



Digital automation and the future of work

STUDY

Panel for the Future of Science and Technology

EPRS | European Parliamentary Research Service

Scientific Foresight Unit (STOA)

PE 656.311 – January 2021

EN

Digital automation and the future of work

Modern capitalist economies are witnessing a period of rapid technological progress. Developments in digital technologies, inclusive of artificial intelligence (AI), are predicted by some at least to create the potential for a great reduction in the volume of work. Others see scope for digital technologies to transform the quality of work.

This report addresses the nature, scope and possible effects of digital automation. It reviews relevant literature and situates modern debates on technological change in historical context. It identifies threats to job quality and an unequal distribution of the risks and benefits associated with digital automation. It also offers some policy options that, if implemented, would help to harness technology for positive economic and social ends.

The policy options range from industry and sectoral skills alliances that focus on facilitating transitions for workers in 'at risk' jobs, to proposals for the reduction in work time. The suggested policies derive from the view that digital automation must be managed on the basis of principles of industrial democracy and social partnership. The report argues for a new Digital Social Contract. At a time of crisis, the policy options set out in the report aim to offer hope for a digital future that works for all.

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LINGUISTIC VERSION

Original: EN

Manuscript completed in January 2021.

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PE 656.311

ISBN: 978-92-846-7281-3

doi: 10.2861/826116

QA-02-20-871-EN-N

<http://www.europarl.europa.eu/stoa> (STOA website)

<http://www.eprs.ep.parl.union.eu> (intranet)

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Executive summary

Digital technologies are accelerating at a rapid rate and are enabling the reduction as well as transformation of work. Developments in artificial intelligence (AI), for some authors at least, offer the possibility of a 'world without work'. Robots are seen to be the future workers, not humans. Other writers, from a different standpoint, suggest that technological change will occur – as in the past – without a major loss of paid work. Rather, it is claimed that the effect of digital technologies will be felt more in the content of work, rather than in its volume.

This report addresses the nature, scope and possible effects of digital automation. It reviews relevant literature and situates modern debates on technological change in historical context. It also sets out a number of policy options that, if implemented, would help to harness technology for positive economic and social ends. The policy options aim to create a future of work where technology works for all.

The report recognises that the impacts of technological change on work and employment are multifaceted. On the one hand, technology impacts on the level of employment. Here it is acknowledged that technology can both create and displace jobs and that the net effects of technology on employment will depend on the relative strength of any job displacement effect. The demise of paid work is not the inevitable product of technological progress – rather, there is scope for paid work to grow with the advance of technology. Indeed, technology itself enables new job creation, particularly in jobs that are hard to automate. On the other hand, technology affects the nature and quality of work itself. How work is done and the allocation of tasks within jobs depends on the kind of technology that is developed and adopted in the economy. Just as technology may help to improve skills and raise the quality of work, so it can produce processes of deskilling and create and embed low paid, low autonomy work. Importantly, while technology can help to preserve work, it can also generate shifts in the qualitative experience of work.

For the purposes of this report, attention is given to digital technologies associated with what has been variously described as the Second Machine Age, the Fourth Industrial Revolution and Industry 4.0. AI together with advanced robotics are key features of the new or emerging digital world. There is a widespread view that digital technologies will gather pace in coming years and that technological breakthroughs in the future will lead to seismic changes in the way that work is conducted in society. The report reviews the evidence supporting this view and outlines the basis for predictions of work's future demise. It also examines the scope for digital technologies to transform how work might be conducted in the future.

Throughout the report, it is recognised that technological progress can present both opportunities as well as risks. On the positive side, digital technologies can create the basis for higher living standards, with less work. They can also potentially lead to up-skilling and improvement in the quality of jobs. On the negative side, digital technologies can lead to skill gaps, greater inequality and a more polarised society. They can also erode job quality by eliminating valuable skills, intensifying monitoring at work, and extending atypical (or 'gig') work. Recent policy debates centre on ways to maximise the benefits and minimise the costs of digital technologies. This report adds to these debates by suggesting policy options that would help society to exploit the bounty afforded by digital technologies.

A purpose of the report is to suggest that technological change, far from being deterministic in its nature and effects, is open to reform. There is no guarantee that digital technologies will destroy jobs, nor any certainty that these technologies will lead to more and better jobs. Rather, it is emphasised that society faces vital choices over what technology it develops and how it is used. Ultimately, society must aim for a digital future where the greatest number of people thrive within work and beyond it.

The suggested policy options range across different levels and scales. They include:

- Skills and training provision
 - industry and sectoral skills alliances that focus on facilitating transitions for workers in 'at risk' jobs
 - reskilling for workers in transformed jobs
 - digital upskilling for working in AI-enhanced environments
 - new protections for workers in hard-to-automate jobs
- Digital work-life balance
 - the establishment of a European-level 'right to disconnect'
 - a reduction of the EU Working-Time Directive to 38-hours per week and removal of the opt-out clause
- Governance
 - greater worker representation, and more democratic workplace organisation
- Duty to Report Directive
 - a new directive for the regulation of technology at work
- Mission-oriented industry policy
 - direct EU involvement in the design and diffusion of digital technologies to ensure decent work objectives are achieved

The policy options set out in the report complement some existing policies, but they also break new ground in seeking a new Digital Social Contract. The report argues that, beyond the existing skills-focused agenda, there is a need for wider reforms, inclusive of work time reduction, to enable the benefits of digital automation to be realised and more widely shared.

This report is written in the context of a new crisis, namely one induced by the Covid-19 pandemic. The latter has itself accelerated processes of digital automation (for example, through the use of digital technologies for remote working). It has also revealed the stark inequalities in society. The poorest and youngest in society have suffered the most from the economic effects of the crisis. This report does not directly address the Covid-19 crisis, but the policy ideas set out in it have relevance for thinking about ways to rebuild the economy after the crisis.

This wide-ranging report offers an extensive review of relevant literature and a set of new policy options. In all aspects, it seeks to offer a way forward in the debate on the future of work. It shows how digital automation, if properly managed, could be a route to economic and social progress. It is hoped that policy-makers will take note of the policy options and that the report will help to spark wider critical reflection on the possibilities for rethinking technology and work in the future.

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1. Introduction

Modern capitalist economies are witnessing a period of rapid technological progress. Developments in new digital technologies, inclusive of artificial intelligence (AI), are giving rise to significant disruption including in the world of work (Brynjolfsson and McAfee, 2014; Ford, 2015; Frey, 2019). For several commentators, the Second Machine Age or Fourth Industrial Revolution that societies have now entered will bring about a significantly different world – indeed, it may create the potential for a 'world without work' (Susskind, 2020). More sceptical voices, however, point to the potential for paid work to withstand any technological revolution. These voices, instead, highlight the scope for technology to transform how we work, including in ways that are regressive in nature (Spencer, 2018; Fleming, 2019).

This report addresses the nature, scope and possible effects of digital automation. It reviews relevant literature and situates modern debates on technological change in historical context. It is recognised that modern debates on automation are not in any sense new, but rather follow a long tradition of thought. A purpose of the report is to show the continuities as well as possibilities for change in the use and application of digital technologies.

As the report will show, the impacts of digital technologies are complex and varied. Just as digital technologies threaten some jobs, so they can help to facilitate new job creation. They can also lead to changes in the type and composition of tasks within jobs. Here jobs may be preserved, but in ways that require different skills from workers. Digital technologies, in turn, can lead to qualitative changes in work – while they can help to create more interesting work and potentially reduced work hours, they can also be used to increase monitoring at work and to undermine pay and job security. The report discusses in detail how digital automation will impact on the employment sector of modern capitalist economies, showing how digital technologies can alter both the volume and content of work.

The report engages directly with issues of policy. It is argued that the nature and evolution of technology in society is not pre-determined, but rather is influenced by wider economic and social factors. Importantly, there is scope for reform in the way that digital technologies are developed and implemented. The report reviews current policies to deal with the impacts of digital automation. It also offers various policy options that could be used to ensure that digital technologies realise net benefits to all in society.

The key policy options include: industry and sectoral skills alliances that focus on facilitating transitions for workers in 'at risk' jobs and reskilling for workers in transformed jobs; digital up-skilling for working in AI-enhanced environments; new protections for workers in hard to automate jobs; the establishment of a European-level 'right to disconnect'; a reduction of the EU Working-Time Directive to 38-hours per week and removal of the opt-out clause; greater worker representation and more democratic workplace governance; a new directive for the regulation of technology at work; and direct EU involvement in the design and diffusion of digital technologies to ensure decent work objectives are achieved.

The policy options identified in the report complement some existing policies, but they also break new ground in seeking a new Digital Social Contract. It is argued that beyond the existing skills-focused agenda, there is a need for wider reforms, inclusive of work time reduction, to enable the net benefits of digital automation to be realised and more widely shared.

This report is written in the context of a new crisis, namely one induced by the Covid-19 pandemic. The latter has itself accelerated processes of digital automation (for example, through the use of digital technologies for remote working). It has also revealed the stark inequalities in society. The poorest and youngest in society have suffered the most from the economic effects of the crisis. This report does not

directly address the Covid-19 crisis, but the policy ideas set out in it have relevance for thinking about ways to rebuild the economy after the crisis.

The report is offered as a way forward in the debate on the future of work. The hope is that it will inform current policy debates and help produce the reforms required to exploit the bounty of digital automation, while minimising its costs. A goal of the report is to show the possibilities for change in society, including the creation of a digital future that maximises societal well-being.

2. Methodology

The research contained in this report adopted a mixed-method approach to reviewing previous literature, combining systematic review techniques with more traditional strategies. This section discusses why these methods were adopted and how they were utilised. The principle methodological challenges facing this study were how to identify high quality research among a huge quantity of literature. The literature covering issues around AI, automation, employment, skills, tasks, and occupations runs to many thousands of articles in scientific journals alone, not to mention a huge quantity of secondary, tertiary, and grey literature, as well as trade journals, specialist media coverage, and popular journalism. A considerable proportion of this literature, however, simply comments on, or speculates about, the impact of digital automation. Consequently, it was necessary to develop a clearly defined methodology in order to compile a firm scientific basis for the identification of key issues, analysis, and the development of policy options.

Three principal methodologies are available for literature reviewing: systematic review, scoping review, and traditional methods. A *systematic review* offers a way of overcoming bias in both the selection of literature and the criteria of assessment applied to that literature (Petticrew and Roberts, 2008). In a field as crowded and contested as digital automation, this approach presents clear benefits. However, true systematic reviewing also brings significant difficulties. As a method first developed in medicine and healthcare, systematic reviewing is best suited to research that aims to answer a clear and specific question; most commonly, assessing evidence supporting a particular therapeutic intervention or treatment (Mulrow, 1994). By contrast, systematic reviews are much less suited to answering more general questions, such as: identifying themes within a wider body of literature (Pettigrew and Roberts, 2006); where research requires the bringing together of literatures from different fields, which may use different definitions, methodologies, or standards of research and evidence (Curran et al., 2007); and in the social sciences in general, where research is more often designed to develop causal explanations than to assess specific interventions (Jesson et al., 2011; Tranfield et al., 2003). Furthermore, systematic reviewing is very time-consuming (Arksey and O'Malley, 2005). Clearly, these considerations all applied to the present research, which aimed both to cover a very great range and variety of literature, and to do so within a relatively compressed timeframe. Consequently, it was not feasible to rely exclusively on systematic review methods for this report.

A second approach, developed to address some of these difficulties, is the *scoping review*. Scoping reviews aim to maintain the standards of rigour provided by systematic reviews, but apply them to questions that are broader and more general, including where published studies use a variety of differing research designs and methods (Arksey and O'Malley, 2005; Levac et al., 2010; Pham et al., 2014). The appeal of this approach for the present research, with its wide focus, is obvious. However, scoping reviews are best suited to giving an overview of the whole literature on a particular topic. As quickly became apparent, however, the literature dealing with digital automation is already far too large to be comprehensively mapped in a single study.

The third main approach to reviewing literature is commonly termed *traditional* (Victor, 2008) and usually entails experts reviewing their own collections of literature, compiled during the course of previous research, with additional searches based on current journals, and the reference lists of notable publications and previous literature reviews (sometimes termed 'snowballing'). The main advantage of this method is speed: literature is already collected and has often been read and discussed previously. The obvious disadvantage, especially where research is intended to inform policy-making, is that literature selection is likely to be skewed by previous research interests and specialism. Within the timeframe available for this study, traditional reviewing was justified because of the speed advantage, provided that the problem of bias could be adequately addressed. Consequently, the report combines traditional and systematic methods – to guard against bias – as follows.

Traditional reviewing methods comprised the principle approach adopted for the literature search and review strategy. As a team of five experienced researchers, the authors of the report had already assembled a considerable quantity of literature relating to issues around digital automation. This literature included publications from a variety of perspectives, and a range of disciplines and fields of research, including law, economics, management studies, employment relations, public policy, sociotechnical and technology studies. As stipulated in the project specification, the report paid careful attention to the inclusion of primary and secondary sources, which it was felt had been under-represented within the broader literature; a view subsequently confirmed by the results of the systematic review (see below). Nevertheless, there was also awareness that, given the current rapid development of research in this area, tertiary and grey literatures would also be important for the report. Sources such as conference proceedings, working papers, and commercial consultancy reports are central to current debates and, therefore, crucial for maintaining the scope of the report and the breadth of evidence under consideration. These literatures were already well-represented in the collected literature, and the available selection was further strengthened by snowballing from references of leading publications, previous literature reviews and additional online searches at the margins and on specific topics. In the final list of references for this report, over half were supplied by these traditional methods (see discussion below).

The second component of the mixed-method approach was a systematic literature review. This was important for two reasons. Firstly, it was important to ensure that any potential biases in the pre-existing collections of literature were strictly minimised. Secondly, there was a need to test the overall comprehensiveness of the traditional searches. In particular, it was identified that there was an apparent shortage of high quality primary research in the main area of interest. Therefore, in order to assess and, where necessary, to strengthen the primary research basis of this report, as per the project specification, a systematic review was designed and conducted, as follows.

Firstly, drawing on the methods discussed above, a search protocol was devised using relevant search terms in Boolean combinations. Selecting the most appropriate terms and combinations for this search was far from straightforward. Initial searches confirmed the huge volume of literature relating to digital automation and employment. For instance, an initial search trialled the following protocol:

('artificial intelligence' OR AI OR blockchain OR 'machine learning' OR 'deep learning' OR automation) AND (employment OR unemployment OR 'labour market' OR job).

This search produced more than 270,000 hits on only one database (ABI/Inform – ProQuest). Since the project specification required us to identify the most rigorous scientific research, the search was narrowed by including additional selections for academic journal articles and peer reviewed research, and also specified English language (in practice, the latter had little effect). Re-running the search with these new terms included still resulted in a count of more than 151,000 articles. A variety of smaller combinations of these and similar terms was then tested, which produced smaller numbers of hits for each individual search, but also produced many duplicates. Nevertheless, several search combinations produced more than 15,000 hits each. One problem that became apparent was that search terms such as 'digital' and 'automation' have recently become research buzzwords. As a result, many articles were found that included these terms despite those substantive issues not forming part of the research focus of the articles. For instance, many articles on skills or training mentioned the terms more or less in passing in the introduction or conclusion, while speculating about possible future developments. By contrast, the research of interest to this report tended to use additional, slightly more specialist terms, such as 'artificial intelligence' or 'machine learning'. Consequently, it was possible to exclude terms such as 'automation' and 'digital' without excluding the scientific literature that was being investigated. Furthermore, by retaining some more general terms, such as 'skills' and 'occupation', it was possible to locate research from a range of literatures that did not share discipline-specific terminologies. A non-exhaustive list of disciplines covered by the studies identified in the report includes law, economics, psychology, management studies, public administration, and medicine. Thus, a combination of some

more general and some more specific terms, arrived at by progressive trialling, provided the best overall framework for the systematic search.

After trialling combinations of search terms as described above, the search settled on the following protocol:

('artificial intelligence' OR blockchain OR 'machine learning') AND (employment OR unemployment OR 'labo?r market' OR skills OR occupation OR profession).

This search was run on four business databases: ABI-Inform (ProQuest), EBSCO, JSTOR, and Web of Science. As with previous studies (e.g. Arksey and O'Malley, 2005), different databases produced widely divergent results. For instance, JSTOR produced 230 hits, whereas ABI-Inform (ProQuest) produced more than 5,600. It is unclear whether such divergences were due to different availability of sources or differences in the search algorithms on each database.

In order to check that no significant results had been missed by excluding search terms such as 'digital' and 'automation', searches using these terms were run, in the following combinations:

digital AND (employment OR unemployment OR 'labo?r market' OR skills OR occupation OR profession)

and:

automation AND (employment OR unemployment OR 'labo?r market' OR skills OR occupation OR profession).

Again, the ABI-Inform (ProQuest) database was used (which persistently returned the highest number of hits). Here the 'digital' test returned 28,751 hits: among the first 100 returns, only two were potentially relevant to the study, and one of those had already been found in the main search combination. The first 100 returns for this search included many examples of the application of well-known modelling techniques (discussed below) to particular countries or regions, but with no substantive addition to theoretical knowledge or overall analysis. The 'automation' test returned 8,560 hits: again the first 100 returns included only two potentially relevant articles, one of which had already been identified. Once more, the first 100 results of this search were dominated by the application of modelling techniques to countries or regions. Finally, the below combination was tested:

digital AND automation.

This search produced 8,572 hits. Of the first 100 returns, three were relevant to the research covered by the report, and all of these had been identified by the main search protocol. The remainder of the first 100 hits were dominated by a mix of technical articles about the application of digital automation in particular fields of production, speculative discussions about the possible effects of future technological developments, or local applications of modeling. Overall, the result of these tests indicated that the selected search protocol, using a tested combination of search terms, had achieved a more than satisfactory coverage of the existing research; had focused significantly on the scientific literature (as per the project specification); had increased the relevancy rate of the findings (reduced the proportion of irrelevant hits); and had not unduly excluded research from a range of disciplines and fields of research.

Next, the study applied further inclusion and exclusion criteria to the initial search results. To begin with, search results dating from January 2010 to the present were included; that is, research dating from the beginning of the recovery from the global financial crisis – the period also coinciding with the post-recession growth in tech companies and markets. Attention was given to findings that were peer-reviewed, that appeared in scholarly journals, and that were published in English (again, in practice, this language stipulation had little effect). The large number of results produced by the ABI-Inform

(ProQuest) database was reduced by sorting by relevance, and then by exhaustion; specifically, database findings were listed by relevance and then sorted manually, and manual sorting was halted after 3,200 items, by which point no new items of interest had been identified in more than 200 hits, suggesting that very few further relevant findings would be discovered by continuing. Finally, the results of the four database searches were combined and duplicates eliminated.

The combined database findings were then filtered by title-abstract screening, abstract screening, full-text screening where necessary, and online checks of journal reviewing practices. Articles based on interviews, book reviews, invited commentary, and editorials were excluded. Articles that were not based on empirical research, and empirical studies with a narrow focus on particular markets that did not add to wider analysis, were also excluded. Despite the stipulated search criteria, the databases returned many articles or working papers that were not peer reviewed. Thus, the study identified only 64 articles that met all the criteria of rigour for primary sources. This confirmed the initial expectations about the limited base of high quality, empirical research (see above), among the huge volume of commentary on issues around digital automation, most of which comprises secondary, tertiary and grey literature. Nevertheless, the systematic search identified a large number of articles that, while they did not meet all criteria for primary sources, appeared to be of a high standard, and could be selected for inclusion in the literature review. As a result, the systematic part of the literature search produced a final total of 236 sources. To put these findings in perspective, this represents fewer than half of the publications listed in the references at the end of this report. Nevertheless, the systematic part of the literature review appears to be strongly justified.

Overall, the mixed-method approach to literature reviewing worked well. The systematic review, despite contributing only a minority of the literature used in this report, achieved two important goals. Firstly, it filled out previous findings and brought assurance as to the reliability of the selection of literature, by ensuring that the traditional literature collection methods used in the report had not led to significant blind-spots or omissions. Secondly, it contributed sources from disciplines and fields outside the specialisms of the research team; in particular, bringing to the attention of the team research in specialist and technical literatures from sectors of the economy that are most likely to be affected by digital automation. The traditional component of the approach taken in the report started with a considerable, previously assembled collection of literature, which was further strengthened by additional searches and snowballing, which boosted coverage across a range of areas, especially at the margins. As noted previously, traditional methods of literature reviewing produced more than half of the literature used in the preparation of this report. Consequently, an unexpected but perhaps welcome conclusion of this report is a qualified reaffirmation of the methods of traditional literature reviewing. Indeed, the traditional methods provided by a group of experienced researchers with expert knowledge of the field proved essential. Without these methods, compiling this report would not have been possible. As a result, the choice and implementation of this mixed-method approach to literature searching and reviewing appears vindicated.

A further outcome of the literature review was a framework for addressing the topic of digital automation. The review helped to identify key contributions as well as a structure for analysing digital automation. In particular, it offered a way to see how digital automation might alter the volume and nature of work. It also provided a basis for developing possible policy options. In choosing policies, the report was guided by the critical assessment of literature. The above aspects of the literature review and the links to policy are developed below. But first consideration is given to some issues of terminology.

3. What is digital automation?

The present wave of technological change has been variously described as the Second Machine Age, Fourth Industrial Revolution, or Industry 4.0. It is distinguished from what has been termed as the Third Industrial Revolution, which entailed the rise of information and communications technologies (ICT), including computerisation and the internet. The various technological innovations that have enabled the current technological wave have been made possible by the exponential expansion of computing power and data storage, and the decreasing cost of software and hardware.

Digital information, or data, have become a strategic resource. Data capture and storage are now a central activity for many firms and organisations. Artificial Intelligence (AI) relies on these elements and is fundamental to the power of technology to extend and deepen the process of digital automation. The key aspect with digital automation is that it allows the human input into production to be reduced, while leveraging the power of networks and data to expand the role of machines. That is, it enables the move to more automated processes where the work undertaken by humans is less extensive.

