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A report from the Deloitte Center for Government Insights

How much time and money can AI save government?

Cognitive technologies could free up hundreds of millions of public sector worker hours

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Introduction

AI-based technology brings both optimism and anxiety

All kinds of institutions today run on data, and that means endless staff hours spent inputting, processing, and communicating. The work needs to get done, so *someone* has to spend that time pecking away at a keyboard, right?

THE promise of reducing—or even eliminating—all that drudge work is one reason why many managers are enthusiastic about new applications based on artificial intelligence (AI). Finally, staff resources could be freed up to do *real* work, with people having time to focus on creative projects and deal directly with clients and customers.

But of course, there's no guarantee that any new labor-saving technology will make everyone's daily lives more rewarding rather than simply wiping out entire categories of employment.[1] And that's why AI applications make plenty of people anxious as well, especially since cognitive technologies are increasingly capable of carrying out tasks once reserved for knowledge workers.[2]

> There's no guarantee that any new labor-saving technology will make everyone's daily lives more rewarding rather than simply wiping out entire categories of employment.

Technology, from farm equipment to factory robots to voice mail, has *always* displaced low-skilled workers. But only recently has it threatened white-collar professionals' positions: Computer scientists are building machines capable of carrying out almost any task, even those—such as composing music—seemingly at the core of our humanity.[3] Knowledge workers, whose jobs once seemed secure, are feeling directly threatened for the first time.

So there's a blend of anticipation and dread within a wide range of organizations and industries—and public sector agencies are no exception.[4] Conversations with government executives suggest that most lack a clear vision of how AI applications might affect their staff and missions, which is understandable, since prior research hardly offers an actionable forecast. The US Bureau of Labor Statistics optimistically predicts that government workforces will see almost no job losses between now and 2024,[5] while a recent study by Deloitte UK and Oxford University suggests that up to 18 percent of UK public sector jobs could be automated by 2030.[6]

We've attempted to bring clarity to the confusion, for agency chiefs looking to future workforce needs.

Our view is that the key to planning ahead is understanding how much time cognitive technologies could save. And indeed, our research, based on a new method for studying AI-based technology's effects on government workforces, indicates that cognitive technologies could free up large numbers of labor hours by automating certain tasks and allowing managers to shift employees to tasks requiring human judgment.

These new applications could save hundreds of millions of staff hours and *billions* of dollars annually. But the shift's size and impact will depend on many factors, some political and some financial. With adequate investment and support, we believe, AI could

free up *30 percent* of the government workforce's time within five to seven years. Lower levels of investment and support would yield lower savings, of course: Minimal investment in AI would result in savings of just 2 to 4 percent of total labor time.

Breaking government work into tasks to clarify AI's effects

YOU need to know where you are before you can decide where you're going; this truism certainly applies to predicting the effects of AI on government work. Most existing quantitative models begin by tallying workers by occupation and predicting which jobs will be replaced by technology. In other words, they rely on *occupations* as the unit of analysis.[7]

But we know from a long history with these issues that technology typically doesn't replace jobs wholesale, at least at first.[8] Instead, it often substitutes for specific tasks, while the workers who previously performed them shift to jobs complementary to the new technology. Over time, technology often results in a complete rethinking of what organizations produce and what the goal of that production is. Recent history shows this pattern has also been true for government work (see sidebar, "How cartography went digital").

Deloitte has developed a new methodology for measuring the amount of time government workers spend on the tasks that fill up their work days. We believe we're the first to quantify government work at the task level. The appendix explains details of our method.

HOW CARTOGRAPHY WENT DIGITAL

The US Geological Survey (USGS) began producing topographic maps of the nation in 1879,[9] and for most of its history, it printed its maps on paper. If you were an active hiker or camper in the 1980s, you'll likely remember shelves and shelves of USGS topo maps at outdoor stores, but over the following decade, USGS transformed its mapmaking techniques by embracing digital map production. This transformation, which relied on a major Reagan-era investment in geospatial information systems technology, was disruptive *and* productive. It significantly improved the efficiency of production—and *completely* changed the nature of cartographers' jobs.[10]

Before the transformation, USGS cartographers worked as skilled craftsmen, performing painstaking tasks such as drawing elevation contours on acetate sheets. Today, their duties primarily involve collecting and disseminating digital cartographic data through the National Map program.[11]

Today, USGS officials recall a bumpy transformation. Veteran cartographer Laurence Moore says, "We were slow to appreciate how fundamentally GPS and digital map data would change the world, and tended to think of these technologies as just tools to produce traditional maps faster and cheaper."

Today, the agency employs only a tenth of the cartographers working there at the peak of the paper-map production era. But paradoxically, the total number of cartographers and photogrammetrists employed by federal, state, and local governments has risen by 84 percent since 1999.[12] And the Bureau of Labor Statistics forecasts a 29 percent growth in employment for cartographers and photogrammetrists through 2024, largely due to "increasing use of maps for government planning."[13]

For this article, we've applied this method to the federal civilian workforce and to the workforce of a large, representative Midwestern state (figure 1). The state was chosen due to the similarity of its workforce to many other state governments and because it provides detailed open workforce data through cutting-edge transparency. We expect patterns we find in this state to be broadly applicable to a number of others.

Figure 1. Federal civilian and state government workforces at a glance

	Federal civilian workforce	Representative state government workforce
2016 employment	2.067 million	58,837
2016 salary and wages	$168 billion	$2.4 billion
Top three occupations by employment	1. Miscellaneous administration and program officers (98,405) 2. Information technology management officers (82,969) 3. Nurses (82,875)	1. Corrections officers (7,077) 2. Administrative staff (2,983) 3. Therapeutic program workers (2,608)

Sources: Deloitte analysis of Office of Personnel Management Fedscope March 2016 employment data. Note: Federal and state data include both full- and part-time employees.

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What do government workers do all day?

