McKinsey Global Institute

Technical appendix

Agents, robots, and us: Skill partnerships in the age of AI

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Overview of this research

Our analysis focuses exclusively on paid productive hours in the US workforce, encompassing full-time and part-time work across industries, functions, occupations, and skill levels. We assess only the share of time awake that is spent on work-related activities, totaling roughly 45 percent of waking hours. Our analysis excludes time spent on unpaid tasks and leisure, but agents and robots could be used in related activities to support productivity and personal well-being.

MGI's automation and adoption models

This analysis builds on a methodology that was first developed in 2017 and refreshed for this research on the US labor market. Our approach draws on the US Bureau of Labor Statistics' (BLS) O*NET breakdown of about 800 occupations into roughly 2,000 detailed work activities (DWA). We compare the level of capability required to perform each activity successfully with a set of 18 human capabilities that have potential for automation. We also surveyed experts to estimate current performance levels for each capability and how they are likely to advance over time.

In this latest research, we updated our assessments of technology performance across capabilities based on a new survey of AI experts. We also updated employment and wage data at the BLS occupation level. Using these refreshed assessments, we estimated the technical automation potential of work in 2025—the frontier of what is possible with currently demonstrated technologies.

To understand how quickly this potential might be realized, we then modeled scenarios for the pace of automation adoption. Our adoption model comprises three steps. First, we estimate the time required to implement a solution that could automate each detailed work activity once all capability requirements are met by technology development. Second, we estimate a range of potential technology costs at introduction, declining over time based on historical precedents. We assume that adoption for a specific activity begins when automation costs reach parity with human labor.

Finally, based on past analyses of technology diffusion, we modeled timelines from initial uptake to plateau using sigmoidal (S-shaped) curves.[1] While many work activities are already technically automatable, widespread diffusion typically takes time. Plateau adoption—the point at which a technology reaches its highest penetration among users—has generally taken one to three decades. These timelines implicitly capture factors including regulation, investment, management decisions, and user preferences. The modeled scenarios define a range from earliest to latest adoption for automating current work activities, with the expected pace represented by the midpoint scenario.

How we group occupations by technical automation potential

We determined the technical automation potential of the US workforce by analyzing about 2,000 work activities for roughly 800 occupations, using data from the BLS and O*NET. To capture how automation potential differs by occupation, we examined the specific mix of detailed work activities (DWAs) for each occupation and the capabilities required to perform them. Our assessment reflects how people currently carry out these tasks rather than how technology might eventually reshape them. The analysis draws on expert input to determine which of 18 physical, social and emotional, and cognitive capabilities could be automated given current and emerging technological trends.

Each work activity was classified according to its automation potential and the capabilities it requires. Activities not yet technically automatable are those performed by people. Among automatable activities, those involving physical capability (gross motor skills, fine motor skills, or mobility) are classified as those that could be performed by robots, while those relying only on cognitive or social and emotional capabilities are classified as ones that could be performed by agents.

We then grouped occupations into seven archetypes based on the share of work hours devoted to activities that could be performed by people, agents, or robots. Occupations that would devote over 55 percent of their current work hours on any one of the three are considered "centric" occupations—people-centric, agent-centric, or robot-centric. For example, registered nurses are people-centric as they devote about 70 percent of their hours to activities that can only be performed by people.

Combined occupations draw on a more balanced mix of people, agents, and robots. Roles dominated by two activity types—people–agent, people–robot, or agent–robot—spend more than half of current work hours on them, while others show a near-even mix across all three.[2]

These archetypes reflect technical automation potential, not predictions of actual future work models. Actual adoption rates depend on factors such as solution timelines, technology versus labor costs, and the speed at which technologies diffuse.

How we quantify a skill's potential to change

Our assessment of how skills could change integrates four inputs: employment in various occupations, detailed work activities (DWAs) of each occupation, the skills relevant for each DWA, and the McKinsey automation adoption model, which estimates the automatability of each DWA. Our model draws full-time-equivalent (FTE) employment and average wage data for about 800 occupations from the BLS, data from O*NET on about 2,000 DWAs linked to occupations, and data on roughly 34,000 skills linked to about 2,000 occupations from Lightcast.