Historically, technological change has served to replace humans – either wholly or partly – in the performance of particular tasks. Industrial automation was originally limited to manual tasks – for example, in manufacturing, the expansion of machinery has displaced many millions of manual workers. Capitalist economies have developed processes of deindustrialisation, in part, due to the greater use of automated forms of production.

In the present, advances in computation offer the basis for the automation of routine intellectual tasks, threatening many jobs in the service sector that make up the majority of employment in modern capitalist economies. With AI-driven digital automation, there is now the capacity to automate or augment human activity that requires adaptation and learning. 'Smart' machines have the potential to mimic and even supersede the intelligence of humans in certain tasks. New digital technologies, in this case, promise to reduce the labour input into production and allow for the elimination of jobs previously thought to be immune to automation. These same technologies also promise to change how work is done.

There are a number of key terms that relate to, and underpin, the notion of digital automation. It is important to define these terms to maintain a consistent analysis throughout the rest of the report. The key terms focused on below are: automation, robotics, digitalisation, the Internet of Things, datafication, blockchain and AI.

Automation: The term automation was coined in 1947 by Ford Motor Company Vice President Delmar S. Harder (Noble, 1984). Harder was referring to the increased use of electromechanical, hydraulic, and pneumatic machinery. As Noble (1984) points out, the development of 'self-acting' production machines and automatic transfer machines were what made possible the integrated control of factory operations that enabled the reduction of labour in the manufacturing sector. Today, the National Academy of Sciences (2017) defines automation as 'the technique, method, or system of operating or controlling a process by highly automatic means, as by electronic devices, reducing human intervention to a minimum'. Here the definition of automation is expanded to include 'electronic devices', which have been a key element of the automaton process since the 1970s.

Robotics: There is no single agreed definition of what constitutes a robot. All definitions include the criteria that the task performed by a robot must be completed without human intervention. Some definitions require the task to be completed by a physical machine that responds to its environment, while others also include tasks completed by virtual machines such as software (this would also include AI: see below). The International Federation of Robotics [IFR] adopts the International Organisation for Standardisation (ISO) definition 8373 of an industrial robot: 'An automatically controlled,

reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications' (IFR, 2017). A service robot is defined according to the same criteria; however, its application corresponds to the performance of useful tasks for humans or equipment excluding industrial automation application. In this case, the application of robots is extended to personal and professional services, expanding the potential range of automation.

Digitalisation: Digitalisation, in the most basic sense, refers to digitation, or the process of converting analogue information into a numerical format readable by a computer. Digitation 'allows information of all kinds in all formats to be carried with the same efficiency and also intermingled' (McQuail, 2000: 34). Digitalisation marks the shift from analogue to digital information in work and society more generally through the adoption of ICT. ICT encompasses hardware such as computers, telephones, servers as well as software such as computer programmes and mobile applications. The term ICT is typically used in the literature from the late 1980s to the early 2000s, while the terms digital and digitalisation are more frequently used in recent publications. Digitalisation paved the way for the adoption of smartphone technologies, data analytics, encryption services, the use of algorithms to regulate production, networks, the 'internet of things' (see below), and the use of AI, among others. In industry, these are referred to as 'Industrial Digitalisation Technologies' (IDTs) (Maier, 2017: 18). Such technologies tend to push companies toward customer-centric business models and personalised products. IDTs enable physical and virtual worlds to merge and are driving what has been called the Fourth Industrial Revolution (Schwab, 2017).

Internet of Things: The Internet of Things (IoT) is essentially a global network infrastructure that relies on sensor, network, data processing, and communication technologies to connect a wide variety of devices allowing for remote and digitally automated control. The concept of a IoT was first introduced in the 1980s at Carnegie Mellon University and then gained popularity in 1999 with the Auto-ID centre at MIT when it was combined with Radio-frequency identification (RFID) (Liu and Chen, 2009; Martinelli et al., 2019). RFID is a foundational technology for IoT because it allows microchips to automatically identify, track and monitor a particular device through wireless communication (Xu et al., 2014). It is widely used in logistics, supply chain management, pharmaceuticals and retail. Wireless sensor networks (WSN) are another foundational part of IoT and are now used in the monitoring of environmental conditions, health, and traffic. With the normalisation of smartphone usage and sensor network technologies in everyday appliances, IoT has proliferated. IoT has now evolved into the 'Internet of Things and Services' (IoTS), expanding its reach and span of control (Kagermann et al., 2013).

Datafication: Datafication refers to the acceleration of data collection, transfer and storage (Hazas et al., 2016; Sadowski, 2019). Discussions of data typically focus on user data from apps and social media; however, the industrial use of data from machinery, transportation, commerce and other activities has become the norm. The proliferation of data sets has come to be known as 'big data' and the analysis of such large data sets, typically through the use of AI, can reveal hidden patterns, correlations and other trends that inform organisational strategy. The term 'big data' was first used in the context of the growing volume of data in the mid-1990s and continues to be used to refer to the changes in volume, velocity and variety of data received because of the different analytical approaches required to process it. Growth in data normally follows what is known as Cooper's law, in which traffic roughly doubles every 2.5 years (Björnson and Larsson, 2018). Most companies now rely on 'cloud computing', which refers to the use of third-party, off-site networked and distributed facilities, rather than their own servers for data storage and processing. This data infrastructure allows companies to be more dynamic and flexible, responding to changes in demand by renting additional capacity from cloud platform providers (Holtgrewe, 2014). At the same time, direct and triangulated data on worker and consumer behaviour is becoming a form of capital (Crain, 2018). Such data is transformed into an intangible asset and is used to develop and reproduce virtual machinery via machine-learning AI (Ciarli et al., 2018). The data broker industry alone is estimated to generate \$200bn in annual revenue (Crain, 2018) and is

expanding rapidly since the margin between the monetary value of data and the compensation provided to those producing it is substantial (Roderick, 2014).

Blockchain: There is not one blockchain technology, but rather several, and almost all of the components originated in academic research from the 1980s and 1990s (Narayanan and Clark, 2017). Blockchains were first described by their pseudonymous inventor(s) Satoshi Nakamoto as Distributed Ledger Technology (DLT) in 2009. DLTs are best understood as an innovative combination of existing mechanisms forming 'a class of technologies' (Beck et al., 2018). Blockchain can be described as a synchronised and shared database stored across multiple nodes (computers that store a local version of the DLT) and maintained by a consensus algorithm. The main purpose of a blockchain is to share information across all nodes that access it in such a way as to ensure that the shared information is protected against modification. There is no singular point of failure or attack at the hardware level (Finck, 2019). DLTs serve as an accounting system that can be used by many actors to standardise and link data to 'enable credible accounting of digital events' (Bartoletti et al., 2019). The first widespread commercial implementation of DLT was the Bitcoin cryptocurrency, though its use and application has broadened out into sectors such as retail, transportation and accounting.

Artificial Intelligence [AI]: AI refers to what is essentially a virtual machine or an 'information-processing system that the programmer has in mind when writing a program, and that people have in mind when using it' (Boden, 2016: 4). In the nineteenth century, Ada Lovelace theorised virtual machines that formed the foundations of modern computing, including stored programmes, feedback loops and bugs, among other things. Alan Turing is credited with making the theoretical breakthrough in 1947 that led to modern computation and AI. There are many competing definitions of AI. Margaret Boden (2016: 1) defines AI as the attempt 'to make computers do the sorts of things that [human] minds can do'. For purposes of this report, we use the OECD (2019) AI Group of Experts (AIGO) definition of an AI system as a:

machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner e.g. with machine learning or manually); and use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy.

Today, even the most advanced AI is of a narrow type (often called 'Artificial Narrow Intelligence or ANI), in that its intelligence is generally limited to the frame in which it is programmed. Some AI systems can evolve autonomously through machine learning, but these are still a weak form of AI relative to human cognition. In an influential essay from the 1980s, John Searle makes the distinction between 'weak' and 'strong' AI. This distinction is useful in understanding the current capacities of AI versus human intelligence. For weak AI, 'the principle value of the computer in the study of the mind is that it gives us a very powerful tool'; while for strong AI 'the appropriately programmed computer really is a mind, in the sense that computers given the right programs can be literally said to understand and have other cognitive states' (Searle, 1980: 417). For strong AI, the programmes are not merely tools that enable humans to develop explanations of cognition; rather the programmes themselves are essentially the same as human cognition. Clearly, with the potential development of strong AI, the scope for humans to be replaced in production and service delivery is increased significantly.

Digital Automation: Digital automation has been occurring in industry since the introduction of mass computing. Computerisation initially digitised automatic machinery and back office processes (Campbell-Kelly, 2015). The digital automation of production eventually developed into the digital automation of aspects of consumption with the massification of internet and mobile technologies. In the early twenty-first century, advances in computer power, sensor technologies (IoT) and human behaviour (from online mobile activity) have produced an avalanche of new data (Zuboff, 2019). This

ongoing connectivity and data capture has catalysed a historic rise of AI applications in industry and society more generally. The significance of the current wave of technological advancement is that digital automation is now enabled and driven by AI. Vertically integrated digital platforms are expanding across the globe and are poised to dominate many sectors of the economy (Srnicek, 2016). The expansion of these platforms is based on tech companies' monopolistic control over data and data infrastructure (Kitchin, 2014; Montalban et al., 2019). AI-enabled and driven digital automation is growing to such a degree that data-based intelligent systems are re-organising and coordinating whole sectors of the economy.

The concepts and technologies outlined above are the drivers of the so-called Fourth Industrial Revolution (also referred to as the Second Machine Age). They tend to be interdependent and together capture a wider infrastructural shift in the economy and social life, largely based around the convergence of physical and virtual machines enabled by data, networks, and AI. This broader socio-economic shift is what the popular colloquialism of the Fourth Industrial Revolution refers to. Another, more focused concept, is Industry 4.0, which refers to a primarily German endeavour to take advantage of new technologies in manufacturing and services in order to maintain competitiveness (Holtgrewe, 2014). Whatever terminology is used, however, there is the view that developments in digital technologies will have enormous impacts not just on how we interact with one another, but also on the quantity and quality of our daily work. The notion that we are experiencing a fundamental change feeds a view of a society in which everything in life (including work and employment) is set to be upended. Yet, as will be shown in the next section, discourse on technological disruption has endured and the present round of debate on the future of technology and work covers some old ground.

4. Technological change in context

Historically, industrial revolutions have involved technological innovations that have disrupted whole sectors of industry such that they either undergone major transformations or disappeared altogether. Such disruptions have tended to be one primary factor driving structural transformations in economy and society. Commentators from Karl Marx to Joseph Schumpeter have referred to cycles of change linked to technology. These cycles have not been smooth nor automatic, but instead have been associated with social conflict and resistance.

In Britain, for example, the First Industrial Revolution during the period from roughly 1771 to 1830 featured opposition from the so-called Luddites. The latter resisted the loss of their skills and livelihoods through the introduction of new machines. They were not alone. In 1814, printers at *The Times* of London took strike action in protest at the arrival of steam-powered presses, which threatened their jobs. This protest was quelled only after the paper's owners promised to retain printers (Eisenstein, 1979). Agricultural workers participating in the 'Swing Riots' of 1830 successfully revolted against steam-powered threshing machines in Southern and Eastern England (Stevenson, 1979: 243). While employment remained high during the nineteenth and early twentieth century confounding predictions made by the Luddites and others that employment would fall, the use of machinery did little to ease the burden and oppression of factory work (Mokyr et al., 2015). In this case, technology remained a contested issue.

In the late nineteenth century, the 'machinery question' (i.e. the effects of technology on employment) receded from view in the discourse of classical, non-Marxist political economy (Berg, 1980: 130). As Mokyr et al. (2015) point out, the question returned in the early twentieth century in the writings of Knut Wicksell who argued that technological progress could either lower or raise the marginal product of labour and wages depending on whether technology substituted for labour or augmented it (Wicksell, 1901). During the Great Depression, interest in the job-destroying effects of technology again rose in prominence, not least because of concern about the collapse in labour demand.

In his famous essay 'Economic Possibilities for our Grandchildren' published in 1930, the great economist, J.M. Keynes viewed the possibility for labour-saving technological progress as real. Keynes (1933) used the term 'technological unemployment' to describe a situation in which innovation that economised on the use of labour outstripped the pace at which new jobs could be created. Keynes predicted that technological unemployment would grow in the future, as capital accumulation accelerated. Capitalism would end up creating fewer jobs, through the great use of labour-saving technology. But Keynes was sanguine about the effects of a move to a jobless world. While there would be costs of adjustment, the reduction of paid work in society was to be welcomed – indeed, it was to be embraced as a means to improve the quality of life. If technology could be harnessed to reduce work time, while maintaining living standards, then society could live better than now. For Keynes, technological progress promised liberation from work and a leisured existence.

Keynes' dream of a future leisure society failed to materialise. Instead of diminishing with technological progress, employment remained high, while work hours failed to fall in the way Keynes predicted (Keynes famously predicted that the working week would fall to fifteen hours per week by 2030 – current trends in work hours suggest this prediction will not be realised). The loss of employment in agriculture and manufacturing has been more than offset by the rapid expansion of service-based industries (Stewart et al., 2015). Consumerism, in general, has put paid to a leisured future, while the loss of power of unions and rising inequality after the 1970s has helped to slow (and indeed reverse) the secular decline in work hours (Spencer, 2018).

More recently, as has been discussed above, commentators have predicted a new wave of automation. These commentators suggest that society is entering a technological phase where many existing jobs

will cease to exist. Brynjolfsson and McAfee's *The Second Machine Age* (2014) is a major reference in this respect. They historicise technological change according to the First and Second Machine Ages. The First Machine Age is what some economic historians refer to as the Second Industrial Revolution. It was driven by the invention of the steam engine: a form of technology that enabled machines to replace human and animal muscle-power. The Second Machine Age is an age catalysed by exponential advances in computer technology in which intelligent machines substitute for human brain power. It describes the present and future of capitalism, where machine race ahead of humans, creating the basis for a profoundly different (and possibly workless) society.

Brynjolfsson and McAfee outline the main features of the Second Machine Age as: 'sustained exponential improvement in most aspects of computing, extraordinarily large amounts of digitized information, and recombinant innovation' (Brynjolfsson and McAfee, 2014: 90). Their argument relies on the work of anthropologist Ian Morris, whose research attempts to quantify human social development ('a group's ability to master its physical and intellectual environment to get things done') from 14,000 BCE to the present. His metrics consist of four attributes: energy capture, organisation, war-making capacity, and information technology, each converted into a number from zero to 250 that varies over time. Based on Morris' metrics, Brynjolfsson and McAfee divide human history into two distinct machine ages. In doing so, they cut the history of industrial capitalism in two, with the first period covering nearly two centuries and the second, unsurprisingly, beginning now and extending into the future.

This approach is problematic for a number of reasons. For example, it ignores the economic history literature that generally periodises technological change according to the infrastructural and social effects of industrial revolutions (see Perez, 2002; 2010). Location and infrastructure, together with organisational and social factors, play an important role in technology adoption and diffusion (MacKenzie and Wajcman, 1999). In this case, technology does not have its own logic and momentum, but instead is shaped by context and place. Another issue with the account of Brynjolfsson and McAfee is that it places the US at the centre of technological transformation, a role that it did not hold for the first 150 years of industrialisation and a role that is challenged now by developments in Europe and China. Further, even if we agree with the authors that we face a historically unprecedented transformation, their approach to analysing technology is marred by a form of technological determinism that misses the historical and social context in which technology is developed and used. In particular, Brynjolfsson and McAfee miss how digital technologies may be stymied and limited in their effects by the politics of production (see Spencer, 2017). Any assessment of the degree to which technological change influences the labour market must also consider workers' agency and broader social factors influencing the diffusion and application of technology.

Another major contribution to the recent literature on technological change is Frey's (2019) *The Technology Trap*. Frey provides a history of technological development in the UK and US from preindustrial times, through the rise of mass industrial production and the middle classes, and finally to the present wave of AI-driven digital automation. Central to this account is the idea that technological change benefits societies in the long-run. Frey's argument hinges on a distinction between labour-enabling technologies that complement workers, increase productivity and create new areas of employment, and labour-replacing technologies, which substitute machines for jobs, push workers out of the labour market and force them to re-skill. Here he draws on the influential work of Daron Acemoglu and Pascal Restrepo as well as David Autor. Acemoglu and Restrepo (2018a) argue that the wage trends over the past several decades are best understood as a race between enabling and replacing technologies. Frey uses this schema to periodise history into eras in which technology benefitted workers and those in which it harmed them. He illustrates the disruptive 'short run' costs to workers with the famous example of 'Engels' Pause' – the period 1780-1840 during the First Industrial Revolution, when output per worker grew by 46 percent, yet weekly wages only grew by 12 percent (Allen, 2009).

In what Frey (2019: 190) refers to as the Second Industrial Revolution, by contrast, workers largely benefited from technological developments in their own lifetime: 'factory electrification allowed workers to produce more and thus earn more'. He draws on Acemoglu and Restrepo (2018b: 1489) who note that the technological changes that occurred during the period from 1875 to the early twentieth century led to the creation of new labour-intensive tasks, creating jobs for a 'new class of engineers, machinists, repairmen, conductors, back-office workers and managers' (Acemoglu and Restrepo, 2018b: 1489). Frey characterises the first three quarters of the twentieth century as 'the great levelling', which he claims was a result of labour-enabling technologies situated within an era of welfare capitalism driven by the New Deal (Frey, 2019: 200). Workers voted for policies that matched with their interests and thus benefitted from labour-enabling social welfare policies. In contrast to the foregoing era, a 'great reversal' has occurred during the *longue durée* of neoliberalism from the 1970s to the present. Working conditions today are incomparable to those of the first industrial revolution, but 'the trajectories of per capita output and people's wages look exceedingly similar' (Frey, 2019: 244). In the US, labour productivity since 1979 has grown eight times faster than hourly compensation. Frey does not dwell much on the political and institutional changes that have driven these outcomes, but instead favours an argument that gives emphasis to technological shifts as drivers of change in the wider economy.

A final approach to the historicisation of technological change focuses more specifically on the relationship between general purpose technologies (GPT), the social transformation of infrastructure, and productivity effects. This approach recognises how technologies and society mutually shape one another and offers a more specific historical perspective on the occurrence of technological disruption. GPT's are characterised by three criteria: their pervasive effect on society, their inherent potential for technical development, and 'innovational complementarities' that facilitate increasing returns-to-scale (Bresnahan and Trajtenberg, 1995). Productivity typically refers to a measure of how much output (or income) is generated for a fixed amount of input, usually an average hour of work. Perez (2002) provides a very useful framework in this regard. She argues that economic growth since the end of the eighteenth century has gone through five distinct stages characterised by successive technological revolutions, the last of which has been marked by computerisation and the development of ICT.

In the context of Perez's (2002, 2010) periodisation of technological revolutions, the diffusion of AI-driven digital automation technology under the so-called Fourth Industrial Revolution can be understood as a sixth industrial revolution. This 'revolution' is defined by the capacities of intelligent machines to capture and transform data, and to exponentially scale new forms of digital technology through network effects (Haskel and Westlake, 2017; Hendler and Golbeck, 2008). It relies on the technologies outlined in the previous section, which have facilitated the automation of tasks that previously were not able to be performed by machines.

The increase in datatification and the use of AI has enabled the rise of the so-called 'intangible economy', which refers to the steady move to intangible investment: a type of investment that is fundamentally different from tangible investment (Haskel and Westlake, 2017). The intangible components of capital include intellectual property rights, branding, reputation, and data networks. Thanks to previous industrial revolutions and the progress in digital technologies, the marginal cost of the production of many goods and services is approaching zero. Guellec and Paunov (2017), for example, note that the capital requirement for developing software, which is at the foundation of digital innovation and transformation, is significantly lower than that for other types of technological innovation (e.g. pharmaceutical laboratories, chemical experiments and mechanical prototyping).

The low marginal cost of such intangible innovation and the capacity for exponential scaling up through consumer connectivity facilitates the creative destruction that is at the core of the latest industrial revolution. Entry barriers to the AI-driven intangible economy are significantly lower than with previous industrial revolutions, which catalyses the process of creative destruction through perpetual updating of applications and software (Bresnahan and Trajtenberg, 1995). Zysman and

Kenney (2017: 55) argue that a growing 'ecosystem of organisations and networks now exists to provide funding for entrepreneurial experiments made possible by the technological changes, reducing the cost of starting an ICT firm'. These investors are concerned with securing market power and large short-term returns, often at the expense of workers. The global reach of digital products also allows for new opportunities for service delivery and rent capture.

Studies of technological change, as sketched out above, provide an important historical lens through which to understand the effects of the present wave of digital automation on work and employment. Major technological disruptions have led to industrial revolutions that have fundamentally changed society, eliminating entire sectors and the occupations within them, while augmenting others or creating entirely new ones. Such changes, in turn, have been met with resistance and led to social upheaval, but they have also provided huge productivity gains and, at times, wage increases, that have increased living standards and brought fewer hours of work for many millions of people.

Yet, at the same, there have been continuities. The persistence of paid work has been one key feature of the evolution of technology. Each new technological revolution has changed the type and often the content of work on offer (as well as wages and work hours), but it has not led to any lessening in the work we are required to do. Rather, most of us have continued to work, despite (and indeed often because) of technological change. This reflects the fact that technology can create work, as well as displace it, and that changes in technology can be labour-augmenting. History proves this fact. Still, we are now faced with predictions that work will – finally – disappear, in the Fourth Industrial Revolution. Such predictions are assessed in the following sections.

5. Effects of digital automation

There are multiple ways in which digital automation can impact on work and employment. In this section, the effects of digital automation are viewed from three different angles. Firstly, there are the direct effects on employment. Here the discussion engages with arguments and predictions concerning job destruction through digital automation. Secondly, there are the effects on wages. Again there are different arguments about the impacts of digital automation on wages, some positive, others negative. Thirdly, there are the effects on the nature and content of work itself. In this case, attention is given to the different ways in which digital technologies could transform work, as opposed to vary its volume. Will digital technologies, for example, lead to higher skilled work and reduced work hours? Or will they deskill work and increase the intensity and possibly duration of work?