SO how *do* government workers spend their time? We estimate that the two workforces collectively work 4.3 billion (federal) and 108 million (state government) hours a year. We group the tasks they perform into "generalized work activities," using the US Department of Labor's (DOL's) O*NET activity framework.[14]

For both federal and state workers, by far the most time-consuming activity is *documenting and recording information*, a task capturing 10 percent of both federal and state government work hours. And while a few workers undoubtedly love documentation for its own sake, for most this activity surely isn't the most rewarding part of the day.

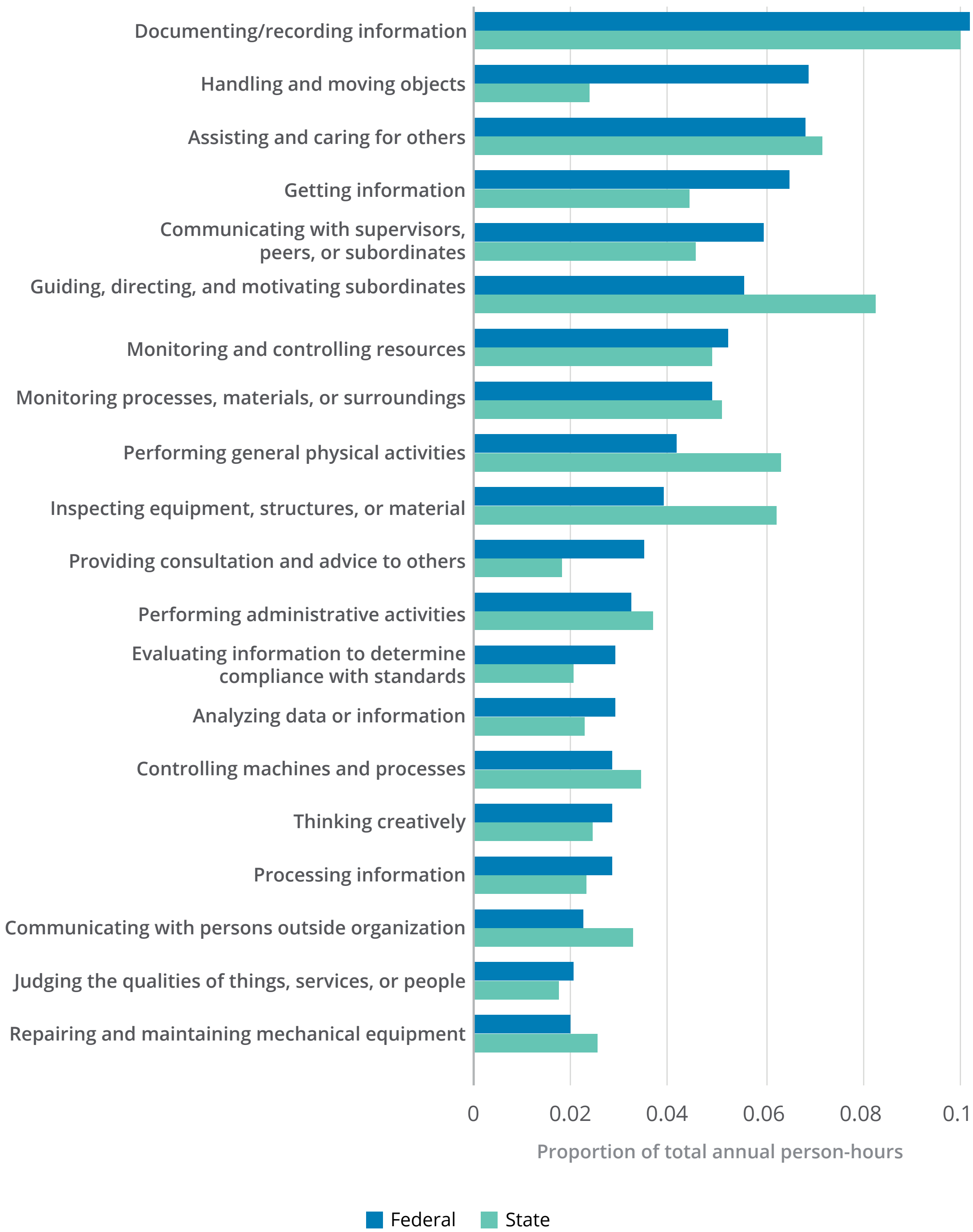
For both federal and state workers, by far the most time-consuming activity is *documenting and recording information*, a task capturing 10 percent of both federal and state government work hours.

Few observers will be surprised to find that paperwork can get in the way of government workers' more critical functions[15]—just think of, for instance, all the times you've seen TV police officers groan over having to write and file lengthy reports. But the amount of time devoted to seemingly peripheral activities is sobering.

A quick glance at figure 2, unsurprisingly, shows several tasks that might be highly amenable to automation. Now consider figure 3: the five most labor-intensive activities performed by the federal workforce, and their suitability for automation.

AI-based applications can almost certainly improve some activities, such as filling out forms or moving objects. For others, such as caring for patients, cognitive technologies aren't ready to replace people. (The appendix describes how we rank activities for their automation potential.)

Figure 2. A year in the life of the government workforce, federal vs. a Midwestern state



Source: Deloitte analysis of Office of Personnel Management Fedscope, state government workforce, and O*NET data.

