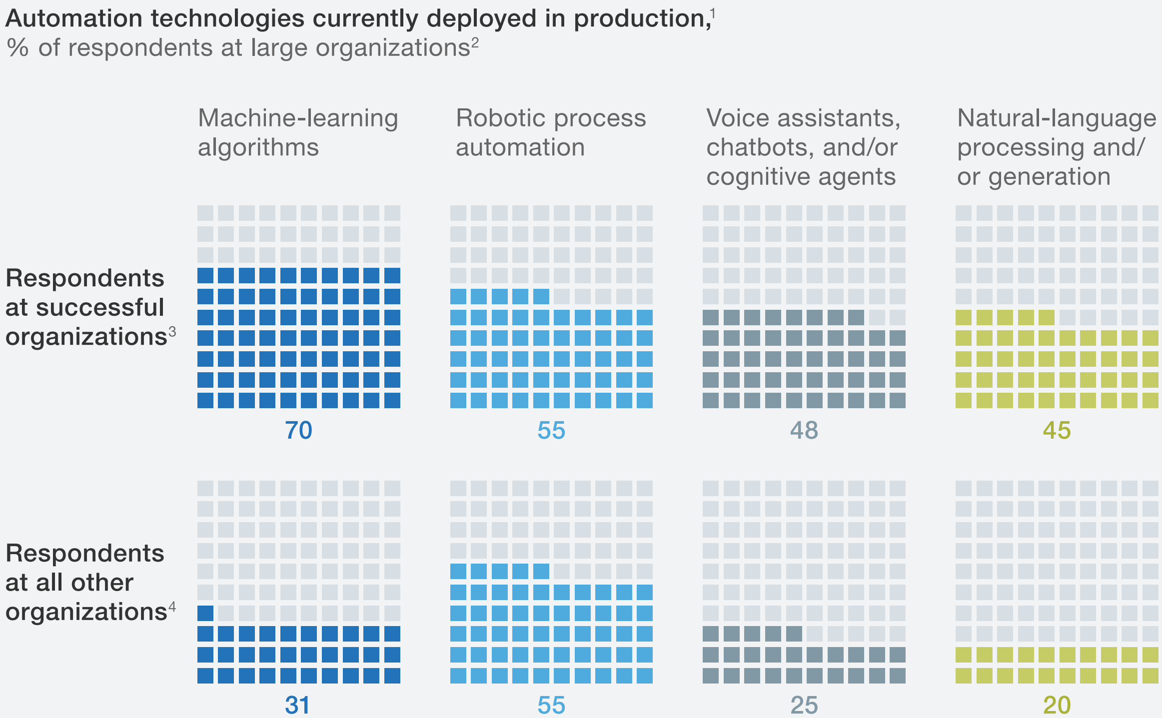
Prioritize workforce management

Among all large organizations reported to be pursuing automation, a majority of respondents

[7] For more information on optimizing total cost of ownership, see Kalle Bengtsson, Tyler Duvall, Samuel Magid, and Robert Palter, "Releasing the pressure on road agencies," February 2011, McKinsey.com.

EXHIBIT 4

Success-group respondents are twice as likely to report deployment of machine learning, cognitive agents, and natural-language processing.



[1]That is, deployed beyond the piloting phase.
[2]Respondents working at organizations with annual revenue of $1 billion or more, n = 162. Respondents who answered "other" or "don't know" are not shown.
[3]Respondents who say their organizations have been successful or very successful at meeting targets for automation efforts.
[4]Respondents who say their companies have been unsuccessful, very unsuccessful, or neither successful nor unsuccessful at meeting targets for automation efforts.

predict that their companies will face automation-related skill gaps in the future. Only 8 percent believe there will be no gaps to address. And while most respondents say addressing potential automation-related skill gaps is a top ten priority for their organizations, respondents at successful organizations are more than three times likelier than others to consider the effort a top five priority (Exhibit 6).

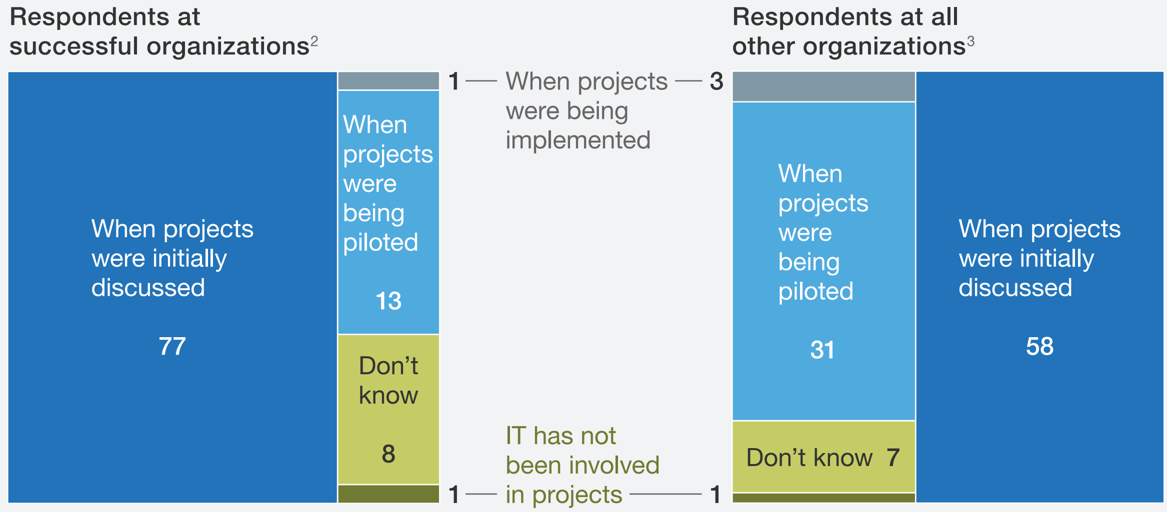
What's more, organizations with successful automation efforts are more likely than others to report concerns about talent acquisition. They are five times likelier (40 percent, compared with 8 percent) to say acquiring employees with the right skills will be their organizations' most significant automation-related challenge in the next three years.

What success looks like at small companies

Smaller companies are less likely than larger companies to automate processes, but their success rate is higher. The findings from these organizations show that several differentiators for success hold true regardless of company size.

EXHIBIT 5 **Successful automation efforts tend to involve IT early.**

Project stage when central IT groups were first involved in automation planning, % of respondents at large organizations[1]



[1]Respondents working at organizations with annual revenue of $1 billion or more, n = 162.
[2]Respondents who say their organizations have been successful or very successful at meeting targets for automation efforts.
[3]Respondents who say their companies have been unsuccessful, very unsuccessful, or neither successful nor unsuccessful at meeting targets for automation efforts.

As with large companies, IT's involvement in small companies' automation efforts is greater at successful companies. More than 80 percent of respondents at successful small companies say their IT functions were involved in the initial discussion phase of planning for automation projects, compared with two-thirds of respondents at other small companies. And 64 percent of respondents from successful small companies report the automation of at least one business process in IT, compared with 41 percent of their small-company peers.

Understanding costs also is a marker of success at smaller firms. At successful small companies, nearly half of respondents say their leaders understand the total cost of ownership of automation efforts very well or completely, while only 28 percent of respondents from other companies say the same. The findings also suggest that automation-related talent management is top of mind for leaders at successful small companies. And like their large-company peers, respondents from the most successful small companies are likelier than others to say that addressing potential automation-related skill gaps is at least a top ten priority for their organizations.

Looking ahead

The findings from this survey can be applied to organizations at all stages of the automation journey. Depending on an organization's current state, its leaders can take several steps to reap the rewards of automation.

- *Prioritize automation.* Organizations that are just launching automation programs would

EXHIBIT 6

Successful organizations are more likely to make potential automation-related skill gaps a priority.

Importance of addressing potential automation-related skill gaps compared with other priorities,
% of respondents at large organizations[1]

[1]Respondents working at organizations with annual revenue of $1 billion or more, n = 162. Respondents who answered "don't know" are not shown.
[2]Respondents who say their companies have been successful or very successful at meeting targets for automation efforts.
[3]Respondents who say their companies have been unsuccessful, very unsuccessful, or neither successful nor unsuccessful at meeting targets for automation efforts.

benefit from making automation a strategic priority from the outset. Ways to put this in action include defining clear strategic objectives for automation, having an executive sponsor for the program, beginning automation work with a comprehensive understanding of both the costs and benefits, and making automation an enterprise-wide, rather than functional, mandate.

- *Focus on roles and people.* Organizations that are struggling to implement automation successfully would do well to elevate the role of IT—for example, involving the function often and as early as possible in all future efforts. These organizations also should take a discerning look at workforce management. This includes development of an approach to capture value from automation and an assessment of the skills and new roles for the workforce that accompany future-state automated processes.

- *Expand ownership and adoption.* Finally, organizations that are successfully deploying automation technologies should also look to expand the governance of and buy-in on automation. They can benefit from encouraging a truly enterprise-wide program and pursuing more advanced cognitive automation technologies. Structuring automation programs to be technology neutral will allow organizations to keep pace with the rapid advances being made, rather than rethinking their approach every time they adopt a new technology. ◆

The contributors to the development and analysis of this survey include **Alexander Edlich**, a senior partner in McKinsey's New York office; **Fanny Ip**, an associate partner in the Southern California office; and **Rohit Panikkar** and **Rob Whiteman**, an associate partner and partner, respectively, in the Chicago office.