A comment can be added at the outset. The effects outlined below do not exist in isolation, but rather interconnect. Job destruction, for example, can coincide with erosions in wages and falls in job quality. Further, these effects are not guaranteed, nor predetermined. Rather they are highly mediated and subject to change. In practice, they may also lead to active resistance and prompt the need for reform. It will be argued that technological change will need to be managed, if it is to yield net benefits to workers. The kinds of reform needed to secure a better digital future are outlined in a later section.

5.1 Job destruction

The most immediate effect of digital automation is to displace jobs. Technological unemployment can be seen as the effect of rapid expansion of digital technologies. But here questions are raised about the extent and nature of job displacement. How many jobs could be lost through digital automation? In which sectors and locations will jobs most likely disappear? And, crucially, how quickly will jobs disappear? The answers to these questions clearly carry major implications for the types of policies that will be needed to manage digital automation. As will be discussed below, however, the answers to these questions are, to date at least, far from clear, and in a number of cases, contested.

By far the most influential of the recent wave of predictions about the impact of digital automation on employment has been that of Frey and Osborne (2013, 2017). First published as an Oxford University working paper in 2013, its impact was immediate. The reason is not hard to discern. Frey and Osborne (2017: 265) conclude that '47 percent of total US employment is [at] high risk' of automation within the next twenty years. If accurate, this stark prediction, from a US perspective, implies huge challenges for workers, policy-makers, and society in general. Although Frey and Osborne's study has been subject to a number of criticisms (discussed below), it identifies important issues that have become recurring themes in the literature, and which represent still unresolved problems for predicting the impact of digital automation on employment.

Firstly, there is the question of methodology. A particular feature of Frey and Osborne's own estimate and many other similar estimates is that they derive from economic models built around the expectations of experts about what computers may be capable of in years to come. The greater the expectations, the higher the estimate of predicted job losses. The fact that expectations are based on opinion (and hence subject to potential biases) makes the above approach far from ideal. At the same time, other researchers have developed alternative approaches, designed to overcome the methodological problem of reliance on expert opinion. Some studies work from data about the impact on employment of previous waves of technology, while others are grounded in surveys of senior managers concerning their plans for technological investment. Examples of both types are discussed below. However, these approaches bring their own difficulties, which, in part, explain the continuing influence of studies based on expert opinion.

Secondly, there are complex issues in understanding how any given technical capacity for digital automation is linked to levels of employment. Automation operates at the level of tasks, not jobs, so estimates of impacts on employment depend on how expectations of task-shifts are translated into numbers of actual jobs. Furthermore, most research expects that digital automation will have differential effects on different sectors of the economy, with some sectors likely to lose more jobs than others. At the same time, there is a common expectation that digital automation will also create jobs (discussed below). Thus, the problem is not simply to estimate how many jobs will be destroyed, but overall *net job losses*, when those impacts are balanced against jobs created elsewhere. Any robust estimate of net job losses must accurately capture complex interactions between sectors where jobs are lost and other parts of the economy where jobs may be created.

Thirdly, the question of timescale: over what period of time will the predicted changes take place? For policy-makers, in particular, this is a crucial issue. In practice, technologies such as driverless cars have proved much more elusive than enthusiasts have repeatedly assumed. Moreover, as discussed further below, the diffusion of digital technologies depends on a range of social, economic, and political factors, in addition to any purely technological developments.

It can also be noted that attempts to estimate the impact of digital automation on employment produce significantly varied results. Findings from a selection of the most influential studies are summarised in *Table 1*. Differences are apparent in the extent and also timing of the estimated employment effects of digital automation. Headline differences often reflect differing approaches to the problem of how to link task-level analysis to job-level employment numbers, or how to articulate the relationship between sectors most impacted by digital automation and other parts of the economy. Different estimates also reflect attempts to overcome the problematic reliance on expert opinion, by developing alternative methodologies. Overall, it is clear from the table that there is no consensus over the extent of job destruction through digital automation – rather, there is a range of estimates, each pointing to different outcomes for the volume of employment. Further discussion of the alternative methodological approaches taken to arrive at these estimates is taken up below.

Table 1: Estimates of Job Destruction

Study	Region	Timescale	Estimate (summary)
Frey and Osborne (2017)	USA	'a decade or two'	47% of jobs highly (over 70%) susceptible to computerisation
Arntz et al. (2017)	USA	N/A	9% of workers face high (over 70%) risk of automation
Acemoglu and Restrepo (2017)	USA	N/A	Each additional robot reduces aggregate employment by around 5.6 workers
Nedelkoska and Quintini (2018)	OECD countries participating in PIAAC	N/A	14% of jobs at high (over 70%) risk of automation; 32% of jobs at lower (50% to 70%) risk of automation

PWC (2018)	27 OECD countries, plus Singapore and Russia	By mid 2030s	Proportion of jobs likely to be automated: range between 22% (Finland and South Korea) and 44% (Slovakia)
MGI (Manyika et al. 2017)	Global workforce	By 2030	Proportion of global workforce displaced by automation: Midpoint = 15% Fastest = 30%
Bughin et al. (2018)	USA and Western Europe	By 2030	25% reduction in total hours worked using manual and basic cognitive skills; 60% increase for technological skills.
Vermeulen et al. (2018)	USA	'Forthcoming 10 years'	Job loss 'limited'; job creation 'substantial'; overall, 'usual structural change'.

5.1.1 Tasks, occupations and jobs

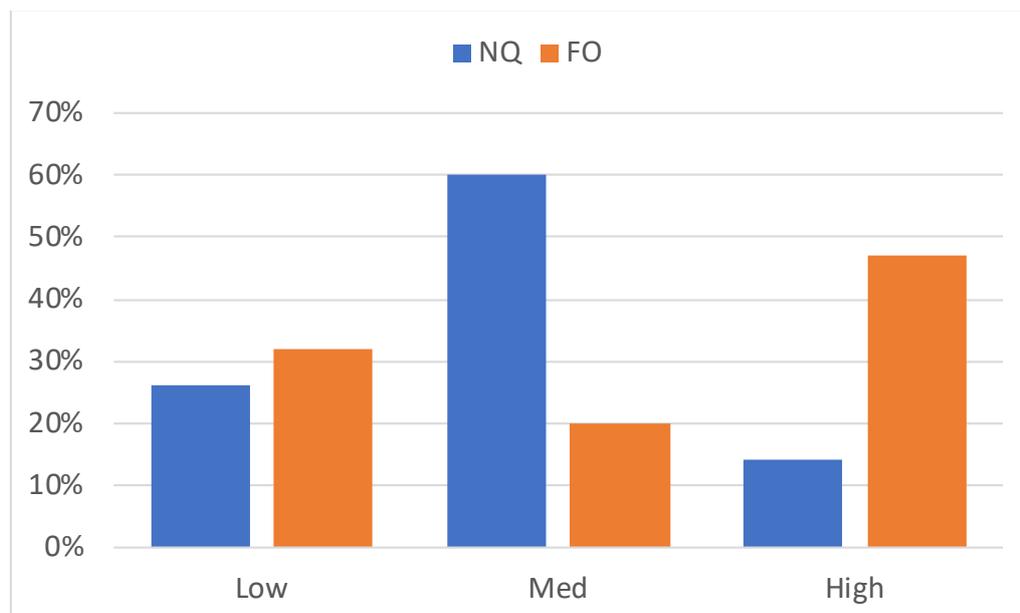
One important source of variation in estimates of the job-destruction potential of digital automation concerns the accurate identification of exactly what it is that might be automated. Again, as Frey and Osborne (2013, 2017) recognise, automation takes place at the level of tasks; that is, specific, concrete actions that are grouped together to make up jobs. Because jobs – or, alternatively, occupations – are made up of a more or less varied mix of tasks, digital automation will have differing impacts according to the type and combination of tasks involved in different types of work. Jobs with a high proportion of tasks that can be automated are more at risk than jobs comprised of more varied or less automatable tasks. Frey and Osborne tackle this issue by assessing tasks that are typical of different categories of *occupations*, based on US data. In this way, they are able to link the automation of tasks to impacts on labour markets, via the mediating notion of occupations, to arrive at the high figure of 47 percent of US jobs being at risk of automation. This estimate is grounded in the judgement of machine learning experts about whether it is possible to automate – now or in the future – the main task of each of seventy occupations, according to the task-level characteristics of each occupation as detailed in the US O*NET database of occupational task composition.¹ Furthermore, information from this exercise is then used to estimate the probability that occupations not judged directly by the experts are automatable. Importantly, though, in presenting their analysis at the level of *risk* of automation, Frey and Osborne are explicit in *not* answering questions about the scale of actual job-destruction: 'We make no attempt to estimate how many jobs will actually be automated' (2017: 268). Moreover, Frey and Osborne also assume that workers whose jobs are lost to automation will seek work elsewhere, as has happened with previous waves of disruptive technology – providing, that is, that these workers are able to gain appropriate new skills, especially 'creative and social skills' (ibid.: 269) that are thought to be less susceptible to future waves of computerisation.

¹ The O*NET database can be found here: <https://www.onetonline.org/>

Frey and Osborne's way of linking tasks to jobs – via occupations – has been subject to considerable criticism. In particular, Arntz et al. (2016, 2017) argue convincingly that this approach fails to take into account the extent to which jobs are different from one another, *even when these jobs are in the same occupation*. That is, the job of a nurse, printer, or university lecturer, for example, can be very different in different employing institutions, in different departments, in different economic conditions, or at different stages of a career. As a result, more recent studies have used additional data from the workplace level to take into account variation in the combination of tasks in actual jobs (as opposed to ideal type occupations). In taking this approach, Arntz et al. (2017) have arrived at much lower estimates for job destruction in the USA: 9 percent of jobs at high risk of automation (see *Table 1* above). Taking a similar approach but applying their modelling technique to data from a range of OECD countries, Nedelkoska and Quintini (2018) estimate 14 percent of jobs to be at high risk of automation (see also Autor 2015, and *Table 1* above). Thus, different ways of linking task-level analysis to occupation- and job-level data give quite different results for estimated impacts of digital automation on overall employment levels.

Despite significant differences in the headline figures of these various studies, the overall findings of these studies are perhaps less different than they first appear. As shown in *Chart 1*, differences in the estimates for automatability given by Frey and Osborne (2017) and Nedelkoska and Quintini (2018) are concentrated in the higher range of expectations. For jobs considered at high risk of automation (over 70 percent), Frey and Osborne give the estimate of 47 percent whereas Nedelkoska and Quintini (2018) estimate 14 percent. For jobs considered at medium risk (30-70 percent), however, the position is reversed: Frey and Osborne estimate only 20 percent of jobs to be at medium risk, while Nedelkoska and Quintini give the figure of 60 percent (including percent in the 50-70 percent risk range). In other words, Frey and Osborne (2017) estimate 67 percent of occupations to be at medium or high risk of automation, whereas Nedelkoska and Quintini (2018) put the figure at 74 percent. This suggests that only a relatively modest shift between medium and high-risk categories could make a significant difference to estimated outcomes in terms of job losses. Moreover, as Frontier Economics (2018) note, these differing estimates for the risk of automation are based on the same 'expert' technical assessments of automatability, which indicates that estimates are highly sensitive to both modelling methods and choices between different datasets of job-characteristics (for instance, differences between US and European data on job composition).

Chart 1: Differences in automatability, according to Frey and Osborne (2017), Nedelkoska and Quintini (2018)



Source: Frontier Economics (2018)

Other studies, meanwhile, are based on predictions of even faster rates of technological change, which *ipso facto* lead to higher estimates for the impact of digital automation. Research for the McKinsey Global Institute (Manyika et al., 2017) adopts considerably more ambitious assumptions about the likely development of AI and related digital technology and, not surprisingly, estimates the employment impacts of digital automation to be significantly higher. Using a range of alternative estimates for the speed of technological change, Manyika et al. (ibid.) estimate that, over the period up to 2030, a middling pace would displace 15 percent of the global workforce, while 30 percent would be displaced by the highest predicted pace. It is left unclear, though, on what basis Manyika et al. (ibid.) arrive at higher estimates of technical change than other researchers. Research for PWC (2018) also arrives at figures in the higher range, estimating some 22–44 percent of jobs across thirty-two OECD countries to be at high risk of automation by the mid-2030s, despite adopting the task-job approach associated with the lower estimates of Arntz et al. (2017) and Nedelkoska and Quintini (2018). The reason for these higher estimates appear to derive from a faster assumed rate of technological development. The PWC authors distinguish three waves of digital automation: first, an 'algorithm wave ... focused on automation of simple computational tasks and analysis of structured data', which is 'already well underway'; second, an 'augmentation wave ... focused on automation of repeatable tasks ... and statistical analysis of unstructured data', which is 'likely to come to full maturity in the 2020s'; and, third, an 'autonomy wave ... focused on automation of physical labour and manual dexterity, and problem solving in dynamic real-world situations that require responsive actions', which 'may only come to full maturity on an economy-wide scale in the 2030s' (ibid.: 1). In other words, this research incorporates estimates for two (out of three) phases of technological development which have not yet taken place. These estimates for digital development are then incorporated into an algorithm and applied to task and job datasets (for details on methodology, see PWC, 2017). Once more, then, very significant variations in the findings of different studies for the number of jobs at risk of automation appear to be based on little more than differing assumptions and 'modelling choices' (Frontier Economics, 2018: 43).

Estimates of job losses also imply shifts in employment – in particular, they suggest certain types of jobs that are at high risk of destruction. The following section discusses which jobs have been identified as most vulnerable to automation.

5.1.2 Which jobs are at risk?

The occupations that Frey and Osborne see as most susceptible to computerisation are at the lower end of the labour market in terms of skills and earnings. In this regard, their analysis departs from the familiar model of 'hollowing-out' of employment through the destruction of jobs in the middle of the labour market. Occupations seen as most at risk include 'a substantial share of employment in services, sales and construction' (Frey and Osborne, 2017: 265), through the continued elimination of routine manual and non-manual tasks. Risk is associated with those occupations within sales which exhibit the least need for social intelligence, for example, cashiers, counter and rental clerks and telemarketers (ibid.). They attribute susceptibility in construction occupations, as likely to be driven by trends towards prefabrication in factories, which enables tasks to be more readily routinised.

Occupational characteristics are assessed in relation to nine 'bottleneck' factors; that is, variables which are thought to present barriers to automation. Frey and Osborne (2017: 261) identify three significant 'inhibiting engineering bottlenecks' that have so far limited the spread of computerisation into important sectors of employment: 'perception and manipulation tasks', 'creative intelligence tasks', and 'social intelligence tasks'. Their prediction that 47 percent of US jobs are at 'high risk' of automation depends on technical solutions being found that enable automation to penetrate these areas of employment, within their 'decade or two' timescale. As they put it, 'our predictions are based on expanding the premises about the tasks that computer-controlled equipment can be expected to perform' (ibid.: 268); 'premises' provided by the expectations of experts in the field of computing. For

Frey and Osborne, this putative shift towards the computerisation of low skill and low pay jobs represents a positive outcome of digital automation, since it will offer a way for workers to find work in more meaningful employment. While much of the literature assumes that the destruction of jobs will have negative impacts (see discussion below), Frey and Osborne are unusual in seeing a positive outcome (ibid.: 267).

Modelling of the risk of automation in OECD countries by Nedelkoska and Qunitini (2018) suggests that the tasks most exposed to automation are likely to be concentrated in primary and secondary sector occupations which are intensive in those tasks; predominantly in manufacturing and agriculture. These will tend to be jobs with few skill requirements such as food preparation assistants, labourers, refuse workers, cleaners and helpers. In jobs that require some training, risk is higher where interacting with machines is a large component of the job; these jobs encompass machine operators, drivers and mobile plant operators in manufacturing. A cross-sectoral modelling of US occupational data by Vermeulen et al. (2018) concluded that activities with the highest job losses as a result of automation are in 'old' occupations – jobs in production, such as machine assembly, operators and setters – which have routine tasks that are easily standardized. The study by McKinsey Global Institute, similarly found that, in manufacturing, automation is replacing manual and physical skills at twice the rate as in other sectors, affecting jobs such as machine feeders and operators (Bughin et al., 2018).

Job displacement, according to these studies, tends to align with the automation of low-skill, routinised manual labour. McKinsey Global Institute undertook modelling to project net job changes due to automation and projected an 11 percent decline in total work hours dedicated to physical and manual skills between 2016 and 2030 (Bughin et al., 2018). They found that skills such as general equipment operation and navigation and inspecting and monitoring are likely to be replaced by machines fastest. Though it is worth noting that physical and manual tasks are not, in themselves, an indicator of susceptibility to automation – even with this predicted 11 percent decline, these tasks are still likely to be the largest category across all jobs, accounting for 26 percent of all hours worked. This reflects a continued need for human labour for tasks that require dexterity or must be carried out in cramped or irregular spaces. Here it is possible to see limits to automation linked to the specificity and adaptability of human labour (see also discussion on changes in the nature of work, below).

While most automation will be concentrated in manufacturing and agriculture, studies indicate there will be a continued decline in routine cognitive tasks, such as those requiring basic data and processing skills (Bughin et al., 2018; Colombo et al., 2019); jobs such as computer and telephone operators, typists, and data entry worker. Vermeulen et al. (2018) predict some limited job growth in middle-skill routine jobs such as receptionists, information clerks, stock clerks and order fillers. They speculate this growth may be due to higher demand in these areas combined with a preference for human labour over machines and poor performance by technology in these roles. But, overall, they find that office and administration jobs comprise a large proportion of those with a high susceptibility to automation.

A number of studies have surveyed business leaders to determine their short-term plans for technological investment and how they expect technology will change jobs and skill demand. A survey of UK business leaders by Royal Society of Arts (RSA) (Dellot and Wallace-Stephens, 2017) found that executives in the logistics (transport and distribution) and retail sectors have the highest expectation of automation – both employers of low-skill, manual work. Finance and accounting sector leaders in this study also expected job losses, suggesting that some high-skill, non-manual work may also be vulnerable to automation. This accords with a McKinsey Global Institute study where one quarter of employers in finance and accounting (25 percent) also expect that there will be a high level of automation in their sector over the next ten years (Bughin et al., 2018).

Overall, while there is evidence that digital automation will have wide-ranging effects on the level of employment, there is a common view that digital technologies will have the greatest impact on the

most routine and low skill work. Predictions of net job losses, in this case, derive from the view that technology will be labour-saving at the lower end of the labour.

5.1.3 Timescale

As detailed in *Table 1*, estimates for the impact of digital automation tend to be somewhat vague about how long the process will take, and some give no timescale at all. For policy-makers and other stakeholders, this is clearly problematic. To some extent, uncertainty over timescale is inherent in the question under consideration: it is inescapably difficult to predict how fast digital technologies will develop. As noted above, Frey and Osborne's (2017) estimate for the impact of digital automation depends upon the expectation that technology will soon overcome 'engineering bottlenecks' associated with automating non-routine tasks involving 'perception and manipulation', 'creative intelligence', and 'social intelligence', none of which are trivial technical challenges. Their estimate also implies that other barriers to automation – e.g. social and legal – can be overcome. Of course, if technical advances fail to keep up with expectations, then the estimated impact on employment will similarly be reduced.

Frey and Osborne (*ibid.*: 265) suggest that their estimate of future job losses could be realised in 'perhaps a decade or two'. For economic historians, this time-frame is quite limited; for policy-makers, however, the difference between ten and twenty years is considerable. What is more, this timescale assumes that digital automation will be overwhelming and replace jobs at a rapid rate. Frey and Osborne's analysis dates from 2013 – so, we are already almost halfway through their expected timescale, with little sign to date of the expected wave of automation.

In practice, as Frey and Osborne (*ibid.*: 268) recognise, 'the actual extent and pace of computerisation will depend on several additional factors' omitted from their analysis. These include the availability (or otherwise) of cheap labour, the price of capital, the price of labour more generally ('long-run wage levels'), as well as the regulatory environment. Thus, estimates of the likely impact of digital automation on employment must include an understanding of the key influence of economic, social, and political conditions, and must see the state and other regulatory bodies as active participants in the process of automation, not passive bystanders to inexorable technological development.

Research that examines the impact on employment of previous waves of technological change comes to fairly clear conclusions about timescale (see discussion above). Moreover, historical understandings of technological change also have important conclusions about how change comes about. Historians of technology commonly cite five previous waves: the introduction of steam power in the 1780s–1790s; iron in the 1840s–1850s; steel and electricity in the 1890s–1900s; electromechanical and chemical technologies in the 1950s–1960s; and information and communication technologies in the present era (Atkinson, 2018). Typically, these waves have evolved over a period of around thirty-years, starting in particular sectors of the economy before later expanding into others, leading to overall increases in productivity of around 75 percent. Clearly, as a headline figure, this represents a very significant impact. Spread over the thirty-year period, however, it translates into a 3 percent increase in productivity each year (Atkinson, 2018), which would comprise a significant change, but not the huge dislocation foreseen by some recent accounts.

This raises a further question about timescale that appears often in the recent literature: will it be different this time? For writers such as Ford (2013, 2015, 2018), AI and robotic technologies represent a break with the past so radical that 'the historical record may not be predictive' any longer (Ford 2013: 38). By contrast, for Atkinson (2018: 81), 'there is no reason to believe that this coming technology wave will be any different in pace and magnitude than past waves'. In one sense, of course, things *are* different this time: the technological innovations of digital automation certainly are novel. But that has also been the case with each previous wave of new technology. On each occasion, some jobs have been eliminated, others transformed radically, and yet others created anew. Digital automation, as

discussed further below, will affect particular tasks and jobs in specific ways, and these impacts will be different from those of previous waves. Considered in this qualitative way, then, digital automation will clearly be different. In quantitative terms, though, in relation to extent and – especially – in terms of timescale, there remains no clear consensus in the literature to date.