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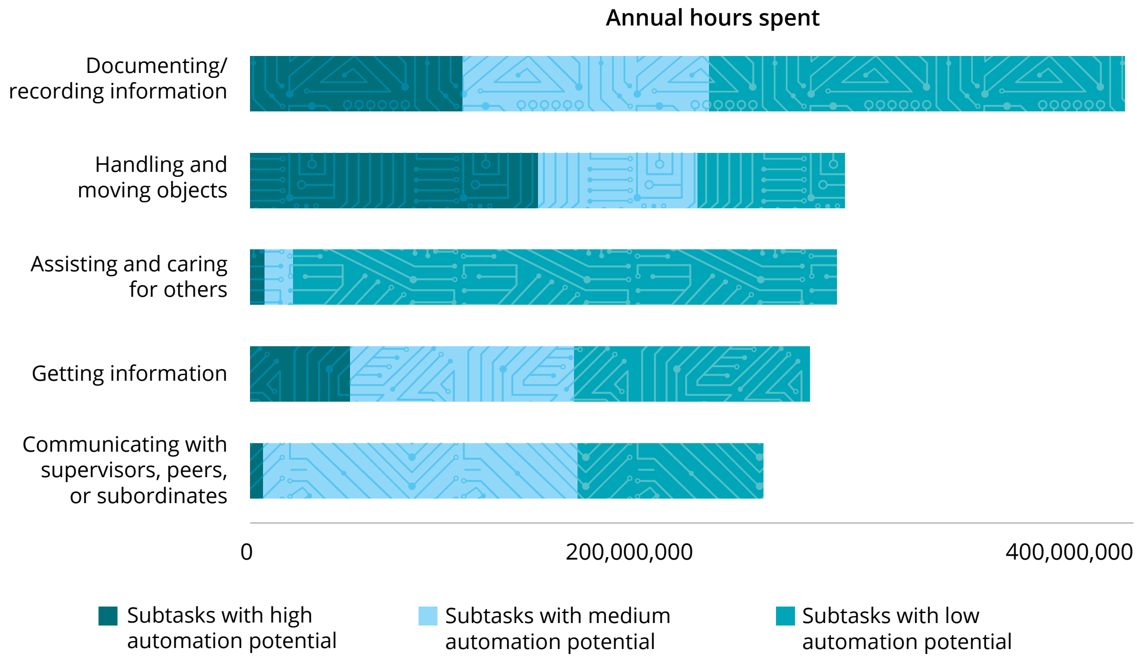
Figure 3. Automation potential of subtasks within the five most labor-intensive federal activities



Source: Deloitte analysis of OPM Fedscope and DOL O*NET data.

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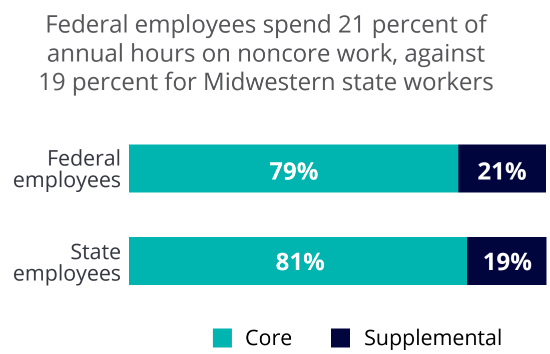
Government employees spend a day a week on "supplemental" tasks

We estimate that federal and state workers spend *at least* 20 percent of their time on tasks they consider unimportant (figure 4).[16] It's a low-end estimate based on the DOL's restrictive definition of "supplemental" tasks. If you asked government workers directly, they might give you a much higher figure.

Figure 4. Government workers spend 20 percent of their time on noncore tasks



Source: Deloitte analysis of O*NET and federal and state workforce data.

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Activities most likely to be automated

"SUPPLEMENTAL tasks" is a very broad description, of course, and can mean different things in different contexts. As agency executives consider incorporating AI-based technology into their work, where should they begin?

Just because a task *can* be automated doesn't mean it will or should be anytime soon. Several factors tend to influence which tasks are both most conducive to automation and most *likely* to be automated. We've identified these from our research on 13-year trends in work activities as well as the widely accepted findings of labor market economists.

The factors are *task importance, skill requirements, work volume*, and *technological barriers*. We examine each below.

1. Peripheral tasks

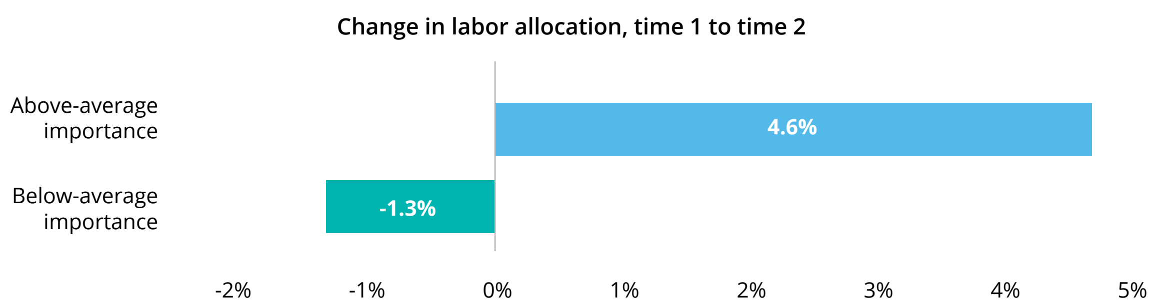
It would be logical to assume that industries would automate their most important tasks first, to gain the maximum benefit from technology's cost-effectiveness and reliability. The opposite is often true, however—automation usually begins with unimportant tasks or, at least, those perceived as unimportant.

The same is true for work activities. We studied 13 years of changes to the length of time spent on individual tasks, using data from the DOL O*NET database. Over the study period, tasks considered less important consumed less and less time, implying some degree of technological substitution (figure 5).

In our data set, tasks with above-average importance gained labor inputs by 4.6 percent, while tasks with below-average importance lost labor inputs by 1.3 percent. A task's importance correlated positively and significantly (rho = .09, $p < .0001$) with a change in the amount of time spent on it.

Thus, we can comfortably expect that agencies will look to begin integration of AI-based technology with tasks considered less important.

Figure 5. Peripheral tasks and declining labor inputs, 2003–16



Source: Deloitte analysis of O*NET database, 13,356 pairs of tasks observed at two different years between 2003 and 2016.

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2. Middle-skilled tasks

A task's skill requirements also affect its likelihood of automation. In employment settings, "middle-level" skills generally refer to positions requiring education beyond high school but less than a four-year college degree. More broadly, one author has defined middle-level tasks as "cognitive or manual in nature and requir[ing] one to follow precise procedures."[17] In government, various clerking positions provide good examples.

