SERGEI BAZYLIK
University of Chicago, USA
MICHAEL GIBBS
University of Chicago, USA, and IZA, Germany

I Z A
World of Labor
Evidence-based policy making

How is new technology changing job design?

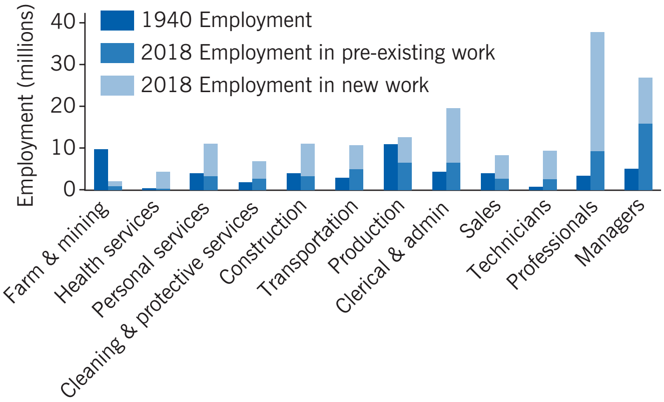
Machines' ability to perform cognitive, physical, and social tasks is advancing, dramatically changing jobs and labor markets

Keywords: job design, technology, artificial intelligence, cognitive tasks, labor market polarization

ELEVATOR PITCH

The IT revolution has had dramatic effects on jobs and the labor market. Many routine manual and cognitive tasks have been automated, replacing workers. By contrast, new technologies complement and create new non-routine cognitive and social tasks, making work in such tasks more productive, and creating new jobs. This has polarized labor markets: while low-skill jobs stagnated, there are fewer and lower-paid jobs for middle-skill workers, and higher pay for high-skill workers, increasing wage inequality. Advances in AI may accelerate computers' ability to perform cognitive tasks, heightening concerns about future automation of even high-skill jobs.

Employment in job titles existing in 1940 or added later (new work), 2018



Source: [1].

KEY FINDINGS

Pros

- Technology complements and creates many non-routine tasks, increasing productivity, quality, and innovation.
- Big data and machine learning are increasing machines' ability to perform cognitive, physical, and even some social (language) tasks, especially ones involving prediction.
- Greater access to data, analysis tools, and telecommunications allows many workers to focus more on social interactions, collaboration, continuous improvement, and innovation.
- This dynamic process creates many new types of jobs, products, and industries. Prior automation has never led to mass unemployment.

Cons

- Machines substitute for humans in many routine manual and cognitive tasks, eliminating those jobs.
- Labor markets have polarized, and inequality has risen, with relatively less demand for mid-skill workers and increased value for high-skill workers.
- The pace at which machines gain the ability to perform cognitive tasks is faster than in the past, making adaptation by workers more difficult.
- Older and credit-constrained workers displaced by automation face the most difficulties acquiring new skills and finding employment in other industries.
- Market and tax incentives may inefficiently push firms toward too much automation rather than labor augmenting technologies.

AUTHOR'S MAIN MESSAGE

Technology facilitates automation of routine tasks, creating fewer and less motivating middle-skill jobs. Conversely, it complements social and innovation tasks, creating more interesting low- and high-skill jobs. This causes polarization, "hollowing out" demand for middle-skill workers and increasing wage inequality. Some claim that computers will soon replace many workers as AI advances. Others are skeptical, as previous technological advances did not cause mass unemployment, and the extent of automation has always fallen short of initial predictions. Policymakers have a crucial role in controlling the pace of automation to avoid inefficient investment, smoothing transitions for displaced workers, and fostering education and training that help workers adapt to change.

doi: 10.15185/izawol.344.v2 | Sergei Bazylik and Michael Gibbs © | August 2022 [Previous version March 2017] | wol.iza.org

MOTIVATION

Since at least the Luddite movement of 1811–1816, the effects of new technology on jobs and employment have generated great controversy. In the last few decades, enormous improvements in information and communications technologies (ICT) have had dramatic effects, which have benefitted some workers but eliminated the jobs of others.