We filtered the skills data set to include only those appearing in more than 5 percent of job postings for each of the approximately 1,800 Lightcast occupations, narrowing the sample to about 7,000 skills. We then mapped the BLS occupation, wage, and FTE data onto the Lightcast occupations.

Next, we mapped all skills to their corresponding DWAs within occupations, creating about 3.4 million occupation–DWA–skill links. We used OpenAI's GPT-4o model through the asynchronous chat-completions endpoint. Each occupation–DWA–skill pairing was processed as an individual application programming interface (API) call with a standardized prompt to ensure consistent outputs. To verify quality, we first created a manually built 1,000-cell template for the generative model to replicate and infer from. We conducted iterative quality testing—spot-checking outputs, refining prompts, and rerunning samples—until the model produced reliable and consistent mappings.

To assess a skill's potential to change as a result of AI and automation, we used two lenses.

First, we classified skills into three groups—people-led, AI-led, and shared— based on the technical automation potential of their associated work activities. For each skill, we calculated the total time spent in the United States across these mapped DWAs and identified the share of that time associated with automatable versus non-automatable work. Skills with 55 percent or more of their time in non-automatable activities were classified as people-led, while those with 55 percent or more in automatable activities were classified as AI-led. AI-led skills were further divided into agent- or robot-led depending on whether the underlying work activities required physical capabilities. All other skills were categorized as shared. The exhibit below shows how we classified three sample skills based on their current activity mix.

Exhibit

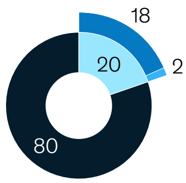
AI-led skills are associated with more automatable work activities.

Distribution of time spent on work activities in the US, by technical automation potential, %

● Not automatable ● Automatable | Automatable with: ● Agents ● Robots

Skills required for people-led work

Example: Conflict resolution

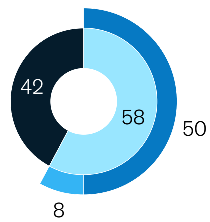


Select activities

- Manage HR activities
- Supervise employees
- Direct organizational projects or services
- Respond to customer problems or complaints
- Monitor access or flow of people to prevent problems

Skills required for work done by a combination of people and AI

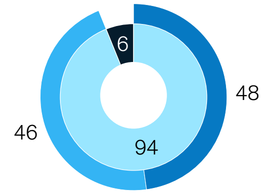
Example: Detail orientation



- Collect information from people through observation or interviews
- Operate on patients surgically to treat conditions
- Analyze health-related data
- Verify accuracy of financial or transactional data
- Implement organizational process changes

Skills required for AI-led work

Example: Ability to operate machines



- Direct operational or production activities
- Enter commands, instructions, or specifications into equipment
- Program equipment to perform production tasks
- Package products for storage or shipment
- Remove products or workpieces from production equipment

Source: Lightcast; O*NET; Current Population Survey, US Census Bureau; ESCO level 1 skill categorization; McKinsey Global Institute analysis

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Second, we assessed each skill's level of change by 2030, calculated from the average automation adoption projected for that year across specific occupation–DWA combinations mapped to the skill, weighted by time spent. The analysis relies on the midpoint automation-adoption rate for 2030 for each DWA, drawn from the latest (2025) update of the McKinsey automation model.

The resulting scores for each skill constitute our Skill Change Index (SCI), a single measure of skill-change potential that makes it possible to identify which skills are most and least sensitive to automation.

Endnotes

[1] Sigmoidal curves represent growth over time that follows an "S" shape—typically starting slowly, accelerating rapidly, and leveling off as it reaches maturity or saturation.

[2] Combined roles are defined as those in which at least 55 percent of current work hours are spent on a combination of two activity types.

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