In the future tasks requiring middle-skill levels will likely be automated sooner, on average, than both high- and low-skill tasks. Many low-skilled tasks have already been replaced by previous waves of automation, and those yet to be automated may pose some barrier to automation (such as requiring a worker to navigate an unpredictable physical environment), or wages may be so low as not to justify investing in automation technology.[18]

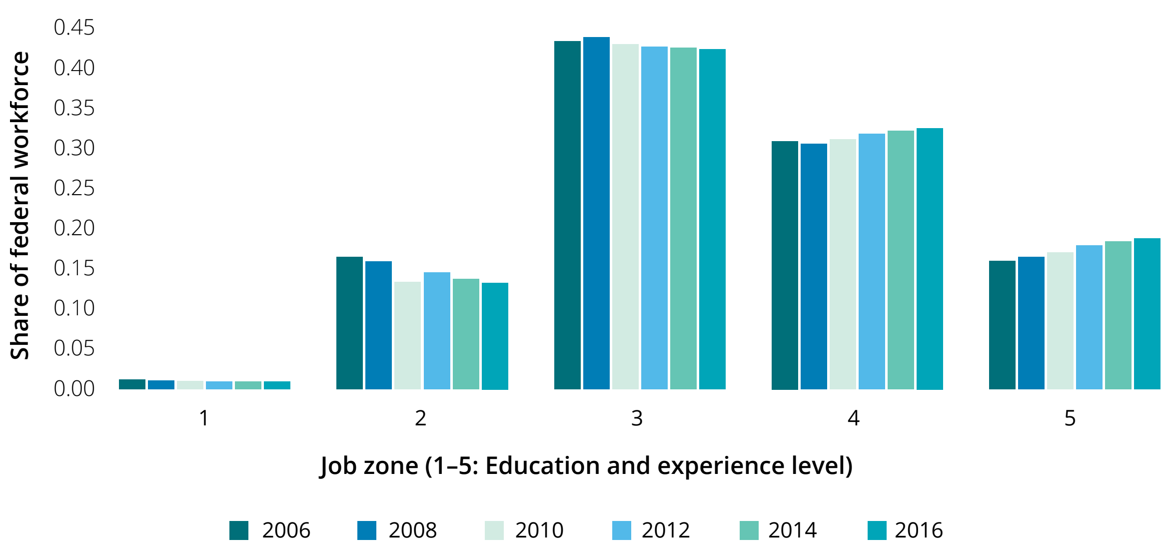
It may seem counterintuitive, but this tendency to hollow out the middle of the labor market first is a well-known characteristic of technological change. Multiple studies have demonstrated how well it explains historical trends in employment and wages.[19] These tasks are the easiest targets for technological replacement because enough people perform them (providing enough "volume") and the wages paid are high enough to justify investing in the technology.

American labor market economists usually highlight skills-biased technological change by showing that employment for high-skilled workers has risen rapidly over time, while the middle-skilled workforce has shed jobs.[20] And as middle-skilled workers lose jobs, they're forced to compete for lower-skilled jobs, driving down wages.

Employment trends in government jobs follow the pattern you'd expect for skills-biased technological change. In the past decade, middle-skill government employment fell while high-skilled employment rose (figure 6).

Figure 6 shows 10 years of federal jobs data broken into five skill levels, using the DOL's formula for "job zones." The share of federal workers in higher-skilled jobs (job zones 4 and 5) rose in every year of the study period, while middle-skill employment (zones 2 and 3) shrank. Many of the jobs lost in government were positions such as clerks or administrative professionals. Though considered white-collar work, the tasks involved were routine enough to allow them to be automated by what Tom

Figure 6. Higher-skilled workers gain share in the federal workforce



Source: Deloitte analysis of O*NET and OPM Fedscope data.

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AUTOMATING MIDDLE-SKILL TASKS TO SPEED UP CIRCUIT TESTING

In 2016, the US Army Research Labs (ARL) automated testing of electronic silicon wafers used in military radios and cellphones (figure 7). Testing circuits is critical to making sure that soldiers' communication equipment functions properly, but the testing process was time-consuming and dull, requiring mid-level skills (such as those possessed by engineering graduate students) and painstaking attention to detail. Testing was viewed as a bottleneck in the production process, and delays encouraged ARL to automate the testing tasks.[23]

ARL developed an automated probe that can test the circuits imprinted on the wafers, freeing up the engineers to focus on core responsibilities. "Those core responsibilities such as forming hypotheses and designing experiments to test them, or designing systems using input from the data analysis, are much more difficult to perform and require high skill and creative intelligence," in the words of ARL scientist Ryan Rudy. Automation has sped up testing time by a multiple of 60. Previously, an ARL intern might test 10 percent of one silicon wafer in three months; after automation, an entire wafer can be tested in two weeks.

Davenport and Julia Kirby call the second era of automation—when computers take over the "dull jobs."[21]

Since overall government employment trends follow skills-biased trends, we expect similar trends at the task level, determining which government tasks will be replaced sooner than others.[22] (See sidebar "Automating middle-skill tasks to speed up circuit testing" for a discussion of how Army Research Labs is automating middle-skill tasks to free up scientists for higher-level work.)

3. High-volume tasks

A third factor determining where AI investments may be most effective is volume of business. Decades of economic research support the idea that industries with more business volume are better able to invest in expensive labor-saving technologies.[24]

The *volume* concept can help guide government executives in targeting AI investments. Since we can break government work into activities and estimate how many hours are spent on each, we can identify time-consuming tasks with high potential for automation—a useful tool for government agencies directing precious investment funds.

Figure 7. Testing silicon wafer circuits for military radios at Army Research Labs

Pictures used with permission of ARL.