They wish to thank Gary Herzberg for his contribution to this work.


Photo credit: Getty Images

How to avoid the three common execution pitfalls that derail automation programs

Rahil Jogani, Sanjay Kaniyar, Vishal Koul, and Christina Yum

Automation has great potential to create value—but only for businesses that carefully design and execute it.

Encouraged by the much-vaunted potential of automation, organizations around the world are embarking on their own transformation journeys. On paper, the numbers look compelling. The McKinsey Global Institute estimates that about half the activities that workers are paid $15 trillion in wages to perform in the global economy have the potential to be automated by taking advantage of current technologies (see sidebar, "Key automation technologies").[1] Looked at another way, at least 30 percent of work activities in about 60 percent of all occupations could, in principle, be automated.

With their eyes on the automation prize, companies have set aspirational targets that run to hundreds of millions of dollars. As they launch their first, second, and third waves of automation, however, most are finding it harder than they expected to capture the promised impact. In our experience, about half of current programs are delivering value on some

[1] "A future that works: Automation, employment, and productivity," McKinsey Global Institute, January 2017, on McKinsey.com.

Key automation technologies

Cognitive agents are a virtual workforce used to support customers or employees in settings such as service centers.

Machine learning identifies patterns in data through supervised and unsupervised learning, using decision algorithms and other means.

Natural-language processing (NLP) is a way of creating seamless interactions between humans and technologies in applications such as data-to-story translation.

Robotic process automation (RPA) automates routine tasks such as data extraction and cleaning via existing user interfaces.

Smart workflow is an approach to integrating tasks performed by groups of people and machines, such as month-end reporting processes.

fronts, but only a handful are generating the impact at scale that their business cases promised.

Teething troubles are to be expected with an effort as wide-ranging as automation. Applying a largely unfamiliar portfolio of technologies in a fast-moving, complex business is enough to break even the most experienced leaders and teams. In the C-suite, executives are approving major investments that promise generous paybacks in a matter of months; meanwhile, down on the factory floor, project teams are constantly scrambling to extend timelines and trim back impact estimates. We have seen robotic process automation (RPA) programs put on hold and CIOs flatly refusing to install new bots—even when vendors have been working on them for months—until solutions have been defined to scale up programs effectively.[2] In case after case, early adopters are left writing off big investments.

Though the reasons for poor results vary, we see three common execution pitfalls that derail automation programs.

Underestimating the complexity

At one global bank, leaders developed a multimillion-dollar business case for automation. First up in the program was basic RPA. Estimates of the potential value that could be captured in the first year shrank from 80 percent to 50 percent to 30 percent, and finally to less than 10 percent once development got under way. The effort quickly lost traction. A platform combining RPA and artificial intelligence (AI) was then proposed and developed for more than a year, but much the same thing happened again.

Treating automation as a technology-led effort can doom a program to failure. Process problems can rarely, if ever, be tackled simply

[2] See "Burned by the bots: Why robotic automation is stumbling" on p. 44 of this collection.

by introducing a new technical solution. Often there are many underlying issues—poor quality of input data, accommodating too many client variations, "off script" procedures that cannot be quickly understood in high-level process demonstrations or requirements documents. The reality is that automation solutions are complex because they tend to affect multiple processes with significant interdependencies across technologies, departments, and strategies. If these issues and elements are neglected, they tend to undermine a company's automation objectives during implementation. Other, more thoughtful approaches—process reengineering, organization redesign, policy reform, technology-infrastructure upgrades or replacements—need to be considered in parallel with automation solutions.

To ensure that automation complements rather than clashes with other strategic priorities, senior leaders, technology experts, application owners, and automation teams need to work together to define a joint vision for how business processes will function in the future.

Companies that succeed with automation take care to base their vision on reality. They start by understanding their technological maturity, tracking customer and employee touchpoints, mapping information flows, and setting expectations for exception handling, metrics, and reporting.

This is generally known as enterprise architecture management. Taking an end-to-end view of processes enables companies to shape and prioritize automation initiatives. This clear view also allows the business to better pinpoint which of the various automation technologies are most appropriate and how they can be combined to create more value. For instance, a basic RPA program alone can enable an organization to address 12 to 18 percent of general and administrative tasks, but the addition of smart workflows, natural-language processing (NLP), cognitive agents, and other technologies could increase the scope for automation to 21 to 27 percent (Exhibit 1). Combinations of technologies can also deliver other benefits, such as shorter cycle times and better quality.

When one enterprise decided to overhaul its customer-care operations, for example, it began by scrutinizing the journeys customers took to complete a given task. After creating a comprehensive view of the various processes and dependencies, it was able to set targets and select solutions with clear business outcomes in view. These included automating basic front-line processing using chat and voice-enabled cognitive agents; offering online self-service for 30 to 60 percent of customer transactions; seamlessly integrating customer journeys with back-end transactions and servicing; improving response times; integrating social, messaging, digital, and voice-driven channels to develop omnichannel customer inputs; and having a clear view of strategic customer-relationship management (CRM) tools, systems, and interfaces to lay the foundation for automation.

Armed with this process-centered vision, automation teams had a clear framework within which to plan and execute their initiatives. Because they had a clear grasp of their scope, accountabilities, and expected impact on the business from the outset, they were able to minimize duplication of effort, tackle dependencies between systems and processes more easily, and better manage change both for the customers using the new features, services, and channels and for the teams introducing and supporting them.

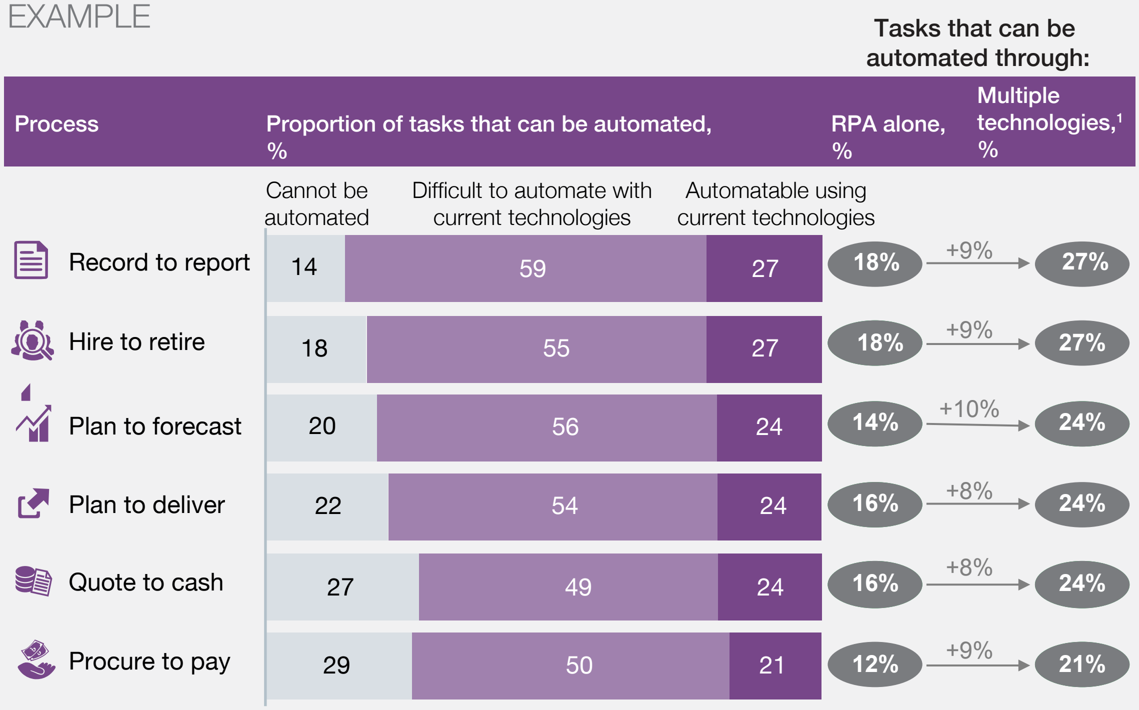
Automating inefficient and complex processes

A professional-services firm was automating its shared service centers as part of a cost-reduction strategy. Its first priority was to automate the processes offering the greatest scope for efficiency savings, so it began by targeting a team of 20

EXHIBIT 1

Over a third of tasks are currently automatable for all processes, while over three-quarters of tasks may become automatable as technologies mature.

EXAMPLE



[1]Including smart workflows, machine learning, natural-language processing, optical character recognition, and chatbots.

who all handled transactions manually. With a potential saving of 60 percent of their workforce costs, development began. However, further analysis revealed that the team served hundreds of customers, each with its own requirements for the creation and submission of transactions. Not only that, but the team worked with more than five different input systems, each with its own slew of transaction formats.

As a result, some of the process steps that leaders assumed would be automatable proved not to be. The solution that eventually emerged was hypercomplex: it had hundreds of variations, required manual intervention at multiple points, and was a nightmare to maintain. Before long, development was abandoned, and the program was replaced by a traditional integration project run by IT.