The current debate focuses on how far, and how fast, job automation will proceed. Recent advances in artificial intelligence (AI) methods are pushing past previous limits on the types of tasks that can be automated. Machines increasingly perform cognitive tasks, use natural language, and have greater dexterity and mobility. Some observers claim that a high fraction of jobs is at risk of being automated, including high-skill jobs for the first time, potentially leading to large-scale unemployment. Others are more skeptical, noting barriers to technological advancement and implementation, and pointing out that labor markets have always managed to absorb new technologies in the past, in large part because new technology creates new opportunities.

The public policy implications are extremely important. Recent applications of new technology have improved productivity of high-skill workers, while doing the opposite for middle-skill workers. This has led to “polarization” of the labor market and growing economic inequality.

DISCUSSION OF PROS AND CONS

How does technological change affect job design?

Think of a job as a set of tasks that require various types of skills. New technology raises relative employee productivity in some tasks, creates new tasks, and replaces employees in other tasks. Firms respond by changing job design—the mix of tasks assigned to workers—and subsequently their demand for workers with different skills.

Automating tasks (in machinery or software) has several advantages. It reduces variation since machines tend to perform identically every time. This lowers uncertainty and helps improve the quality of decisions, products, or services. Machines, and particularly computers, often generate large economies of scale. Firms can avoid the complexities of managing employees, including conflict, incentive problems, and absenteeism. Therefore, if the cost of automating a task falls far enough, firms are likely to automate that task. Of course, costs of computing have fallen rapidly, while computer capabilities have risen rapidly. Thus, computerized automation has accelerated in the last three to four decades.

Early technology tended to increase productivity of low-skill manual laborers by providing better tools, machinery, and cheaper raw materials. This was reflected in gradual mechanization of agriculture, and the movement from artisan to factory manufacturing in the late 1800s [2]. However, by about 1910, new technology began favoring middle- and high-skill workers. Factories shifted to electric power, which facilitated batch or continuous production methods, and assembly lines. Factory foremen, machinists, and managers became more productive, overseeing more resources and output. Meanwhile, many manual jobs were mechanized.

This is an early example of a general point. Technology sometimes complements employees by increasing their ability to perform certain tasks, and sometimes substitutes for employees by automating some or all of their tasks. It thus changes job design by refocusing the employee on tasks that are difficult to automate. Additionally, the effect of new technology can change over time. Initially, it complemented low-skill work. Later, it substituted for that while complementing middle- and high-skill work. Today it complements high-skill work but often substitutes for middle-skill work. It is reasonable to expect that ICT's effects may change again in the future.

For example, some medical diagnostic tests have been automated, eliminating many medical technician jobs. Some nursing tasks have been replaced by bedside machines that monitor patients and dispense medicine, but the nurse's interaction with the patient is largely impossible to automate. Finally, virtually all surgeries are still performed by humans, but surgeons have advanced tools that allow them to perform these surgeries more quickly, safely, and effectively. Both nurses and surgeons are still around, but the content of their jobs—the tasks they perform and the amount of time they spend on each task—has been greatly altered by technological advances.

This process can lead to dramatic differences in employees' work [3]. For jobs that are mostly automated, managers tend to make most or all decisions and workers simply perform their prescribed tasks. This is because much of the process has already been optimized, so the worker can add little new knowledge, and few decisions or changes need to be made. These jobs usually require few skills, involve only a few repetitive tasks (which are too costly to automate yet), require little thinking, and therefore tend to have low intrinsic motivation. By contrast, jobs that are complemented or added by technology tend to require more skills, including problem-solving and social skills. They tend to make more use of decentralization so that employees learn, and then develop, test, and implement ideas and solutions. As a result, such jobs have high intrinsic motivation. Consistent with these ideas, investment in ICT and research and development are positively associated with more enriched job designs, large-scale organizational change, continuous improvement, and greater competition.

Which tasks are easiest and most difficult to automate?

Tasks that are most easily understood, optimized, and codified in advance are easiest to automate. Thus, routine, simple tasks have been most susceptible to mechanization and computerization [4]. As noted above, initially automation was of manual tasks in manufacturing. Industrial efficiency experts devised methods to break production into specific steps, and then optimize each step. Doing so codified the task, which facilitated mechanization. From the 1970s onward, the ICT revolution enabled similar automation of many routine, predictable tasks in clerical and white-collar jobs. Work involving information processing, producing financial forms, making routine calculations, and so on, was easily taken over by computers. This "re-engineering" eliminated many middle-skill jobs (e.g. clerical work, data entry, bookkeeping), and reduced the number of layers in corporate hierarchies.

