

The impact of artificial intelligence on work

An evidence synthesis on implications
for individuals, communities, and societies



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Executive summary

Artificial intelligence (AI) technologies are developing apace, with many potential benefits for economies, societies, communities and individuals. Across sectors, AI technologies offer the promise of boosting productivity and creating new products and services. Realising their potential requires achieving these benefits as widely as possible, as swiftly as possible, and with as smooth a transition as possible.

The potential of AI to drive change in many employment sectors has revived concerns over automation and the future of work. While much of the public and policy debates on AI and work have tended to oscillate between fears of the ‘end of work’ and reassurances that little will change in terms of overall employment, evidence suggests neither of these extremes is likely. However, there is consensus that AI will have a disruptive effect on work, with some jobs being lost, others being created, and others changing.

There are many different perspectives on ‘automatability’, with a broad consensus that current AI technologies are best suited to ‘routine’ tasks, albeit tasks that may include complex processes, while humans are more likely to remain dominant in unpredictable environments, or in spheres that require significant social intelligence.

Over the last five years, there have been many projections of the numbers of jobs likely to be lost, gained, or changed by AI technologies, with varying outcomes and using various timescales for analysis. Most recently, a consensus has begun to emerge from such studies that 10–30% of jobs in the UK are highly automatable. Many new jobs will also be created. The rapid increase in the use of

administrative data and more detailed information on tasks has helped improve the reliability of empirical analysis. This has reduced the reliance on untested theoretical models and there is a growing consensus about the main types of jobs that will suffer and where the growth in new jobs will appear. However, there remain large uncertainties about the likely new technologies and their precise relationship to tasks. Consequently, it is difficult to make precise predictions as to which jobs will see a fall in demand and the scale of new job creation.

The extent to which technological advances are – overall – a substitute for human workers depends on a balance of forces, including productivity growth, task creation, and capital accumulation. The number of jobs created as a result of growing demand, movement of workers to different roles, and emergence of new jobs linked to the new technological landscape all also influence the overall economic impact of automation by AI technologies.

While technology is often the catalyst for revisiting concerns about automation and work, and may play a leading role in framing public and policy debates, it is not a unique or overwhelming force. Other factors also contribute to change, including political, economic, and cultural elements.

Studies of the history of technological change demonstrate that, in the longer term, technologies contribute to increases in population-level productivity, employment, and economic wealth. But these studies also show that such population-level benefits take time to emerge, and there can be periods in the interim when parts of the population experience significant disbenefits.

Substantial evidence from historical and contemporary studies indicates that technology-enabled changes to work tend to affect lower-paid and lower-qualified workers more than others. This suggests there are likely to be transitional effects that cause disruption for some people or places.

In recent years, technology has contributed to a form of job polarisation that has favoured higher-educated workers, while removing middle-income jobs, and increasing competition for non-routine manual labour. Concentration of market power may also inhibit labour's income share, competition, and productivity.

One of the greatest challenges raised by AI is therefore a potential widening of inequality, at least in the short term, if lower-income workers

are disproportionately affected and benefits are not widely distributed.

This evidence synthesis provides a review of research evidence from across disciplines in order to inform policy debates about the interventions necessary to prepare for the future world of AI-enabled work, and to support a more nuanced discussion about the impact of AI on work. While there are a number of plausible future paths along which AI technologies may develop, using the best available evidence from across disciplines can help ensure that technology-enabled change is harnessed to help improve productivity, and that systems are put in place to ensure that any productivity dividend is shared across society.

Introduction

Introduction

1.1 Safely and rapidly harnessing the power of AI

Artificial intelligence (AI) technologies are developing apace, with many potential benefits for economies, societies, communities, and individuals. Realising their potential requires achieving these benefits as widely as possible, as swiftly as possible, and with as smooth a transition as possible.

Across sectors, AI technologies offer the promise of boosting productivity and creating new products and services. These technologies are already being applied in sectors such as retail, manufacturing, and entertainment, and there is significant potential for further uptake, for example in pharmaceuticals, education, and transport.¹

The UK is well-placed to take advantage of the opportunities presented. It has globally-recognised capability in AI-related research disciplines, has nurtured clusters of innovative start-ups, and benefits from a policy environment that has been supportive of open data efforts.

1.2 Policy debates about automation and the future of work

With this potential, come questions about the impact of AI technologies on work and working life, and renewed public and policy debates about automation and the future of work. There are already indications that such questions have entered public consciousness, with the British Social Attitudes 2017 survey showing that 7% of respondents felt “it is likely that many of the jobs currently done by humans will be done by machines or computer programmes in 10 years’ time”, and public dialogues by the Royal Society highlighting ‘replacement’ as one area of concern about AI technologies for members of the public.²

In considering the potential impact of AI on work, a range of studies and authors have made predictions or projections about the ways in which AI might affect the amount, type, and distribution of work. While strong consensus exists among scholars over

1 The Royal Society (2017). *Machine learning: the power and promise of computers that learn by example*. Retrieved from <https://royalsociety.org/-/media/policy/projects/machine-learning/publications/machine-learning-report.pdf>

2 Phillips, D., Curtice, J., Phillips, M. and Perry, J. (eds.) (2018), *British Social Attitudes: The 35th Report*, London: The National Centre for Social Research. Retrieved from <http://bsa.natcen.ac.uk/latest-report/british-social-attitudes-35/key-findings.aspx>

historical patterns, projections of future impacts vary, particularly quantitative ones such as those estimating the number of job losses. Such studies indicate that there are many plausible future paths along which AI might develop.

Notwithstanding this significant uncertainty surrounding the future world of work, evidence from previous waves of technological change – including the Industrial Revolution and the advent of computing – can provide evidence and insights to inform policy debates today. Meanwhile studies from across research domains – from economics to robotics to anthropology – can inform thinking about the role of different forces, actors, and institutions in shaping the role of technology in society.

Though much of the public debate on AI and work has tended to oscillate between fears of ‘the end of work’ and reassurances that little will change in terms of overall employment, evidence from across academic disciplines and research papers suggests neither of these extremes is likely. Instead, there is consensus in academic literature that AI will have a considerable disruptive effect on work, with some jobs being lost, others being created, and others changing.

In this context, two types of policy-related priorities emerge:

- Ensuring that technology-enabled change leads to improved productivity; and
- Ensuring that the benefits of such change are distributed throughout society.

This synthesis of research evidence by the Royal Society and the British Academy draws on research across several disciplines – by economists, historians, sociologists, data scientists, law and management specialists, and other experts. It aims to bring together key insights from current research and debates about the impact of AI on work, to help policy-makers to prepare for the impacts of change among different groups, and to inform strategies to help mitigate adverse impacts.³

3 For the Royal Society, this project is part of a wider programme of policy activities on data and AI. More information about this work is available at this link: <https://royalsociety.org/topics-policy/open-science-and-data>

The Royal Society and British Academy's evidence synthesis on AI and work

The Royal Society and British Academy's evidence synthesis on AI and work

Building on the key messages of the Royal Society's 2017 report on *Machine Learning*, in 2018, the Royal Society and British Academy convened leading researchers and policy experts to consider the implications of AI-enabled technological change for the future of work.

This evidence synthesis – which follows a programme of research and engagement with key academic and policy stakeholders – is designed to provide a digest of academic literature and thinking on AI's impact on work. It is based on a review of recent literature conducted by Frontier Economics, as well as two seminars attended by leading authors, scholars, and AI practitioners.⁴

The Frontier Economics literature review, published alongside this paper, collected over 160 relevant English-language documents published since 2000, across a wide range of disciplines. These included articles published in peer-reviewed journals and academic manuscripts, as well as reports published by public sector organisations, international organisations, think-tanks and consultancies. A short list of 47 documents to be reviewed in detail was selected from the long list of 160, including evidence on historical and recent effects of technology on work; theoretical frameworks for considering AI's future impacts; and specific projections on future impacts of AI. This literature review was complemented and informed by the workshops, and by interviews with leading thinkers and policy-makers.⁵ It was further refined by expert peer review, within Frontier Economics⁶ and at the Royal Society and the British Academy.⁷

The evidence synthesis that follows starts by noting the potential of AI across business sectors and the current state of AI adoption, before exploring the different insights that come from across disciplines when considering the impact of AI on the overall amount of work and the quality of work available. It then considers the factors influencing the impact of AI on economies and societies, and the ways in which societies share the benefits of these technologies.