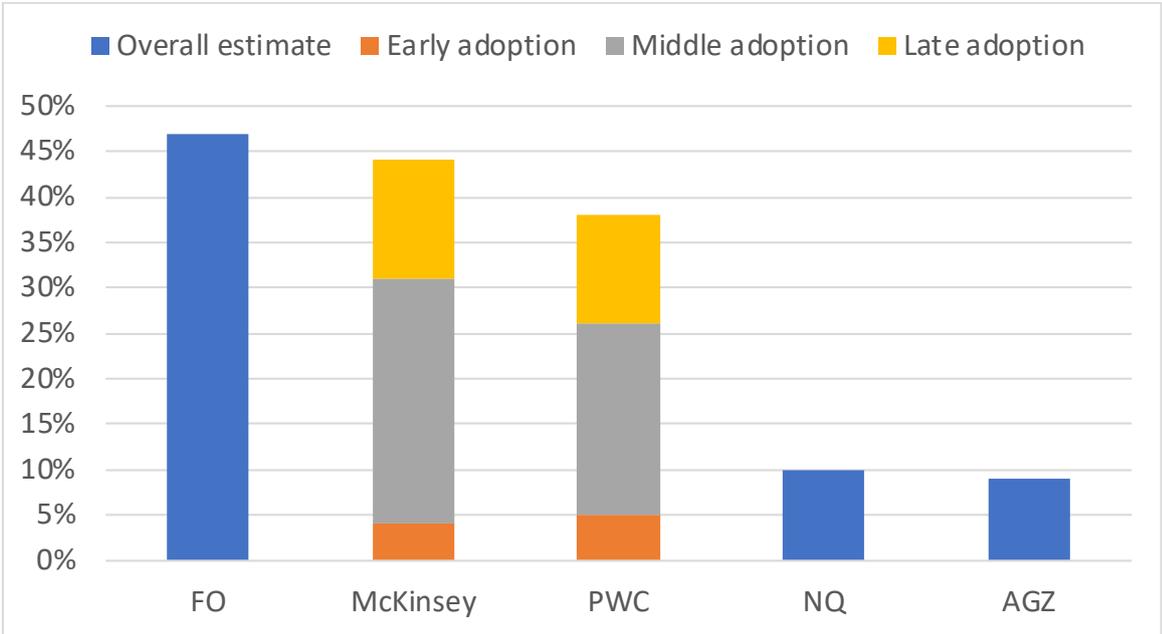
5.1.4 Non-technological factors

Several authors note that the scale of impact of digital technologies on employment will be influenced significantly by non-technological factors. As noted previously, Frey and Osborne (2017) identify the importance of the price of labour and of capital, and the regulatory environment, for the likely pace of computerisation. Research by Frontier Economics (2018: 32) argues that the pace of digital uptake by businesses will be influenced by 'economic considerations, regulatory concerns, individual preferences and social norms, and by the need to reorganise production processes to take advantage of AI'. Manyika et al. (2017: 2) extend the list to include:

'the cost of developing and deploying automation solutions for specific uses in the workplace, the labor market dynamics (including quality and quantity of labor and associated wages), the benefits of automation beyond labor substitution, and regulatory and social acceptance.'

To date, however, there is very little evidence about the extent or effects of these factors on the actual pace of digital automation. Some studies attempt to make allowances for non-technological factors by including estimates for speed of take-up of the technologies of digital automation. For instance, both PWC (2018) and Manyika et al. (2017) give estimates for early, middle and late adopters, as shown in *Chart 2*. Unfortunately, there is little discussion of the basis for these differential take-up rates, and in both studies, discussion is based on end-point figures, both for penetration of the technology and timescale.

Chart 2: Job destruction estimates of differential uptakes of digital automation technology, as proportion of current US employment.



Source: Frontier Economics (2018)

Consequently, as discussed above, the most influential studies (see *Table 1*) base their models on the elicited expectations of experts in the fields of AI, robotics, and related fields, as a result of which

estimates tend to be driven strongly by technological feasibility. In practice, then, despite warnings of the importance of non-technological factors, models tend to assume that what can be automated will be automated. Clearly, the influence of non-technological factors in the dissemination of digital automation is an important area that urgently needs further research.

The rapid advancement in the capacity of AI relative to human intelligence has spurred investment as companies believe AI is the next digital frontier for value extraction (Bughin et al., 2018). However, even among AI-aware companies, only roughly 20 percent are actually using AI in a core business process or at scale (Chui et al., 2018). One fifth of business leaders surveyed by the RSA in the UK (Dellot and Wallace-Stephens, 2017) want to invest in AI technologies, but only 14 percent had invested in, or were about to invest in any AI technology, with 20 percent saying they wanted to adopt but it would take several years, and the rest claiming it was too expensive (14 percent) or not yet properly tested (15 percent).

The social, legal and political hurdles to the diffusion of AI technology are not insignificant. For example, while the AI which enables self-driving cars has advanced so quickly in recent years that the cars have become symbolic of the advances in AI generally, the greatest barriers to their widespread implementation are considered not to be technical, but legal. Legislators and legal experts are grappling with how to deal with liability for collisions, injuries and fatalities and there is no clear end to the debates on the issues in sight.

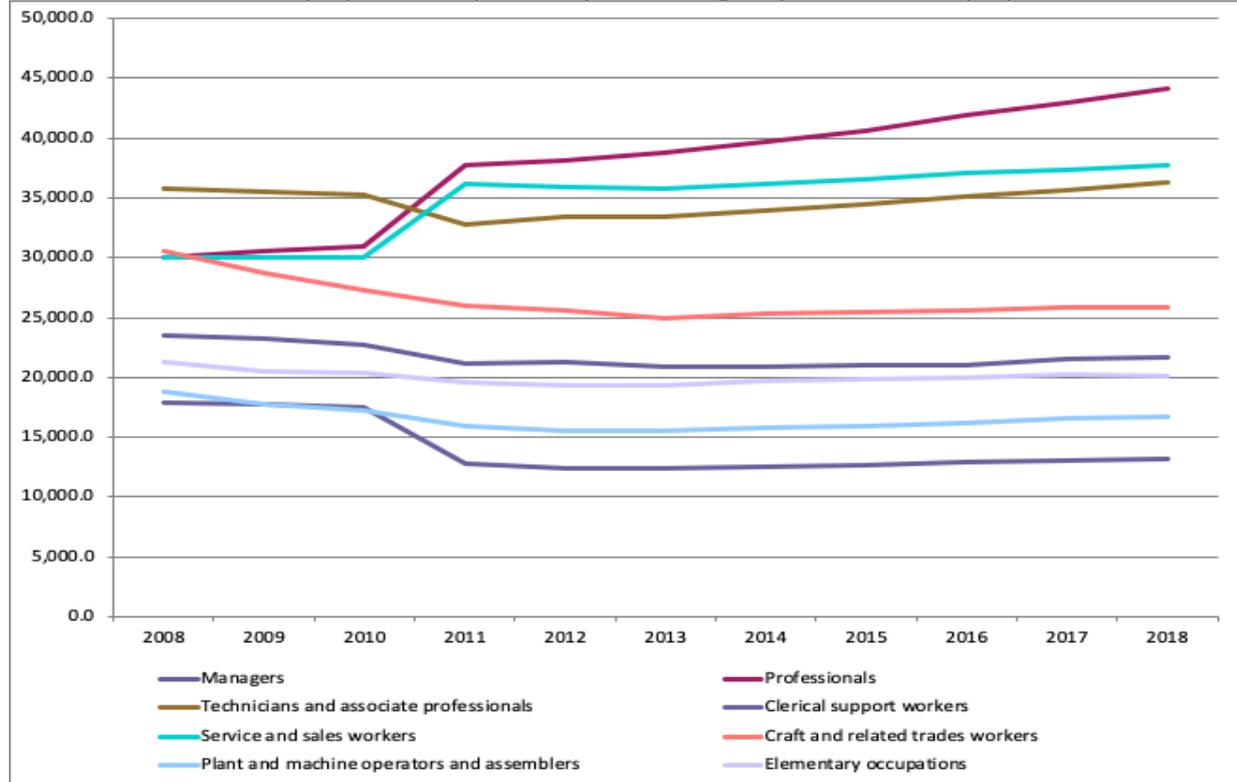
There are equally strong social barriers to the use of AI relating to individual preferences and social norms. In services, there remain customer preferences for human service and a lack of user engagement with automated systems (Montalban et al., 2019). With analytic and algorithmic systems, there are ethical concerns, particularly around algorithmic bias (Davidson et al., 2019; Noble, 2018). The introduction of AI into some areas of prediction and to support decision-making in areas such as policing and the judiciary, human resources, and public services, has prompted considerable discussion about the relationship between humans and machines from a social and ethical perspective (Eubanks, 2018; Noble, 2018; O'Neil, 2016).

The public perception of AI and digital automation is mixed. An Oxford study on the attitudes of Americans toward AI found that a substantial minority (41 percent) somewhat support or strongly support the development of AI, while a smaller minority (22 percent) somewhat or strongly oppose it (Zhang and Dafoe, 2019). A large majority (82 percent) believe that robots and/or AI should be carefully regulated and managed; a figure comparable to survey results from EU respondents (ibid.). These results, together with the legal and social barriers highlighted above, suggest that digital automation will be likely uneven, delayed, and in places, non-existent.

5.1.5 EU employment: recent trends

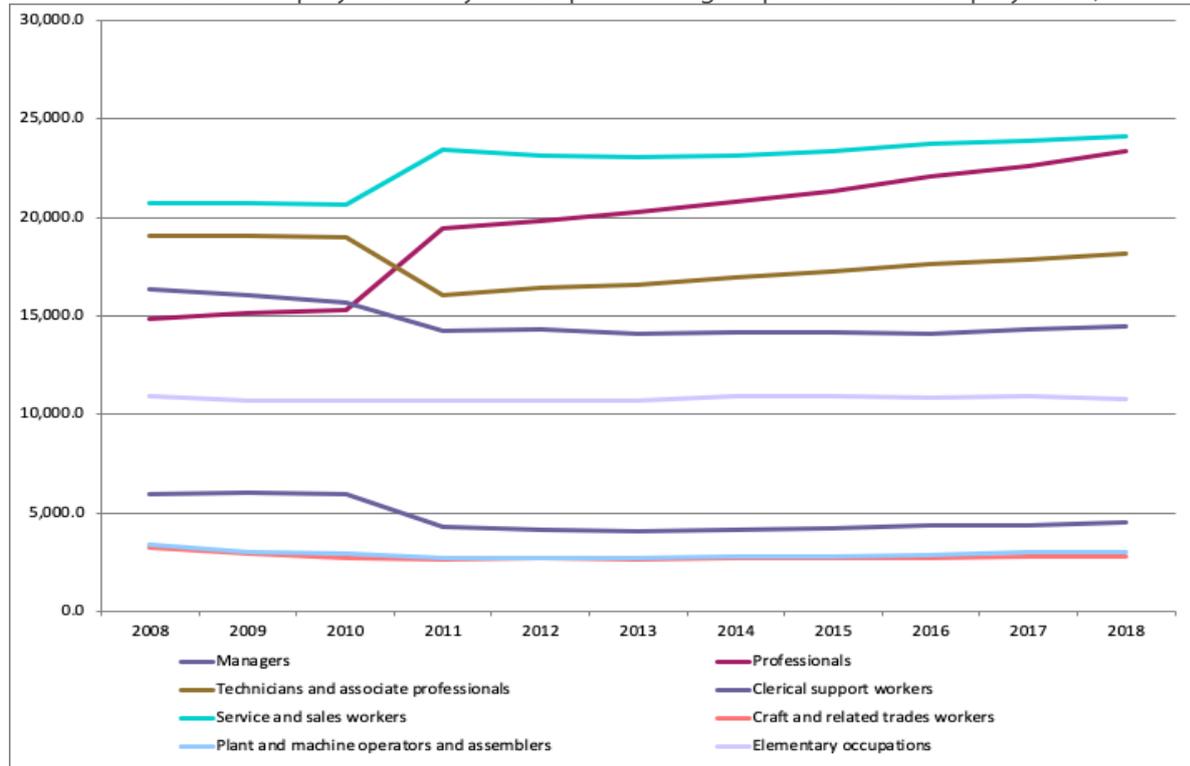
Finally, there are recent trends in EU employment data. Given that studies such as Frey and Osborne (2017) predict significant employment impacts of digital automation starting from a baseline in 2010 data, it might be expected that employment statistics would by now capture some effects. As shown in *Charts 3, 4 and 5*, however, EU employment data show little, if any, effect. Taking an overview of EU employment by broad occupational groups and by gender, over the last ten years for which data are available (2008-2018), by far the biggest impact over this period was from the recession following the global financial crash of 2007-2008.

Chart 3: EU28 employment by occupational group: total employment, 2008-2018



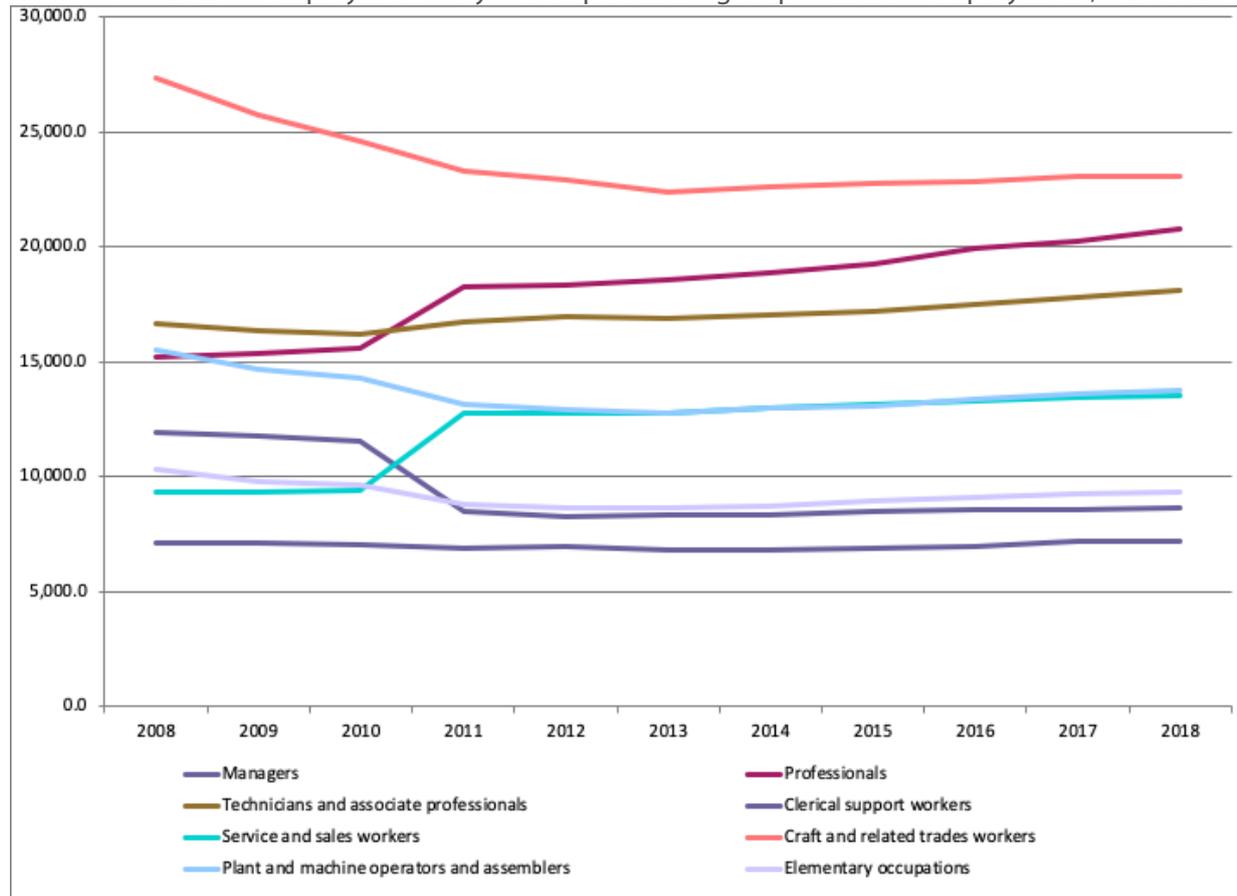
Source: LFS, not including agriculture, forestry and fishing; armed forces.

Chart 4: EU28 employment by occupational group: female employment, 2008-2018



Source: LFS, not including agriculture, forestry and fishing; armed forces.

Chart 5: EU28 employment by occupational group: male employment, 2008-2018

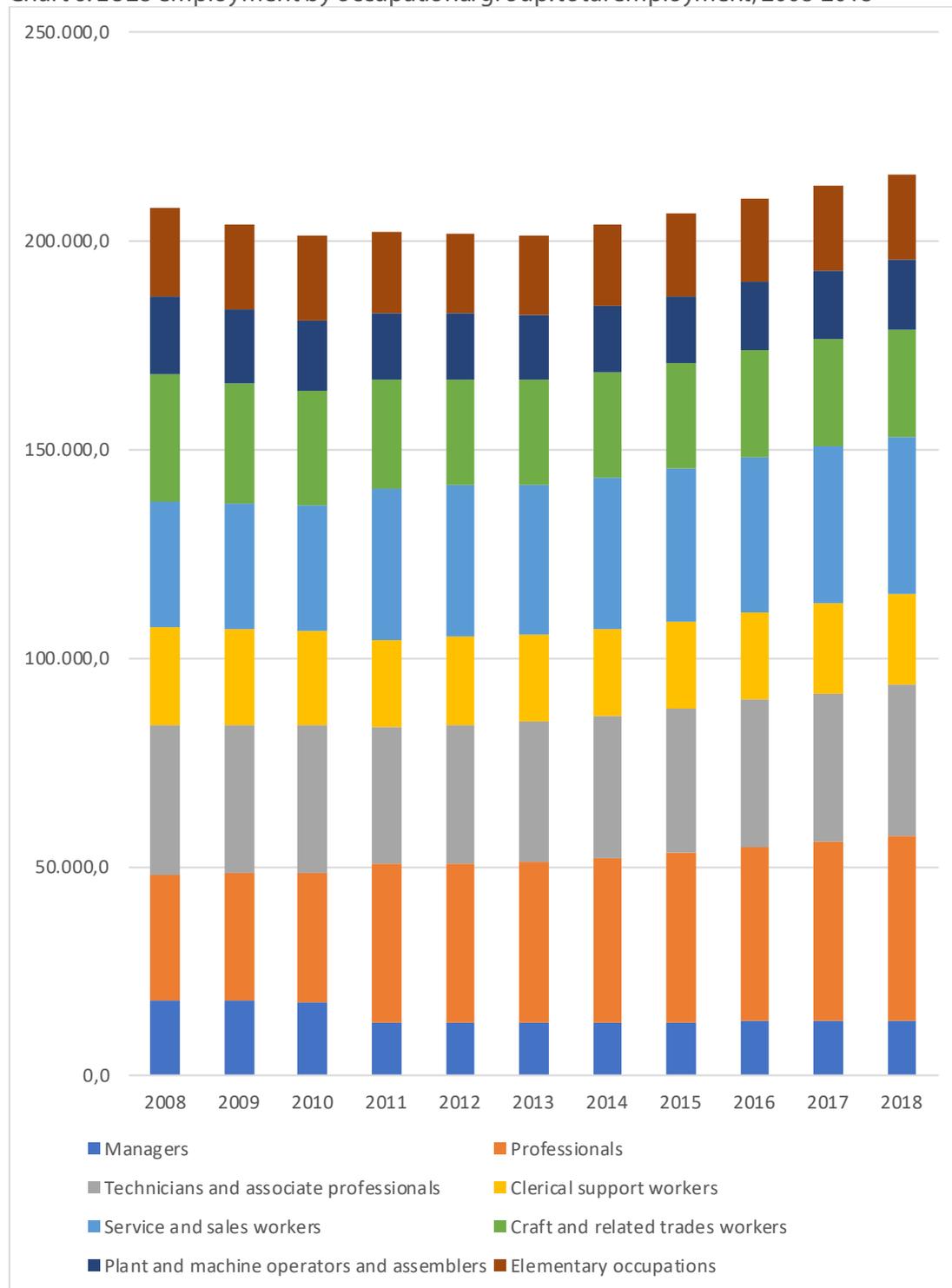


Source: LFS, not including agriculture, forestry and fishing; armed forces.

For some occupational groups, deep recession led to a step-change in trends, marking significant reductions or increases in employment. For instance, the number of managers declined sharply in 2010-11, with smaller declines in the numbers of technicians and associate professions, and clerical support workers. Over the same period, by contrast, there were marked increases in the numbers of service and sales workers and, especially, of professionals. During the post-recession recovery period, the number of professionals continued to increase relatively rapidly, outstripping the average seen across the rest of employment. At the same time, numbers employed as technicians and associate professionals recovered to earlier levels. As shown in *Chart 6*, total employment in the EU 28 now stands well above the immediate post-recession level, indicating no significant impact of 'technological unemployment' to date.

Trends for recession-driven reductions in the number of managers and increases in service and sales workers, as well as technical and associate professionals, are replicated when the figures are disaggregated according to gender: hence, the same overall shifts in employment are reflected in the data for women and men – although, gender differences in overall patterns of employment between men and women remain marked. Thus, for instance, the long-term declines in manual work are especially clear in the reduction over the last decade in male employment in craft and related trades, and in plant and machine operators and assemblers. Nevertheless, the rate of decline of employment in these sectors of the labour market has slowed noticeably in the post-recession recovery, and the data even show modest increases as economic growth has revived.

Chart 6: EU28 employment by occupational group: total employment, 2008-2018



Source: LFS, not including agriculture, forestry and fishing; armed forces.