Well-defined, more stable, and predictable environments favor automation for two reasons: ease of optimization and technological longevity. For tasks to be automated, the firm must invest resources in analyzing and optimizing that part of the process. Perfecting part of a process takes resources (e.g. consultants, total quality management methods). This investment will be more profitable if the optimization problem is easier to define and if the new knowledge can be deployed longer in the future, as is the case with stable and predictable environments.

For example, online travel sites have automated and nearly eliminated the job of a travel agent. Instead of seeking information and advice from an agent (who has an incentive to sell the customer more expensive tickets), travelers have fast access to an enormous amount of well-structured information on itineraries, options, and pricing. This improves their travel decisions. These sites then automate much of the process of making reservations for the customer, which is relatively straightforward and does not change much over time.

Which tasks are the most difficult to automate (Figure 1)? First, not all manual tasks have proven easy to automate. Physical tasks sometimes involve fine motor coordination and dexterity, which machines have not been able to easily replicate so far. They also often involve observing and interpreting the worker's physical environment, as well as moving within random physical spaces. Computers and machines have historically lacked these capabilities, including vision and image recognition.

Figure 1. Types of (non-routine) tasks that are most difficult to automate

Type of task	Attributes that are difficult to automate	Example
Manual	Object recognition Mobility in unmapped space Fine dexterity	Sorting and (un-)packing random objects Restaurant table service, janitor, law enforcement Surgery, live music, beauty services
Cognitive	Creativity, innovation Abstract analysis	Research, invention, and arts Law and consulting services
Social	Leadership, collaboration, and negotiation Teaching Human interaction	Executive, project manager, politician, orchestra conductor, sports coach Professor, teacher, career coach Nursing, mental health counselor, bartender, sales

Source: Author's own compilation.

I Z A World of Labor

Cognitive tasks have also been difficult to automate. They require higher-order thinking skills, while computers have tended to only perform specific, programmed operations. Instead of being automated, jobs involving analysis, decision making, abstract thinking, learning, innovation, and creativity are often complemented by new technology. For example, the job of an aircraft design engineer has changed dramatically. In the past, it involved substantial tedious work, producing complex blueprints by hand calculation and drawing. Now engineers have computers that perform these tasks, freeing them up to focus more on design and complex configuration options [5]. Furthermore, engineering software creates new tasks and jobs for high-skill individuals.

Social tasks have also proven difficult to automate. Computers and robots do not have the ability to empathize with colleagues and customers, inspire employees, use intuition, or listen and communicate with subtlety. Tasks involving social interactions, often in low-skill service jobs and high-skill management jobs, have largely avoided automation. Social skills have become increasingly valuable in the labor market, and employment growth has been largest in jobs that are high in both cognitive and social skill requirements [6]. That is, social and cognitive skills appear to be complementary.

Summing up, a job is a bundle of manual, cognitive, and social tasks. The effect of technology on job design rests on a continuum from automation, to augmentation, to addition of tasks. For some jobs, most or all tasks can be automated. For some jobs, few tasks can be automated, but human work can be augmented by technology. Finally, technology creates new tasks, jobs, and industries, which increases labor demand. Other jobs lie in between, with some tasks automated, some unaffected, and some added and complemented [1].

How far and how fast is automation of tasks proceeding?

How technology affects job design has recently changed. Initially, computers had largely automated tasks that could be well-defined and guided by humans, either via traditional computer programs that specify what the computer should do, or expert systems designed to categorize and replicate human decision making. Recently, however, computer scientists have made significant strides in machine learning, in which computers develop, evaluate, and refine their own algorithms, with little or no human intervention. This presents a new opportunity: automation of cognitive tasks. Moreover, such algorithms have improved mobility, dexterity, vision, and object recognition in robotics, increasing automation of physical tasks.