- 4 From 19–21 February 2018, The Royal Society and American Academy of Arts and Sciences co-hosted a workshop exploring the impact of AI on working life. On 15 March 2018, The Royal Society and British Academy hosted a joint workshop on the subject 'is this time different?', exploring the economic and social implications of AI-enabled changes to work and the economy.
- 5 In compiling its review, Frontier Economics interviewed: Andrew Haldane, Chief Economist, Bank of England; Professor Stephen Machin, Director – Centre for Economic Performance, London School of Economics; Geoff Mulgan, Chief Executive, Nesta; and Richard Susskind, IT Adviser to the Lord Chief Justice of England and Wales, and chairman of the Advisory Board of the Oxford Internet Institute.
- 6 By Sir Richard Blundell, David Ricardo Professor of Political Economy at University College London.
- 7 In addition to review by the project steering group, Frontier Economic's work was reviewed by an external review group, consisting of: Professor Jon Agar, Professor of Science and Technology Studies, UCL; Professor Pam Briggs, Professor of Applied Psychology, Northumbria University; Helen Ghosh, Master of Balliol College, Oxford; Professor Patrick Haggard, Professor of Cognitive Neuroscience, UCL; and Professor Nick Jennings, Professor of AI, Imperial.

This synthesis uses 'Artificial Intelligence (AI)' as an umbrella term for a suite of technologies that perform tasks usually associated with human intelligence. Machine learning is the technology responsible for driving most of the current and recent advances within the field of AI, and is a technology that enables computer systems to perform specific tasks intelligently, by learning from data (see Box 1 for further details).

BOX 1 Digital technology, automation, artificial intelligence and machine learning

Digital technology refers to all forms of hardware and software using binary code to perform tasks, from conventional spreadsheets or calculators on personal computers to networked systems and advanced algorithms that enable computer systems to make decisions based on data analysis.

Automation in its broadest sense is the replacement of human beings with machines, robotics or computer systems to carry out an activity. The term can apply to the earliest mechanical devices, the changes seen in the Industrial Revolution and assembly line manufacturing, as well as computing and robotics. In policy debates about artificial intelligence, automation is often used to refer to the migration of human tasks to computers and robots, whether or not AI technologies are necessary to enable this.

Artificial intelligence (AI) is an umbrella term that describes a suite of technologies that seek to perform tasks usually associated with human intelligence. John McCarthy, who coined the term in 1955, defined it as "the science and engineering of making intelligent machines."⁸

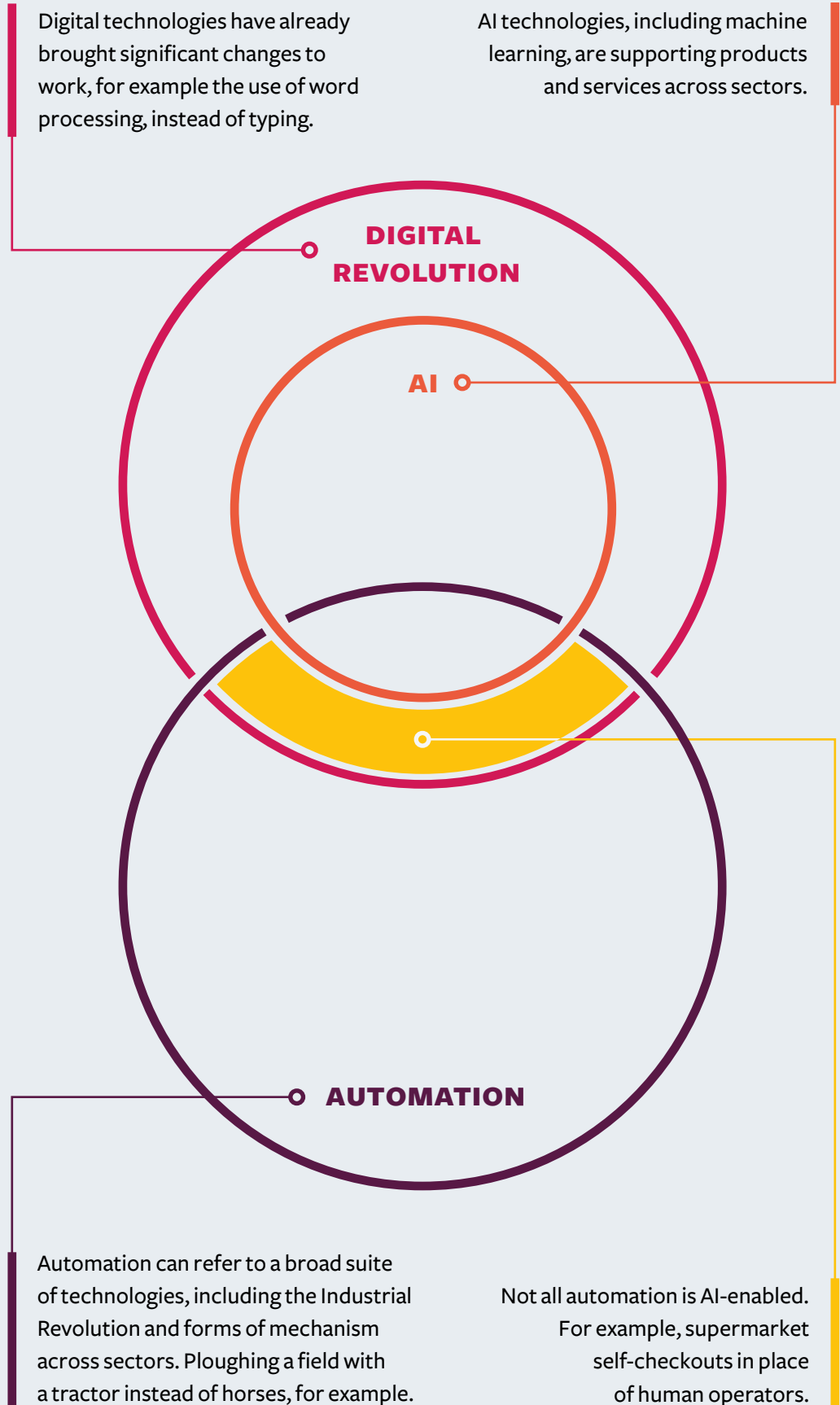
Machine learning is a branch of AI that enables computer systems to perform specific tasks intelligently. These systems carry out complex processes by learning from data, rather than following pre-programmed rules. Recent years have seen significant advances in the capabilities of machine learning, as a result of the increased availability of data; advanced algorithms; and increased computing power. Many people now interact with machine learning-driven systems on a daily basis: in image recognition systems, such as those used to tag photos on social media; in voice recognition systems, such as those used by virtual personal assistants; and in recommender systems, such as those used by online retailers.⁹

Today, machine learning enables computer systems to learn to carry out specific functions 'intelligently'. However, these specific competencies do not match the broad suite of capabilities demonstrated by people. Human-level intelligence – or 'general AI' – receives significant media attention, but this is still some time from being delivered, and it is not clear when this will be possible.

8 McCarthy, J. (n.d.) *What is artificial intelligence?* Stanford University. Retrieved from: <http://jmc.stanford.edu/artificial-intelligence/what-is-ai/index.html>

9 The Royal Society, *Machine learning report*.

FIGURE 1 An illustration of the relationships between automation, the digital revolution, and AI technologies



The impact of AI on economies and work

The impact of AI on economies and work

3.1 AI has significant economic potential

AI technologies are already supporting new products and services across a range of businesses and sectors:

- Intelligent personal assistants using voice recognition, such as Siri, Alexa, and Cortana, are commonplace in many businesses.
- In the transport sector, AI processes underpin the development of autonomous vehicles¹⁰ and are helping manage traffic-flows and design of transport systems.
- In education, AI technologies are supporting personalised learning systems.
- In healthcare, AI is enabling new diagnostic and decision-support tools for medical professionals.
- In retail and logistics, AI is supporting the design of warehouse facilities to improve efficiency.
- In development and humanitarian assistance, data analytics enabled by AI are helping support the delivery of the Sustainable Development Goals and the assessment of humanitarian scenarios.¹¹
- In the creative industries, developers are creating computer systems that can produce simple news reports, for example on business results,¹² compose orchestral music,¹³ and generate short pieces of film.¹⁴
- Across sectors, AI is being put to use to analyse vast quantities of data, to improve business processes or design new services.