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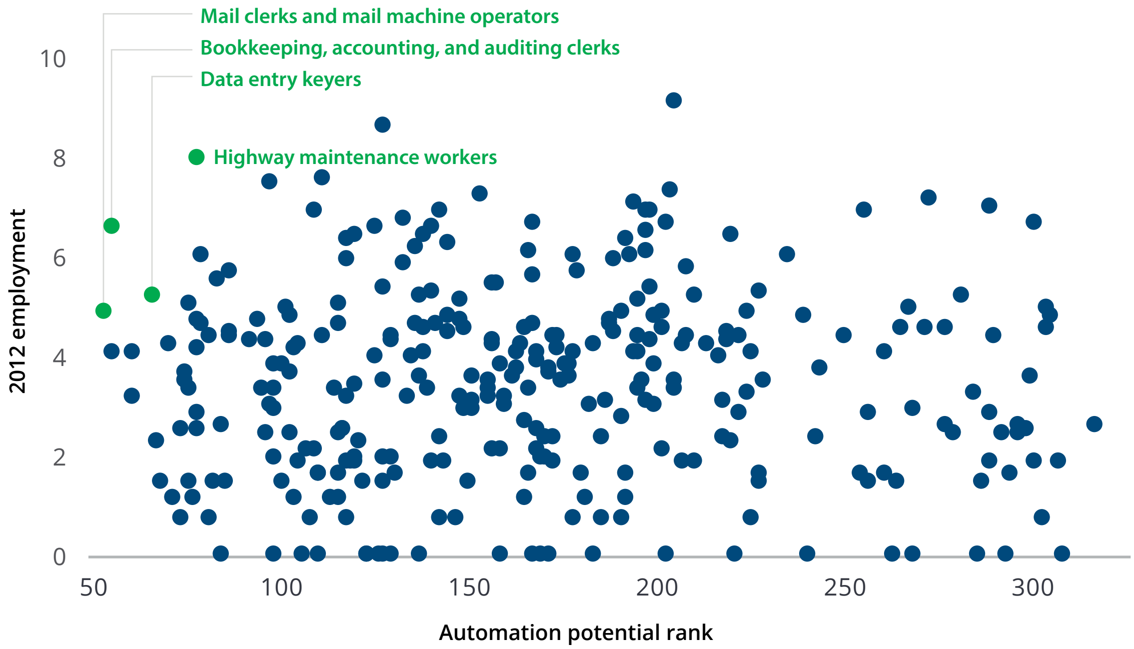
Figure 8. Midwestern state government occupations ranked according to automation potential of their activities



Note: Green dots show selected occupations that have high relative employment and perform many activities with high automation potential—e.g., mail clerks and mail machine operators, data entry keyers, highway maintenance workers, and bookkeeping, accounting, and auditing clerks.

Source: Deloitte analysis of O*NET data, state government job classification catalog, and state transparency portal salaries database.

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Figure 8 ranks state government occupations: on the horizontal axis by the automation potential of their associated tasks (low ranks being easier to automate) and on the vertical axis by employment.

Activities performed by the occupations that figure 8 shows in green (such as data entry workers) could be good starting points for AI investment.

4. Special skill requirements prevent some tasks from automation—for now

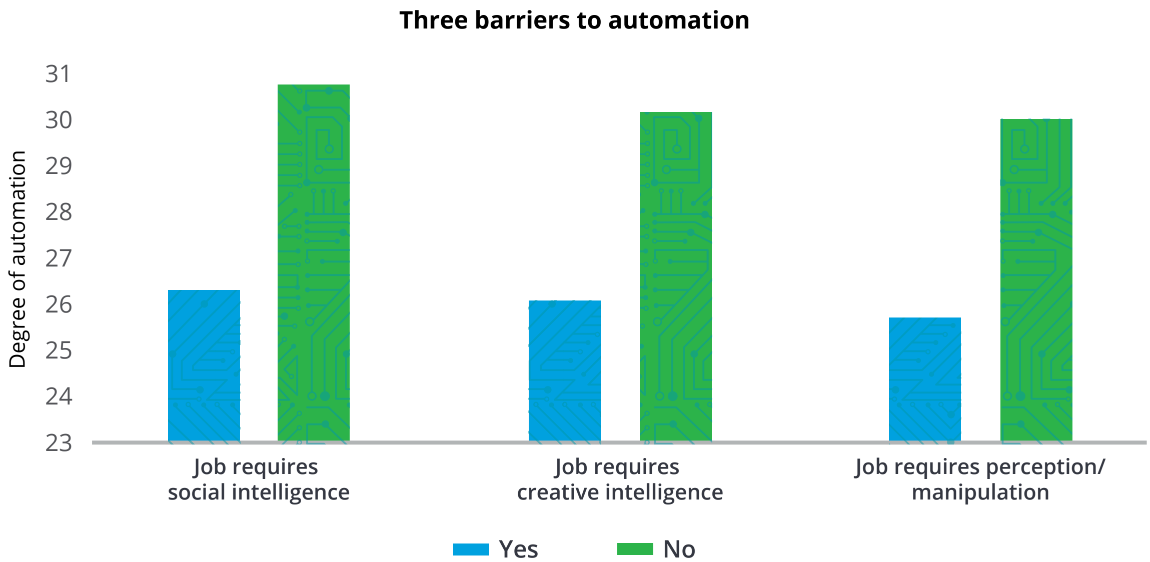
The fourth factor is the type of skill required to complete the task in question. Oxford economists Carl Frey and Michael Osborne have identified three types of "intelligence" as current challenges to AI: *social intelligence, creative intelligence*, and *perception and manipulation*. In their analysis, social intelligence tasks comprise those requiring traditionally human traits: "negotiation, persuasion and care." Creative intelligence involves the basic human ability to generate ideas and things that are novel and interesting, whether a theory or a recipe. Perception and manipulation tasks use our ability to comprehend and interact with the chaotic patterns of real life—the irregular, object-filled worlds of airports, supermarkets, and our own homes.[25]

These are the tasks that will be more difficult—though not necessarily impossible—to hand over to AI technology. For now, "cognitive collaboration" between humans and machines will likely be the most efficient way of carrying out such tasks.[26]

We employ the Oxford study's occupational criteria to identify jobs requiring social intelligence, creative intelligence, or perception and manipulation. Jobs requiring any of these show a lower degree of automation in a sample of 964 occupations from the O*NET database (figure 9).[27]

Figure 9 shows the relation of social intelligence, creative intelligence, and perception/manipulation with automation at the *occupational* level. We expect the same characteristics to constrain AI development at the task level as well.[28]

Figure 9. Social intelligence, creative intelligence, and perception and manipulation correlate with lower average automation index



Source: Deloitte analysis of O*NET database.