Consider the example of AI image classifier algorithms. AI technologies are particularly effective in statistical prediction tasks. In the 2017 ImageNet Top 5 Classification Challenge, the best algorithms surpassed the human performance threshold of 94.9% correct classifications. By January 2021, AI classification accuracy was 98.8%. Concurrently, the average algorithm training time decreased to below one minute in 2020 (a seven-fold decrease from 2018) and training costs plummeted from US$1,100 to US$7 [7]. These advances make powerful classification algorithms available quickly and at very low cost, for a vast population of researchers and practitioners in many areas of business. There is wide application of this technology across the economy. Notably, much of it appears to focus on a firm's core operations, not just support functions. For example, automobile manufacturers are adopting computer vision and robotics in assembly processes. Meanwhile, financial services firms are adopting machine learning and text recognition techniques in risk assessment and service operations [7]. Inevitably, humans will be substituted by machines in most prediction tasks. Future jobs should be designed to ensure complementarity between machine prediction outputs and worker tasks. An excellent example is evaluation of radiological scans. AI allows for fast examination of far more scans than could be evaluated by humans. That increases the likelihood of detecting a medical problem. It also frees up a radiologist's time to interpret anomalous images identified by the algorithm, and work individually with patients to develop customized treatment plans—tasks that are safely out of the reach of automation.

Artificial Intelligence (AI)

Recently, the role of computers at work has changed: they can now learn and evolve from experience. This is largely due to the arrival of *Big Data*—massive increases in affordable computer processing power, storage capacity, and information (numeric and otherwise)—as the new methods are extremely data-intensive.

These methods have enabled computers to perform some cognitive, language processing, and image recognition tasks, consequentially improving robots' mobility and dexterity. Unlike traditional statistics, the new methods usually do not attempt to fit a pre-specified model, but are designed to discover complex relationships between different pieces of information. They are proving extremely flexible and widely applicable. Here are brief descriptions of some of these techniques.

Data mining: exploratory techniques to uncover patterns in data.

Machine learning: similar to data mining, but directed at specific goals. This sub-field of AI develops algorithms for prediction and/or decision making. The most common method is supervised learning, in which the computer is "trained" with example inputs and outputs (e.g. signatures and names on checks), and iteratively develops an algorithm to perform a desired task on any new data. The technique is closely related to statistics, since it involves iteratively fitting a model to data to minimize a cost function.

Neural networks: branch of machine learning inspired by neuroscience. Iteratively develops an algorithm in which a network of artificial neurons processes and passes data to each other, sometimes in complicated configurations. This method is especially effective for very complex problems, since it can handle millions of dimensions, and relationships between objects (e.g. data or symbols) can be non-linear and "tangled" (akin to endogeneity in statistics).

Deep learning: somewhat ill-defined term for advanced techniques in which multiple neural networks work together in layered (hierarchical) fashion. Designed to model high-level abstractions generating the data. For example, one stage might model how to effectively represent an image (a set of pixels or a set of edges between colors). The next stage would use that output to determine some property of the image, such as whether it is a human face. Other steps might then follow. This method has proven particularly useful for mimicking vision and natural language.

Quantum computing: not an AI technique, but worth watching as it may have important implications in the future. Quantum computers use properties of quantum states to perform calculations. Compared to what is possible today, quantum computers may soon operate much faster, and handle much larger calculations, some of which are beyond the capabilities of current computers.

The development of computers that can learn is a potentially dramatic change in task automation. How far these developments are likely to proceed, and how quickly, is the subject of great debate. Some argue that the pace of automation has accelerated, including for the first time in high-skilled jobs. One study analyzes the task content of 7,000 jobs and concludes that nearly half, including many high-skilled jobs, are at high risk of automation in the next ten to 20 years [8]. If that prediction proves true, the implications for labor markets could be far reaching.

This study has provoked controversy. For example, it analyzes the risk of automation at the job level, but jobs comprise a set of tasks, some of which might be automated, while others might not. Other researchers have refined this study and conclude that the fraction of jobs at high risk for automation is not 50%, but closer to 5–10%. Jobs at the least risk of automation are estimated to involve greater use of deductive reasoning, originality, communication, training, problem solving, and reading and writing. They also have greater requirements for pre-job education or training [8], [9]. However, considerably more work needs to be done before researchers will be confident answering these questions.

Labor market polarization

Technological change affects the relative compensation of workers with different skill types. As new technology substitutes or complements different types of tasks, it changes the relative demand for skills needed to perform those tasks. Skills associated with tasks that machines can now perform tend to see a relative decline in demand, while those associated with tasks that are complemented or created by new technology see a relative rise in demand. The supply of workers with different skill types will also change. However, labor supply tends to change slowly since it requires changes in education and training. This means that skills and wages tend to be highly correlated. For that reason, labor economics researchers often proxy “skills” by the level of pay.