Different AI technologies or applications are developing at different paces, and their adoption across sectors and businesses is variable. A recent Stanford University study

10 Stone, P. et al. (2016) "Artificial Intelligence and Life in 2030." *One Hundred Year Study on Artificial Intelligence: Report of the 2015–2016 Study Panel*, Stanford, CA: Stanford University. Retrieved from: <http://ai100.stanford.edu/2016-report>

11 Vacarelu, F. (2018) *Continuing the AI for good conversation: Takeaways from the 2018 AI for good global summit*. United Nations Global Pulse. Retrieved from: <https://www.unglobalpulse.org/news/AIforGoodGlobalSummit2018Takeaways>

12 Lacity, M.C. & Willcocks, L.P. (2016) 'A new approach to automating services'. *MIT Sloan Management Review*, 58(1), 41. Retrieved from: http://eprints.lse.ac.uk/68135/1/Willcocks_New%20approach_2016.pdf

13 Moss, R. (2015) *Creative AI: Computer composers are changing how music is made*. *New Atlas magazine*. Retrieved from: <https://newatlas.com/creative-artificial-intelligence-computer-algorithmic-music/35764/>

14 Hutson, M. (2018) *New algorithm can create movies from just a few snippets of text*. *Science magazine*. Retrieved from: <http://www.sciencemag.org/news/2018/02/new-algorithm-can-create-movies-just-few-snippets-text>

describes progress and implementation as “patchy and unpredictable”.¹⁵ This description is supported by a number of studies describing the attitudes of business leaders to AI. For example, a 2017 survey showed that only 14% of UK business leaders were currently investing in AI or robotics, or plan to in the near future,¹⁶ slightly higher than international adoption rates, with 9–12% of business leaders across 10 advanced economies reporting that they have adopted AI.¹⁷

Box 2 summarises policy measures that can contribute to realising the economic benefits of AI technologies:

BOX 2 Realising the benefits of machine learning

The Royal Society’s 2017 report on Machine Learning investigated the potential of this technology over the next 5–10 years, and the barriers to realising that potential. This study identified the following key areas for action to realise the economic and societal benefits of machine learning in the UK:

- Creating an amenable data environment, based on appropriate open data and standards;
- Supporting businesses to use machine learning, through government advice networks;
- Building skills at all levels, from teaching key concepts in schools to building a pool of informed practitioners at Masters-level, and supporting advanced skills at postgraduate level;
- Renewing governance frameworks to support the use of data; and
- Advancing research in areas of technical and societal interest.

3.2 AI-enabled changes could affect the quantity and quality of work

This section considers the evidence provided by current studies of the impact of AI-enabled automation on work, and the types of insight that can be taken from historical perspectives on technology and the workforce.

15 AI Index Team (2017) *Artificial Intelligence Index: 2017 Annual Report*. Stanford, CA: Stanford University. Retrieved from: <http://cdn.aiindex.org/2017-report.pdf>

16 Dellot, B. and Wallace-Stephens, F. (2017) *The Age of Automation: Artificial intelligence, robotics and the future of low-skilled work*. London: RSA Action and Research Centre. Retrieved from https://www.thersa.org/globalassets/pdfs/reports/rsa_the-age-of-automation-report.pdf

17 McKinsey Global Institute (2017). *Artificial Intelligence: the Next Digital Frontier? Discussion Paper*. Retrieved from: <https://www.mckinsey.com/-/media/McKinsey/Industries/Advanced%20Electronics/Our%20Insights/How%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/MGI-Artificial-Intelligence-Discussion-paper.ashx>

3.2.1 Concerns about automation and the workplace have a long history

Throughout history, waves of technological innovation have catalysed public and policy debates about work and automation.

For example, the 20th century saw renewed predictions that automation would leave humans without work. In 1930, John Maynard Keynes envisaged a world in which the ‘economic problem’ of the struggle for subsistence would be “solved”.¹⁸ In 1950 John F Kennedy spoke of automation as a “problem” that would create “hardship”.¹⁹ In 1965 Time magazine quoted an IBM economist saying automation would bring about a 20-hour week.²⁰ Later, as digital technology advanced, debate arose over whether it would signal ‘The End of Work’ – as termed by the US economist Jeremy Rifkin in 1995.

Such debates are often prompted by fears about job losses, and concerns over whether wider economic benefits will ensue, with expert opinion often divided on the subject.

In seeking to draw historical comparisons, analyses of current trends in AI-enabled automation often look back to the British Industrial Revolution.

At the start of the British Industrial Revolution, thinkers such as James Stuart and David Ricardo believed technology would be generally beneficial, despite concerns around short-term displacement. Others, such as William Mildmay, recognised the logic of adopting technology to compete, but did not think it would benefit society.

In the context of the Industrial Revolution, the adoption of inventions such as mechanical spinning, coke smelting and the steam engine led to a rise in demand for capital for equipment and for cities, homes, and infrastructure. Initially, the increasing rate of return on capital increased the share of profits in national income. However, the purchasing power of wages stagnated – a period of constant wages in the midst of rising output per worker during the 18th century known as ‘Engels’ pause’.²¹

18 Reproduced at: http://www.executiveshift.org.uk/images/site_graphics/downloads/John_Maynard_Keynes.pdf

19 Reproduced at: <https://www.jfklibrary.org/Asset-Viewer/Archives/JFKCAMP1960-1030-036.aspx>

20 Rothman, L. (2015) ‘This 50-Year-Old Prediction About Computers Will Make You Sad’, *Time*. Retrieved from: <http://time.com/3754781/1965-predictions-computers/>

21 Allen, R.C. (2009) ‘Engels’ pause: Technical change, capital accumulation, and inequality in the British industrial revolution’. *Explorations in Economic History* 46(4), 418–435.

By the mid-19th century, the continuing rise in profits led to enough capital formation to create a balanced growth path in which capital and augmented labour both grew at the same rate and real wages then grew in line with productivity. In the same period, technological changes enabled or interacted with large population movements from land to cities in the West, changes in working and earning patterns between generations and genders, changes to the distribution of income and wealth across demographics, and widespread social changes.

Following these changes, research indicates that economic benefits and wage increases took time to emerge, and major displacements of people took place in the process. For example, it has been estimated that if James Watt had not invented the improved steam engine in 1769, the national income of Great Britain in 1800 would have been reduced by only about 0.1 per cent.²² Several studies demonstrate how displacement and job losses occur in the short term while over the longer term, productivity, wealth, and employment all tend to rise.²³

Summary: The potential of AI to drive change in many employment sectors has revived concerns over automation and the future of work. Evidence suggests that AI will not result in the ‘end of work’ but neither will it mean ‘business as usual’. It is set to bring profound change to the world of work.

3.2.2 Studies give different estimates of the number of jobs affected by AI

Projections of the impact of AI on the overall number of jobs in the UK vary, largely depending on their treatment of the input data, with some using a single Delphi poll as their starting point.

A widely-cited and much-debated study of 2013 analysed 702 occupations in the US on the basis of ‘probability of computerisation’ – otherwise described as ‘machine learning

22 Crafts, N. (2010). *The Contribution of New Technology to Economic Growth: Lessons from Economic History* (CAGE Online Working Paper Series 01, Competitive Advantage in the Global Economy). Retrieved from: https://warwick.ac.uk/fac/soc/economics/research/centres/cage/manage/publications/01.2010_crafts.pdf

23 There is reasonably wide consensus on this process in the literature, although an alternative ‘optimistic’ tradition maintains that workers in the British Industrial Revolution fared better than classical economists thought.

and mobile robotics’ – and found that 47% of total US employment fell into the ‘high risk’ category.²⁴ This study prompted intense public debate and encouraged economists and others to explore the issue further.

Many researchers challenged the 2013 study’s ‘occupation-based’ approach of examining the automatability of entire occupations. Subsequent studies have proceeded on the basis that occupations consist of a bundle of separate tasks, each of which can be automated or not.^{25,26} Studies using such a ‘task-based’ approach have tended to identify fewer jobs at risk. For example, a 2016 OECD report, which assessed tasks within occupations, found that only 10% of all jobs in the UK (9% in the US) were “automatable” through “automation and digitalisation”.²⁷

Other task-based studies have provided higher projections of jobs at risk, using more detailed task-related datasets and arguing that these provide more accurate estimates. For example:

- A 2018 report used a dataset compiled by the OECD that looks in detail at the tasks involved in the jobs of over 200,000 workers across 29 countries.²⁸ It projected 30% of UK jobs as being at high risk of automation, albeit adding that the actual impact may be less due to economic, legal, and other constraints and that offsetting job gains are expected. The report took a long-term view of ‘automation’, from computational tasks to driverless cars.
- A further OECD study, covering 32 countries, calculated that close to 1 in 2 jobs is likely to be ‘significantly affected’ by ‘automation’, but with varying degrees of risk.²⁹ It found that 12% of UK jobs had a 70%–plus risk and another 25% had a 50–70% risk.
- A 2017 report examining the global labour market not only used multiple databases of occupations and tasks covering 46 countries but also modelled

24 Frey C., & Osborne, M. (2013) *The future of employment: how susceptible are jobs to computerisation?* Oxford Martin School Working Paper.