Table 2. Share of employment by occupation, 2018 and share of absolute growth 2011 to 2018 by occupation

	EU 15	Austria	France	Germany	Netherlands	Sweden	UK
Managers	0.065	0.049	0.077	0.049	0.053	0.061	0.117
<i>Share of growth</i>	<i>0.033</i>	<i>-0.007</i>	<i>-0.014</i>	<i>0.004</i>	<i>-0.246</i>	<i>0.135</i>	<i>0.221</i>
Professionals	0.213	0.207	0.200	0.184	0.271	0.284	0.257
<i>Share of growth</i>	<i>0.436</i>	<i>0.906</i>	<i>0.488</i>	<i>0.219</i>	<i>0.820</i>	<i>0.609</i>	<i>0.344</i>
Technicians & associate professionals	0.169	0.170	0.204	0.213	0.160	0.184	0.121
<i>Share of growth</i>	<i>0.250</i>	<i>-0.051</i>	<i>0.128</i>	<i>0.426</i>	<i>0.065</i>	<i>0.422</i>	<i>0.169</i>
Clerical support workers	0.103	0.098	0.075	0.133	0.094	0.064	0.096
<i>Share of growth</i>	<i>0.050</i>	<i>-0.085</i>	<i>-0.136</i>	<i>0.190</i>	<i>0.023</i>	<i>0.108</i>	<i>0.057</i>
Service and sales workers	0.178	0.190	0.167	0.145	0.198	0.196	0.181
<i>Share of growth</i>	<i>0.109</i>	<i>0.150</i>	<i>-0.054</i>	<i>0.029</i>	<i>0.180</i>	<i>-0.031</i>	<i>0.068</i>
Craft & related trades	0.116	0.141	0.099	0.133	0.084	0.101	0.087
<i>Share of growth</i>	<i>-0.020</i>	<i>-0.013</i>	<i>0.136</i>	<i>0.090</i>	<i>-0.108</i>	<i>-0.065</i>	<i>0.029</i>
Plant & machine operators & assemblers	0.069	0.062	0.086	0.066	0.048	0.060	0.052
<i>Share of growth</i>	<i>0.043</i>	<i>0.063</i>	<i>0.163</i>	<i>0.039</i>	<i>0.090</i>	<i>-0.190</i>	<i>0.043</i>
Elementary occupations	0.086	0.083	0.092	0.077	0.092	0.051	0.089
<i>Share of growth</i>	<i>0.100</i>	<i>0.037</i>	<i>0.288</i>	<i>0.003</i>	<i>0.176</i>	<i>0.011</i>	<i>0.068</i>

Source: Eurostat, Labour Force Survey data, series employment by occupation and economic activity (lfsa_eisn2); data exclude employment in agriculture, forestry and fishing; public administration and defence. EU15 denotes member states prior to 2004 expansion. Occupational groups derived from ISCO-08 classification.

There has been some debate about the extent to which the long-term decline in manufacturing employment in the global North has been overlaid in recent years by factors rooted in the era of neoliberal globalisation, with disagreements among US commentators over the relative impacts of new technology and work organisation, versus a shift of jobs to emerging economies, on US employment (for a critical overview of these debates, see Moody, 2017). These disputes

notwithstanding, the European figures suggest that while it might be expected that the impact of digital automation would become increasingly visible as the decade progressed – especially in manual work – in fact, the trend has, if anything, been the reverse, as employment in parts of manufacturing have actually increased.

Overall, then, outside of significant shifts that seem clearly linked to the last recession, there has been little change in overall employment levels in the EU28 countries over the last decade. As shown in *Chart 6*, though, changes in the balance of occupational groups within the total appear to indicate the replacement of jobs lost during the recession (such as managers) with jobs created in other sectors – especially of professionals and, to a lesser extent, technicians and associate professionals.

Table 2 shows how relatively routine work remains common in the EU, with over half of jobs in the EU15 accounted for by clerical, sales, craft, operative and elementary roles (e.g. cleaners and labourers). Again, while there has been recovery in employment since the 2007-08 crisis, with some growth in professional and technical roles, there has remained a preponderance of routine work, undermining any idea of a sudden shift to automation in this area.

It is evident that, in general, while employment levels have been influenced by changes in technology, job destruction on a grand scale is some way off. While it is too early to tell what will be the effect of digital technologies, it is clear that these technologies will have to evolve to a significant degree before we can declare the demise of paid work.

5.2 Wage effects of digital automation

In addition to the effects on job destruction, digital automation is also likely to impact on extrinsic aspects of jobs; in particular, on levels of pay and remuneration. A presumed link between (rising) automation and (falling) pay is a recurring theme in the literature, reappearing with each wave of techno-pessimism about the prospects for employment in general, on the straightforward assumption that falling demand for labour will produce falling wages alongside rising technological unemployment (see earlier discussion); a fear first voiced by Keynes in the 1930s and regularly repeated since then (DeCanio, 2016). During the 1980s and 1990s, the first wave of computerisation in white collar work and the large-scale introduction of robots into manufacturing saw these fears repeated (see discussion in Mokyr et al., 2015). More recently, digital technologies have also been linked to the 'hollowing-out' of labour markets in wealthy economies over recent decades, a process which has seen the decline of middle-skilled, middle-paid employment, and the polarisation of jobs at the top and bottom of the labour market (see Goos and Manning, 2007) – notwithstanding disagreements over the extent to which off-shoring and declining union power have also played a part in this process (Moody, 2017). It should not come as any surprise, then, that the recent literature on digital automation recapitulates many of these arguments.

In particular, there is a widespread expectation that digital automation will lead to 'labour immiseration' (Autor and Salomons, 2018: 9), involving both technological unemployment and falling wages (see discussion and references in DeCanio, 2016). Many authors expect digital automation to contribute to a continued hollowing-out of labour markets, with further decline of middle-skilled, middle-pay jobs as technology automates the established but routine jobs that have often attracted dependable wages and stable employment, leading to further polarisation – with employment moving to either highly skilled and high-paid technical jobs, or low skilled, low-paid ones. Indeed, as discussed above, for authors such as Autor (2015), many low-skilled jobs cannot be automated, since they require human cognitive skills and task-flexibility. For Autor (2015), however, this does not imply that low-skill jobs that are resistant to automation will become better paid, since labour oversupply from sectors hit hardest by automation, together with the lack of technological pay-premiums associated with work at the lower end of the labour market, will combine to keep pay low (Autor, 2015). By contrast, Frey and

Osborne (2017) predict the reversal of the trend towards the hollowing-out of the labour market, as employment shifts out of low-skill jobs as the latter succumb most rapidly to digital automation.

Taking a different approach, based on recent shifts in US productivity and employment data, Acemoglu and Restrepo (2017: 217-218) nevertheless agree that the introduction of robots in the US will produce both job-losses and falling wages, at the following rate: 'one more robot reduces aggregate employment by about 5.6 workers ... and one more robot per thousand workers reduces wages in the aggregate by about 0.5 percent'. Despite adopting different approaches, then, these and other studies represent a broad continuity with previous tendencies to draw a simple analytical linkage between falling demand for labour (in one or more parts of the labour market) due to automation, and a consequent reduction in rates of pay for those remaining in work in other parts of the economy.

As is the case in other areas of the recent literature, however, other authors present a far more optimistic picture, in which technologically driven increases in productivity lead not to unemployment but to higher wages (Autor 2014). These accounts start from the observation of Kaldor (1961) that, despite a century of technological advances and radically increased productivity in the US economy, the labour share of GDP had remained remarkably constant. The central argument of this approach is that new technology leads to increased productivity, which in turn leads to increases in GDP, including increased demand for the now cheaper goods and services produced in sectors which adopt new technology, leading to overall economic expansion and the creation of new jobs. As new sources of employment absorb workers shed from automating sectors, demand for labour is maintained, and pressure to reduce wages alleviated: in consequence, the labour share of GDP is maintained (for a critical overview of this approach, see Autor and Salomons, 2018; Berg et al., 2018) Thus, while new technology leads to labour-shedding in some sectors of employment, it also triggers important offsetting effects that maintain a degree of stability in employment and wages over the long term. The problem with this approach, of course, is that, although the empirical trend identified by Kaldor was maintained into the 1980s and 1990s (despite some weakening), since the 2000s, the labour share of GDP has declined significantly in many countries. The key question, therefore, is why are the offsetting mechanisms no longer working as they did previously?

In order to reconcile the long-term stability of the 'labour share' with its recent decline, and to link this shift to the emergence of the technologies of digital automation, a number of studies have attempted to build more complex econometric models that take account of both the labour-shedding and GDP-increasing effects of increased productivity, as well as the time-lag between the two processes and any distributive effects on wages. Acemoglu and Restrepo (2018b) reached relatively optimistic conclusions about the impact of automation on employment and wages, based on a model that sees automation affecting employment at the level of tasks. In this model, automation, 'squeezes out tasks previously performed by low-skill labour' (ibid.: 1526) and puts a premium on high-skill technical labour performing complex tasks, thereby increasing wage and employment inequality over the short term. Over the longer term, however, complex tasks become standardised and move to low-skill labour, thus restoring employment and wages at the lower end of the labour market and cancelling out any tendency for increased wage inequality. Consequently, for Acemoglu and Restrepo, the introduction of digital automation technologies 'generates a self-correcting force towards stability' (ibid.: 1526). What is more, this balanced growth path emerges under a range of 'reasonable assumptions' about economic conditions (ibid.: 1526). In other words, for Acemoglu and Restrepo, a virtuous circle of automation, rising GDP, increased demand for labour, and higher wages would not be difficult to achieve.

Taking a different approach, Autor and Salomons (2018) base their model on industry-level productivity data from the last four decades. According to this model, automation displaces labour in the industries where it is adopted, but the gains in productivity increase demand for labour in 'downstream' industries, which make use of the automated products and services. As a result, workers displaced from one industry are subsequently reabsorbed elsewhere; indeed, GDP gains from

automation increase overall demand for labour in this model. However, Autor and Salomons find that wages in the newly-created jobs are less than those in the jobs displaced by automation. As a result, 'automation ... has been employment-augmenting yet labour-share displacing over the last four decades' (ibid.: 11, original emphasis); that is, employment has increased with automation but the labour share of GDP has declined over the same period, leading to greater inequality. Compared with the model of Acemoglu and Restrepo (2018b) discussed above, then, Autor and Salomons (2018) reach less optimistic conclusions about the prospect for wages, even though employment levels are maintained.

To complete the picture, a third approach reaches far more pessimistic conclusions. In research first published as an IMF working paper, Berg et al. (2018) adopt a modelling approach broadly similar to that of Acemoglu and Restrepo (2018b), but are critical of what they see as a problematically over-simplified model in the latter's research. Most significantly, whereas Acemoglu and Restrepo (2018b) assume that automation technologies will be applied across the economy, Berg et al. (2018) introduce a distinction between sectors that introduce automating technology and those that continue with traditional labour-intensive technologies. Berg et al. (ibid: 120) are thus able to look at the effects on employment and wages for a range of scenarios for the introduction of digital automation:

- Model 1: 'robots compete against labour in all tasks'
- Model 2: robots 'compete only for some tasks'
- Model 3: robots 'substitute only for unskilled labour while complementing skilled labour'
- Model 4: robots 'contribute to production only in one sector'.

This approach enables Berg et al. to assess a range of potential outcomes, thereby taking into account divergent predictions about how far and how fast digital automation will impact on employment, and about which sectors and workers will be affected most significantly.

Despite the wide range of scenarios investigated, however, Berg et al. (2018: 120) find remarkably consistent results: 'automation is very good for growth and very bad for equality in all variants'. In the long run, Berg et al. (ibid.) estimate that automation will boost GDP by between 30–240 percent. When it comes to the impact on jobs and wages, however, the most optimistic scenario puts the time-lag between labour displacement (falling wages) and rising real wages at twelve years. In other cases, 'the low-wage phase lasts 20–50+ years' (ibid.); that is, longer than a working lifetime. In Model 3, where robots substitute only for unskilled labour, Berg et al (ibid.) describe the impact on inequality as 'horrific': 'In our base case calibration, the skilled wage increases 56–117% in the long run, while the wage paid to low skill labour drops 26–56% and the group's share in national income decreases from 31% to 8–18%'. What is more, Berg et al. identify a persistent trade-off such that the biggest increases in GDP and real wages come in the scenarios where inequality increases the most; that is, rising GDP, rising real wages, but declining labour share. In short, the conclusions of Berg et al. could scarcely be more different – or more pessimistic – than those of Acemoglu and Restrepo; with Autor and Salomons occupying something of a middle ground.

So, what are we to make of this huge divergence in estimates of the likely effect of automation on wages? Perhaps the most important point to appreciate is that none of the studies discussed above are actually studies of automation, digital or otherwise. Both Acemoglu and Restrepo (2018b) and Berg et al. (2018) start by making assumptions about which sectors of the economy will be affected by digital automation, which workers will be squeezed, and how fast these processes will develop. Moreover, these assumptions are based on estimates for the rate of automation provided by AI 'experts' and technologists. The problems with this approach are obvious: if these assumptions are mistaken, then the predictions generated will also be wrong, no matter how sophisticated the modelling (see also discussion above). To their credit, the authors are fully aware of these problems. For instance, Acemoglu and Restrepo (2018b: 1527) note a number of assumptions that could be wrong, including the following: their model assumes 'that it is always the tasks at the bottom that are automated; [but]

in reality, it may be those in the middle'; 'there may be technological barriers to the automation of certain tasks and the creation of new tasks' which are not taken into account; and, 'our analysis of the creation of new tasks and standardisation [ignores] the need for workers to acquire new skills to work in such tasks'. Not surprisingly, Acemoglu and Restrepo (ibid.) conclude with a call for further research:

'Finally, and perhaps most important, our model highlights the need for additional empirical evidence on how automation impacts employment and wages ... and how the incentives for automation and the creation of new tasks respond to policies, factor prices, and supplies'.

Similarly, Berg et al. (2018: 140) acknowledge the limits within which their model is constructed. Once more, their model assumes a rapid and significant impact of digital automation:

'Of course, it is not impossible to overturn our main results. If robots do only a very small fraction of tasks, contribute to output in only a very small fraction of the economy, or are poor substitutes for human workers, then they will not increase inequality. But this is another way of restating the premise of the paper: if there is no technological revolution underway of the sort we have been discussing, then there will only be small effects.'

As was the case with our previous discussion of estimates for the impact of digital automation, predictions for its likely effect on wages are built not around empirical research into the actual digital automation process, but on narrowly technical accounts of what the technology is capable of – or, more often, of what it might be capable of in ten or twenty years' time. And, as Berg et al. (ibid.: 120) state, 'The basic problem is that nobody knows what the world will look like in say 2035'.

Rather than rely entirely on 'expert' opinions about automation, Autor and Salomons (2018) attempt to give a more secure empirical basis to their estimates, by incorporating data on industry level productivity for the last forty years. However, as Haltiwanger (2018) points out, it is questionable whether industry-level increases in productivity actually represent the introduction of new technology. There is a large literature addressing the complex set of drivers known to influence productivity, which cannot be reduced to the introduction of new technology. For many authors, a key driver of productivity growth during recent decades has been a simple intensification of work, in a context of weakened trade unions and emboldened management (Baccaro and Howell, 2017; Moody, 2017). The weakening of trade unions has also been a key contributor behind the declining labour share in recent decades (Vidal, 2013); something that Autor and Salomons recognise their model cannot fully explain (2018: 53). Moreover, as Haltiwanger (2018) reminds us, for the period under consideration, many industries have experienced stagnant or declining productivity. Until research has developed a more detailed understanding of the dynamics, timescales, and effects of the introduction of digital automation at firm level, the interpretation of industry-level data will remain highly problematic. In the absence of such research, studies such as Autor and Salomons (2018) can only 'document conditional correlations' (Rogerson 2018: 72) rather than presenting causal explanations.

In summary, then, research into the likely effects of digital automation on wages present many of the same problems encountered previously in studies attempting to estimate its impact on employment levels. In particular, studies to date rely very heavily on estimates for the scale, extent, and speed of digital automation that are provided by technology experts. These estimates tend strongly to assume that what can be automated will be automated and, in many cases, that what currently cannot be automated will be automated at some point in the not-too-distant future. As discussed previously, these assumptions are highly problematic bases on which to formulate policy. Once more, policy-makers and other stakeholders would benefit greatly from considerable further research on actual processes of digital automation, in order to gain greater insights into the complexities of the processes involved.

5.3 Changes to the nature of work and job quality

The previous two sections have discussed the effects of digital automation on the volume of jobs and wages, respectively. This section focuses on the effects of digital automation on the nature of work and job quality. It focuses on several dimensions, from the effects on work organisation and the composition of jobs, through to challenges to the employment relationship from new forms of work such as platform work. It discusses how transformations in work and new configurations of human and machine work have the potential to affect the skill composition and quality of jobs, together with working time. As it will be shown below, it seems likely that digital automation will have a more complex and gradual effect on occupations than simply wholesale job destruction, with the potential to both help improve and impair the nature of work and job quality.

5.3.1 Changes in occupations

While there is agreement within the academic literature that some jobs – notably those with routine tasks – will be at high risk of automation in the future (see above discussion), there is also a consensus that many jobs – existing and new ones – will outlast the onset of any future technological revolution. In this case, for very many workers, the principle effect of digital automation will be felt through changes in how work is performed. Work will not disappear, but rather will be done differently and within a transformed work environment. In this case, the concern will be more about how workers will interact with technology in their work lives than about whether they will be made redundant by technology.

To help illustrate this fact, Case Study 1 below provides a summary of changes happening in radiology as AI is increasingly used in diagnostics. Here we are able to see how digital technologies, while job preserving, are capable of shaping and reshaping the nature of work. In this particular case, the results for medical workers can be seen as broadly positive, with the use of digital technologies extending the scope for task variety in work.

CASE STUDY 1: RADIOLOGY AND MEDICAL DIAGNOSTICS

Radiology, as a high-skilled occupation in medicine, is undergoing a transformation assisted by advancements in computer vision AI² which can improve the accuracy of diagnoses through advanced image analysis. Radiology provides a good example of the way in which skill complementarity between humans and machines results in improved outcomes, in this case, in diagnostics. AI is able to detect detail in images which is not perceptible to the human eye and can use pattern recognition to interpret complex relationships in new ways (Hosny et al., 2018). The use of AI allows for faster, more accurate diagnoses than trained medical specialists. Human involvement is retained, however. For example, medical expertise is required to engage with the complexities of human biology beyond specific diagnoses. Because it can analyse images very quickly, radiologists expect that AI can be used to prioritise their workflow – with potential life-saving effects – and allow them to redirect their efforts towards direct patient care and research (Royal College of Radiologists, 2018). In this way, their time at work could be spent in more rewarding tasks.

Improved workflows and prioritisation of work due to the greater use of AI may also address the increase in demand for cross-sectional imaging (CT and MRI) in medical diagnoses. The use of AI may also help to alleviate the current shortage of trained radiologists (Frey and Osborne, 2017).

² Computer vision AI allows intelligent machines to be able to detect, analyse, and generate images by coding such images with numerical or symbolic information (Craig et al., 2017; Idrees et al., 2018).

Studies show that medical professionals expect the advancement of AI into areas such as diagnosis and prognosis will lead to an emphasis on the communicative, emotional and decision-making aspects of their work. General Practitioners, for example, believe there are important human skills in their work which machines are unlikely to replace, including the ability to communicate and empathise, to collect accurate and relevant data from patients, and to make judgements about treatments which take into account patient values and preferences (Blease et al., 2019). In addition, patients tend to respond better to humans than to machines (Nadarzynski et al., 2019).

AI is also being applied to a variety of medical contexts including pharmaceutical research (Varnek and Baskin, 2012), patient monitoring, diagnostics, prognostics (Blease et al., 2019), surgery (Zahedi et al., 2019) and, as has been shown above, radiology (Richardson et al., 2020). As a result, medical students increasingly want training in AI as part of their degree, though currently a minority actually receive it (Sit et al., 2020). This suggests challenges for training provision in the medical sector, as the use of AI is extended.

To illustrate further the effects of digital technologies on the nature of work, it is useful to draw on the research of Fossen and Sorgner (2019). They decompose the impact of digital technologies into two effects: i) job destruction – where digital technologies substitute for human labour; ii) transformation – where digital technologies are complementary to human labour. They argue that jobs can be subject to both of these effects to differing levels and their findings suggest that most occupations face *either* a high or a low risk of the destructive effects of digital technologies and some level of transformation. They categorise occupations into four categories along the above two axes:

- **Rising star occupations** (37 percent)³ – digitalisation has a highly transformative effect but low levels of job destruction because these occupations require above-average levels of almost all tasks that currently constitute automation bottlenecks, namely social perceptiveness, assisting and caring for others, persuasion, and originality. Workers in these occupations are likely to work with new AI technologies under transformed conditions of work.
- **Collapsing occupations** (38 percent) – these are the occupations discussed in the earlier section which face a high risk of digital job destruction because tasks within them require routine and manual skills and the level of bottleneck tasks is below average, so there is little barrier to automation.
- **Machine terrain occupations** (11 percent) – these occupations face both a high level of digital job destruction alongside above-average levels of non-routine tasks where AI has recently made advances and leaves few tasks for human labour. These occupations are likely to face radical transformation.
- **Human terrain occupations** (12 percent) – these occupations have a low exposure to digital job destruction technologies and above average levels of bottleneck tasks such as caring for others and working in a cramped space, so tend to be unaffected by digital technologies (except through effects on demand and labour supply).

³ Figures based on total employment in the US.