Automation in recent years has tended to focus on middle-skill jobs. High-skill jobs comprise non-routine cognitive tasks, social skills (management and leadership), and creativity. While some low-skill jobs have been automated, those requiring greater dexterity, teamwork, or interactions with customers have not been widely automated. By contrast, middle-skill jobs tend to involve routine information processing, calculation, and decision making. They have therefore been hardest hit by automation with the advent of cheap, powerful computers, and greater access to data.

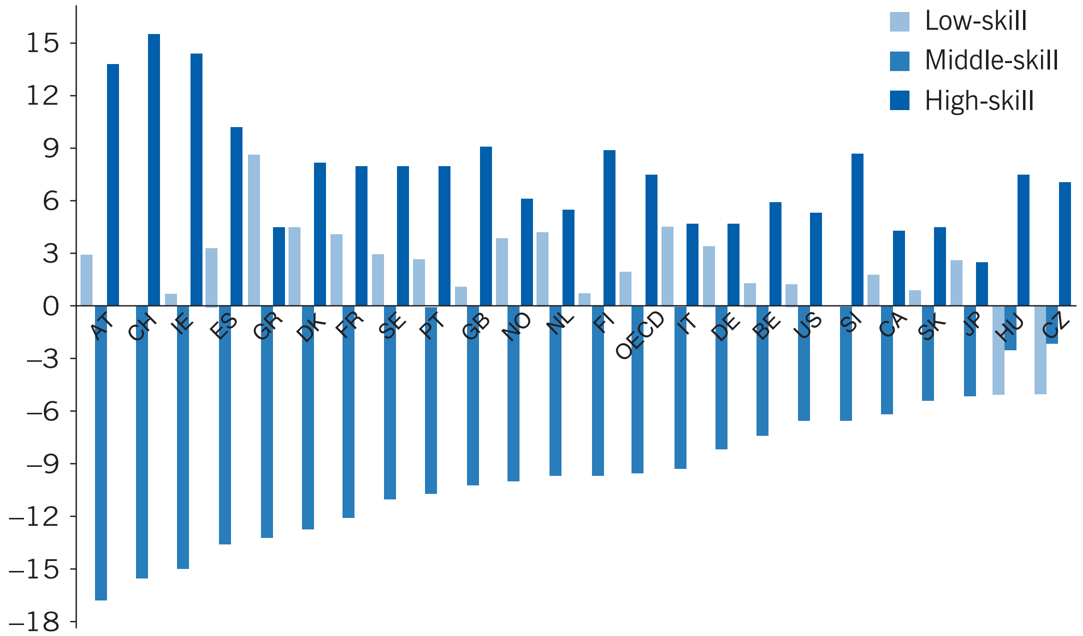
This pattern is often termed labor market polarization [10]. Polarization has two aspects. First, there has been a “hollowing out” of the labor market. Demand for low-skill jobs has stagnated, while demand for high-skill jobs has increased due to the augmentation effect of technological change. At the same time, there are fewer jobs for middle-skill workers due to automation. Second, this has increased wage inequality, since middle-skill jobs have fallen in prominence, while complementarity with technology has increased relative compensation for high-skilled workers. Figure 2 illustrates this for OECD countries.

Polarization is a relatively new phenomenon. Until recently, labor markets reflected skill-biased technological change in which technology favored workers with more skill relative to those with less. What is different now is that computers can perform analysis and, to some extent, cognitive tasks. Hence, in the last four decades routine-biased technological change has emerged.

AI may exacerbate labor market polarization. Recent research suggests that AI has had positive effects on the wages of computer scientists and statisticians who are directly involved in AI development. However, it has not had significant effects on pay for other middle- to high-skill workers who use the new tools [11].

Beyond polarization, automation is creating related labor market challenges. Hollowing out may reduce opportunities for employees to accumulate skills on the job, limiting

Figure 2. Percentage changes in occupational employment shares from 1995 to 2015: Low-, middle-, and high-skill occupations, OECD countries



Source: Authors' own compilation based on data from OECD Employment Outlook 2019: The Future of Work. Online at: https://www.oecd-ilibrary.org/employment/oecd-employment-outlook-2019_9ee00155-en

I Z A
World of Labor

career advancement from entry to managerial positions. Also note that firms might risk losing tacit knowledge if jobs that provide learning opportunities are automated. For example, automation of assembly workers prevents the development of hands-on expertise useful for supervisory managerial positions.