25 Autor, D. (2015) ‘Why Are There Still So Many Jobs? The History and Future of Workplace Automation’, *Journal of Economic Perspectives* 29(3), 3–30.

26 Artzn, M., Gregory, T. & Ziehran, U. (2016) *The Risk of Automation for Jobs in OECD Countries* (OECD Social, Employment and Migration Working Papers No. 189). Paris: OECD. Retrieved from: https://www.keepeek.com/Digital-Asset-Management/oecd/social-issues-migration-health/the-risk-of-automation-for-jobs-in-oecd-countries_5jlz9h56dvq7-en#page1

27 Ibid.

28 PwC (2018). *Will robots really steal our jobs? PWC Report*. Retrieved from: <https://www.pwc.co.uk/economic-services/assets/international-impact-of-automation-feb-2018.pdf>

29 Nedelkoska, L. & Quintini, G. (2018) *Automation, skills use and training* (OECD Social, Employment and Migration Working Papers, No. 202). Paris: OECD. Retrieved from: https://read.oecd-ilibrary.org/employment/automation-skills-use-and-training_2e2f4eea-en#page1

AI-related factors alongside other non-AI related labour market drivers such as rising incomes, healthcare demand, and infrastructure.³⁰ It concluded that around about half of all work activities globally (43% in the UK according to a related study)³¹ have the technical potential to be ‘automated’ by 2030 – through “robotics (machines that perform physical activities) and artificial intelligence (software algorithms that perform calculations and cognitive activities)”. However, it also calculates that the actual proportion of work potentially displaced by automation, will be lower, ranging from almost zero in some countries to 30% in others, for example 9% in India and 24% in Germany.³²

- Another recent report focusing on the UK finds that, over 20 years, the one-fifth of existing jobs displaced by AI in the UK is likely to be approximately equal to the additional jobs that are created, assuming productivity and real incomes rise and new and better products are developed.³³

In 2017, demonstrating the evolving nature of the literature, one of the authors of the original 2013 study contributed to a report that stressed the positive impacts of AI and projected that that around 20% of the workforce worked in occupations likely to shrink while 10% was in occupations likely to grow.³⁴

In interpreting the results of such studies, it is helpful to note that:

- Studies vary in their definition of the process by which humans are fully or partly replaced in the workplace – whether AI technologies, some form of computing, and robotics, or a broader view of ‘automation’.

30 McKinsey Global Institute (2017) *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*. Retrieved from: <https://www.mckinsey.com/-/media/McKinsey/Global%20Themes/Future%20of%20Organizations/What%20the%20future%20of%20work%20will%20mean%20for%20jobs%20skills%20and%20wages/MGI-Jobs-Lost-Jobs-Gained-Report-December-6-2017.ashx>

31 McKinsey Global Institute (2017) *Where machines could replace humans – and where they can’t (yet)*. Retrieved from: <https://public.tableau.com/profile/mckinsey.analytics#!/vizhome/InternationalAutomation/WhereMachinesCanReplaceHumans>

32 The report goes on to say that this displacement may be offset by increased productivity and demand, new tasks and non-AI factors. “A growing and dynamic economy – in part fuelled by technology – would create jobs. This job growth could more than offset the jobs lost to automation”.

33 PwC (2018) *UK Economic Outlook*. Retrieved from: <https://www.pwc.co.uk/economic-services/ukeo/ukeo-july18-full-report.pdf>

34 Bakhshi, H., Downing, J.M., Osborne, M.A & Schneider, P. (2017). *The Future of Skills: Employment in 2030*. Report prepared by Nesta and Oxford Martin School. Retrieved from: https://www.nesta.org.uk/sites/default/files/the_future_of_skills_employment_in_2030_o.pdf
The authors concluded that “[t]he study challenges the false alarmism that contributes to a culture of risk aversion and holds back technology adoption, innovation, and growth.”

- This literature varies in timescale. Some studies focus on the automatability of jobs or tasks without close attention to timing. Longer timescales tend to result in high numbers of jobs being affected or created.
- Such studies rely on judgements about what will be technologically feasible over different timescales. The empirical evidence behind these often consists of a small number of opinion-gathering exercises. There are limitations on the extent to which this type of evidence can be relied on.

Further studies of this type have been published over the past five years. The current prevailing consensus suggests that around 10% to 30% of current jobs in the UK could be subject to some level of ‘automation over the next two decades’.^{35,36} Given methodological limitations, such studies may be most useful in catalysing discussion about what kinds of jobs might be at risk.

There is a consensus that AI and automation will introduce innovations that remove some jobs and create others, potentially with time lags between technology adoption and positive economic impacts, during which some workers may be displaced and see wages fall.³⁷

Much of the evidence contests an ‘end of work’ hypothesis by projecting that AI will nonetheless resemble previous waves of change in changing and creating jobs as well as rendering others obsolete.³⁸

Summary: Many projections of jobs lost, gained, or changed by AI have been published over the last 5 years. More recently, a consensus has begun to emerge that 10-30% of jobs in the UK are highly automatable, meaning AI could result in significant job losses. Many new jobs will also be created. The rapid increase in the use of administrative data and more detailed information on tasks has helped improve the reliability of empirical analysis. This has reduced the reliance on untested theoretical models and there is a growing consensus of the main types of jobs that will suffer and where the growth in new jobs will appear. However, there remain large uncertainties about

35 Arntz, M., Gregory, T. & Ziehran, U. (2016) *The Risk of Automation for Jobs in OECD Countries* (OECD Social, Employment and Migration Working Papers No. 189). Retrieved from: https://www.keepeek.com/Digital-Asset-Management/oced/social-issues-migration-health/the-risk-of-automation-for-jobs-in-oecd-countries_5jlz9h56dvq7-en#page1

36 PwC, *Will robots really steal our jobs?*

37 Acemoglu, D. & Restrepo, P. (2018) *Artificial Intelligence, Automation and Work* (NBER Working Paper No. 24196). Cambridge, MA: National Bureau of Economic Research.

38 PwC, *Will robots really steal our jobs?*

the likely new technologies and their precise relationship to tasks. Consequently, it is difficult to make precise predictions as to precisely which jobs will see a fall in demand and the scale of new job creation.

3.2.3 Jobs and tasks may be affected by AI in different ways

Automation affects different elements of work in different ways – with some tasks being more susceptible to automation than others.³⁹

At present, a prevailing view is that the most ‘automatable’ activities include tasks in highly structured, predictable environments. Studies suggest that such tasks might include transportation, preparing fast food, collecting and processing data, paralegal work, accounting, and back-office work.^{40,41}

There is strong consensus that lower paid and lower skilled jobs are more at risk than in previous waves of technological change. However, personal care work and manual work in unpredictable environments appear to be exceptions to this trend.⁴²

Automation is expected to have a lesser effect on jobs with a high proportion of tasks that involve managing people, applying expertise, and social interactions. Manual and practical jobs in unpredictable environments, such as gardeners, plumbers, or providers of health and care services for children and older people are also expected to experience lower levels of automation by 2030, due to both the level of technical difficulty involved and the economic incentives at play (these roles often command relatively lower wages, diminishing the incentive to automate).

Aside from occupational distinctions, some researchers show a correlation between lower educational attainment and automatability. In the UK, PwC found that for those

39 McKinsey Global Institute (2017) *A Future that Works: Automation, Employment, and Productivity*. Retrieved from: <https://www.mckinsey.com/-/media/McKinsey/Global%20Themes/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works-Executive-summary.ashx>

40 PwC, *Will robots really steal our jobs?*

41 McKinsey Global Institute, *A Future that Works*.

42 Frey & Osborne and Arntz et al agree that humans are likely to have advantages in complex situations, unstructured challenges, creativity and social intelligence – which includes responding to a human with empathy, persuading, negotiating or caring. PwC agree that automatability is lowest in health and social work (17%).

with just GCSE-level education or lower, the estimated potential risk of automation is as high as 46%, but this falls to only around 12% for those with undergraduate degrees or higher.⁴³

However, a developing line of research highlights the risk of automation in ‘professional’ occupations. For example, Susskind & Susskind note that while legal counsel provided by humans may involve non-automatable qualities such as empathy or judgement, consumers may attach greater value to the outcome of accurate legal advice, by whatever means it is achieved.⁴⁴ How and where professional tasks are automated therefore relies on a combination of the accuracy and consistency offered by computer systems, and the human interaction that customers may feel is important, especially in moments of significant life change.