Table 3: The effect of AI on occupations

Transformative Effects	<p>High</p> <p><u>Rising Star</u> registered nurses general and operations managers first line supervisors of office and admin support workers airline pilots, co-pilots and flight engineers physicists surgeons air traffic controllers dentists</p>	<p><u>Machine Terrain</u> heavy and tractor-trailer truckdrivers executive secretaries and admin assistants accountants and auditors</p>	
	<p><u>Human terrain</u> customer service representatives janitors and cleaners stock clerks and order fillers teacher assistants funeral attendants locker room, coatroom and dressing room assistants</p>	<p><u>Collapsing</u> retail sale persons cashiers; office clerks labourers and freight, stock and material movers secretaries and admin staff bookkeeping, accounting and auditing clerks wholesale and manufacturing sales reps security guards manicurist and pedicurists non-restaurant food servers telemarketers models</p>	
Low	Destructive Effects		High

Source: Derived from Fossen & Sorgner, 2019

Table 3 indicates how an array of occupations could change with the development of digital technologies. For some 'rising star' occupations, the changes are profound, but these changes are linked to the maintenance and growth of mostly high-paid work (e.g. pilots and dentists). For 'human terrain' occupations, there is little change in what remains low-paid work (e.g. cleaners and stock clerks), other than possible wage compression through higher labour supply. Workers in 'collapsing' occupations (e.g. retail assistants and cashiers) face redundancy, while those in 'machine terrain' occupations (e.g. drivers and accountants) face continued employment but in workplaces with a greater use of technology.

What the research of Fossen and Sorgner confirms is the uneven effects of digital automation, with job destruction coexisting with work transformation. This research also highlights the potential strong impacts that digital technologies can have on the content of work within jobs – a theme that is pursued in the sections that follow.

5.3.2 Changing skill demand and the effect on job quality

The automation debate – where it addresses the transformation of work – focuses on how new technologies will change the skills composition of particular jobs and occupations (Autor et al., 2003; Autor and Dorn, 2013; Bughin et al., 2018; Colombo et al., 2019; Felten et al., 2019; Nedelkoska and Quintini, 2018). Most of the research and policy discussion is concerned with which skills are in demand; where there are perceived gaps or potential skills shortages; and the extent to which there are notable gaps in the skills of particular groups of workers. The changing skill composition of the labour force can

also have implications for the quality of work and the debates on technology-driven change and skill provide evidence that different groups of workers are likely to be affected in different ways.

There are essentially two views on the effects of digital technologies on skills (and by extension, the quality of work). One view is that digital technologies will replace tasks requiring manual, routine skills. By contrast, these technologies will leave tasks that require analytical thinking and innovation, emotional intelligence, as well as what are often termed 'soft' skills – creativity, originality and initiative, critical thinking, persuasion and negotiation. This view accords with discussions on AI and work which suggest that digital technologies are still poor at incorporating context, such as making decisions that incorporate customer or patient preferences, needs or values – which could be considered a core element of professional practice (Pasquale, 2019). The above view implies that digital technologies will free up people to undertake the creative, communicative and analytical tasks which make the most of their skills. The result, then, will be a trend towards up-skilling, with workers enjoying more high-skilled, high-quality jobs (e.g. Bughin et al., 2018; Manyika et al., 2017).

For example, some companies in the German auto industry are making increasing use of collaborative robots ('cobots') to improve ergonomics, lighten the physical burden of work, and augment the work of an ageing workforce (McGee, 2019). In general, cobots take over physically demanding assembly tasks, shifting the emphasis of workers towards supervisory and decision-making roles. Workers who have been surveyed about how AI will change their jobs expect it will lessen administrative or clerical burdens and repetitive tasks (e.g. Blease et al., 2019; Brougham and Haar, 2017). In this case, there is a perception that digital technologies have the potential to be skills-biased – i.e. they can increase demand for high-skilled labour – especially where high-skilled jobs are more likely to be comprised of the creative and analytical tasks which protect them from threats of automation.

As a further example, presented as Case Study 2 below, we discuss the effects of AI and blockchain on the accounting profession. Here the use of digital technologies has spurred the demand for more high-skilled workers. Yet, as with other areas where digital technologies could be used, the scale and extent of the adoption of new digital technologies (including blockchain) remains uncertain.

CASE STUDY 2: ACCOUNTING, AI AND BLOCKCHAIN

Accounting is often cited as a profession which stands to be automated, or at least radically transformed, by AI and blockchain. The use of Robotic Process Automation (RPA) has removed repetitive tasks within auditing such as internal control testing (Moffitt et al., 2018) and AI can use large datasets to analyse patterns in transactions to predict how tax evasion schemes are likely to develop over time and which schemes are more likely to evade detection (Hemberg et al., 2015). Big data analytics (BDA) and AI are combining to free workers from labour-intensive tasks, allowing them more time to apply their skills to critical evaluation-type tasks or key audit judgements (Kend and Nguyen, 2020). As a result, accounting firms are increasingly looking to hire graduates who have analytical and coding skills in addition to accounting and auditing knowledge (Cooper et al., 2019).

Blockchain, as discussed above, is a form of Distributed Ledger Technology (DLT) that acts as a database for storing or linking data (Beck et al., 2018). It is a form of synchronised and shared database stored across multiple nodes, maintained by a consensus algorithm (Walport, 2016) with applications principally in the areas of accountability, auditing, monitoring. Accounting firms are in the very early stages of blockchain adoption, often using it in conjunction with AI for tasks such as continuous audits, manual data extraction and audit preparation tasks (Schmitz and Leoni, 2019), with the hope that it can improve transparency and access to data for accountants (Yermack, 2017) and reduce human error and fraud (Faccia and Mosteanu, 2019).

Yet, despite proclamations of its far-reaching effects, particularly in the business press (see Tapscott and Tapscott, 2017), blockchain seems to have made somewhat limited inroads into the way that accounting is practiced. Accounting business leaders in the so-called 'Big-four' accountancy firms along with those in smaller accountancy firms were interviewed in an Australian study (Kend and Nguyen, 2020). They reported that they were still unsure or confused about the applications of blockchain technologies in accounting, and unconvinced that they are likely to change the work of accountants. This suggests the diffusion of blockchain is not widespread, even in an industry where it is considered to have the greatest potential for application and potential disruption, which means that how it will be applied to accountancy and auditing and how it will affect those working in the profession remains highly speculative.

The second view of the effects of digital technologies on skills is less optimistic. It suggests that, alongside providing more high-skilled work, these technologies will also coincide with the growth of more low-skilled work, in which the opportunities for progress into high-skilled work is limited. There is an emphasis in the automation literature and policy discussions on the need for up-skilling and reskilling, but not all technology-driven job creation is expected to be high-skilled. The growth of low paid, low-skilled work, particularly of 'in-person services' jobs, is set to continue (Autor and Dorn, 2013). These are jobs that require low levels of education, but which are less susceptible to automation, such as caring and cleaning work, food preparation and services (e.g. in restaurants), hairdressing and gardening (Deloit and Wallace-Stevens, 2017). These jobs fit with the 'human-terrain' occupations highlighted by Fossen and Sorgner.

The view taken here is that, at least some of the jobs of the future, will not offer workers high-quality work, but to the contrary, will continue to offer them menial tasks that carry low pay as well as low recognition. In this case, there is not a welcoming of the process of digital automation, but a regret that this process is not helping to up-skill workers and remove low-skilled, low paid work. The below discussion will use the example of the rise of platform work – a development facilitated by digital technologies – to further illustrate the potential growth of low-quality work.

5.3.3 Deskilling and skill depreciation

Where work is reorganised and jobs redesigned as a result of new digital technologies, it has the potential to result in deskilling or skill depreciation. While this effect is rarely discussed in the automation literature, sociologists of work have long recognised that technological change can result in the standardisation and simplification of work tasks and the elimination of worker creativity and initiative in their jobs (Gallie, 2012). Deskilling occurs where jobs are redesigned to accommodate new technology and generally requires the fragmentation and standardisation of complex work into simple tasks that can be undertaken by a combination of machinery and unskilled or less-skilled labour. This often results in an intensification of work and increased managerial control over labour. The micro-tasks found on crowdsourcing platforms provide an extreme example of how work processes can be restructured to deskill work (Bergvall-Kåreborn and Howcroft, 2014). Lehdonvirta (2016: 58) describes how conventional work has been converted into outsourced microwork through codification: 'breaking tasks into small parts and formalising them, making interdependencies so simple as to no longer require workers to have strong ties to each other, to the employer, or to the end-client'. These online work interfaces have been designed in such a way that labour must behave like computer software: available at any time and any place and able to scale up rapidly; for the humans undertaking these tasks, work becomes commodified and robot-like.

The displacement of middle-skill workers into lower skilled jobs could be considered a form of deskilling at an aggregate level, but deskilling can also occur *within* the digitally enabled transformation of a particular labour process. For example, high-skilled jobs with AI-complementarity could be reorganised in such a way that humans are inserted into work processes not to design,

interpret or develop creative solutions based on the product of AI computations, but simply to act upon decisions or predictions manufactured by AI, or choose between machine-derived solutions. For example, case workers in the civil service may be reduced from assessing cases, to communicating the outcomes of AI-driven assessments to service users, or call centre workers reduced to undertaking the scripted, deskilled work of communicating automated decisions (see Bader and Kaiser, 2019).

In Case Study 3 below, we address the effects of AI on police work. In particular, we show how AI is speeding up the collection and preparation of some data tasks undertaken by the police, but at the cost of the reduction in the skill content of police work. Predictive AI technology, in this example, can be seen as a specific threat to professional knowledge and judgement.

CASE STUDY 3: AI AND PREDICTIVE POLICING

In policing, AI is already being used in license plate recognition, social media threat analysis, predictive policing software and facial recognition. Laborious repetitive tasks such as recording suspicious movements, 'searching through observational records for known offenders' or 'producing factual reports and preparing evidence for court' are now in many police departments being done by virtual machines using AI (Bowling and Iyer, 2019). This is shifting the necessary skill sets of front-line police and security officers toward more 'knowledge work' requiring data management, computer operation and analytical skills. Predictive policing – anticipating future criminality based on past and current behaviour (Ferguson, 2017) – has been introduced in Germany (Egbert, 2018), Spain (Camacho-Collados and Liberatore, 2015), the UK (Bowling and Iyer, 2019), and the Netherlands (Waardenburg et al., 2018).

Legal experts have suggested that the greater use of AI – particularly where it is driven by cost-cutting – could deskill police work (Joh, 2019). While AI performs some policing tasks better than humans, such as rapid scanning and ID-ing of license plates, the use of predictive algorithms to identify high crime areas or suspicious behaviour amounts to the transfer of key professional policing skills involving problem solving from workers to AI and, in doing so, removes police discretion. Other technological change, such as the introduction of body-worn video (BWV) over the past two decades, has created a video-data pipeline for AI-driven policing technologies to be introduced in many countries. The use of BWV has undermined certain aspects of police work, particularly the craft skills of close observation, note-taking, investigative analysis, report-writing and preparation of evidence for the courts. In effect, BWV has automated significant aspects of policing and surveillance (Bowling and Iyer, 2019). The combination of BWV with predictive AI, in general, can be seen as regressive, to the extent it has resulted in lower discretion, variety of work and skill in policing.

To summarise, digital technologies bring with them the real possibility of upgrading work to remove the repetitive, mundane and burdensome aspects of jobs so that people can focus on more creative, analytical and communicative aspects of work. Yet, they also bring the threat of deskilling. As the above discussion of policing suggests, workers may undergo losses in valuable skills, as digital technologies take on more of their tasks. What matters here is how workers can shape technology in ways that protect their skills. Other dimensions of work where digital technologies can be expected to have an impact are discussed below, beginning with work time.

5.3.4 Working time

Technological change was accompanied by a gradual reduction in average working time over the greater part of the twentieth century; however, this trajectory has stalled over the period since the 1970s (De Spiegelaere and Piasna, 2017). While both labour and multifactor productivity have increased since the late 1970s in OECD countries, average working hours have only fallen slightly

(OECD, 2020). Further, these headline figures of declining average hours of work mask a situation where an increasing number of mostly high-skilled workers in Europe are working very long hours; 50 hours per week or more (Burger, 2018). They also miss the growing problem of underemployment among younger workers, particularly in the service sector, as a result of the growth in 'non-standard employment' (Benanav, 2019).

The recent mass adoption of mobile devices has, for many workers, enabled a 'constant connectivity' with work, including outside of standard hours of work (Wajcman and Rose, 2011). Mobile technologies have been shown in some cases to improve worker well-being by increasing work/life balance, flexibility and effective communication (ter Hoeven and van Zoonen, 2015). Yet, such technologies also create the possibility for a lengthening of work time, via the creation of an 'always on' work culture (Gold and Mustafa, 2013). They also present the possibility for the extension of surveillance and mobile remote management – this has become a particular problem for low-skilled service workers (Lehdonvirta, 2018; Moore and Hayes, 2017; Moore and Newsome, 2018; Wood et al., 2018). Among professionals, the increase in connectivity and the use of mobile devices has led to an 'autonomy paradox', with the blurring of the divide between work and non-work life and the increase of work-related stress (Mazmanian et al., 2013). Different groups of workers have very differing capacities to negotiate this connectivity, with male professionals overall benefiting more than other groups (Wajcman, 2015).

The use of mobile devices has also impacted on the scheduling of work. For some workers, work has become more regimented, with time allocated for work more strictly defined – time for travel and breaks, for example, can be excluded in the calculation of work time and hence wages, leading to greater work intensity and lower overall pay (Bell and Tuckman, 2002; Rubery et al., 2015). The use of these devices has made work more unpredictable for many service workers (Schneider and Harknett, 2019) and for others, especially those in piecework or gig-work platforms, imposed a time-discipline, with customers and clients dictating work-time despite workers operating as independent contractors (Gold and Mustafa, 2013; Lehdonvirta, 2018). Freelancers and service workers have increasingly faced working irregular hours in response to employer or client demands, often creating work/life conflicts and making it difficult to switch off from work (Barber and Jenkins, 2014; Butts et al., 2015; Gold and Mustafa, 2013)

Overall, while offering some benefits in terms of flexibility over managing work, digital technologies pose a challenge to the time that workers devote to work. Indeed, at worse, they can be seen to facilitate a lengthening of time spent at work, with negative effects on the quality of work and life.

5.3.5 Surveillance

Digital automation has the potential to create an unprecedented extension of worker surveillance, gathering and utilising greater volumes of employee data to measure and evaluate the effects of workforce practices and behaviours on individual performance (Moore et al, 2018). There has been an exponential rise in the use of smart phones and tracking technologies, including Fitbits and other wearable trackers, digital personal assistants (e.g. Siri, Alexa), and social media network analytics at work. The saturation of working life with such technologies has subjected some workers to constant extraction and processing of data for analytic or AI training purposes with minimal options to opt out (Crain, 2018; Sadowski, 2019).

Digital technologies have extended employer surveillance of employees' actions, communication behaviours and even inner states. Sensortechnology, such as RFID and GPS, allow employers to track workers' physical location continuously, while an increasing variety of wearable technologies can monitor factors such as employee heart rate and sleep, and AI-powered 'sentiment analysis' of text, voice or facial expressions is used in some workplaces to identify worker fatigue or mood (Moore et al,

2018). Such data collection has been justified on the basis that it can improve productivity, optimise systems, and more accurately target consumers or management efforts.

Two of the main issues raised in relation to these extensions of employee monitoring is that they lead to excessive monitoring and, in turn, higher levels of stress and anxiety. The use of AI technology has also raised concerns as it is advancing faster than public understanding and is increasingly used to control social behaviour (Karen and Lodge, 2019).

Employee data which is collected through surveillance are now being used in data-driven HR applications (Tambe et al., 2019) and have raised issues about profiling and discrimination. Predictive AI systems have the capacity to infer personal information including emotional states, habits and politics from a small number of data points (Moore et al., 2018; Zuboff, 2019). These systems have frequently been found to perpetuate existing inequalities, principally through replicating past biases and drawing on partial or incomplete data (Benjamin, 2019; Eubanks, 2018; Noble, 2018). For example, facial recognition AI has attracted controversy for two interrelated reasons; firstly, many systems are less effective at accurately identifying people of colour, because they were designed by white men (Buolamwini and Gebru, 2018) and developed to have greater sensitivity to whiter faces (Benjamin, 2019); and second, because they have been used to disproportionately monitor and police black communities and people of colour (Whittaker et al., 2018).

Additionally, there are issues of employee privacy and the legitimate boundaries of the employment relationship, where the collection and manipulation of employee data is seen to blur these boundaries. The weakness of organised labour has made it more difficult and less likely that workers can limit employer surveillance and new technologies and methods challenge the ability of the law to protect worker privacy in the US (Ajunwa et al., 2017) and Europe (Aloisi and Grammano, 2019). For workers and their representatives, the collection of worker data for use in AI-driven HR decision-making has presented urgent issues, including that employees be made aware of what data is being collected and how it is being used and whether workers, or the collective parties to the employment relationship, can negotiate the collection and use of data and ownership issues around the data itself.

Again we are faced with the potential for digital technologies to be used with negative effects on worker well-being. In this case, the particular concern is the negative effect on the autonomy and freedom of workers. Here this concern adds to other worries regarding the effects of the same technologies on skills and the length of work time.

5.3.6 Platform work

Technology may change the content of work, but in some cases its greatest effect is on labour relations, particularly where it is used to reframe the employment relationship, which may or may not affect the content of work. One such area of AI-enabled work that has attracted much recent attention is *platform work* – by which is meant, paid work mediated via an online platform or app. Companies offering platform work provide a wide range of services (discussed below) but share a common pattern of what has been termed a 'triangular' work relations, between platform, worker and customer (Bergvall-Kåreborn and Howcroft, 2014; Joyce, 2020). Algorithms embedded in the platform or app link worker and customer, mediate their relationship, facilitate payment, and sometimes monitor and direct the conduct of work, including its price. Commonly, a platform also includes a facility for customers to give a rating to the worker carrying out the task(s), and platforms use these ratings as part of monitoring and control procedures. Platform companies seek to profit from these arrangements (in reality, many operate at a loss) by taking a commission on each transaction, usually between 10–30 percent of its value.

Research has identified two main types of platform work; online and offline (Forde et al., 2017). Online platform work is carried out entirely online and has two main variants; simple and repetitive tasks, such

as labelling photographs, cleaning datasets, commonly termed *clickwork* or *microtasking*, where workers earn a small amount of money on completion of each task – sometimes as little as two cents (USD) – meaning that workers must complete very many tasks to earn a worthwhile income (Berg, 2016; Berg et al., 2018). Alternatively, online platform work may involve more complex tasks, such as graphic design, translation work, or other creative or technical work (Wood et al., 2018, 2019), organised on a project-by-project basis and somewhat akin to traditional freelancing but with online platforms taking the role of traditional freelance agents (Huws, 2017). Offline platform work, by contrast, requires the presence of the worker at the time and place where the service is required: the well-known example is Uber but offline platform work also incorporates household cleaning services, food and grocery delivery, domestic chores, home maintenance, skilled trades, laundry services, and even dog-walking (Forde et al., 2017).

Platforms have direct impacts on the way work is organised, and on the pay and conditions of workers thus engaged. As a result of the experience of many workers, platform work has become associated with low pay, poor conditions, and precarious work. Most platform workers are not legally classified as employees, but as self-employed or independent contractors. As a result of this classification, platform workers often miss out on a range of employment and social protections (Forde et al., 2017). Pay for platform work is typically based on piecework systems rather than hourly or salary payment and is generally much lower than for similar work carried out in conventional employment, often below legal minimum wage levels (Berg, 2016). In the case of online platform work, many platforms have effectively created genuinely global labour markets, with workers in Europe and North America competing for work with workers in low wage economies. Thus, one of the paradoxes of online platform work is that, in developing economies, online platform work often represents a significant increase above average hourly earnings, while in the global North, this type of work is often at the lowest end of the earnings range (Berg et al., 2018; CIPD, 2017; Wood et al., 2018).

In addition, many platform workers argue that the algorithms mediating their work and pay are non-transparent, and lack any means of recourse in the event of decisions that are felt to be unfair; for instance, in cases of non-payment for work done, unexpectedly low ratings, or difficulties accessing higher-paid tasks. Some workers also face being locked out from the platform altogether, meaning that their right to recourse is denied. Instances of lock-out are referred to as 'deactivation' and entail a form of dismissal. Deactivation is often linked to customer ratings, with platforms usually requiring an average score of more than four-out-of-five to access further work. Reasons for reduced scores are often obscure or unfair, and there are many examples of platform workers experiencing abusive, discriminatory or even criminal behaviour from platform service-users, but feeling unable to contest or escape such situations for fear of receiving a low score or deactivation (Calo and Rosenblat, 2017; Huws et al. 2017; Ravenelle, 2017; Rosenblat et al., 2017).

Given this range of problems, it is unsurprising that many platform workers have raised grievances and protests, through legal challenges, online campaigns, public demonstrations, and even militant trade union actions (Cant, 2019; Woodcock and Graham, 2019). As a result, regulatory authorities in many places are currently engaged in policy reviews and efforts to re-regulate this area of paid work (Neufeind et al., 2018); as seen, for instance, in California's statutory re-definition of employment status (Conger and Scheiber, 2019), and rulings in European courts over the employment status of Uber drivers (for instance, Khan and Ram, 2017; Butler, 2018). In response, many platforms continue to claim that the 'flexibility' of the work they offer is an improvement on traditional forms of employment. Many workers say they value this aspect of platform work; however, in reality this flexibility is often severely constrained by other aspects, such as low pay and lack of available work, which leads to many unpaid hours looking for work, and work patterns that entail unsociable hours (Berg, 2016; Forde et al., 2017; Schor and Attwood-Charles, 2017; Wood et al., 2018).

In relation to our discussion of the spread of digital automation technologies, it should be noted that, apart from the technology of platforms and apps, many of the distinctive features of platform work are

not technological at all. These essential but non-technological aspects of platform work include the 'triangular' sub-contracting arrangements and piecework payment system mentioned previously, as well as practices such as workers providing their own work equipment, and work being carried out on an as-needed basis. Not only are these features not technological, they are also not new, dating instead from the earliest days of industrial capitalism (Stanford, 2017).