With so much value at stake in automation, leaders are often tempted to get straight into technical development. That approach leads businesses to try to automate inefficient or obsolete processes. If processes (and the organizations supporting them) are not reconfigured before automation, savings often prove elusive.

The enterprises that do best at automation take the time to consider how they could redesign their processes, their organization, and their underlying technologies to pave the way for automation. Thoughtful redesign can reduce development times, simplify maintenance activities, create cleaner handoffs between people and machines, and improve metrics and reporting.

Companies that are good at uncovering redesign opportunities use four key techniques (Exhibit 2):

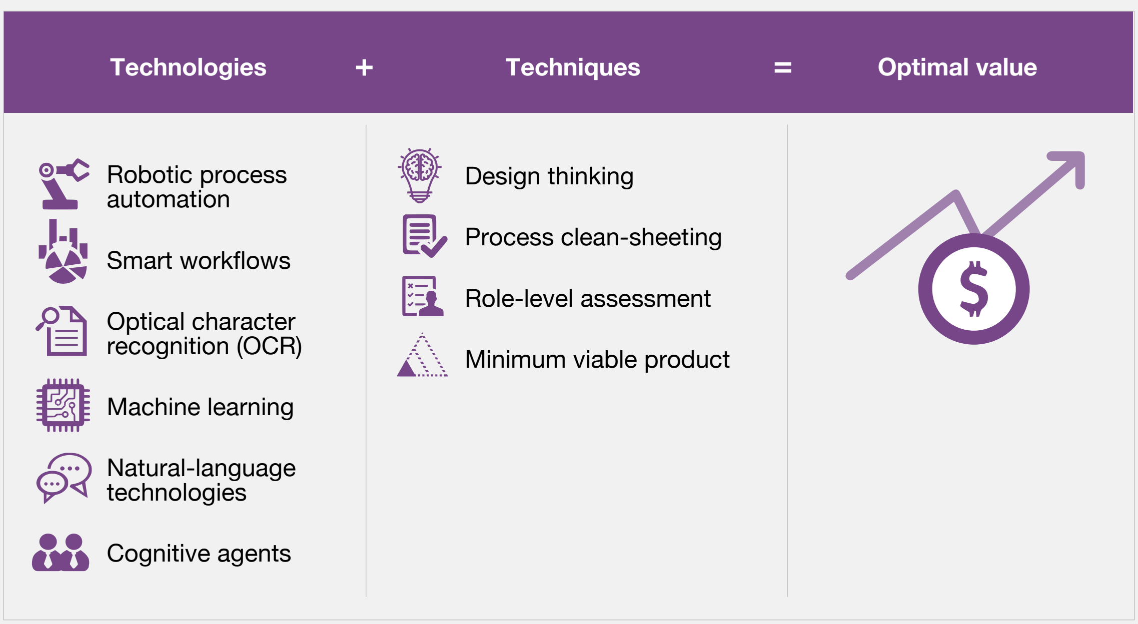
- *Design thinking:* taking a people-centered and journey-based view to process optimization that accounts for human empathy as well as analytical criteria
- *Process clean-sheeting:* designing an optimal process from scratch rather than making incremental changes to an existing process
- *Role-level assessment:* analyzing type and hierarchy of roles within the organization or function when evaluating the potential for automation
- *Minimum viable product:* developing a new process that addresses the most basic criteria via agile sprints and rollout in releases every three to four months to test and adapt in the marketplace.

Spending time considering redesign opportunities may initially slow down time to market, but it will also take some of the risk out of implementation and help ensure that operational results are sustainable and easy to maintain. In many cases, work on redesign, restructuring, and optimization opportunities can be pursued in parallel to capture quick wins, provided that a company's underlying technologies are mature.

A North American bank identified automation opportunities in its record-to-report process. Instead of automating the existing process, it performed a clean-sheet redesign that re-envisaged

EXHIBIT 2

To maximize value capture, leading businesses draw on a range of automation technologies and application techniques.



how the whole process would operate using RPA, AI, and natural-language generation, complemented with manual tasks where needed. The new design eliminated one approval cycle, removed unnecessary handoffs between five teams, and reduced processing time from 12–15 days to 6–8 days. The new design automated 70 percent of process steps and reduced risk of error through automated quality-control checks and complete audit trail.

Underinvesting in change management

A large financial-services organization set RPA bots onto labor-intensive back-office operations for certain regions. In parallel, it was exploring other technologies (machine learning, chatbots, natural-language tools) and traditional technology enhancements. The teams absorbing the changes found that although their best people were spending hours with project teams providing requirements, they were unable to get answers on how the different technologies would work together and had no idea how to train staff to operate in the new way. Months of frustration later, there was still no impact in sight. Worse, the RPA bots were not performing and were disrupting established working routines. One by one, project teams were withdrawn, and the team resumed manual processing as before.

Unless companies understand the impact of automation on their employees and plan for it, automation programs can be highly disruptive, sow confusion in the ranks, and foster resistance. To prevent this kind of disruption, the most successful companies do the following:

- *Design for the operator, agent, or customer experience.* Automation program decisions must always be made with end users in mind. If incorporating automation into a process is unnecessarily disruptive to the operator's experience—if it involves too many new steps, say, or requires accessing additional systems or files or unnecessary wait time—it will trigger significant resistance. Any newly designed process should take advantage of familiar ways of working as much as possible.

- *Think realistically about technical and executional maturity.* Piloting technologies early and rapidly will build organizational awareness and demonstrate value. However, savvy leaders also consider how quickly the business and the automation team can absorb change. They are selective in focusing their energies where they can build a deep capability. They start with basic, lower-cost automation technologies such as RPA, optical character recognition, and workflow to ensure they're not taking on too much at once.

- *Adopt agile implementation.* Automation programs are most effectively run in iterative sprints. Building components rapidly allows for early user input and quick identification of any technical constraints that could jeopardize delivery. Data-driven prioritization, in which agile teams use data on the volume of exceptions to inform what types of enhancements to implement, helps teams course-correct and improve performance as implementation progresses.

- *Set clear and considered expectations.* With complex processes, getting from the current to the target state involves many stages. The best organizations set expectations at the outset that clearly describe the operator experience at each stage through live, hands-on demos. Business and project teams actively discuss trade-offs between time and functionality. Taking some additional time can deliver real benefits, such as more effective and sustainable solutions, reduced production incidents, and positive sentiment. But it may require holding back a project team that is hungry to see savings.

- *Engage with their employees, then engage some more.* Automation poses more challenges to the workforce because of the need to upgrade skills and shift the culture to support continual adjustments to the way people do their work. The best companies move away from a project-focused mind-set, partner with the business to plan changes, and treat automation releases and upgrades as a routine part of daily operations. We have found that providing employees with hands-on experience and live demos early, clearly explaining constraints, and discussing design decisions in partnership with development teams are crucial for the workforce to adopt new automation programs. We have also seen successful companies invest in structured capability-building programs, innovation labs, and rotational programs to foster interest and broaden awareness.

A professional-services organization introducing an automation program began by specifying which types of transactions would be tackled in the first release and which would not, and checked with affected employees that the plan made sense and would have a positive impact. Before the first release, the automation team worked with the business on a series of sprints to clarify how the team would work in conjunction with the automation, how training would be done, and what the timeline would be. When the automated process went live, the team knew exactly what to do and how to work with it and immediately started gathering ideas for the next release. Teams acknowledged the success of the effort, were happy with the changes in their roles, and—as estimated—30 percent of capacity was strategically redeployed.

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Automation technologies give leaders an exciting new toolbox for increasing efficiency, reducing cost, and improving quality. But unlocking all this potential isn't just a technical exercise. Leaders must give careful consideration to the full array of issues, from redesigning processes to aligning work teams, if they want automation to deliver the full potential value. ◆

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Photo credit: Getty Images

The new frontier: Agile automation at scale

Federico Berruti, Geet Chandratre, and Zaid Rab

Large-scale automation of business processes requires a new development approach.

Across sectors, business processes are undergoing the most profound transformation since companies replaced paper files with electronic records. A new suite of technologies, including robotic process automation (RPA), smart workflows, and artificial-intelligence techniques such as machine learning, natural language tools, and cognitive agents, promises to radically improve efficiency while eliminating errors and reducing operational risk. Research by our colleagues at the McKinsey Global Institute suggests that, across industries, there is already the potential to automate more than 30 percent of the tasks that make up 60 percent of today's jobs. In finance and insurance, for example, workers spend more than half their time collecting and processing data, tasks that are eminently suitable for automation using techniques that are already available today.

Many companies have identified significant opportunities to apply automation, and the results of pilot projects and technology demonstrators have been encouraging. So far, however, most have struggled to capture the full potential of these new approaches by applying them at scale across their operations.

There are multiple reasons why implementing automation is challenging. Some of the technologies involved are still relatively immature, for example. Applying them outside a carefully controlled test environment can reveal unforeseen weaknesses and limitations. And with thousands of processes involving tens of thousands of employees, organizations find it difficult to build workable road maps for large-scale automation.

The devil in the development detail

Then there's the challenge of software development and implementation. Companies need to tailor and customize their chosen technologies so they work in the context of the wider organization. And because automation involves significant changes to existing roles and tasks, they need to coordinate technology development within a wider change-management process.