Several studies note the scope for improving outcomes of work through integrating capabilities of humans and machines. For example, a research team from Harvard Medical School and Beth Israel Deaconess Medical Center have demonstrated that while an automated diagnostic method achieved a 92% success rate in identifying the presence or absence of metastatic cancer in a patient’s lymph nodes, and a human pathologist scored 96%, the combination of human and machine yielded a 99.5% success rate.⁴⁵

Summary: There are many different perspectives on ‘automatability’, with a broad consensus that current AI technologies are best suited to ‘routine’ tasks, while humans are more likely to remain dominant in unpredictable environments, or in spheres that require significant social intelligence.

3.2.4 Commercial, social, and legal factors may influence AI adoption

Many studies stress that ‘jobs at risk’ cannot be equated with actual or expected net employment losses, which are likely to be fewer, if any, for several reasons.

43 PwC, *Will robots really steal our jobs?*

44 Susskind, R., & Susskind, D. (2015) *The future of the professions: How technology will transform the work of human experts*. Oxford: Oxford University Press.

45 Prescott, B. (2016) *Better Together: Artificial intelligence approach improves accuracy in breast cancer diagnosis*. Harvard Medical School. Retrieved from: <https://hms.harvard.edu/news/better-together>

First, the pace of adoption is affected by commercial, social, legal, and other factors. For example, businesses may not invest in adopting AI technologies, consumers may not switch to AI-enabled products and services, and legislators may take time to create legal frameworks for innovations using AI technologies.

Second, technological change can generate additional jobs, especially when product costs fall and rising demand for products and labour grows (see section 3.3.1 for further discussion).⁴⁶

Third, economies and firms may adjust to new technologies by switching some displaced workers to new tasks. Examples of this include a decrease in typists being offset by an increase in call centre staff, banks moving tellers into customer relationship roles.⁴⁷

Fourth, as existing industries become more competitive and grow or new types of work emerge, new jobs are created. One report estimated that around 6% of all UK jobs in 2013 did not exist at all in 1990.⁴⁸ Categories of possible new jobs could include ‘trainers’ (workers engaged in training AI systems), ‘explainers’ (workers interpreting AI outputs for accountability), and ‘sustainers’ (workers monitoring the work of AI systems).⁴⁹ Meanwhile, advances in industrial robotics could generate employment in robotics support services to manufacturing firms, as well as in the manufacturing of robots.⁵⁰

Summary: The extent to which technological advances are – overall – a substitute for human workers depends on a balance of forces, including productivity growth, task creation, and capital accumulation. The number of jobs created as a result of growing demand, movement of workers to different roles, and emergence of new jobs linked to the new technological landscape all also influence the overall economic impact of automation by AI technologies.

46 McKinsey Global Institute, *Jobs Lost, Jobs Gained*.

47 Ibid.

48 PwC (2015) *New job creation in the UK: which regions will benefit most from the digital revolution?* <http://www.pwc.co.uk/assets/pdf/ukeo-regional-march-2015.pdf>

49 Accenture PLC in Acemoglu, D. & Restrepo, P. (2018a). *Artificial Intelligence, Automation and Work* (NBER Working Paper No. 24196). Cambridge, MA: National Bureau of Economic Research.

50 Eurofound (2017). *Advanced industrial robotics: Taking human-robot collaboration to the next level*. Retrieved from <https://www.eurofound.europa.eu/sites/default/files/wpfomeef18003.pdf>

3.3 The impact of technology-enabled change on economies and employment

Having summarised the evidence relating to the number and nature of jobs that might be affected by AI, this section reviews research on the broader and deeper trends underlying the impact of technology on the world of work. First, it examines general and theoretical studies into how technology affects economies and the structure of employment. Second, it looks at how technology affects workers, concluding by focusing on the challenge of distributing the benefits of new technology.

3.3.1 *Forces shaping the impact of technology on economies and the structure of employment*

A number of underlying forces shape how economies respond to technology-enabled automation: the economic processes by which technology displaces and creates work; the way in which social, economic, and technical systems combine to affect different groups in different ways; the time-lag between the adoption of new technology and its positive impacts; and the effect of market concentration.

Economic forces contribute to shaping the displacement and creation of work

A growing body of work has considered the economic processes at hand when technology affects jobs, seeking to create frameworks to describe and gauge the forces at work. While this is a new area for research, initial studies (such as Acemoglu & Restrepo)⁵¹ suggest that the extent of the short-term *substitution effect*, in which labour is replaced by AI, is counteracted by other effects including:

- a *productivity effect* as technology enables goods and services to become cheaper and better, stimulating additional demand for the products and thus the labour required to produce them (seen for example in US textiles to the 1930s and US steel to the 1950s.);
- a *new task effect* as new types of jobs emerge, related to the technological changes; and
- a *capital accumulation effect* as more machines are deployed, driving down costs and enhancing the productivity effect.

51 Acemoglu, D. & Restrepo, P. (2018). *Artificial Intelligence, Automation and Work* (NBER Working Paper No. 24196). Cambridge, MA: National Bureau of Economic Research.

Within this framework, while substitution effects may dominate in the short term, if a technology enables a strong-enough productivity effect, then this substitution can be off-set in the longer-term with new tasks and capital accumulation.

According to this model, the most disruptive technologies may have more positive long-term impacts on work as they create the strongest productivity, new jobs and capital accumulation effects. In 19th-century Britain, for example, there was a rapid expansion of jobs related to new technology such as engineers, machinists, repair workers, conductors, back-office workers, and managers. Similarly, the mechanisation of agriculture created jobs in farm equipment supply and maintenance.⁵²

However, some forms of automation can simply have a substitution effect without generating sufficient productivity gains, new jobs or capital accumulation effects to offset the decline in jobs – as in the case of some deployment of industrial robots in the US.⁵³

Under these frameworks, while jobs may not be lost on a net basis, the share of income accruing to workers relative to owners of capital may fall as labour market structures change more generally, with self-employment and ‘gig economy’ work becoming more common across the workforce, while large unionised workforces in manufacturing and other industries become less familiar.

Technology-enabled changes to work affect different groups in different ways

A key theme emerging from studies of changes enabled by information and communications technology and automation between the 1980s and 2000s is ‘job polarisation’ or ‘hollowing out’ of the workforce.

Such studies show that middle-educated workers who are displaced by automation do not move into high level non-routine cognitive work, as it is already occupied by high educated individuals – for whom demand increases – and so compete for non-routine manual work. This competition can dampen wage growth for low-educated workers.^{54,55}

52 Acemoglu, D. & Restrepo, P. (2017) *Robots and Jobs: Evidence from US Labor Markets* (NBER Working Paper No. 23285). Cambridge, MA: National Bureau of Economic Research.

53 Acemoglu, D. & Restrepo, P., 8 *Artificial Intelligence, Automation and Work*.

54 Autor, D., Levy, F. & Murnane, R.J. (2003) *The Skill Content of Recent Technological Change: An Empirical Exploration*. Retrieved from: <https://economics.mit.edu/files/581>

55 Acemoglu, D., & Autor, D. (2011) ‘Skills, tasks and technologies: Implications for employment and earnings’, in: *Handbook of Labor Economics* (Vol. 4, pp. 1043–1171). Elsevier.

For example, a study by Goos & Manning focuses on how such polarisation occurred in the UK between 1975 and 1999, demonstrating growth in low-paid service jobs and professional and managerial occupations, while clerical jobs and skilled manual jobs in manufacturing declined.⁵⁶

Looking ahead, some researchers expect less of a polarisation effect from AI, with more impact concentrated on lower-income, lower-skill jobs. Others stress that while many economies may not see such pronounced job polarisation, wage polarisation could continue as demand for higher paid occupations rises and that for lower-wage work declines.⁵⁷

There is also evidence that economic ‘shocks’ affect different geographies in different ways (discussed later).

There can be time lags between the adoption of technology and its benefits appearing

While technology ultimately contributes to economic growth, there is frequently a time lag between technological change and an increase in productivity:

- Studies of the British Industrial Revolution suggest that productivity growth was quite modest in the decades following major inventions such as the steam engine and spinning mule, finally acquiring momentum in the latter half of the 19th century – decades later.⁵⁸
- Uptake of computers also took time to be reflected in productivity, leading to economist Robert Solow’s 1987 observation that: “You can see the computer age everywhere but in the productivity statistics.” However, US productivity growth then accelerated from an average rate of 2.08% in the 1973–1995 period to a rate of 4.77% in 1995–2000.⁵⁹

56 Goos, M. & Manning, A. (2004) ‘Lousy and Lovely Jobs: the Rising Polarization of Work in Britain’. *The Review of Economics and Statistics*, 89(1), 118–133.