Of particular concern is the effects on workers whose jobs are automated out of existence. Acquiring new skills mid-career is not easy. Combined with borrowing and other constraints, displaced workers often find it difficult to obtain similar employment in other sectors. These effects are even more significant in economies with older populations, and when innovations favor skills that are possessed by a relatively smaller part of the labor force. These forces place greater demands on governments to expand social welfare and job training programs. Importantly, employers do not internalize these costs. Moreover, tax codes may be biased in favor of capital and at the expense of labor. For these reasons, some argue that firms have distorted incentives when implementing new technologies, resulting in inefficiently high levels of automation instead of augmentation and adding new jobs [12], [13].

LIMITATIONS AND GAPS

A significant limitation of the current debate on technological change is that it is difficult to predict future advancements, effects on job design, and labor market responses. Computer scientists are uncertain of how much progress will be made, and at what pace. AI has proceeded in spurts, with occasional advancements followed by slower periods in which obstacles have proven difficult to overcome. Furthermore, experts may overestimate likely progress in their own field.

Even if the extent of future change was known, research on potential task automation is speculative and at an early stage. Equally important, but understudied, is the likelihood that ICT and machine learning might further complement tasks and create new jobs rather than automate them. Mechanisms by which technology complements work are not as well understood as those by which it substitutes. More evidence is needed on how machine learning and other technologies are implemented, and on how they substitute or complement different tasks, as well as the ultimate effect on job designs.

It can be said with more certainty that in the past new technologies eventually resulted in the expansion of jobs, though these jobs were very different from those previously existing. The Illustration on p. 1 shows that despite enormous technological change, employment expanded greatly in the US from 1940 to 2018. Only farming and mining experienced a decrease in employment, which was vastly outweighed by increases in all other occupations. Remarkably, the majority of new employment is in job titles that did not exist in 1940. These emerged with the introduction and evolution of new technologies, while employment in "old" job titles contracted.

The speed at which new technology will be implemented is uncertain. Past experience suggests that adoption can be slow and difficult. It takes time for organizations to learn practical implementation. Change is slow, complex, and may require high pressure to succeed. Indeed, research indicates that changes in jobs to exploit routine-biased technical change are more significant during recessions. The recent Covid-19 pandemic is likely to have accelerated these trends. The incentive to safeguard production processes against future pandemics aligns with automation incentives, as many occupations with high automation potential also exhibit a high risk of viral infection transition. Finally, new technology often faces regulatory hurdles, as well as resistance from political and special interest groups.

The future extent of labor market polarization is likewise unclear. Job design and work-focused research and design are endogenous. New technology has not always complemented high-skill jobs and may not in the future. As middle-skill workers become relatively cheap, firms are motivated to find ways in which technology can complement their work. For example, health care providers are investing in technology that would allow nurses, home health aides, and other middle-skill workers (who are relatively inexpensive compared to doctors) to perform some diagnostics and provide limited patient treatment. Some developments are likely to lead students, employees, and firms to change the type of skills they invest in. International trade allows some types of tasks to be offshored more than others, affecting relative demand for different types of skills. Trade also affects job design, as ICT reduces geographical barriers to collaboration or offshoring. These interactions are not yet fully understood and are likely to change in the future.

SUMMARY AND POLICY ADVICE

Some believe that the pace of automation, including of high-skill cognitive and social tasks, is accelerating. However, it is important not to overreact. New technology has always generated dire labor market predictions that have never come to fruition. Technological change has not always complemented high-skill work while replacing low-or middle-skill jobs, and may not in the future either. Humans are capable of much that is hard to automate, even with the advent of AI. Technology can be used to help people focus on customer service, artisanal and craft work, innovation, education, and more. Furthermore, ICT improves productivity and quality, and generates new products and services. These generate growth, which can increase labor demand.

Much of the research on robotics and AI is aimed at mimicking humans, which biases toward automation. Policymakers should encourage research into how technology can instead augment human creativity and collaboration, particularly in middle- and low-skill jobs.