As many organizations have already discovered, established software-development methodologies do not work well in this complex environment. The first to fail has been the traditional "waterfall" approach, in which analysis, specification, design, coding, and testing are conducted sequentially. Automation projects organized this way have been plagued by delays and cost overruns, as companies discover unexpected issues or limitations late in the project-development lifecycle. That can be a particular problem when efforts are centralized at the enterprise level. After a successful proof-of-concept project, for example, one mining company used the waterfall approach to automate an important back-office process. The company was ten weeks into implementation when it discovered that its infrastructure design couldn't be scaled up to handle the work. By the time it identified and fixed the problem, the project was already delayed by more than four months, causing costs to spiral.

Experiences like this are encouraging more companies to pursue agile development approaches in their automation projects. With its emphasis on tight-knit cross-functional teams, focused development efforts, and continual testing, agile has proved highly successful in addressing similar challenges in other areas of software development.

Yet applying agile to automation projects has brought its own challenges. That's because process automation differs from the development of a conventional software product in a number of significant ways.

Scrum, an agile methodology that leverages quick iterations to develop features, works by breaking a complex problem or feature down into discrete chunks or "stories." Teams work in these chunks one at a time, focusing on quality and releasing software frequently as opposed to at the end of the project. In a conventional software product, that usually means that products start by offering a limited range of features, with new ones added over time. In process automation, however, it can be difficult to break a feature down in this way. The individual components within a process are often tightly coupled: it either works end to end or it doesn't work at all.

In addition, the disruptive nature of process automation, which may involve significant changes to the roles and responsibilities of hundreds of employees, can make frequent release cycles unfeasible. Sometimes the incremental value captured by a single component is not enough to justify a release.

Then there is the issue of ownership. In scrum, there is a dedicated "product owner" who acts as the representative of the end customer, working closely with development teams to answer questions, prioritize work, and give feedback on prototypes. Process automation may span multiple business functions, units, and geographies, making it difficult to find an individual with the requisite knowledge and connections. And because automation is new, the most appropriate "process owner" within the organization may have little or no experience at working on software-development projects, let alone the fast-moving, intensely iterative agile environment.

Agile automation at scale

In response to these limitations, some companies are adapting and evolving the scrum framework for process automation. This "agile automation" approach operates as a variant of scrum, with a few distinctive characteristics (exhibit).

- *Team structure.* Agile automation uses a flexible team or "pod" structure, which includes developers, testers, IT staff, and business stakeholders. Each pod is jointly led by a product owner, with expertise in the specific automation technology, and a subject-matter expert from the business, who provides essential business and domain knowledge.

- *Up-front design.* Agile automation involves an up-front effort that fully defines the process before development work begins in earnest. This work ensures that the automation project will integrate with the wider business and comply with regulatory requirements and other constraints. It also allows stakeholders in affected parts of the organization to prepare their people for coming change.

- *Trigger-driven stories.* To break the project down into addressable chunks, agile automation replaces conventional user stories with the concept of "trigger-driven stories." This process identifies a trigger event, such as the availability of certain data or a user action; it then defines the actions required in response to that event and the output to be produced. Using this approach allows teams to separate processes into manageable parts. Moreover, because the inputs and outcomes of each chunk are clearly defined, teams can work in parallel, accelerating development work.

- *Release management.* Agile automation decouples releases of prototype and production software. To minimize disruption to the wider organization, production releases are carried out on a controlled schedule that is tightly coordinated with the affected parts of the business. Prototypes are released more frequently into a dedicated test environment where their performance is evaluated on representative data sets.

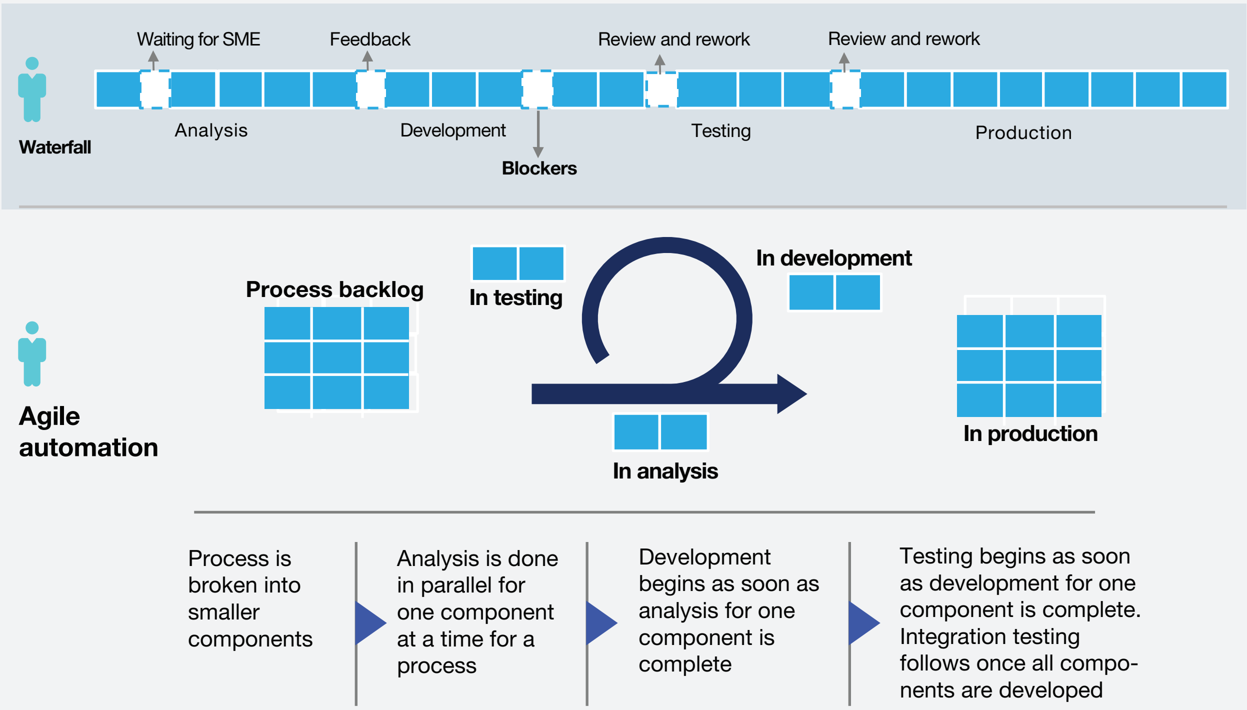
- *Program support.* Agile automation necessitates deep organizational change, as it requires companies to subject business-critical activities to unfamiliar technologies and new working methods—all at the same time. Especially in early stages, such efforts require significant support. Most organizations find it useful to establish a dedicated program office to provide expertise, establish good practices, and monitor the progress of the overall automation effort.

It is still early days for agile automation at scale, but the approach is already delivering encouraging results. After its early stumbles, the mining company we described above rebuilt its automation efforts using agile principles. Its second attempt to roll out the project went twice as fast as the first and saved around 5,000 employee hours in its first year, thereby paying back its cost in less than ten months.

Another company, this time in financial services, has built a large-scale agile capability to support its ambitious automation objectives. In a phased approach, the company first introduced agile techniques in its software-development teams. It then applied agile across teams to coordinate efforts

EXHIBIT

Agile automation breaks analysis, development, and testing into parallel phases.



and share best practices. Finally, the company persuaded its program leadership to adopt the approach as the standard for all automation efforts. Since the change, the company has seen project-delivery time fall by around 30 percent and costs by 15 to 20 percent across six different business lines.

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For large businesses, today's automation will reach its full potential only when it reaches full scale. A thoughtful application of agile concepts helps cut through the complexity for those willing to commit to change—not only in how they think about software, but in how they work every day. There's no time to wait. ◆

Federico Berruti is a partner in McKinsey's Toronto office, where **Geet Chandratre** is a digital specialist and **Zaid Rab** is a digital analyst.

Part

03

Understanding functional nuances

Photo credit: Getty images

How bots, algorithms, and artificial intelligence are reshaping the future of corporate support functions

Alexander Edlich, Fanny Ip, and Rob Whiteman

Industrial companies are discovering additional sources of value in applying advanced technology to general and administrative support functions. The results can be impressive for businesses that can adapt to the disruption of legacy systems.

As advanced industrial companies continue to grow, support functions are coming under more and more pressure to deliver value, manage complexity, and reduce cost. Many organizations have already tapped the potential of traditional levers such as centralization, offshoring, and outsourcing. To succeed, today's leaders are turning to digital solutions and automation to improve performance and reduce costs across finance, human resources, and IT.

As technologies such as robotic process automation (RPA) mature, an increasing amount of the work done by people will be transferred to bots and algorithms. Our experience shows that companies following a systematic approach to tech-enabled transformation can reap substantial efficiency gains in their general and administrative (G&A) functions. The resources freed up in this way can then be deployed in more valuable activities such as business counseling and scenario analysis. This article explores the value that can be created through tech enablement in administrative functions; looks at real-life examples from finance, HR, and IT; considers key success factors; and suggests how companies can make the best start on their transformation journeys.