57 McKinsey Global Institute, *Jobs lost, jobs gained*.

58 Crafts, N. (2002) ‘Productivity Growth In The Industrial Revolution: A New Growth Accounting Perspective’, *The Journal of Economic History*, 64(2), 521–535.

59 Van Reenen, J., Bloom, N., Draca, M., Kretschmer, T. & Sadun, R. (2010). The Economic Impact of ICT (SMART report N.2007/020). Retrieved from <https://warwick.ac.uk/fac/soc/economics/staff/mdraca/cstudytheeconomicimpactofictlondonschoolofeconomics.pdf>

Productivity growth in the UK and other advanced economies has been weak by the standards of the last 50 years, and economists have offered several possible explanations for this ‘productivity puzzle’.⁶⁰

Brynjolfsson et al⁶¹ suggest the most likely option – as in the past – is lags in implementation and impact of technological advances, as production processes need to be reorganised to take advantage of new technology. Other possible explanations include:

- Misplaced optimism – that digital technology can provide benefits in terms of new products and services but does not have the potential to raise productivity substantially.
- Measurement errors – that there have been productivity gains, but they are not evident from official statistics, for example because investments such as machine learning processes are intangible and services are provided to consumers at low or no cost.
- Distribution issues – that productivity gains are concentrated among a small group of leading firms.⁶²
- Implementation lags – that technology-led productivity gains do not materialise immediately as production processes need to be reorganised.

Since 2016, research focusing on the impact of market concentration on productivity and employment in the digital economy has begun to emerge.⁶³

Digital technologies may contribute to concentration of market power, by enabling the emergence of ‘platform’ markets, which tend to be dominated by one or two firms.⁶⁴ Platforms benefit from snowballing direct network effects – whereby the value to a customer increases as the number of other customers using the same platform rises.

60 Haldane A. (2017) *Productivity puzzles*: Speech given by Andrew G Haldane, Chief Economist, Bank of England.

61 Brynjolfsson, E., Rock, D. & Syverson, C. (2017) *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics* (NBER Working Paper No. 24001). Cambridge, MA: National Bureau of Economic Research.

62 Andrews, D., Criscuolo, C. and Gal, P.N. (2015) *Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries* (OECD Productivity Working Papers November 2015, No. 02). Retrieved from: https://www.oecd-ilibrary.org/economics/frontier-firms-technology-diffusion-and-public-policy_5jrql2q2jj7b-en

63 The Economist (2018) *Can Netflix please investors and still avoid the techlash?* Retrieved from: <https://www.economist.com/leaders/2018/06/28/can-netflix-please-investors-and-still-avoid-the-techlash>

64 Furman, J. & Seamans, R. (2018) *AI and the Economy*. (NBER Working Paper No. 24689). Cambridge, MA: National Bureau of Economic Research.

In this context, the most productive businesses can become ‘superstar’ firms that employ relatively few workers in terms of share of labour in revenue.

Some argue that, while the emergence of such dominant players may support economic growth, it depresses labour’s share of income, limits competition, and may not lift average productivity – thereby contributing to the lag in sharing of benefits.⁶⁵

History provides examples of governments acting against market dominating companies, from the UK’s removal of the East India Company’s monopoly over trade with India in 1813 to the break-up of AT&T’s US telecoms monopoly in 1982. A recent report noted that such companies have tended to face action when their profits had grown to represent between 0.08% and 0.54% of GDP.^{66,67}

Technology is not a unique and overwhelming force

While technology is often the catalyst for revisiting concerns about automation and work, and may play a leading role in framing public and policy debates, it is not a unique or overwhelming force driving societal changes. The notion of technological determinism needs to be tempered by consideration of the other factors that also contribute to change.⁶⁸

In the context of the Industrial Revolution, for example, Crafts notes how high labour costs and low energy costs provided a fertile environment for new technology in 18th century England.⁶⁹ Meanwhile Pomeranz argues that the Industrial Revolution was

65 Autor, D., Dorn, D., Katz, L.F., Patterson, C. & Van Reenen, J. (2017) *The Fall of the Labor Share and the Rise of Superstar Firms*. Cambridge, MA: Massachusetts Institute of Technology. Retrieved from <https://economics.mit.edu/files/12979>

66 The Economist (2018) *History’s biggest firms*. Retrieved from: <https://www.economist.com/business/2018/07/05/historys-biggest-firms>

67 National and international authorities have taken action against companies in the digital sector on competition grounds. For example, in 2001, Microsoft and the US Government settled a case over the company’s bundling of its Internet Explorer browser with its Windows operating system with the company agreeing to share its application programming interfaces. In 2018, Google was fined a record £3.9bn by the European Commission over requiring handset and tablet manufacturers to pre-install certain software before allowing them to offer access to its Play app store. For example, see: <https://www.bbc.co.uk/news/technology-44858238>

68 MacKenzie, D. and Wajcman, J. (1999) *The social shaping of technology*. Buckingham, UK: Open University Press. Retrieved from: [https://eprints.lse.ac.uk/28638/1/Introductory%20essay%20\(LSERO\).pdf](https://eprints.lse.ac.uk/28638/1/Introductory%20essay%20(LSERO).pdf)

69 Crafts, N. (2010) *The Contribution of New Technology to Economic Growth: Lessons from Economic History* (CAGE Online Working Paper Series 01, Competitive Advantage in the Global Economy). Retrieved from: https://warwick.ac.uk/fac/soc/economics/research/centres/cage/manage/publications/01.2010_crafts.pdf

nurtured not only by technology and skills but by the ability of imperial countries to use the ‘ghost acreage’ provided by colonies that could yield resources or provide markets for manufactured goods.⁷⁰

Summary: The extent to which technological advances are – overall – a substitute for human workers depends on a balance of forces, including productivity growth, task creation, and capital accumulation. The number of jobs created as a result of growing demand, movement of workers to different roles, and emergence of new jobs linked to the new technological landscape all also influence the overall economic impact of automation by AI technologies.

While technology is often the catalyst for revisiting concerns about automation and work, and may play a leading role in framing public and policy debates, it is not a unique or overwhelming force driving societal changes. Other factors also contribute to change, including political, economic, and cultural elements.

In recent years, technology has contributed to a form of job polarisation that has favoured higher-educated workers, while removing middle-income jobs, and increasing competition for non-routine manual labour. Concentration of market power may also inhibit labour’s income share, competition, and productivity.

3.3.2 AI technologies may also affect working conditions

In addition to changing the overall amount of work, technologies can also shape the nature of work and working conditions, both for those who remain with the same employer, and for those in new roles.

For those remaining in large-scale working environments, automation of routine tasks could lead to greater autonomy and learning opportunities.⁷¹ However, the proliferation of machines, typically equipped with sensors, could subject workers to more monitoring and lessen autonomy.

70 Pomeranz, K. (2000) *The Great Divergence: China, Europe, and the Making of the Modern World Economy* (The Princeton Economic History of the Western World). Princeton: Princeton University Press.

71 Eurofound (2017). *Advanced industrial robotics: Taking human-robot collaboration to the next level*. Retrieved from <https://www.eurofound.europa.eu/sites/default/files/wpfomeef18003.pdf>.

There are also questions about the equality implications of AI technologies. For example, AI could be used to automate recruitment and promotion processes, speeding up candidate screening and improving matching of people to roles.⁷² Instances of algorithmic bias, such as computers sending management level job alerts to more men than women, have already been documented.⁷³ Conversely, absent such legacy bias, there is potential to improve recruitment decisions, and Kahneman and Thaler note that in many cases humans are outperformed by even simple statistical models in decision-making.⁷⁴

A number of studies consider changes to work in the context of broader developments in digital technologies, including the emergence of platform-based systems to organise work (as part of the so-called ‘gig economy’).⁷⁵ The extent to which AI is a cause or enabler of the gig economy is not clear, however these technologies are often invoked in discussions about broader, potentially algorithmically-enabled, changes to working life.