Governments have many market and policy instruments that might be deployed to direct the evolution of new technologies. Technology spillovers in new areas such as AI may be large, which would justify subsidies to basic research, or to collection of publicly available training data sets for algorithms. For example, Chinese government contracts for facial recognition technologies led to a surge in development of related algorithms in the private sector. On the other hand, since firms do not internalize the costs of displaced workers, and the tax code may distort their incentives toward inefficient levels of automation, some propose a "robot tax" on investments in automation capital. That might slow the pace of automation and redistribute the resulting surplus, to smooth the transition for affected workers and counterbalance increasing inequality [13].

What skills are most likely to be valuable with future technological change? First, abstract thinking, analytical, and problem-solving skills. For this reason, mathematics, statistics, science, engineering, and economics have risen in prominence. Second, creativity, and social and communication skills. Furthermore, labor markets now value most people who possess both general types of skills. Educational institutions should teach this combination of skills.

Acknowledgments

The authors thank two anonymous referees and the IZA World of Labor editors for many helpful suggestions on earlier drafts. The authors also thank Geoffrey Gibbs and Kathryn Ierulli for valuable comments, and Grant Hayes for excellent research assistance. Financial support from the University of Chicago is gratefully acknowledged. Version 2 of the article significantly updates the text, figures, and reference lists.

Competing interests

The IZA World of Labor project is committed to the IZA Code of Conduct. The authors declare to have observed the principles outlined in the code.

REFERENCES

Further reading

Brynjolfsson, E., and A. McAfee. *The Second Machine Age*. New York: W.W. Norton, 2016.

Domingos, P. *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World*. New York: Basic Books, 2015.

Key references

[1] Autor, D., A. Salomons, and B. Seegmiller. New Frontiers: The Origins and Content of New Work, 1940–2018. MIT Working Paper, 2021.

[2] Goldin, C., and L. F. Katz. "The origins of technology–skill complementarity." *Quarterly Journal of Economics* 113:3 (1998): 693–732.

[3] Bresnahan, T., E. Brynjolfsson, and L. M. Hitt. "Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence." *Quarterly Journal of Economics* 117:1 (2002): 339–376.

[4] Autor, D. H., F. Levy, and R. J. Murnane. "The skill content of recent technological change: An empirical exploration." *Quarterly Journal of Economics* 118:4 (2003): 1279–1333.

[5] Levy, F., and R. J. Murnane. *The New Division of Labor: How Computers Are Creating the Next Job Market*. Princeton, NJ: Princeton University Press, 2005.

[6] Deming, D. J. "The growing importance of social skills in the labor market." *Quarterly Journal of Economics* 132:4 (2017): 1593–1640.

[7] Zhang, D., S. Mishra, E. Brynjolfsson, J. Etchemendy, D. Ganguli, B. Grosz, T. Lyons, J. Manyika, J. C. Niebles, M. Sellitto, Y. Shoham, J. Clark, and R. Perrault. *The AI index 2021 Annual Report.* AI Index Steering Committee, Human-Centered AI Institute, Stanford University, 2021.

[8] Frey, C. B., and M. A. Osborne. "The future of employment: How susceptible are jobs to computerisation?" *Technological Forecasting & Social Change* 114 (2017): 254–280.

[9] Brandes, P., and R. Watternhofer. "Which tasks of a job are susceptible to computerization?" *Bulletin of the European Association for Theoretical Computer Science* (2016).

[10] Autor, D. H. "Why are there still so many jobs? The history and future of workplace automation." *Journal of Economic Perspectives* 29:3 (2015): 3–30.

[11] Humlum, A., and B. Meyer. *Artificial Intelligence and College Majors*. U. Chicago Working Paper, 2021.

[12] Beraja, M., and N. Zorzi. *Inefficient Automation*. NBER Working Paper No. 30154, 2022.

[13] Acemoglu, D., A. Manera, and P. Restrepo. "Does the US tax code favor automation?" *Brookings Papers on Economic Activity* (2020): 231–300.

Online extras

The **full reference list** for this article is available from:

https://wol.iza.org/articles/how-is-new-technology-changing-job-design

View the **evidence map** for this article:

https://wol.iza.org/articles/how-is-new-technology-changing-job-design/map