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AI shows enormous potential for labor time savings

DECISIONS concerning how to invest in cognitive technology, and how much, could have major implications for government efficiency and effectiveness. Our research quantifies the likely upper and lower bounds of these effects over the next five to seven years. We don't use predictive analytics to model these scenarios because cognitive technology is changing so fast that extrapolations are likely to fail. Only 12 years ago, for example, MIT researchers confidently predicted that AI would never replace human drivers on America's roads.[29]

Instead, we use Monte Carlo simulation—a method for modeling the probability of different outcomes—to describe three different scenarios for the likely near-term effects of automation on government work.[30] For each, we select the base mean of the change in labor inputs to each government task and adjust it according to intrinsic task characteristics. We then simulate changes to task labor inputs by sampling from the normal distribution using the adjusted mean, with standard deviation chosen using O*NET values (figure 10).

Given low, medium, and high levels of government resourcing and investment in AI, our simulations generate the scenarios shown in figure 11.

Figure 11 shows that even low levels of effort behind AI adoption could save government workforces between 2 to 4 percent of all their labor hours. With middling investment levels, much bigger savings become possible. The midrange scenario, which we consider realistic based on our experience with public and private sector automation projects, indicates

Figure 10. Simulation parameters: low, medium, and high levels of effort

Level of investment	Base mean for simulation	How value was chosen
Low	Task labor inputs decline on average by 20%	Low-end threshold of time savings for process automation
Medium	Task labor inputs decline on average by 100%	100% approximates average percent time saved on back-office functions through robotic process automation projects
High	Task labor inputs decline on average by 200%	200% approximates the savings in testing time for silicon wafer circuits at Army Research Labs (see page sidebar "Automating middle-skill tasks to speed up testing"); reflects the higher end of time savings

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Figure 11. Time and money savings from AI under three levels of investment

Level of investment	Savings category	Federal	State government
Low	Annual person-hours	96.7 million	4.3 million
	Hours as percentage of total	2.23%	3.94%
	Salary	$3.3 billion	$119 million
Medium	Annual person-hours	634 million	15.3 million
	Hours as percentage of total	14.63%	13.93%
	Salary	$21.6 billion	$420 million
High	Annual person-hours	1.2 billion	33.8 million
	Hours as percentage of total	27.86%	30.84%
	Salary	$41.1 billion	$931 million

Source: Deloitte simulation of likely changes to labor inputs to government tasks.

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savings of 13 to 15 percent in time requirements within five to seven years. Finally, with strong support for AI adoption, we can simulate a ceiling of potential benefits: 27 to 30 percent time savings within five to seven years. Since IT costs continue to plummet and cognitive technologies are developing rapidly, even the high-end scenario may be within reach.

Conclusion

Minimizing disruption and enabling innovation

EXPERIENCE teaches us that AI, like other forms of technology, will likely cause disruption among government workers whose jobs it changes. But agency heads can take steps in advance to minimize the effects.[31]

First, agencies should provide maximum advance notice of plans to replace or augment certain tasks with AI-based applications. Good communication lowers employee stress levels as they undergo technological transformation.[32]

Second, agency technology leaders should coordinate with human-capital planners to synchronize their upgrades with workforce trends. For example, if an agency anticipates a high rate of retirement within a given occupation, it might prioritize AI investments in that area.[33]

Third, HR executives can cushion the effects of disruption by encouraging employees to develop new skills. Government might create program offices to oversee curricula and learning incentives relevant to cognitive technologies. Such programs could boost the skills of wide swathes of government employees. Just as foreign-language program offices boosted government skills in mission-critical languages such as Farsi and Arabic in the last two decades, AI training offices could promote targeted curricula and incentives for data analytics, machine learning, and designing human-to-machines interfaces. More broadly, government organizations can improve their training for human skills that are most likely to complement AI-based technology in the long run: problem solving, social intelligence, and creativity.[34]

Finally, after the IT department installs AI applications, the technology doesn't run itself; often, maintaining it requires a surprising amount of human labor. Asking software vendors to design accessible training, tuning, and maintenance interfaces for their AI products would help ensure that the employees asked to incorporate AI technology into their work can participate in its use.

We've seen that cognitive technologies can potentially free up millions of labor hours for government workers, with the magnitude of those savings dependent on policy decisions. But what will government workers *do* with those liberated hours?

Senior policymakers will have a choice—one that mirrors our perennial national debate about big versus small government. Some may see AI-based technology as a lever to shrink government workforces, aiming to deliver the same services with fewer employees. Other jurisdictions may choose to use the applications as *tools* for their workers, encouraging them to find new ways to use liberated work hours to improve the services they provide to citizens. The most forward-leaning jurisdictions will see cognitive technologies as an opportunity to reimagine the nature of government work itself, to make the most of complementary human and machine skills.

AI will support all these approaches. It will be up to government leaders to decide which will best serve their constituents.

Appendix

Data and methods

DATA used in this research originates from two main sources: information on numbers of workers, their demographic characteristics, and their salaries collected by the federal Office of Personnel Management (OPM) and our large Midwestern state's Department of Administrative Services; and data on tasks performed by 1,110 occupations collected by the US Department of Labor as part of its O*NET OnLine database. The first source provides information on *who* is in the workforce; the second tells us what they do.

Analyzing the data requires linking both sources via a crosswalk, and OPM helpfully publishes one at www.eeoc.gov/federal/directives/00-09opmcode.cfm. The Midwestern state does not provide such a crosswalk, so we created one using state employee salary data and the state's online job classification handbook.

Establishing the current baseline

O*NET contains the results of worker surveys asking respondents to estimate the time spent on each of their work activities for 19,125 detailed, occupation-specific tasks. We convert those frequency scale ratings to annual task-hours, assuming 2,080 total person-hours per full-time equivalent, using these equivalences:

Less than yearly	0.5 hours/year
Yearly	1 hours/year
Monthly	12 hours/year
Weekly	52 hours/year
Daily	260 hours/year
More than daily	520 hours/year
Hourly	1,043 hours/year

We use 1,043 as the equivalent for "hourly" on the assumption that even tasks performed around the clock take up no more than half of a worker's time, with the other half used for non-occupation-specific activities. Multiplying by the proportion of respondents, choosing each value, and summing over the task, we calculate the average annual hours for the activity. This provides *annual task-hours*.