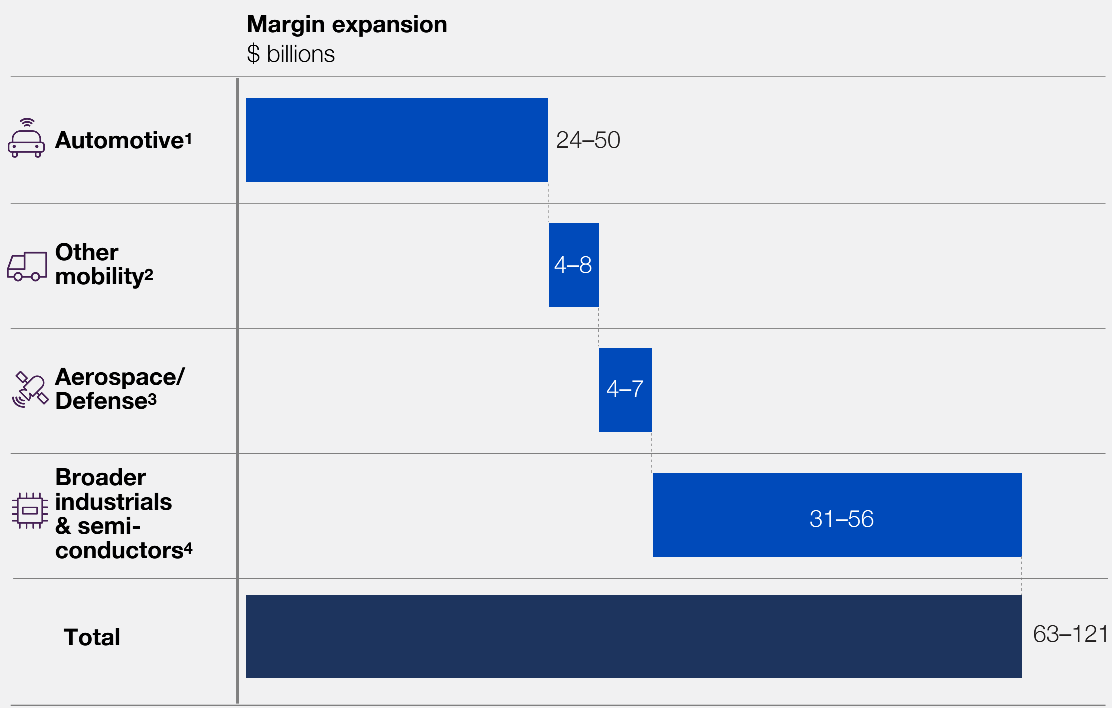
Sources of value

Today's better, faster, and cheaper technology is set to reshape support functions—and will do so without the years of pain often associated with traditional tech initiatives such as enterprise resource planning (ERP) systems. Early results in other industries show that companies can achieve 5 to 10 percent cost savings in as little as 18 to 24 months, with long-term savings of more than 30 percent.

Across the advanced industrial sector, the median spend on G&A expenses accounts for 4 to 8 percent of revenue. Our estimates indicate that the value that could be created from tech enablement is in the region of $60 billion to $120 billion globally, albeit with considerable variation between segments (Exhibit 1). Although the direct cost savings may appear small when compared with those in areas such as procurement or manufacturing, McKinsey analysis indicates that a company's ability to deliver productivity improvements in G&A is one of the biggest predictors of its ability to outperform its industry in total returns to shareholders. Approached in the right way, then, automating routine G&A tasks through a tech-enabled

EXHIBIT 1

The value from tech enablement in G&A activities varies by industry sub-segment.



[1] Whole value chain including tier 1 suppliers, automotive OEMs, and dealers.
[2] Commercial vehicles and off-highway equipment (e.g., for construction and agricultural use), including tier 1 suppliers, equipment manufacturers, and dealers and distributors.
[3] Includes tier 1 suppliers and equipment manufacturers.
[4] Includes industrials, food processing and handling, motion and controls, industrial automation, and electrical, power, and test equipment across the value chain: component suppliers, equipment manufacturers, distributors, VARs, engineering and services providers, and product companies.

transformation can deliver substantial impact to the whole organization.

Modernizing the finance function

At many organizations, the finance function is beginning to evolve toward a more integrated consultative model that supports value-based decision making. However, companies often have difficulty devoting enough attention to the analysis required to support this model because of the demands of day-to-day transactional activities. The sheer scale of these activities makes them ripe for automation: in fact, our analysis shows that 27 percent of finance activities could be automated using technologies already available (Exhibit 2).[1]

About a third of this opportunity could be captured using basic technologies such as RPA, a type of general-purpose software that can sit on top of existing IT systems. Capturing the remaining two-thirds of the opportunity requires advanced cognitive automation technologies such as machine learning algorithms and natural-language tools.

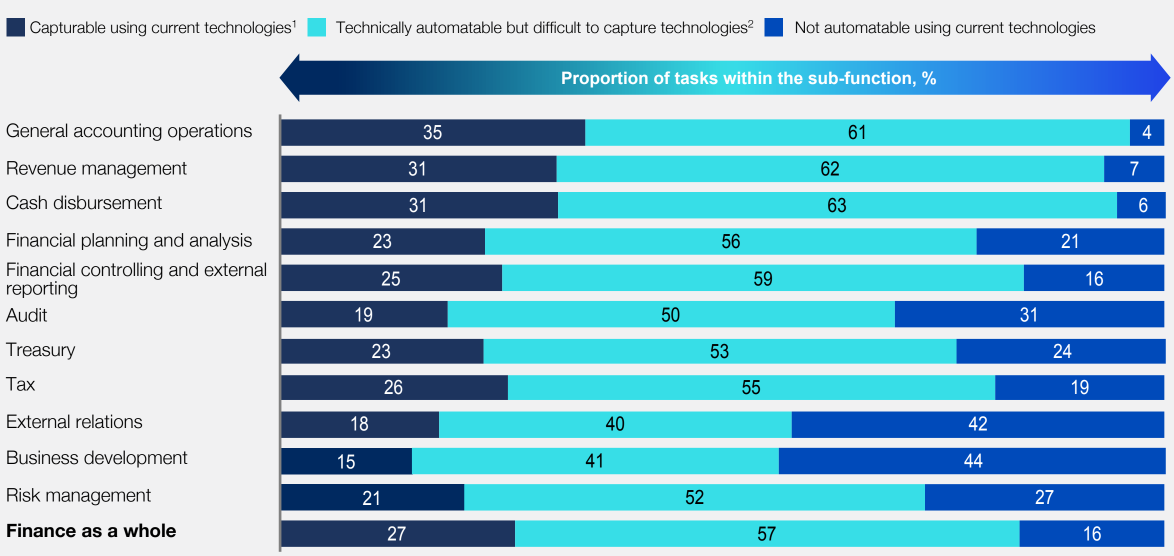
At one company that was trying to verify whether employees were reporting vacation time accurately, the internal audit function developed an algorithm that compared declared vacation days with data from badge swipes and computer-usage data. Another company reengineered every part of its record-to-report process by redesigning activities

[1] For details of the analysis, see Frank Plaschke, Ishaan Seth, and Rob Whiteman, “Bots, algorithms, and the future of the finance function,” January 2018, McKinsey.com.

EXHIBIT 2

Many sub-functions in finance can be automated using current technologies . . .

Potential for automation using proven technologies



[1] Taking into account the relative complexity and expense of different types of automation technology: robotic process automation, machine learning, smart workflows, cognitive agents, and natural-language processing.
[2] Because of investment requirements and technological complexity.

and organizational structures around a portfolio of technologies. Managers introduced RPA for tasks such as preparing journal entries and applied machine learning to reconcile differences between accounting records. Having demonstrated that natural-language tools could be successfully deployed to produce report commentary, the company has redesigned processes to enable this technology to be introduced later. Overall, the company expects to see cost savings of 35 percent over the next two years from implementing its automation road map.

As the finance function becomes the hub for enterprise data, automation efforts need not be limited to finance processes alone. One agricultural equipment manufacturer successfully automated its sales and operations planning process by turning a handful of data scientists loose on financial and operational data managed within the finance function. By introducing machine algorithms into the process, the company not only improved efficiency but also enhanced its ability to react to natural business cycles.