This mix of new, technologically-enabled practices, together with older forms of work organisation, gives platform work some characteristic features. Platform work is often likened to a form of 'digital Taylorism' or even 'virtual Taylorism' (Valenduc and Vendramin, 2017) or 'computer-assisted Taylorism' (Laviolette, 2016). However, this characterisation oversimplifies a more complex reality. Although a case can be made that clickwork and micro-tasking represent a form of Taylorism – comprising fragmented tasks outsourced to an online 'crowd' of low-skilled workers, for completion at low wages via piecework payment – other forms of platform work do not fit this pattern. Thus, online creative and freelancing work via platforms such as Upwork are quite different, with workers retaining 'high levels of autonomy, task variety and complexity, as well as potential spatial and temporal flexibility' (Wood et al., 2019: 15).

Similar caution is needed regarding offline platform work, such as taxi-driving, food delivery, domestic cleaning, or dog-walking. In these examples, work that was previously done independently and often organised entirely informally by word-of-mouth or local advertising, has been brought under the partial control of a large company running an online platform. Far from being outsourced, these tasks are more formalised, and carried out more under the direction of a large, centralised company. Thus, platform work entails a number of simultaneous but differentiated processes: some types of work are being outsourced and made more insecure and precarious; other types of work are becoming more formalised.

The important point to grasp here concerns the non-determining role of technology. In platform work, essentially similar algorithmic applications are embedded in quite different forms of work and work organisation. In relation to employment, many of the disruptive effects of platform work are not due to technology but to other aspects of the business model; specifically, what has been termed 'legal and regulatory arbitrage' (Kaminska, 2016), including the circumventing of employment and other regulations. For instance, Uber and other taxi-apps have sought to avoid regulation as transport companies – and the additional costs involved – by defining themselves as tech firms (Khan and Ram, 2017). The widespread practice of (mis)classifying a workforce as self-employed, rather than as employees, results in considerable payroll savings for the companies concerned. In the UK, social insurance contributions and holiday pay constitute some 25 percent of the wages bill for a company with a workforce of employees. But these payments are not required for self-employed workers. In this sense, while new technology facilitates platform work, it does not determine its overall form, and neither is it the main driver of its growth (Forde et al., 2017).

Official statistics have struggled to capture the number of workers involved in platform work, but although numbers still appear to be rising (BLS, 2018; Collins et al., 2019; Farrell et al., 2018), growth is slow as a proportion of the total working population. Furthermore, most participants in platform work use it as a source of supplementary income, in addition to income from elsewhere. Often, the other source of income is a full-time job; although that job may well be insecure and low-paid (Joyce et al., 2019). There is also variation in levels of platform work between and across countries and evidence from qualitative research suggests that key drivers of platform include broader economic and institutional factors, including tax policies, wider labour market conditions, and even the prior extent of the grey economy (Forde et al., 2017). Although platform work has established a presence in the labour market and continues to grow, it is not in the process of transforming employment, contrary to numerous predictions that it would. More than ten years after the founding of Uber (in 2009), there is still little evidence that workers actually face 'the end of the job' (Kessler, 2018) as a result of the

platformisation of work. In other words, the proven technological potential of platforms has not led to a rapid and general transformation of work and employment.

In summary, then, platform work provides several important lessons for understanding the impact of new digital technologies on employment. Most significantly, it is clear that digital technology has been an enabler of platform work but not its main determinant or driver. This is demonstrated by the fact that, although platform technologies are essentially similar, they are embedded in a very wide range of different types of work and work organisation. Undoubtedly, digital technology created the possibility of platform-based paid work, but the main drivers of its growth were a combination of the huge influx of venture capital that continues to fund the expansion of platform companies that have not, so far, made any profits, together with business strategies based on the avoidance of employment and other regulatory requirements, and the cost-savings that follow. By the same token, the limits to the growth of platform companies have not, for the most part, been technological. Rather, platforms have more often run into difficulties retaining workers – at least, as post-recession labour markets have tightened – and have increasingly faced renewed regulatory pressures and growing worker organisation and contestation. Thus, to date, it is far from clear that the platform companies which have become household names have a business model that is viable in the long-term. It is also clear, though, that these companies have pioneered a new way of organising and managing paid work, based around a novel digital technology, which may turn out to be their most lasting legacy. However, unless or until this way of working is brought within the remit of wider employment regulation, it will continue to be uncondusive to workers enjoying a higher standard of living and strong employment protection – to the contrary, it represents a race-to-the-bottom as far as wages and labour standards are concerned.

5.3.7 Summary

The digital automation debate has been framed largely in terms of how new technology will affect the volume of jobs, with varying estimates of potential job losses. What is clear, however, is that digital automation will have wider effects beyond the level of employment. Digital automation is also likely to impact on wages and the quality of jobs. In the latter case, there is scope for many jobs to be transformed in regressive ways, as digital technologies are used to reduce the autonomy of workers and add to work time. AI-enabled workplaces in some organisations (e.g. Amazon), for example, have been linked to harsh and health-limiting work conditions. The rise of platform work offers another example of where digital technologies have, in some cases at least, undermined job quality. Workers, in short, may not be replaced by robots, but may face having to work as if they are robots. Based on the differential effects of digital automation, the following sections explore policy options that could help to ensure the above highlighted negative impacts are minimised.

6. Policy context

This section sets out the policy context for addressing the potential impacts of digital automation on employment. In particular, it summarises the key policy proposals identified in the literature and existing EU policies of note.

6.1 EU policy on digitalisation, work and skills

Policy makers at national and supranational levels have been grappling with how to respond to the potential challenges posed by digital automation for work and skills. Developing such policy is far from easy for the simple reason that the future is uncertain, while the evidence base often lags hyperbolic prediction. Nonetheless, a review of the literature suggests some common points of departure for how to understand the context within which policy should be formulated, along with a relatively common set of proposals for the type of policies that are needed to address the challenges of digital automation for the future of work.

The general academic consensus, as presented above, is that apocalyptic predictions of mass job loss or the end of work are largely unfounded, although the likely impact of digital automation on the restructuring of work is likely to be profound and multifaceted. In other words, the challenges for policy makers around digital automation is not just about the automation of jobs, but how technology 'will also define the kinds of new jobs that we will end up with in the future, and how jobs that we currently have may change' (Neufeind et al., 2018: 542; Bernhardt, 2017). In understanding these challenges, debates on digital automation tend to be heavily influenced by concepts such as skill-biased technological change, routine-biased technological change and capital-biased technological change (see Dachs, 2018; Neufeind et al., 2018), with each giving rise to potentially different policy prescriptions.

Against this backdrop, Goos et al. (2019), in an EU Joint Research Council Technical Report, set out a 'general framework' for how to understand the potential effect of technology on the labour market. Influenced by the work of Autor et al. (2003), Acemoglu and Restrepo (2017, 2018b) and Goos et al. (2014), the authors of the report present a framework that considers the possibility that digital automation can have *displacement* and *compensating* effects, an approach that is commensurate with the focus of this report on the destructive and transformative effects of technology. Displacement effects occur where firms simply use technology to substitute labour, thereby reducing labour demand. In contrast, adjustment mechanisms can run in the other direction and potentially lead to compensatory increases in labour demand, through *productivity effects*, *capital accumulation effects* and *reinstatement effects* (where technology leads to the creation of new tasks). These compensatory effects can mean that net displacement is relatively small, but set within a wider context of significant restructuring, which could have major implications for the polarisation of workforce skills. For Goos et al. (2019), this general framework suggests that policy interventions are needed across a broad range of areas, including: education and training policies; labour market policies; income support and tax policies; and technology and regulation policies. Similar policy domains are identified in much of the literature.

Drawing from the above discussion, the wider literature covered in this report and ongoing deliberations within EU policy circles, the key policy options typically elaborated include:

Education and training policies: There is a general consensus that new policies on education and training will be needed to address the impact of digital automation. A key argument is that a premium accrues to those with higher skills, who are likely to receive higher wages and have greater security from the threat of automation. Workers with lower and medium level skills, in contrast, are seen as more susceptible to the threat of automation. Investing more in the supply of skills, to a generally

higher level across the labour market, is thus seen as a necessary, though not in itself sufficient, response to digital automation. The fact that employers' demands for skills are likely to change, along with the suggestion that workers will need to change their skills and jobs during their working lives, means that investments in education and training will need to be structured over the life course and working lives. Thus, commentators such as Neufeind et al. (2018) stress the importance of early childhood education, tertiary education, initial vocational education and training, and continuous lifelong learning to ensure the employability of workers in a world of fast-moving technology.

A key point of consideration relates to the type of skills likely to be needed in the future, namely digital skills. According to the OECD (2016), the rise of digital automation is raising the demand for four broad areas of skills (taken from Neufeind et al., 2018): generic ICT skills; specific ICT skills; complementary ICT skills; and general cognitive skills. The need to respond to increased demand for digital skills has been recognised across a number of EU policy domains. Notably, the *Council Recommendation on Key Competences for Lifelong Learning* was updated in 2018 (from the 2006 declaration) to include a greater emphasis on digital skills. The European Commission's (2018a) *Digital Education Action Plan* notes that 90 percent of jobs require some level of digital skills, yet some 44 percent of EU citizens have low or no basic digital skills. In this context, the acquisition of digital skills is seen as an essential protective measure, for both skilled and unskilled workers, against the threat of digital automation (Goos et al., 2019).

In a practical sense, many of the policy options proposed by commentators connect with well-established or currently debated EU policies on skills:

- The European 'Pillar of Social Rights' states that 'everyone has the right to quality and inclusive education, training and lifelong learning in order to maintain and acquire skills that enable them to participate fully in society and manage successful transition in the labour market'. Arguments for policies aimed at enhancing digital skills fit with this right. In funding terms, EU Social Funds offer a means to support training in digital skills.
- The New Skills Agenda for Europe was adopted by the European Commission on 10 June 2016. It launched ten actions to enhance training and skills provision in the EU. The ten actions include, amongst others, the 'Digital Skills and Jobs Coalition' (European Commission, 2020a), and the 'Blueprint for Sectoral Cooperation on Skills' (European Commission, 2017), both of which offer potential responses to the challenges of digital automation. A further review in 2006, 'Recommendations on Key Competences for Lifelong Learning', included a greater focus on digital skills. As part of the New Skills Agenda all EU Member States were directed to establish national digital skills strategies by mid-2017, with the implementation of national strategies supported by national coalitions. Most recently, the European Commission adopted a new communication on adopting a new vision of a 'European Skills Agenda for sustainable competitiveness, social fairness and resilience' (European Commission, 2020b), as a response to Covid-19. This includes a renewed commitment to address gaps in digital skills. A key target is that, by 2025, 70 percent of adults aged 16-74 will have at least basic digital skills, a significant increase from a 2019 baseline of 56 percent.
- The stress on employability connects with a longstanding commitment of the EU to the concept of flexicurity, where it is recognised that the flexibility of labour markets is supported by active labour market measures to get people back into work. A key focus is on how displaced workers can be retrained. Though a contested concept, flexicurity is part of a broader policy move to ensure that workers remain employable in the labour market, including in the context where the technological and skill requirements of jobs are shifting.
- There is increasing interest in 'activity accounts', 'lifelong learning accounts' and educational leave as policy mechanisms to foster continuing education and training. These mechanisms

help to ease worker transitions, both from unemployment to work and between jobs. The recent communication on a European Skills Agenda commits the Commission to assessing the possibility of a European initiative on individual learning accounts and how such accounts may facilitate individuals to successfully navigate labour market transitions. Such accounts have previously been trialled in a number of EU Member States, such as the UK, and currently exist in France financed through a levy on employers.

- The Digital Skills and Jobs Coalition (European Commission, 2020a) brings together EU Member States, companies, social partners, non-profit organisations and education providers, in order to tackle the lack of digital skills in Europe. The Coalition was established as part of the EU Digital Single Market Strategy, and builds on the Grand Coalition for Digital Skills (2013-2016). Under the Coalition, organisations can sign up for membership, with a commitment to take a specific action around the development of digital skills. The digital skills needs of four broad groups are given attention: digital skills for all; digital skills for the labour force; digital skills for ICT professionals; and digital skills in education. The Coalition has set a number of goals (to be achieved by 2020), including: training one million young unemployed people for vacant digital jobs; internships/ traineeships, apprenticeships and short-term training programmes; the up-skilling and retraining of the workforce; and the modernisation of education and training systems, so that digital capacities are embedded in curricula.
- The Blueprint for Sectoral Cooperation on Skills is one of the key initiatives of the New Skills Agenda for Europe, and can be seen as responding to commitments enshrined in the EU Social Model. Under the Blueprint, stakeholders work together in sector-specific partnerships (also called sectoral skills alliances) to develop and implement strategies to address skills gaps in particular sectors. Partnerships can bring together stakeholders from business, unions, research institutions, education and training institutions, and public authorities. The first blueprint partnerships started in January 2018 and covered some specific sectors: automotive; maritime; space; textile, clothing, leather and footwear; and tourism. Four further partnerships started in January 2019, with six more scheduled at the end of 2019/ start of 2020. From November 2020, the Blueprint will combine with a new Pact for Skills, to be launched as a new cooperative action in response to the Covid-19 pandemic. The Pact for Skills will give initial priority to the health, construction, automotive and transport, and tourism sectors.

Most EU Member States have put increased emphasis on raising levels of digital skills, typically as part of wider programmes designed to increase the uptake by industry of digital technologies. National initiatives for the digitalisation of industry are covered at the EU level by the Digitising European Industry Strategy, launched in April 2016, which aims to reinforce EU competitiveness through industry level investment in digital technologies. An evaluation by the European Commission (2018e) suggests that two-thirds of EU Member States have made the digitalisation of industry a national priority, with a focus on raising competitiveness and improving workforce digital skills. Specific national level initiatives include *Smart Industry* (Netherlands); *Produktion 2030* (Sweden); *Industrie 4.0* (Germany); and *Catapult* (UK). However, while all national initiatives include a focus on skills, only 16 percent give priority to skills ahead of infrastructure and technology (European Commission, 2018e), with notable initiatives reported for France, Germany and Portugal. For example, the French 'Grand Plan d'Investissement' commits to invest €15 billion across 2018-2020 to help support those with lower level qualifications gain routes in employment.

Labour market policies and social protection: Recommendations on labour market policies typically focus on adjustment costs and responses and the potential role of employment agencies and labour market intermediation, to help job seekers find jobs. These policies encompass activation measures and jobs matching. Activation measures are well-developed in most EU Member States, and are particularly advanced in Nordic countries, with advanced policies to help assist displaced workers and the unemployed back into work, such as labour market activation measures in Denmark and Job

Security Councils in Sweden. The role of Public Employment Services in facilitating activation measures is under scrutiny in the context of the challenges of digital automation, with commentators stressing the need for more embedded collaboration between Public Employment Services, companies, trade unions and the third sector.

The European Globalisation Adjustment Fund (EGF) is a notable instrument at the EU level designed to rapidly assist dismissed workers back into the work. While the EGF is focused primarily on large scale incidents of redundancy or company closure, the threshold has recently reduced to 250 workers, with an increasing focus on the 'dissemination of skills required for the digital age' (European Commission, 2018e: 16). There is also a proposal to update the provisions of the EGF so that it can assist workers that lose their jobs as a result of digital automation. For the European Economic and Social Committee (2018), this proposal is a 'step towards the establishment of a fully-fledged European Transition Fund which would help manage the digital transformation in a responsible way'.

A second area of concern under labour market policies and social protection relates to non-standard work that may arise through new business models, such as the type of gig employment that is associated with on-demand platforms (see discussion above). Digital automation is seen to encourage business models that deny workers key social protections. Accordingly, there is discussion about extending social protections to those on gig-type contracts, including minimum wage regulations, minimum hours of work, social security measures, tax incentives (see below) and potentially union representation. This type of employment also raises much broader questions about the regulation and definitional status of what it means to be employed. Jobs created through online platforms are often defined as self-employed, although in a number of high profile cases (such as the Uber business model), this status is being questioned. There is an ongoing debate about a 'third category' of employment that sits between a standard employment relationship and self-employed status. This category already exists in a number of EU Member States, such as 'auto-entrepreneur' status in France, 'worker' status in the UK, and 'quasi-subordinate worker' in Italy, and its existence affords individuals in this kind of work some degree of employment protection. However, there is no consistent EU policy on employment status in the gig economy. Likewise, while the Directive 2019/1152 on Transparent and Predictable Working Conditions offers protections for workers in more precarious contractual arrangements, it does not address ambiguities in employment status. The status of and protections for platform workers thus remains a live policy issue, with the European Commission announcing, as part of the Covid-19 response, that they will put forward new proposals for those working via technology platforms in 2021.

Income support and tax policies: Income support policies can also be covered through welfare arrangements, tax credits and minimum income measures, together with social protection policies. There is ongoing debate about the unequal distribution of rents from processes of digital transformation and the unequal balance of taxation on capital and labour income, with a need to rebalance in favour of the latter. A frequently mentioned policy option is the expansion of earned income tax credits, a policy favoured by commentators such as Brynjolfsson and McAfee (2014). Another option is a basic income scheme, which has been trialled in a number of national and regional contexts. Academic support for such a scheme is mixed, however. Goos et al. (2019: 25), for example, argue that a basic income would erode work incentives particularly for low skilled workers (Goos et al., 2019: 25), though no evidence is presented to suggest this would be the case. The idea of a basic income has again risen in prominence in the context of the Covid-19 crisis and is seen by some as an important mechanism for addressing existing (and deepening) inequalities in society.

Technology regulation policies: Here the focus of policy is on the regulation of the nature and use of technology itself. There has been some debate, for example, on the taxation of robots, though such taxation has received little support, in part, because of the predicted negative effect of a 'robot tax' on investment and innovation levels. An alternative approach offered by Goos et al. (2019: 27) entails regulation of the 'design and implementation of digital technologies', so that 'investments in new technologies should focus on those technologies that minimise the direct threat of automation for

workers and that maximize the positive countervailing effects that increase labour demand'. This approach is supported by the ILO's Global Commission on the Future of Work (ILO, 2019).

New labour relations: The *High-Level Expert Group on the Impact of Digital Transformation on EU Labour Markets* recommended that existing structures of labour relations be adapted to fit contemporary labour market realities. Concrete actions proposed include: new employee assistance programmes to mitigate increased occupational health and safety risks, particularly those relating to mental health; the equal treatment of those on standard and non-standard work arrangements, particularly in terms of access to government services and wider social benefits; and the 'reinvigoration' of social dialogue. Again, this can be seen to connect to the EU's commitment to the social model; however, there is increasing interest not only in expanding the more traditional scope of collective bargaining, for example, through new technology agreements, but also in new forms of dialogue more suited to the environment of those working in the platform economy (such as online forums).

A new social contract: A new social contract is presented by the *High-Level expert Group on the Impact of Digital Transformation on EU Labour markets* as a mechanism for 'upgrading the social fabric of our labour markets'. Policy considerations include equal social protection no matter what the terms of employment (similar to the discussion above on social protections for non-standard workers); a 'digital single window' for those working on online platforms to make contributions and taxes; and a commitment to 'redistributing the value of digital ownership'. The broader idea of a new social contract also connects to the work of Kochan (2015) in the American context.

In support of the perceived need for policy responses to digital automation, in April 2018, EU Member States signed a Declaration of cooperation on AI (European Council, 2018). During the same month, the EU issued a Communication on AI for Europe (European Commission, 2018d) with three main objectives:

- Boosting the EU's technological and industrial capacity, through investments in research and innovation and better access to data;
- Preparing for socio-economic changes brought about by AI by encouraging the modernisation of education and training systems, nurturing talent, anticipating changes in the labour market, supporting labour market transitions and adaptation of social protection systems;
- Ensuring an appropriate ethical and legal framework.

These objectives set a broader policy framework for addressing the challenges posed by digital technologies in economy and society.

6.1.1 Summary

There has been extensive debate on the types of policies needed to address the impacts of digital automation on work and employment. For the most part, however, debate has not translated into concrete actions. High level commissions and reviews on the future of work have taken place in many advanced countries, such as the Taylor Review of Modern Working Practices in the UK, or Industry 4.0 in Germany, but this work has rarely led to the development of specific initiatives designed to address the impacts of digital automation. Far more common have been attempts to respond to the challenges of digital automation through existing policy instruments. This is particularly evident at the EU level.

At a basic level, EU policy is primarily focused around two key goals. First, a commitment to accelerating digital automation as a means to enhance EU competitiveness. Second, in recognition of the fact that

digital automation poses challenges for employment, both for transitions into work and those in work, an emphasis on raising the demand for and supply of skills. It is recognised that addressing the challenges of digital automation demands policy responses that are wider than the skills agenda. For example, the Council of the European Union encourages Member States to develop comprehensive measures that offer a 'life cycle' approach to addressing the challenges of the changing world of work. A lifecycle approach should include the development of integrated and inclusive policies covering issues such as work-life balance, diversity, health and safety, social protections, decent work, careers, skills and lifelong learning. EU policy provisions are also typically located within the Pillar of Social Rights and the working mechanism of the social model. This orientation is reflected in all policy. Nonetheless, in a practical sense, for all the debate on the need for a wider policy focus, EU initiatives designed to address the potential impacts of digital automation on work and employment seek to encompass established EU instruments and levers and remain largely centred on issues of skills development, education, training and lifelong learning.

A primary focus on skills, however, has been questioned by the European Economic and Social Committee (2018) in its report, *Artificial Intelligence: Anticipating its Impact on Jobs to Ensure Fair Transition*. As the EESC (2018: 25-26) notes, 'A focus on education, reskilling and training in the context of transformation that AI brings to jobs as presented by the European Commission is not enough. There needs to be a debate on taxation, the financing of public budgets and social protection that should also touch on the redistribution of the benefits of digitalisation'. Such concerns guide the policy options outlined in this report, which, while recognising the importance of education, reskilling and training, aim to pursue a more radical agenda for reform designed to enhance the quality of work, workplace representation and the distribution of the benefits of digital automation.

7. Policy options

The policy options outlined in this report link to existing policies and are guided by the European Commission's recommendation to develop a new social contract for the digital era (European Commission, 2019). The options seek to establish a **Digital Social Contract** around the development, management and use of digital technologies. Guiding the Digital Social Contract should be the establishment of a social protection floor at a European level, for all workers, regardless of their contractual status.