We then tally the annual task-hours performed by each occupation, multiply by the workforce-specific employment in that occupation, and apply a scale factor (0.45 for the federal workforce and 0.25 for the state workforce) to estimate total task-hours performed by all members of the workforce. This provides the *labor inputs* to a task.

The 19,125 O*NET tasks are further linked to more than 2,000 "detailed work activities," 331 "intermediate work activities," and 37 "general work activities," allowing us to analyze annual task-hours and labor inputs for work tasks at any desired level of specificity.

Understanding changes in task labor inputs

The O*NET program surveys workers in each occupation repeatedly, but at irregular intervals. For 13,356 of the 19,125 detailed ONET tasks (70 percent), ONET reports two or more observations of task frequency at different time points. In this sample, the earliest observation of a task took place in 2003; the latest was in 2016. The length of time between observations averaged 7.03 years, with a minimum of two years and a maximum of 13.

Given two observations of the labor inputs to a task at time 1 (t_1) and time 2 (t_2), we calculate the percent change in annual task-hours for that task. We use the formula (t_1-t_2)/average(t_1, t_2) to calculate percent change for this and other time trends in this paper.

A decrease in labor inputs to a task over time can have many explanations, including structural changes to the occupation and changes in customer demand; dry cleaners don't do much sewing anymore. One explanation, however, is that technology has substituted for part of the labor of the task.

We calculate the correlation between percentage change in task labor input and task importance using Pearson product-moment correlation to demonstrate that, on average, peripheral tasks are automated before core tasks.

We measure the standard deviation of the changes to task labor input and use that value to constrain the Monte Carlo simulation of levels of AI investment described in the following section.

Ranking activities and occupations according to automation potential

The realization that tasks requiring social intelligence, creative intelligence, or perception and manipulation are less easy to adapt to AI technology allows us to rank O*NET's 331 intermediate work activities (IWAs) according to their automation potential.

For each of the 19,125 O*NET detailed tasks, we code it with three binary variables according to whether the associated occupation requires social intelligence, creative intelligence, or perception and manipulation. We use the same O*NET indicators that Carl Frey and Michael Osborne used[35] to assign those binary values. Each IWA is linked through O*NET's database structure to one or more tasks. For each, we average the binary values for social intelligence and call this the IWA's social index, which measures how many of the tasks included in the IWA are performed by occupations requiring social intelligence. We do the same to build a creative index and a perception/manipulation index. We then sum the indices for each IWA, ranking them according to the sum of the three indices. IWAs with lower combined index values are easier to automate than activities with higher index values.

We rank the 331 IWAs according to automation potential and combine that ranking with employment to rank occupations. We do so by linking each occupation to the IWAs it performs. We use the average combined automation index for all the IWAs linked to an occupation, weighted by number of task-hours spent on each IWA, to represent the automation potential of the activities of the occupation. We rank occupations according to combined IWA automation index and employment.

When applied to the 669 federal occupation series established by the Office of Personnel Management, this method yields the following 20 jobs with both the highest automation potential and highest employment (figure 12).

Monte Carlo simulation of AI technology adoption scenarios

We begin with the data set of 19,125 detailed O*NET task descriptions, representing each using intrinsic task characteristics discussed above: task importance and the binary variables for whether the occupation requires social intelligence, creative intelligence, or perception and manipulation.

For the three levels of effort in the scenarios, we choose a base mean for the normal distribution as shown in figure 10 and set the standard deviation to 0.63 based on the percentage changes to 13,356 task labor inputs described above.

We run the simulation as follows. For each task, if the task requires social intelligence, creative intelligence, or perception/manipulation, we set the distribution mean to zero. Otherwise, we set the distribution mean to the base mean times the reciprocal of task importance, on a scale of one to six. We then sample percentage change to the annual task-hours from that distribution and store the results. We report scenario results by running the simulation 10 times and averaging the results.

Figure 12. Federal jobs with high employment and automation potential

OPM occupation series	OPM occupation title	Employment	Average IWA automation rank
1980	AGRICULTURAL COMMODITY GRADING	1572	29.57
1981	AGRICULTURAL COMMODITY AID	1194	29.57
0305	MAIL & FILE	5547	52.59
0503	FINANCIAL CLERICAL & TECHNICIAN	8104	58.53
0525	ACCOUNTING TECHNICIAN	6251	58.53
4701	MISCELLANEOUS GENERAL MAINTENANCE & OPERATIONS WORK	2423	55.97
4742	UTILITY SYSTEMS REPAIRING-OPERATING	1854	55.97
6907	MATERIALS HANDLER	6872	66.14
4754	CEMETERY CARETAKING	693	49.68
0540	VOUCHER EXAMINING	1585	58.53
7408	FOOD SERVICE WORKING	7637	77.54
0561	BUDGET CLERICAL & ASSISTANCE	838	58.53
5003	GARDENING	480	54.25
7407	MEATCUTTING	1380	63.94
3566	CUSTODIAL WORKING	12908	86.07
0303	MISCELLANEOUS CLERK & ASSISTANT	56589	100.54
0998	CLAIMS ASSISTANCE & EXAMINING	3180	74.36
0356	DATA TRANSCRIBER	2142	72
5703	MOTOR VEHICLE OPERATING	5363	81.21
4102	PAINTING	3979	78.52

Source: Deloitte analysis of OPM Fedscope and O*NET data.