Benefits for those migrating into the ‘gig economy’ include flexibility and control, while adverse impacts can include lack of job security and uncertainty over legal issues, such as the employment status of such workers.⁷⁶ Such platforms may also demand additional skills. For example, one study reports that workers such as nannies or care workers require ‘self-branding’ skills in order to gain sufficient profile on marketplace platforms to generate a living wage.⁷⁷

Some research suggests that employment protection regulation can influence the relationship between technology and productivity. One paper found that “high levels of labour and product market regulation are associated with a lower productivity impact

72 O'Donnell, R. (2018), *AI in recruitment isn't a predication – it's already here*. HR Drive. Retrieved from: <https://www.hrdrive.com/news/ai-in-recruitment-isnt-a-predication-its-already-here/514876/>

73 Gibbs, S. (2015) *Women less likely to be shown ads for high-paid jobs on Google, study shows*. The Guardian. Retrieved from: <https://www.theguardian.com/technology/2015/jul/08/women-less-likely-ads-high-paid-jobs-google-study>

74 Kahneman, D. (2018). Commentary on Camerer (2018), *Artificial Intelligence and Behavioral Economics*, Chapter in forthcoming NBER book *The Economics of Artificial Intelligence*. Retrieved from <http://www.nber.org/chapters/c14016.pdf>; Thaler, R. (2015). *Who's Afraid of Artificial Intelligence?*. Response posted at <https://www.edge.org/response-detail/26083>

75 The ‘gig economy’ tends to refer to people using apps, such as Uber and Deliveroo, to sell their labour.

76 Davies, R. (2017) *Uber loses appeal in UK employment rights case*. The Guardian. Retrieved from: <https://www.theguardian.com/technology/2017/nov/10/uber-loses-appeal-employment-rights-workers>

77 Ticona, J., Mateescu, A., & Rosenblat, A. (2018) *Beyond Disruption: How Tech Shapes Labor Across Domestic Work & Ridehailing*. Data & Society. Retrieved from: https://datasociety.net/wp-content/uploads/2018/06/Data_Society_Beyond_Disruption_FINAL.pdf

of ICT”, with labour market regulation in the EU offsetting the main impact of ICT after 1995 by approximately -45%.⁷⁸ Such regulation is identified as one reason why the gap between US and EU output per worker grew from 1.8% in 1995 to 9.8% by 2004.⁷⁹ However, this relationship is not clear-cut. Sociology papers demonstrate the importance of the industrial relations environment in determining the influence of technology on working conditions within large organisation. Gallie showed how similar processes of automation at British and French oil refineries led to different outcomes because British managers were more accommodating towards trade unions and allowed workers to have more influence over working conditions, grading, staffing levels, deployment of personnel, and use of contractors.⁸⁰

A variety of historical studies have examined the way that technology influences the nature of work across different eras. As described by Humphries and Mokyr, the move of textile production – hand-spinning and weaving – from the home to the factory involved workers being placed in a hierarchical structure, a separation between work in the factory and leisure at home, and an increase in the predictability of work.⁸¹

Related studies note that changes between home-based and factory or office-based work influenced gender roles. For example, prior to the migration of the spinning of yarn into factories, hand-spinning enabled women to contribute to family income or remain independent – as “spinsters”. The loss of this employment created dependence on men and on their wages, and contributed to the notion that families should be headed by male workers while wives and mothers should devote themselves to domestic work and childcare.⁸²

Summary: AI and automation can affect working conditions in several ways, and are contributing to changing working patterns following the growth of the ‘gig’ economy.

78 Van Reenen et al, *The Economic Impact of ICT*, p 6.

79 Ibid.

80 Gallie, D. (1978). *In Search of the New Working Class. Automation and Social Integration Within the Capitalist Enterprise*. Cambridge, UK: Cambridge University ePress.

81 Humphries, J. & Weisdorf, J. 2015. The Wages of Women in England, 1260–1850. *The Journal of Economic History*, 75(2), 405–447.

82 Humphries, J. and Schneider, B. (2016) *Spinning the Industrial Revolution*. (Discussion Papers in Economic and Social History, No.145). University of Oxford. Retrieved from: <https://www.economics.ox.ac.uk/materials/papers/14544/spinning-the-industrial-revolution-for-discussion-paper-series-final.pdf>

3.3.3 How might the benefits of AI be distributed?

Across literature from different disciplines, a common theme is the concern that AI will disproportionately affect lower-paid and lower-educated workers and that its benefits will not be distributed across society, with a consequent increase in inequality.

Innovation provides widely enjoyed benefits over the long term, supporting technological, social, and economic advances that improve societies' health, wealth, and wellbeing.⁸³ For example, one study of the US economy found that only a fraction of the social returns from technological advances over the 1948–2001 period was captured by producers, indicating that most of the benefits are passed on to consumers.⁸⁴ However, in the Industrial Revolution, rising labour demand and pay only followed after an 80-year period of stagnant wages, increasing poverty and harsh living conditions.

Today, similar concerns over AI have implications for:

- The people most affected by AI;
- The places where AI has the biggest impact; and
- The pace at which these impacts are felt by different groups and sectors.

In terms of people, one study ranked occupations (according to the Frey and Osborne 2013 analysis) and found that 83% of jobs making less than \$20 per hour would come under pressure from automation, as compared to 31% of jobs making between \$20 and \$40 per hour and 4% of jobs making above \$40 per hour.⁸⁵

A bias towards higher-qualified staff is already evident in the US economy. Since 2010, the economy has added 11.6 million jobs of which 11.5 million have gone to workers with at least some post-secondary education and 8.4 million have gone to workers with a Bachelor's degree or higher.⁸⁶

83 Allas, T. (2014) *Insights from international benchmarking of the UK science and innovation system* (BIS Analysis Paper No.03). Department for Business, Innovation and Skills. Retrieved from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/277090/bis-14-544-insights-from-international-benchmarking-of-the-UK-science-and-innovation-system-bis-analysis-paper-03.pdf

84 Nordhaus, W.D. (2004) *Schumpeterian Profits in the American Economy: Theory and Measurement* (NBER Working Paper No. 10433) Cambridge, MA: National Bureau of Economic Research.

85 Furman, J. (2016) *Is This Time Different? The Opportunities and Challenges of Artificial Intelligence*. Remarks at AI Now: The Social and Economic Implications of Artificial Intelligence Technologies in the Near Term, New York University.

86 Carnevale, A.P., Jayasundera, T. & Gulish, A. (2016) *America's Divided Recovery: College Haves and Have-Nots*. Georgetown University Centre on Education and the Workforce. Retrieved from: <https://cew.georgetown.edu/wp-content/uploads/Americas-Divided-Recovery-web.pdf>

In terms of the relationship between productivity and equality, there is statistical evidence that, in the US, growth in labour productivity ceased to be associated with growth in median income from the late 1990s – referred to as ‘the great decoupling’.⁸⁷

In terms of places, there is an important regional dimension to the adoption of new technology and its impacts. As well as inequality between socio-economic groups, technological change can exacerbate inequality between regions. Some regions suffer disproportionately while those with strong leadership or high proportions of groups favoured by the changes can prosper. Economic shocks have disparate impacts across countries and regions, with economically weaker areas being more likely to suffer from adverse impacts.⁸⁸

Research has also shown that highly-educated people have increasingly clustered geographically.⁸⁹ In the future, new jobs linked to AI may be concentrated in different areas to those where there are job losses. This could pose significant challenges, particularly given evidence that low-educated workers are less likely than high-educated workers to move in response to potential job opportunities.⁹⁰ A report by Centre for Cities finds that the proportion of workers in occupations likely to shrink (as identified by Bahkshi et al.) varies from 13% in Oxford and Cambridge to 29% in Mansfield, Sunderland, and Wakefield.⁹¹

Globally, as well as the general risk of premature de-industrialisation across developing countries, certain regions face specific risks. For example, one report suggests that job losses in South East Asia resulting from robots in manufacturing could contribute to increased numbers of labour abuses.⁹² Box 3 summarises the results of existing international comparisons of the potential impact of AI technologies on work.

- 87 Bernstein, A. & Raman, A. (2015) *The Great Decoupling: An Interview with Erik Brynjolfsson and Andrew McAfee*. Harvard Business Review. Retrieved from: <https://hbr.org/2015/06/the-great-decoupling>
- 88 Martin, R. & Morrison, P.S. (eds) (2003) *Geographies of Labour Market Inequality*. London and New York: Routledge.
- 89 Diamond, R. (2016) ‘The determinants and welfare implications of us workers’ diverging location choices by skill: 1980–2000’. *American Economic Review*, 106(3), 479–524.
- 90 Manning, A. & Petrongolo, B. (2017) ‘How local are labor markets? Evidence from a spatial job search model’. *American Economic Review*, 107(10), 2877–2907.
- 91 Centre for Cities (2018). *Cities Outlook 2018*. London, UK: Centre for Cities. Retrieved from <http://www.centreforcities.org/wp-content/uploads/2018/01/18-01-12-Final-Full-Cities-Outlook-2018.pdf>.
Bahkshi, H., Downing, J.M., Osborne, M.A & Schneider, P. (2017). *The Future of Skills: Employment in 2030*. Report prepared by Nesta and Oxford Martin School. Retrieved from: https://www.nesta.org.uk/sites/default/files/the_future_of_skills_employment_in_2030_o.pdf
- 92 Verisk Maplecroft (2018) *Human Rights Outlook 2018*. Retrieved from: <https://www.maplecroft.com/portfolio/new-analysis/2018/07/12/slavery-and-labour-abuses-se-asia-supply-chains-set-spiral-over-next-two-decades-automation-consumes-job-market-human-rights-outlook/>

BOX 3 International comparisons⁹³**Which countries could be most affected by AI and automation?**

Findings on the relative impact of AI and automation across different countries are typically based on examining sectors and roles, specifically the proportion of a national workforce in occupational sectors deemed to have relatively high automation potential, and the extent to which workers in these sectors are working in roles with high automation potential. Many of the academic studies focus on OECD economies, for which detailed data is available, and these tend to show that differences in the organisation of job tasks within economic sectors is more important than differences in the sectoral structure of economies.