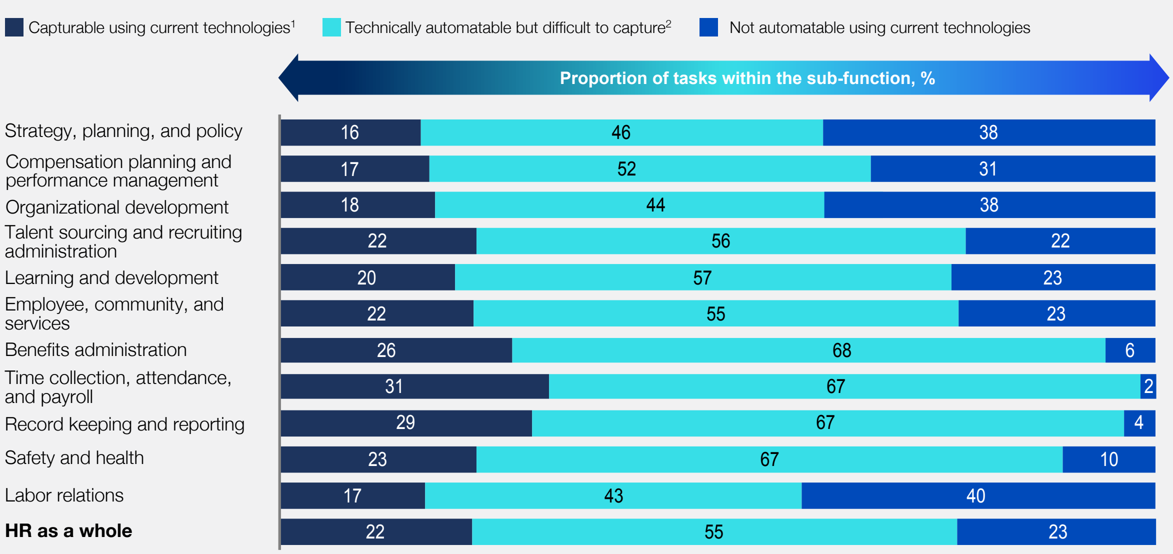
Optimizing workforce deployment (human resources)

As expectations evolve, HR needs a tech-enabled transformation of its own. The possibilities are legion (Exhibit 3). Bots can act as a "third arm" for the HR organization by supporting transactional activities such as time collection, payroll, and record keeping. Activities such as talent sourcing offer huge scope for algorithm-based technologies. Meanwhile, conversational artificial intelligence (AI) platforms such as chatbots and cognitive

EXHIBIT 3

. . . as can many sub-functions in HR . . .

Potential for automation using proven technologies



[1] Taking into account the relative complexity and expense of different types of automation technology: robotic process automation, machine learning, smart workflows, cognitive agents, and natural-language processing.
[2] Because of investment requirements and technological complexity.

agents are beginning to manage inquiries previously handled by HR service centers, including benefits administration and record-keeping activities. Such platforms provide 24/7 coverage and operate alongside the human workforce.

Finally, predictive analytics can be used to improve hiring, retention, and succession planning. One company undergoing a restructuring was trying to identify promising employees to lead its new organization, but found that HR and company data was scattered across the enterprise. Using machine learning capabilities, the company aggregated demographic, performance, and organizational data to pinpoint the key drivers of employee performance, identify the individuals with the greatest potential, and find roles in which they would succeed.

Leaders then transformed the recruiting process to focus on early markers of success and redeploy talent in new roles. These measures enabled the company to achieve improvements of 80 percent in the conversion of new recruits, 26 percent in productivity, and 14 percent in net income.

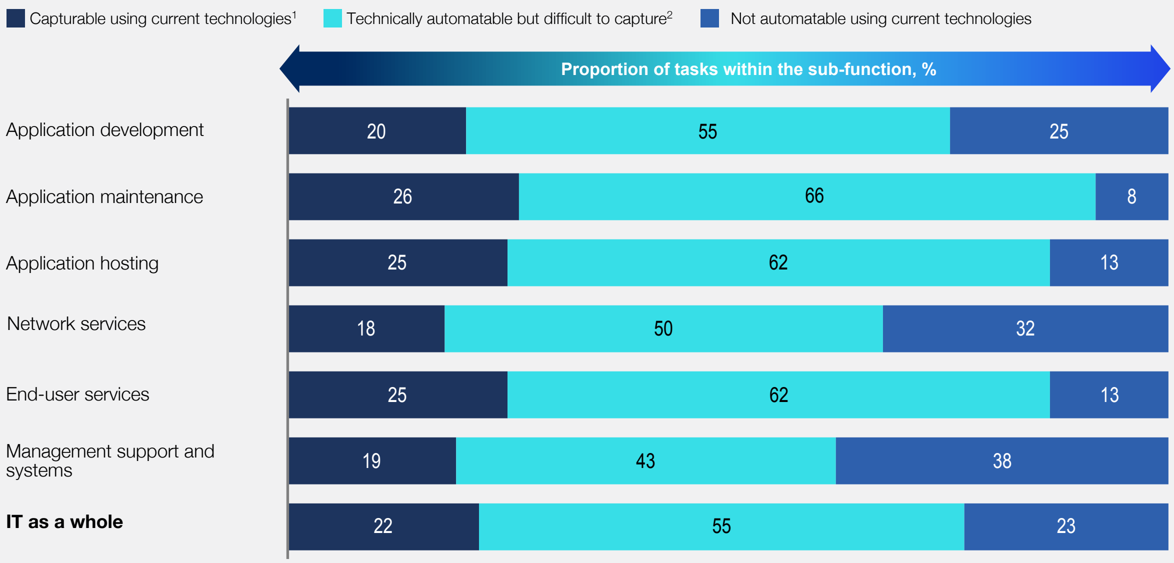
Building a scalable technology backbone

In addition to supporting the deployment of automation technologies in other functions, IT can take advantage of bots and algorithms in its own operations (Exhibit 4). Our analysis shows, for example, that 40 to 80 percent of the basic activities required to resolve service-desk tickets can be automated through RPA and related technologies.

EXHIBIT 4

. . . and many sub-functions in IT

Potential for automation using proven technologies



[1] Taking into account the relative complexity and expense of different types of automation technology: robotics process automation, machine learning, smart workflows, cognitive agents, and natural-language processing.
[2] Because of investment requirements and technological complexity.

When one company analyzed incident tickets, for instance, it found that between 25 and 35 percent of them were requests for "password reset" or "access." To resolve these tickets, it introduced RPA bots that connect with multiple applications via the user interface or application programming interfaces. By adopting automated ticket resolution, the company instantly freed up employee capacity and reduced outsourcing contract costs for help-desk support, as well as reducing resolution times and improving performance. Alternatively, service-desk automation tools exist that support automation of repeatable IT operations workflows such as user provisioning, password resets, and event log monitoring.

Similar use cases exist in areas such as application testing, data migration, and network administration. Automating transactional activities like these can enable IT to free up capital and resources to focus on strategic activities such as modernizing ERP platforms, migrating to the cloud, and developing new digital solutions for the business.

Lessons learned in capturing value

Even the most successful companies face challenges in capturing value from tech-enabled transformations. We have identified a few common keys to success from automation leaders' responses to our recent survey:

Make automation a strategic priority. Organizations whose automation efforts prove successful are more likely than others to have designated automation as a strategic priority.[2] Among advanced industrial companies, about three-quarters of successful automation programs had been prioritized as part of the strategic-planning process.

Deploy automation technologies systematically. Whether companies achieve success through traditional top-down deployment or flexible agile methods, following a systematic rather than ad hoc approach is vital. Our survey found robotic process automation to be the most commonly adopted automation technology. In addition, successful companies were more likely than others to cite the use of advanced technologies such as machine learning, cognitive agents, and natural-language processing to supplement RPA.

Decentralize governance. Traditional transformation efforts tend to follow centralized models, but technology-enablement programs favor decentralized options. In our survey, respondents from successful organizations were more likely than peers to say their functions or business units were accountable for delivering automation efforts, with or without support from a central team. Conversely, less successful organizations were more than twice as likely as successful ones to say a central team had sole responsibility for delivering automation.

Ensure IT is involved. Automation programs stand or fall by the engagement of the IT function. The IT teams at successful organizations are more likely to have automated their own processes and taken part in initial discussions and planning for automation projects prior to the pilot stage. Among advanced industrial companies, 69 percent of successful organizations involved IT early in the automation planning process.

Internalize costs and benefits. Leaders of successful efforts had a deep understanding of the total cost of ownership for automation projects. Across all programs, the most common benefit cited was reduced costs.

Prioritize workforce management. Many large organizations predict their companies will face automation-related skill gaps in the future; successful organizations make addressing this gap one of their top five priorities. They also agree that

[2] See "The automation imperative," on p. 56 of this collection.

acquiring employees with the right skills is their biggest automation-related challenge in the next three years.

How to get started

A tech-enabled G&A transformation journey typically involves three phases: start-up, launch, and scale.

Start-up

In this first phase, a company typically tackles:

Assessment and road map. To decide which sub-functions, processes, and locations will benefit most from tech-enabled transformation, start with a clear understanding of your organization and the activities it performs. Assess the potential for automation by combining top-down analysis with task-by-task validation, then use your findings to inform decisions about which technologies to invest in and where to deploy resources. Finally, translate all this into a road map to guide your program.

Proof of concept. To demonstrate feasibility and potential for impact, build a practical application such as a simple bot or algorithm in weeks, not months. This gives you early experience with technology and a chance to create presentations, videos, and other communications to generate excitement for your broader program.

Vendor selection. Selecting the right technologies to support your transformation is a balancing act between maintaining a simple architecture and maximizing impact. Most companies start with an RPA platform and add complementary technologies such as business-process management or optical character recognition within the first three to six months. More complex automation tools, such as natural-language processing, are typically added after about a year. Emerging technologies, such as cognitive agents, are usually confined to pilots during the early stages of a transformation.

Launch

Areas of focus in the launch phase usually include:

Domain sprints. Companies typically build solutions through multiple rapid, intense working sessions or sprints. A sprint usually consists of five or six use cases relating to a specific "domain": a sub-function, process, or location. Sprints employ agile methods and follow standard IT phases, from preparation and design through to build, test, and refine.