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ENDNOTES

1. Claire Cain Miller, "Evidence that robots are winning the race for American jobs," *New York Times*, March 28, 2017, https://nyti.ms/2ouv37V.
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4. See, for instance, Executive Office of the President, "Artificial intelligence, automation, and the economy," December 20, 2016, https://obamawhitehouse.archives.gov/sites/whitehouse.gov/files/documents/Artificial-Intelligence-Automation-Economy.pdf.
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6. Deloitte, "Deloitte: Automation set to transform public services," October 25, 2016, https://www2.deloitte.com/uk/en/pages/press-releases/articles/automation-set-to-transform-public-services.html.
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8. See, for example, Bureau of Labor Statistics, "Technological change and employment," *Monthly Labor Review*, April 1987, p. 28, https://stats.bls.gov/opub/mlr/1987/04/art3full.pdf: "The content of jobs is being modified by technological change. Although job titles frequently remain the same while innovation is taking place, over time, employers have less demand for manual dexterity, physical strength for materials handling, and for traditional craftsmanship."
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10. Deloitte interview with US Geological Survey officials, November 2016.
11. USGS National Map program, https://nationalmap.gov/, accessed April 12, 2017.
12. Taken from Bureau of Labor Statistics, "Occupational Employment Survey, National Industry Series." In 1999, 2,140 cartographers and photogrammetrists were employed in government jobs; in 2015, the number had climbed to 5,240.
13. Bureau of Labor Statistics, "Occupational Outlook Handbook: Cartographers and photogrammetrists," www.bls.gov/OOH/architecture-and-engineering/cartographers-and-photogrammetrists.htm, accessed April 12, 2017.
14. US Department of Labor, "O*NET OnLine," www.onetonline.org/, accessed April 12, 2017.
15. The obstacle posed by paperwork is well known in the human services professions. Surveys have shown it's considered one of the top three most challenging aspects of human services work, along with caseloads and issues confronting families: See, for instance, National Association of Social Workers, "If you're right for the job, it's the best job in the world," June 2004, www.socialworkers.org/practice/children/NASWChildWelfareRpt062004.pdf.

16. We use the Department of Labor's definition of "core" and "supplemental" tasks, whereby core tasks have importance ratings greater than or equal to 3 and relevance ratings greater than or equal to 67 percent. See "O*NET OnLine Help," www.onetonline.org/help/online/scales, accessed April 12, 2017.

17. Bureau of Labor Statistics, "Middle-skill jobs decline as U.S. labor market becomes more polarized," by Demetrio Scopelliti, *Monthly Labor Review*, October 2014, www.bls.gov/opub/mlr/2014/beyond-bls/middle-skill-jobs-decline-as-us-labor-market-becomes-more-polarized.htm.

18. The second author has a vivid memory of visiting India in 2013 and seeing armies of gardeners down on their knees trimming lawns with sickles. (Sickles!) He was told this was possible simply because wages were so low that it was cost-competitive with mechanical lawn mowers.

19. A widely cited example is David Autor, Frank Levy, and Richard Murnane, "The skill content of recent technological change: An empirical exploration," *Quarterly Journal of Economics*, 2003, pp. 1,279–33, https://economics.mit.edu/files/11574.

20. See, for example, Daron Acemoglu, "The impact of IT on the labor market," Massachusetts Institute of Technology, September 2016, http://economics.mit.edu/files/12118.

21. Tom Davenport and Julia Kirby, "Beyond automation," *Harvard Business Review*, June 2015, https://hbr.org/2015/06/beyond-automation.

22. We have not yet been able to fit quantitative models of the relationship of skill levels with task labor inputs due to the limitations of O*NET task data, but we expect to demonstrate this as our data improves.

23. Deloitte interview with Ryan Rudy and Jonathan Puder, US Army Research Labs, December 2016.

24. See, for instance, Jerome A. Marks, "Technological change in employment: Some results from BLS research," *Monthly Labor Review*, April 1987, https://stats.bls.gov/opub/mlr/1987/04/art3full.pdf.

25. Carl Frey and Michael Osborne, "The future of employment: How susceptible are jobs to computerisation?", University of Oxford, Martin School, September 2013, pp. 27–30, www.oxfordmartin.ox.ac.uk/publications/view/1314.

26. For a complete discussion of humans and AI working as partners, see Jim Guszcza, Harvey Lewis, and Peter Evans-Greenwood, "Cognitive collaboration," *Deloitte Review* 20, January 23, 2017, https://dupress.deloitte.com/dup-us-en/deloitte-review/issue-20/augmented-intelligence-human-computer-collaboration.html.

27. Pearson correlation coefficients from a sample of 961 occupations with social intelligence ($rho=-.14$, $p < .0001$); creative intelligence ($rho=-.09$, $p < .007$); and perception and manipulation ($rho=-.07$, $p < .03$).

28. We have not yet been able to model this constraint quantitatively at the task level, again because of limitations of O*NET data. Specifically, O*NET does not code tasks according to what skills each requires—it codes only occupations in this way.

29. Frank Levy and Richard J. Murnane, *The New Division of Labor* (Princeton, N.J.: Princeton University Press, 2005), cited in Erik Brynjolfsson and Andrew McAfee, *The Second Machine Age* (New York: W.W. Norton, 2016), pg. 18.

30. We constrain the scenarios using findings from our research on task characteristics that affect automation potential: task importance and requirements for social, creative, or perceptual intelligence. We do not yet use task skill level to constrain our model, as we do not yet have good quantitative models of the effect of task skill level on automation. The three scenarios reflect three levels of organizational effort behind the push for AI technology, both in funding and in political will for process change.

31. Analysts have long studied how to manage the disruptive effects of technology. Again, see Bureau of Labor Statistics, "Technological change and employment."

32. For a more complete discussion of how organizations can smooth the transition to cognitive technology, see Jeff Schwartz, Laurence Collins, Heather Stockton, Darryl Wanger, and Brett Walsh, *The future of work: The augmented workforce*, Deloitte University Press, February 28, 2017, https://dupress.deloitte.com/dup-us-en/focus/human-capital-trends/2017/future-workforce-changing-nature-of-work.html.

33. Ibid. Schwartz and colleagues' article lays out some ways in which organizations can redesign multiyear strategic and annual operational workforce planning in light of artificial intelligence.

34. See Angus Knowles-Cutler and Harvey Lewis's treatment of which skills will be most valuable in the era of cognitive technology: *Talent for survival: Essential skills for humans working in the machine age*, Deloitte UK, 2016 https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/Growth/deloitte-uk-talent-for-survival-report.pdf.

35. Frey and Osborne, "The future of employment."

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