Global estimates indicate that nearly two-thirds of the workers associated with technically automatable activities – more than 700 million people – are in four countries – China, India, Japan, and the United States. These are followed by five largest European Union economies – France, Germany, Italy, Spain, and the United Kingdom – with 60 million workers potentially affected.⁹⁴

Studies focusing on the OECD countries show a relatively large variance in automatability, in one paper ranging from 33% of all jobs in Slovakia to 6% of those in Norway. Another study estimates the automatability rates as over 40% for Slovakia, Slovenia and Lithuania compared to the mid 20% range for countries such as Finland, Greece and Russia, with the UK at 30%.

Jobs in Anglo-Saxon, Nordic countries and the Netherlands appear less automatable than jobs in Eastern European countries, South European

countries, Germany, Chile and Japan. The higher risk of automatability does not only arise from the fact that these countries have a relatively larger share of manufacturing jobs, but also from differences in the job content within nominally similar industries and occupations.⁹⁵

Four broad groupings of national economies emerge from international comparisons:

- Industrial economies such as Germany, Slovakia and Italy, which are strong in manufacturing and other sectors and have relatively high rates of potential automation in the long term.
- Services-dominated economies, such as the US, UK, France and the Netherlands, which may have lower susceptibility to automation, assuming services are less automatable on average than industrial sectors.
- Asian countries, such as Japan, South Korea, Singapore and Russia, which while having relatively high concentrations of employment in more automatable industrial sectors have workforces that are relatively less automatable overall.
- Nordic countries, such as Finland, Sweden and Norway, which have jobs that are on average relatively less automatable concentrated in sectors with relatively lower potential automation rates.⁹⁶

The studies that form the basis of this analysis are subject to the methodological limitations set out earlier in this review. However, they help illustrate patterns of differential impact across communities and societies.

93 This comparison draws from: McKinsey Global Institute, *A Future that Works*; PwC, *Will robots really steal our jobs?*; PwC, *UK Economic Outlook March 2017*; Nedelkoska, L. & Quintini, G. (2018), *Automation, skills use and training* (OECD Social, Employment and Migration Working Papers, No. 202). Paris, France: OECD. Retrieved from: <http://dx.doi.org/10.1787/2e2f4eea-en>

In terms of pace, as discussed above, the general consensus from history is that technological advances are likely to benefit humanity in the long term, but also that there are likely to be significant transitional effects which cause disruption for some people or places. Even among those who believe that the AI transformation will ultimately benefit everyone to a degree, like the Industrial Revolution, there is anxiety over short term dislocations, for example in the lags between jobs being displaced and others being created by demand or new activities.⁹⁷

Summary: Studies of the history of technological change demonstrate that, in the longer term, technologies contribute to increases in population-level productivity, employment, and economic wealth.

Such studies also show that these population-level benefits take time to emerge, and there can be significant periods in the interim where parts of the population experience significant disbenefits. Evidence from historical and contemporary studies indicates that technology-enabled changes to work tend to impact on lower-paid and lower-qualified workers more than others. This suggests there are likely to be significant transitional effects which cause disruption for some people or places.

One of the greatest challenges raised by AI is therefore a potential widening of inequality, at least in the short term, if lower-income workers are disproportionately affected and benefits are not widely distributed.

94 McKinsey Global Institute, *A Future that Works*.

95 Nedelkoska & Quintini, *Automation, skills use and training*.

96 PwC, *Will robots really steal our jobs?*; PwC, *UK Economic Outlook March 2017*.

97 Korinek A., & Stiglitz J. (2018) *Artificial Intelligence and Its Implications for Income Distribution and Unemployment*. Background paper for the MBER Conference 'The Economics of Artificial Intelligence'. Retrieved from: https://techpolicyinstitute.org/wp-content/uploads/2018/02/Korinek_AI_Inequality.pdf

Discussion

Discussion

This synthesis provides a summary of the ‘state of play’ of current understandings of the impact of AI technologies on work, reflecting a research discussion that has matured away from concentrating on eye-catching figures about potential job losses to a more nuanced discussion about the ways in which AI technologies might influence working lives.

There is now a consensus that AI does not spell the end of work, but neither will the transition be painless for all. Studies of previous waves of technological change can offer insights into the timescales over which benefits and disbenefits from technology-enabled changes to work appear, and which groups in society they affect. This suggests there are likely to be significant transitional effects which cause disruption for some people or places. However, it remains challenging to generate robust theoretical models for future changes.

While there are many uncertainties surrounding the future of AI, it seems clear that major changes are underway – and only just beginning. Policy-makers can shape the way that these novel technologies affect the economy and workforce. Participants at the workshops that helped inform this synthesis offered various suggestions for policy interventions to explore, focused around:

- Ensuring that the workers of the future are equipped with the education and skills they will need be ‘digital citizens’;
- Addressing concerns over the changing nature of working life, for example with respect to income security and the gig economy, and in tackling potential biases from algorithmic systems at work;
- Meeting the likely demand for re-training for displaced workers through new approaches to training and development; and
- Introducing measures to share the benefits of AI across communities, including by supporting economic growth.

Box 4 gives a summary of these suggested interventions.

The evidence outlined in this review also underlines the importance of engagement between government, academia, business and civil society to develop common frameworks and language to describe and discuss developments in this critical field for the UK’s economy and society. By synthesising evidence from across research disciplines in this paper, the Royal Society and British Academy aim to contribute to this discussion, and will continue to create platforms for such engagement.

BOX 4 Potential policy responses

Participants in the workshops that informed this review suggested a range of potential policy responses to address the impact of AI on work, whether through building resilience amongst potentially affected communities, mitigating the negative effects of a transition period, or helping ensure rapid diffusion of benefits. A critical issue is whether labour market policies aid redeployment of displaced workers rather than leading to unemployment and economic inactivity. The suggestions below include initial considerations for ways of encouraging paths to successful redeployment when jobs are lost.

Education

Education has a role both in driving AI adoption and in combating inequality. It is central to: equipping all workers to be ‘digital citizens’; providing training in skills to take on new jobs; developing the advanced specialists to work in the AI industry; and creating a pool of informed users to engage with the specialists. Policy responses in this area include:

- teaching key concepts in the technologies behind AI and their ethical implications from Key Stage 2, to help students become digital citizens.
- ensuring access to a broad curriculum throughout compulsory education, giving all students the opportunity to study a range of subjects including mathematics, physics, chemistry and computing, social sciences, creative arts, humanities and languages and developing skills such as communication, research, and independent thinking.
- investing in higher education and research funding to increase numbers of AI specialists.
- retraining for displaced groups and opportunities for lifelong learning.

In the face of significant uncertainty about the nature of work over the next few years and decades, the case for the UK to adopt a broader post-16 curriculum is strong. Educating young people in the sciences, maths, arts and humanities could equip them with a wider range of skills

and the ability to think, interpret and understand across several disciplines and provide a stronger basis for lifelong learning.

Working life

In seeking to maintain an environment of ‘good work’, policymakers may wish to consider:

- reforms to social security to support low income workers, this might include radical proposals such as introducing a universal basic income (UBI), or reviewing the outcomes of UBI trials across the world.
- measures to address concerns over working conditions, including: wages; employment quality; education and training; work life balance; and consultative participation and collective representation.
- ways of managing bias in data, including technology-based solutions and new governance approaches.

Local growth and supporting businesses to use AI technologies

Steps to help ensure that the benefits of AI are shared across regions include measures to support local growth, such as:

- providing advice and support to businesses of all sizes to use AI technologies, for example through the network of Local Enterprise Partnerships and Growth Hubs.
- using industrial strategy to drive AI adoption across sectors.
- supporting local growth and economic development, including the development of plans to support both AI technologies and skills developments at a local level.
- supporting business-university collaborations and talent sharing in AI.

Research and development

Research into AI is evolving and further investment in AI research can help secure technological advances, while developing greater understanding of the impact of this technology.⁹⁸

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