IT support. Even when sprints are led by other functions, involving IT early is critical to securing the right infrastructure and environment and standardizing processes for deployment and maintenance. Successful leaders establish clear lines of accountability between functions, automation resources, and IT support groups to avoid confusion.

Center of excellence (CoE). Most companies choose to set up a tech-enablement CoE to provide governance, build capabilities, and maintain assets. This will typically follow a centralized model initially, with some development capacity embedded in functions, before moving to a federated model as the transformation matures.

Scale

In the last phase, transformations typically complete:

Additional sprints. Once you have conducted a few sprints, it's time to scale up systematically and rapidly deploy technologies in further sprints. As each new process is deployed, maintenance and support teams can resolve issues and manage changes while continuing to refine their support model.

CoE scale-up. The speed at which you scale up your CoE depends on the number of opportunities in your pipeline. As your program scales, the CoE's interaction model with other teams will evolve to shift more responsibilities to the business, and in turn the business will start to undergo a culture shift with employees, in which they begin seeing technology as a source of support, not competition. Ongoing capability-building and change-management efforts will help to build support for the new way of working.

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Fueled by the promise of productivity gains, technology-enabled transformations are beginning to reshape the future of work in support functions. Bots and algorithms are already at work alongside humans, but adapting to the disruption can be challenging, even for an industry familiar with physical automation. Even so, advanced industries are well positioned to capitalize on lessons from other industries that are further ahead in the journey, such as banking, while capitalizing on internal capabilities already embedded in the organization, such as lean. ◆

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Photo credit/Getty Images

A CIO plan for becoming a leader in intelligent process automation

Sanjay Kaniyar, Kapil Bhushan Srivastava, and Ross Tisnovsky

By demonstrating how to automate IT operations first, IT leaders can showcase the expertise needed to lead the business's overall IPA transformation.

Intelligent process automation (IPA)—a set of technologies that combines process redesign, process automation, and machine learning—is rapidly reshaping the global economy, with significant gains for organizations that adopt it at scale. As an earlier McKinsey article[1] explains, some companies across industries have already been able to automate 50 to 70 percent of tasks, with return on investment generally in triple-digit percentages. While people often focus on the cost savings, IPA also provides significant other benefits, including speed, precision, and improved customer service.

But for companies to get the full value of IPA, IT will need to play a leading role. The track record of early adopters clearly demonstrates that IPA projects carried out without the active participation of IT are likely to fail. For CIOs to play a guiding role in IPA, they need to develop a core of expertise and experience developed by implementing IPA programs within IT. And it's important to do so quickly. If CIOs don't support automation across the company, then business executives will start building their own shadow IT organizations or working with external vendors.

[1] Federico Berruti, Graeme Nixon, Giambattista Taglioni, and Rob Whiteman, "Intelligent process automation: The engine at the core of the next-generation operating model," March 2017, McKinsey.com.

However, many IT executives struggle with successfully implementing IPA processes. The most frequently stated reasons are:

- The higher complexity of IT compared to a business process
- Difficulty in understanding the economics of IPA and a lack of clarity on how to best capture the benefits
- Inconsistent and fragmented tools that make IPA hard to scale
- The misconception that IPA is an advanced lever requiring massive process reengineering before embarking on an automation journey

How can CIOs succeed? We have found that there are four key steps on the IPA journey that need to be mastered.

Step 1: Assess the value potential at a high level

The key to developing a clear business case starts with assessing the value potential of the main IT activities by tower (Exhibit 1).

A closer look reveals what some of these pockets of value are[2]:

1. *Responding to incidents and user requests.* A large proportion of incidents originate through a help-desk request, resulting in the creation of a ticket with "low difficulty," level 1. However, while many tickets are resolved in this way, a significant proportion of tickets escalate to more complex level-2 or -3 tickets and are passed on to more specialized IT teams. Most of those ticket types become "trouble tickets" and are costly for IT to address. Since this activity is so well documented, categorizing and sorting them by automation potential provides a reliable assessment of the benefits. For example, tallying all password-reset requests from the previous year and multiplying them by average handling time (AHT) provides a clear indicator of the size of the prize for this year, provided there have been no dramatic changes to IT.
2. *Conducting planned activities.* Planned activities vary significantly in scope and nature, ranging from simple tasks such as backups or patching to more complex security audits, upgrades, and so on. The effort required to perform these activities can collectively add up quickly to about 20 percent of IT spend.
3. *Delivering new applications.* As far as the business is concerned, these activities represent the largest source of IT value and can account for another 20 to 40 percent of IT effort. This is not just limited to application development but includes testing and hosting, demanding the efforts of both application and infrastructure groups.

Note that automation is equally effective for outsourced or subcontracted activities.

Step 2: Drill down to specifics to understand which use cases are best suited for implementing IPA

How to implement IPA can vary significantly across identified activities and often requires digging into root causes for issues, untangling complex systems, and developing a clear understanding of how to approach implementing IPA to get the value. In some cases, we've seen businesses use specific IPA tactics to help unlock the necessary insights.

Responding to incidents

Understanding how to go about automating incidents starts with identifying which of them are most

[2] While a large proportion of the IT budget may be spent on purchasing hardware, software, and network bandwidth, little of that can be automated.

EXHIBIT 1 **In spite of complexity of IT, more than 70 percent of enterprise IT spend can be targeted with automation.**

Incidents, planned activities, and application delivery are suitable for automation.

IT spend by activity type

Cost baseline	IT spend (100%[1])	Incidents ~35%	Planned activities ~20%	Application delivery ~20%	Hardware and software spend
Application development	20%	~0%	~5% (e.g., security audits)	~80% (e.g., develop-ment projects)	10-20% (e.g., SW licenses)
Application maintenance	30%	50-70% (e.g., bug-fix requests)	20-30% (e.g., source code management)	~5%	~10% (e.g., vendor maintenance)
Data center	25%	30-40% (e.g., level-2 escalations)	~20% (e.g., backup/ restore)	20-40% (e.g., provisioning, hosting)	20-30% (e.g., hardware,)
End-user services	10%	50-60% (e.g., level-1 help-desk calls)	20-30% (e.g., patching)	~0%	~30% (e.g., end-user devices)
Telecom	10%	20-30% (e.g., NOC alerts)	10-20% (e.g., capacity management)	~0%	~60% (e.g., bandwidth)
M&O[2]	5%	~0%	~100%	~0%	~0%
					Not in scope of automation

[1] Typical IT cost breakdown is based on a peer set of industrials (e.g., manufacturing, CPG); actual breakdown may vary significantly.
[2] M&O – management and overhead

Source: Team analyses with McKinsey Digital 20/20 automation and productivity diagnostic

suited to automation, which can be challenging. While incidents are well documented, they are also numerous—a large IT organization can easily generate a million tickets a year—and the root cause of each is often not readily apparent. "I don't receive emails" does not necessarily indicate an email-program issue; it may simply mean "I lost my password." Often businesses will try to automate incident responses without being clear about the "why," resulting in poor outcomes.

Specific text-mining tools that read ticket descriptions in detail and derive the necessary insights can address these complexities. Using this approach, we have been able to define around 50 different ticket types and divide them into IPA categories:

- Automatable
- Requires machine learning
- Highly cognitive/manual

As an example, 80 percent of "reset password" incidents can be automated (Exhibit 2).

The output of this analysis should be a prioritized list of incidents to automate and which IPA element to use for each.

Conducting planned activities

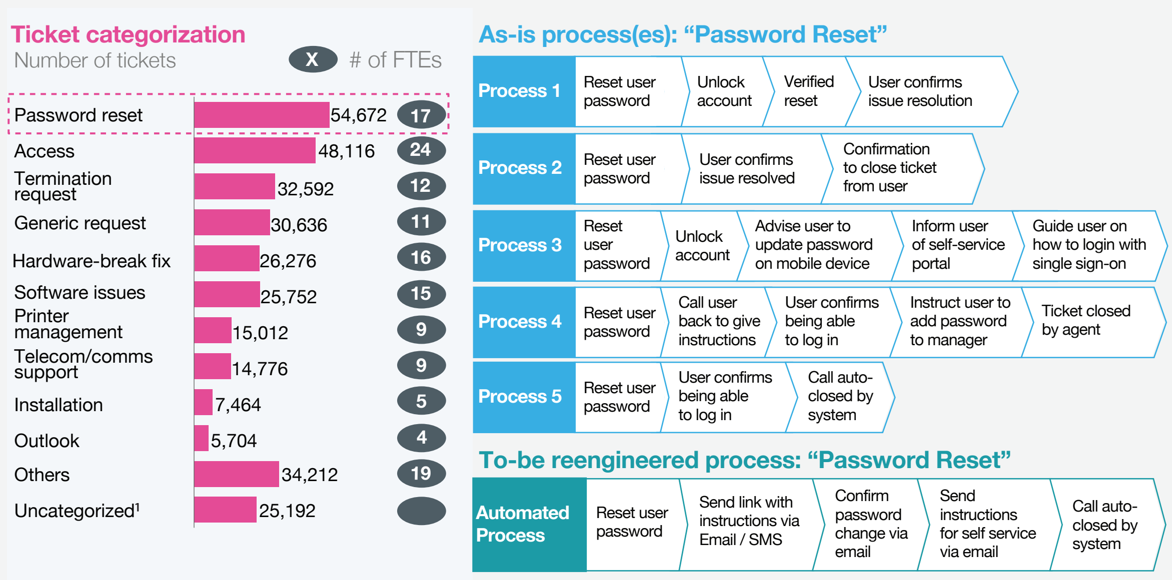
While most IT groups have industry-standard tools for infrastructure management, we have seen that the complexity of configurations means that IT isn't getting as much value from them as they should. A high degree of customization, adjustments because of mergers, and specific user requirements mean that significant manual labor is required to manage the systems.