The policy options also complement the Digital Single Market Strategy for Europe (European Commission, 2018b, 2018c). They are designed to improve skills and training – for example, they support **industry and sectoral skills alliances and investment in digital skills for AI-enhanced environments**. But they also move beyond skills and training by seeking wider change including **a more democratic industrial strategy and reforms to the governance of work and the reduction of working time**.

The report does not propose options for specific occupations. Rather, it advances policy options that can be applied to all groups of workers. The general focus of the policy discussion fits with EU traditions of social dialogue and reflects the system-wide effects of digital automation. Overall, the policy options aim to anticipate and manage the impact of digital automation in a way that benefits all in society.

7.1 Aims

The main aims of the policy options are to:

1. Reskill and upskill present workforces facing job displacement or transformation through improving sector level intelligence about the way digital technologies are changing jobs and adapting skills provision to meet emerging needs;
2. Facilitate sustainable organisational strategies that adapt to the economic and social effects of digital automation in ways that benefit workers and ensure greater diversity, equality and accessibility to decent jobs for all generations of workers;
3. Update labour market policy and regulatory frameworks to create employer accountability on the employment impacts of AI investment decisions at a national level and to ensure meaningful social dialogue on technology-driven changes to work organisation and job design at the enterprise level;
4. Achieve reform in the governance of work and a reduction in work time that enables digital technologies to be used for the purposes of greater human freedom and well-being.

The key policy options that seek to meet the above aims are set out below. These policy options encompass different dimensions and entail change both at the workplace and the economy as a whole. Connections to existing policy instruments and the feasibility of the options are noted. The policy options are ordered from those that are relatively uncontroversial (around skills) to those that are potentially more radical and challenging to implement (around changes in the distribution of rewards). Despite the challenges, however, all the policy options can be regarded as important and in need of implementation.

7.2 Skills and training provision

Skills and training policies will need to account for the degree of exposure of different sectors and jobs to digital automation, as well as to whether the effects of digital technologies on different sectors are destructive and/or transformative. Policy interventions will involve identifying where jobs are 'at risk' of destruction in order to direct timely and targeted measures to workers in those jobs – here the discussion builds on the earlier framing in terms of 'collapsing' occupations and 'machine terrain' occupations. There also needs to be reskilling available for workers in jobs which are likely to be transformed by digital technologies; these jobs will include 'rising star' occupations and jobs that remain in 'machine terrain' occupations. Ensuring that technological adoption results in well-paid employment may also require creating protective measures for those 'human terrain' occupations which are unlikely to be changed by new technologies – here protections would include wage floors to combat the downward pressure on wages as displaced workers seek new forms of employment. The following policy options address these concerns by building better intelligence about the effect of digital technologies on jobs through sectoral cooperation and new forms of data collection, thus allowing for targeted interventions in the area of skills and training provision.

7.2.1 Option 1: Industry and sectoral skills alliances that focus on facilitating transitions for workers in 'at risk' jobs and reskilling for workers in transformed jobs

One of the biggest challenges for states and employers responding to structural change in the labour market and changes in occupations is the uncertainty and lack of empirical evidence about the effects of new technologies on work and employment. Given this uncertainty and lack of evidence, the report recommends drawing on the perspectives and experiences of stakeholders – including industry representatives, trade unions and education and training providers – to form new alliances that can contribute to a shared knowledge of the nature and likely implications of technological change for work and employment. The creation of these alliances, in turn, can be used to inform policy action.

The EU's Blueprint for Sectoral Cooperation on Skills [COM/2016/381] (European Commission, 2016) already provides essential strategic evidence about skill needs in industries and sectors where there is projected growth. The report proposes to extend the remit of the alliances forged under this Blueprint – specifically, it recommends that intelligence is gathered on the anticipated effects of digital technologies on the volume and skill content of jobs. Specifically, the alliances would create intelligence on:

- areas of job decline and jobs 'at-risk' of automation;
- the scale and dimensions of emerging skill needs;
- the scale, nature and pace, at sectoral, regional and occupational levels, of labour market transformation;
- the scope for new training and educational reforms.

By identifying the sectors, industries and occupations that are likely to experience the greatest change as a result of new technology and determining the timeframe within which this change is likely to take place, it will be possible to target policy interventions which limit maladjustment and provide the best outcomes for employment growth and skills utilisation. The new strategic alliances envisaged here would take a proactive approach to labour market intervention and the provision of education and

training, developing policies and programmes that can best manage the effects of job destruction and transformation.

7.2.2 Option 2: Digital skills for working in AI-enhanced environments

Based on the analysis presented earlier in the report, research has identified key knowledge, skills and competencies that businesses and workers will need to work with and alongside digital technologies. Work is already underway as part of the New Skills Agenda for Europe [COM/2016/381] to ensure Europeans have basic digital skills and to address existing digital skills gaps. Basic IT literacy will become an essential skill for all workers for their participation in work and society, but Europe also needs to address technical skills shortages and generalist skills required for high-skill roles in order to build the specific AI capacities within EU Member States. In light of this, the following options aim to augment skills for working in AI-enhanced working environments. Reforms here would relate to education, from secondary through to graduate level:

- Modernisation of education must ensure that teaching and training is weighted towards those complementary skills which are likely to be in high demand and unlikely to face the threat of automation, as identified in the research reviewed for this report. These skills encompass problem-solving capabilities, intuition, creativity, and persuasion. The details of modules and metrics for inserting the above skills into existing education provision should be designed in consultation between key stakeholders, namely education and training providers, industry representatives, and trade unions.
- Digital skills initiatives must include programmes for AI literacy, in particular, specialist training courses for managers and professionals in data analytics, as well as in legal and ethical issues pertaining to data. These could be developed and delivered through higher education institutions and Digital Innovation Hubs (European Commission 2020c).
- AI design, engineering and maintenance capability could be developed through investment in specialist centres for education and training of computer science, data science, machine learning engineering and robotics, fostering collaborations between universities and industry and including opportunities for industry work placements for advanced students and recent graduates.

The above reforms could be supplemented with provision for life-long learning and training, as laid out in the European Pillar of Social Rights, enabling people at different stages in the life-course to access education and to be in a position to engage productively in AI-enhanced environments.

7.2.3 Option 3: Revaluation of work and new protections for workers in hard to automate jobs

Many jobs will survive digital automation – indeed many new jobs may be created, as technology is adopted and used in the economy. Jobs that are likely to persist include those that fall into the category of 'human terrain' occupations, which are comprised of manual tasks requiring situational adaptability, visual and language recognition, and in-person interactions with a strong emotional labour component. These jobs include care jobs. They are often low paid as well as undervalued, despite being necessary for social reproduction.

The proposal here would be that 'human terrain' occupations – notably care work – be revalued. The emphasis on care work as valuable and essential should be part of a broader social dialogue about the value of work and would be an important part of the Digital Social Contract recommended in this report. The aim would be to revalue care work in ways that help to foster higher pay and improved conditions of work. Technology may play a part in lightening work for careworkers, but the goal should be to recognise the value of care work in itself and remunerate it more generously given its essential human elements. Here there is a recognition of the limits to digital automation and the need for a reappraisal of the roles and contributions of particular kinds of work and workers. The Covid-19 crisis has brought into focus the value of care workers (along with other 'key' workers) and proposal here would be ensure that these workers are properly recognised and rewarded for their efforts.

In addition, it is recommended that, where jobs persist, workers are adequately protected including from the depressive effects of wage reductions due to a potential oversupply of labour seeking low paid work. Here policies would include new legal protections for gig-workers. The recognition of occupants of gig work as 'workers' would be a first step. Such an approach would be in line with recent developments in California, where legal classifications have been revised to redefine many gig workers as employees, following a Supreme Court ruling in 2018 (California Supreme Court, 2018) and subsequent passage of new statute law in 2019 (Thomasson et al., 2019). Beyond this, the aim would be to ensure a levelling up of employment rights and protections so that workers in jobs that outlast digital automation are able to meet their needs through paid work.

7.3 Digital work-life balance

7.3.1 Option 4: Establish a European 'right to disconnect'

As highlighted in an earlier section, digital technologies threaten to lengthen the time people work, by creating an 'always-on' work culture. A particular concern is the use of email and smart phones that connect people to work, even during hours when they are not physically at work and being paid to do work. The risk here is a form of 'digital burnout', as technologies tie people to work and prevent them from switching off from work.

Research has shown that people who responded to work communications after 9pm had a worse quality of sleep and were less engaged in work the next day (Barber and Jenkins, 2014). Workers can also suffer from anxiety about work expectations even if they do not check emails during out-of-hours since the mere expectation of being in contact 24/7 is enough to increase strain for employees and their families (Butts et al., 2015).

Based on this evidence and the concerns outlined above, the report recommends an EU-wide 'right to disconnect'. The latter would ensure that all employees feel free to not engage in any work-related electronic communications, including email and messages, outside of normal work hours. Given developments in a number of EU Member States, such a policy would seem feasible and realistic. The Irish government is currently considering legislation that would improve work-life balance by allowing workers to not answer emails or messages outside of office hours. In France, the El Khomri Law introduced the 'right to disconnect' from August 2016. In Italy, a weaker version of the 'right to disconnect' was established through a Senate Act in 2017. More recently, Spain also included a 'right to disconnect' in the 2018 Data Protection and Digital Rights Act. The recommendation is that the EU introduce a law that guarantees similar rights. Article 24 of the Universal Declaration of Human Rights asserts the right to rest and leisure, placing explicit limitations on work time. The 'right to disconnect' recommended here would update this declaration for the digital age, enabling workers to reconnect with their families, friends, and communities, while obliging companies to respect the personal time of their workers during non-working hours.

7.3.2 Option 5: Lower the EU Working-Time Directive to 38-hours per week and remove the opt-out clause

Digital automation creates the opportunity to redistribute working time more evenly across the workforce, allowing the unemployed and underemployed to gain the work they need, while reducing the negative impact of overwork on those who work long hours of work. There is no automatic mechanism linking digital automation with shorter average work hours – to the contrary, as highlighted above, an outcome of some digital technologies may be an increase in the intensity and duration of work time. In this case, policy interventions are needed to ensure that digital technologies feed through to shorter work hours. The need for such interventions is magnified by the stark differences in average work hours that persist between EU Member States – this despite existing policies such as the EU Working-Time Directive (WTD).

Specifically, the report recommends two policies. Firstly, it is suggested that the EU WTD be lowered to a maximum of 38-hours per week. It is realised that, in the short-term, this move would cause disruption for some states and companies. In this sense, a phasing in (by negotiation) may be agreed by Member States. More radically, and potentially less feasibly, the reports suggest removal of the opt-out clause and the move to collective agreement on a cut in work time. Here the goal would be to funnel the benefits of technological progress into shorter working hours. Reform of the EU WTD is long overdue and the proposal here would be to update it for the digital age.

Secondly, in the longer-term, the report recommends a broader commitment to an average 30 hour working week by 2050 across the EU. This commitment represents the ideal of realising in society the basis for expanded free time, with technology adding to the ability of people to live better lives beyond work. It is recognised that this is a radical and ambitious proposal, but it can be noted that there is a large body of empirical evidence which supports the benefits of shorter working hours in terms of individual health and well-being as well as organisational performance (Stronge et al., 2019). This evidence strengthens the case for work time reduction at the EU level.

7.4 Governance policy

7.4.1 Option 6: Worker representation, company reward schemes and workplace governance

Part of the concern about digital automation is that technological changes are imposed on workers as opposed to these changes being decided upon through democratic institutions. Workers, it can be argued, have more to fear from digital automation where they are subordinate in the design and implementation of technology. Here fear relates both to potential job losses and to the use of technology in a manner that erodes the quality of work.

This leads to five policy options. Firstly, there is the option of strengthening the input of unions in the collective decision-making processes around technology. Unions offer a voice for workers and a way to ensure democratic accountability in the innovation process. Secondly, where union presence is limited, suitable provision can be made for direct worker involvement in the way that technology is organised and implemented. Two concrete options recently suggested would be that employees should have 50 percent of the seats on company boards and that the voting power of even the largest shareholders should be capped at 10 percent (Piketty, 2020). Such policies, if implemented at the EU level, could help to share the proceeds of technological progress while mitigating its costs inclusive of lower quality employment. Thirdly, there is the expansion of share ownership schemes that enable workers to gain a direct stake in the firms in which they work. Widening share ownership would help to create a direct mechanism to equalise the distribution of the rewards of digital automation. Here the

EU could consider tax incentives for technology-driven firms that extend share ownership schemes to workers.

Fourthly, there is the application of what the ILO calls a 'human-in-command' principle to the use of AI. This principle responds to the concern that AI reduces human decision-making and instead cedes power to algorithms in the recruitment, management and evaluation of workers. Adopting a 'human-in-command' principle would establish accountability and allow for organisations to counteract the automatic encoding of bias into algorithms that perpetuate inequality and discrimination (Eubanks, 2018). It would also open up space for greater democracy over the uses and application of AI.

Fifthly, there is the encouragement of worker ownership. The concentration of power in the hands of large corporations challenges both national sovereignty and democratic accountability at the workplace level. If society is to be organised in ways that enable technology to enhance human freedom and flourishing, then present governance arrangements need to be shifted decisively towards workers. Here policies could be designed to incentivise worker ownership (from loans for cooperatives to the development of funds that enable workers to become co-owners of platforms).

Again there are issues over the feasibility of the above policies, not least because the policy themselves will be resisted by corporate interests who wish to retain their power over technology as well as firm ownership. But while not underestimating the barriers to reform, it can be argued that such policies are vital, if the rewards of digital automation are to be fairly distributed.

7.5 Duty to Report Directive

7.5.1 Option 7: A new directive for the regulation of technology at work

Data limitations coupled with a lack of regulatory oversight creates uncertainty as well as potential inequities in the evolution and effects of digital technologies. To address these issues, the report proposes a new directive that requires firms to report on the impacts of digital technologies on jobs, wages and the quality of work.

The directive would accomplish four things:

1. Establish a duty whereby firms (employing over 50 employees) are required to report on any technological change that will affect the work and employment of their employees;
2. Require EU Member States to identify or establish a regulatory body to oversee reporting by firms on the use of digital technologies in the workplace;
3. Require worker representation in the regulatory body concerned with the impact of new technology on economy and society;
4. Enable new technology agreements in collective bargaining arrangements at sectoral and firm-level.

A mandatory duty to report technological change would provide new data on the effects of digital technologies on workers as well as a mechanism to make employers accountable for choices around technology, work organisation and job design. Reporting could include measures of the quantitative effect of technology on jobs, such as projected job losses and changes in work hours, as well as measures of decent work at the firm level, drawing on the extensive work undertaken by the ILO (Kucera, 2007).

The directive would also introduce a **technology information and consultation duty** whereby workplaces undergoing significant reorganisation or restructuring as a result of technological innovation would be obliged to make technological changes an item for information and consultation with employees with legal enforceability. This would involve updating Article 27 (ICE) of the EU Charter of Fundamental Rights to create an explicit duty on employers to ensure employee involvement in decisions about technology that affect their work and employment. While clearly a radical move, a new duty to report directive would help to create more transparency and democratic accountability around digital automation. This recommendation would support the goals of equitable governance outlined above.

7.6 Mission-oriented industrial policy

7.6.1 Option 8: Direct EU involvement in the design and diffusion of digital technologies to ensure decent work objectives are achieved

The effects of digital technologies are not fully determined – rather, they are open to change. Indeed, as stressed in this report, there is a need to manage digital technologies in ways that maximise societal well-being. Reflecting on this point, the report recommends that the EU adopt a strategic approach to digital automation that aims to achieve clear goals. Following the work of Mazzucato (2013, 2016), the report argues for a mission-oriented approach to industrial policy. In this case, it is proposed that EU Member States define and lead the innovation process, rather than only incentivise or stabilise it.

The report recommends the adoption of a mission that aims for **an automated future that works for all – offering high quality jobs, the reward of higher living standards and fewer hours of work**. This mission would place the creation of decent work at the centre of the Digital Single Market and the Coordinated Plan on AI, embedding it as an objective in all existing and proposed policy and legal mechanisms directed at the development of AI and AI capacity. Specifically, this would mean developing provisions which ensure that, where AI is introduced into production and business processes, it contributes towards well-being through the creation of better jobs and, where AI technologies improve productivity and competitiveness of European business and industry, the rewards are distributed equitably – including via shorter work hours (see above).

These objectives could be achieved through EU-funded and democratically governed research which draws on the strength of social partnerships to inform the direction of technological progress. Their achievement would also involve developing – through tripartite social dialogue and the work of the European Platform of National Initiatives on Digitising European Industry [COM/2017/479 final] – thresholds for job quality, which could be monitored and applied utilising impact assessments and auditing at three critical stages of the AI cycle, defined as: i) development and generation of technology; ii) diffusion and deployment; and iii) distribution of gains.

Here the mission-oriented approach to industrial policy would be consistent with an inclusive-growth agenda, with the focus on creating an environment where digital automation meets standards of decent work, while extending free time. In the sum, the approach to policy would be to ensure that digital technologies deliver for the many, not just the few.

8. Conclusion

This report has systematically and critically reviewed key literature on digital technologies and the impacts that these technologies have (or may have) on work and employment. As has been stressed at different points, the scale and scope of digital automation is likely to be variegated and contingent upon a number of factors including the level capital investment, the level of wages and the nature of prevailing regulatory frameworks. Technological change, as in the past, remains uncertain and open to reform.

In the course of the report, answers have been sought to some key questions. These included the effects of digital technologies on the volume of work. They also included the effects of these technologies on the quality of work. Using available empirical evidence and academic literature, the report has shown how digital automation could transform key aspects of our lives, from the type of work we do, to the amount of leisure time we have available to us.

The report began with a historical overview of different waves of automation. One thing that was stressed here was the persistence of work, despite rapid technological progress. It has been shown how, like in the past, present and future developments in digital technologies are likely to preserve work. Predictions of the death of work miss the limits to automation and the capacity for technological progress to change tasks within jobs, as opposed to eliminate them. It has been stressed how digital technologies can transform the nature of work – for example, the use of forms of digital surveillance can reduce the autonomy of workers and impair the quality of work. It has also been emphasised how the evolution and outcomes of digital automation depend on the broader economic and social context, including how technology is owned and controlled.

In light of the present and future impact of digital automation on the labour market and workplace, the report has set out a number of policy options. These fall into five categories: 1) **skills and training provision**, including industry and sectoral skills alliances that focus on facilitating transitions for workers in 'at risk' jobs and reskilling for workers in transformed jobs; digital upskilling for working in AI-enhanced environments; and new protections for workers in hard to automate jobs; 2) **digital work-life balance** – the establishment of a European-level 'right to disconnect' and a reduction of the EU Working-Time Directive to 38-hours per week and removal of the opt-out clause; 3) **greater worker representation and more democratic workplace governance**; 4) **a new directive for the regulation of technology at work**; 5) **a mission-oriented industrial policy** that seeks to promote direct EU involvement in the design and diffusion of digital technologies to ensure decent work objectives are achieved.

Taken together, the policy options aim to establish a **new Digital Social Contract** around the development, management and use of digital technologies. A social protection floor at a European level for all workers, regardless of their contractual status, is an essential part of this contract. The social protection floor is guided by the Human-Centred Agenda (HCA) set out by the ILO, which recommends that EU Member States guarantee universal entitlement to life-long learning, support individuals subject to technological transitions at work, implement a programme for gender equality, strengthen social protections at work, and expand time sovereignty (Pastore et al., 2019). Complementing these recommendations, the report seeks to build a digital future where technology works for all in society, not just a privileged few. While it is realised that some of the policy options are radical, it can be argued that their implementation is needed if digital automation is to yield benefits to all.

A final word can be added here on the Covid-19 crisis. The report has been written at a time when national economies are contracting under the effects of a lockdown induced by a pandemic. The Covid-19 crisis represents the worst economic crisis since the 1930s. Policies have been implemented to deal with the crisis, but it is yet to be seen how effective these policies will be, in the event of rising

unemployment. It is clear that the crisis has exposed deep divisions in society and that rebuilding the economy will require broader reforms, inclusive of measures to tackle sources of economic inequality and the urgent threat of climate change.

From the perspective of digital automation, the Covid-19 crisis speeds up digital automation, by creating incentives for firms to automate in order to maintain production under social distancing. Yet, by creating large pools of cheap labour, it also creates the potential for firms to hoard labour, and to forgo costly investments in technology. Where remote working occurs, technology may also be used to monitor workers, changing (in potentially negative ways) the quality of work. It is too early to say how these forces will play out, but it is clear that the present crisis will have impacts on what technology is developed and how it is used.

This report has set out the challenges and possibilities for digital automation. It has proposed policies to ensure that the benefits of digital automation are reaped and more equally shared. The Covid-19 crisis will cause significant disruption, including to the processes of digital automation, and will require new policies, from higher public spending to income protection schemes (including potentially a basic income for all). The arguments and policies advanced in this report complement any wider effort to rebuild the economy after the crisis. In the end, it can be argued that a post-crisis economy must embrace technology to enhance the freedom, health and well-being of people.

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This report addresses the nature, scope and possible effects of digital automation. It reviews relevant literature and situates modern debates on technological change in historical context. It also offers some policy options that, if implemented, would help to harness technology for positive economic and social ends.

The report recognises that technological change can affect not just the volume of work but also its quality. It identifies threats to job quality and an unequal distribution of the risks and benefits associated with digital automation. In response, it recommends a number of policy options – ones that aim to go beyond the provision of skills and training and which seek a human-centred approach to digital transformations of work based on industrial democracy and social partnership. Overall, the report pushes for a new Digital Social Contract and a future of work that works for all.

This is a publication of the Scientific Foresight Unit (STOA)
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ISBN 978-92-846-7281-3 | doi: 10.2861/826116 | QA-02-20-871-EN-N