For example, despite the broad usage of application-monitoring tools (like Prometheus) and infrastructure-monitoring tools (like Zabbix), application support teams are often unable to act quickly and effectively on the logs generated because there are often too many of them, generated for a variety of reasons. The result is companies aren't clear about how to go about implementing IPA.

In this case, a machine learning bot can help make sense of the complexity because it can be trained to learn the reasons behind a given alert and then

EXHIBIT 2

80 percent of "reset password" incidents can be automated.



[1] Tickets not categorized due to insufficient description.

Source: Team analyses with McKinsey Digital 20/20 automation and productivity diagnostic recommend—or even make—better decisions about what action to take (Exhibit 3).

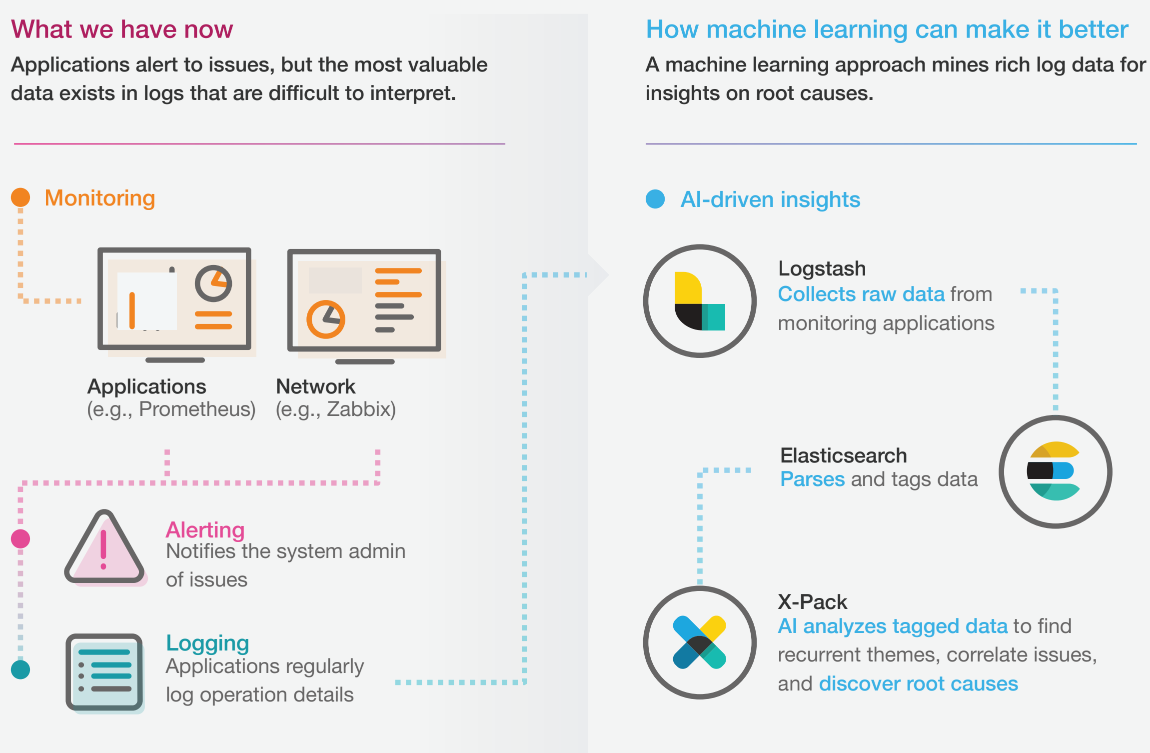
Delivering new applications

However, many CIOs fall into the trap of simply focusing on reducing manual labor, which limits the full value potential of IPA. More accurate and faster application delivery requires designing a new IT operating model, with an emphasis on agile and DevOps. Reviewing the entire process to understand how to make most effective use of agile and DevOps can lead to completely different approaches and ways of working. Some of those new ways of working can be enabled by IPA. Automating testing, for example, allows teams to iterate more quickly; creating a self-serve model for automated server provisioning allows operations to be more responsive.

One major US life insurer approached this issue by developing a phased strategy for IT infrastructure automation. It started with developing a DevOps model for how infrastructure and operations teams could work together. The team then cooperated on building out a comprehensive IPA program supported by a relevant set of application programming interfaces (APIs) that enabled the team to access varied sources of data. As it learned how to manage this approach, it migrated relevant parts of the infrastructure to the cloud to increase flexibility. The result of this effort was that the infrastructure organization, which originally consisted of around 1,400 full-time employees (FTEs), was reduced to about 800 FTEs, while build and implementation speeds increased significantly, even as errors were reduced.

EXHIBIT 3

How machine learning can get the most out of what you already have.



Step 3: Execute a proof of concept

To prove the value is real and validate the business case, the next step for a CIO is to greenlight a proof of concept. A good place to focus that is on incident processing. Companies that have implemented IPA for incident processing have been able to show cost savings of up to 30 percent. Thankfully, there are many work efforts (tickets) that can quickly be automated to serve as a proof of concept, such as incidents that are essentially a front end for already-automated processes based on mature APIs and tools (password reset, setting up access for a new employee, ordering new equipment, and so on).

In its simplest form, a proof of concept requires:

- Workshops with appropriate IT subject-matter experts (SMEs) to understand all the steps and systems involved in a given process. This helps to identify where IPA can best be applied.

- The thoughtful selection of an IPA platform. This decision has significant implications because platform capabilities, ambitions, and service providers vary, in some cases significantly. Some IPA platforms, for example, provide better integration capabilities, such as APIs that tie into existing systems. Others offer prepackaged or customizable bots, while some platforms are moving to provide AI capabilities even as others remain focused on process automation.

- Obtaining the necessary approvals from IT (security guidelines, for example) and the business (access limitations and regulatory constraints)

- Programming the bot(s) using iterative design techniques to ensure speed, accuracy, and scalability. At least one engineer needs to be assigned to manage the extensive testing that is a core element of the iterative design to ensure that the bot learns and adjusts based on live feedback.

- Ongoing monitoring to document the results and ensure value capture

It is also useful to think of a pilot as a kickoff for internal IPA capability building—for example, by using a blend of internal and external developers to jump-start a future center of excellence (CoE). The team should become the home and engine of IPA learning.

Step 4: Build IPA capabilities to scale

Realizing the full potential of IPA in IT requires a focus on building specific skills and capabilities, as well as adapting the new culture of the organization to eventually embed IPA at the heart of the IT organization.

Typically, we see the most successful companies do three things.

1. Ramp up the success to new areas of IT

At this stage, the team is likely to move beyond basic help-desk level 0/1 incidents and pursue the automation of more advanced level-2 and level-3 tickets. The team should also expand beyond incidents and begin working on using IPA for monitoring, dashboarding, and analytics, moving from the help desk to the data center, the network, and even application-maintenance organizations. The long-term success of the automation program is contingent on how quickly the IPA bots are adopted within the IT organization. That depends on how effective leadership is in providing dedicated training and ongoing support, as well as building up a network of internal "reference cases." The goal is to build on the successes to find new and more advanced use cases and opportunities within IT (as a precursor for generating demand across the wider organization). Providing incentives for IT employees in the form of bonus payments or recognition in competitions can be effective.

At this point, the CIO needs to invest in capabilities that support scale, such as risk management and IT infrastructure management. These are different from those capabilities needed for pilots, which focus on getting the technology right, demonstrating value, convincing nonbelievers, and so on. Leaders sometimes mix up up the two and underestimate what's most important about each.

2. Get the word out

With a solid foundation of experience and capabilities in place, the CIO can begin to actively position him- or herself as both an advisor and enabler for the rest of the business. In practice, that means reaching out to leaders across various functions to inform them about the specific benefits of IPA, understanding their priorities and how to best implement and support the technologies, and identifying potential security issues through bots.

IPA is by its nature disruptive. A CIO should have a clear sense of when IPA technologies will augment or replace human workers and put in place a program of clear communications and activities for each outcome.

3. Explore advanced elements of IPA

While most IT organizations have focused on simple process automation (and to a lesser extent, machine learning and natural-language processing), the future belongs to artificial intelligence (AI) and cognitive learning, which have the potential to manage complex IT tasks. Although still somewhat futuristic, the solutions are already emerging, and we expect them to rapidly mature over the next several years. But it takes time to build up the skills and experience needed to use AI effectively, in part because there is still a lot of confusion about what AI actually is. The only way to overcome that confusion is to start working on AI projects. Companies that are building up expertise in this area are developing data lakes, creating meaningful tags for that data, and then dedicating engineers to build and train algorithms to act on that data.

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IPA is rapidly maturing and becoming a core part of the landscape of IT organizations. CIOs who understand how to build up their IPA capabilities can become not just enablers but leaders in this shift. ◆

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