www.pwc.co.uk/economics

# Will robots really steal our jobs?

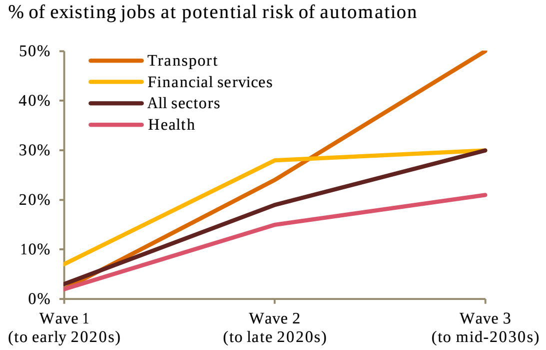
## An international analysis of the potential long term impact of automation

pwc

# Key findings: impact of automation

Financial services jobs could be relatively vulnerable to automation in the shorter term, while transport jobs are more vulnerable to automation in the longer term

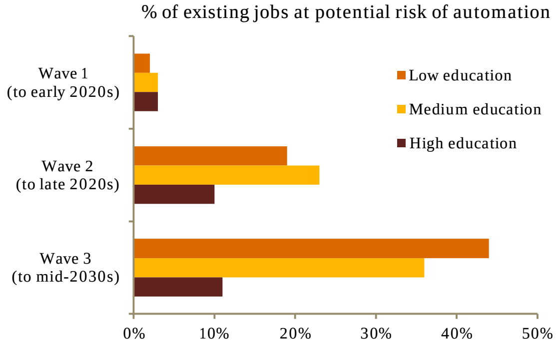
**Figure 1 – Potential job automation rates by industry across waves**




*Source: PwC estimates based on OECD PIAAC data (median values for 29 countries)*

In the long run, less well educated workers could be particularly exposed to automation, emphasising the importance of increased investment in lifelong learning and retraining

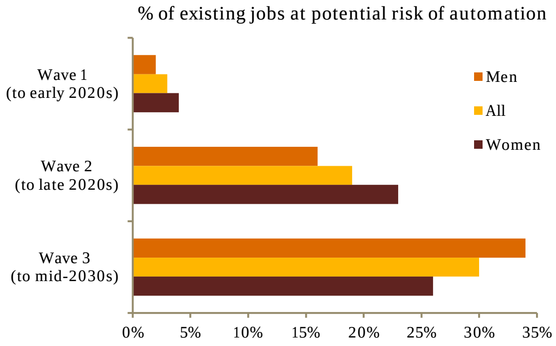
**Figure 2 – Potential job automation rates by education level across waves**




*Source: PwC estimates based on OECD PIAAC data (median values for 29 countries)*

Female workers could be more affected by automation over the next decade, but male jobs could be more at risk in the longer term

**Figure 3 – Potential job automation rates by gender across waves**




*Source: PwC estimates based on OECD PIAAC data (median values for 29 countries)*

| Waves | Description and impact |
|---|---|
| **Wave 1: Algorithmic wave (to early 2020s)** | Automation of simple computational tasks and analysis of structured data, affecting data-driven sectors such as financial services. |
| **Wave 2: Augmentation wave (to late 2020s)** | Dynamic interaction with technology for clerical support and decision making. Also includes robotic tasks in semi-controlled environments such as moving objects in warehouses. |
| **Wave 3: Autonomous wave (to mid-2030s)** | Automation of physical labour and manual dexterity, and problem solving in dynamic real-world situations that require responsive actions, such as in transport and construction. |

# Contents

# 1. Summary

Artificial intelligence (AI), robotics and other forms of 'smart automation' are advancing at a rapid pace and have the potential to bring great benefits to the economy, by boosting productivity and creating new and better products and services. In an earlier study[1], we estimated that these technologies could contribute up to 14% to global GDP by 2030, equivalent to around $15 trillion at today's values.

For advanced economies like the US, the EU and Japan, these technologies could hold the key to reversing the slump in productivity growth seen since the global financial crisis. But they could also produce a lot of disruption, not least to the jobs market. Indeed a recent global PwC survey[2] found that 37% of workers were worried about the possibility of losing their jobs due to automation.

To explore this further we have analysed a dataset compiled by the OECD that looks in detail at the tasks involved in the jobs of over 200,000 workers across 29 countries (27 from the OECD plus Singapore and Russia). Building on previous research by Frey and Osborne (Oxford University, 2013)[3] and Arntz, Gregory and Zierahn (OECD, 2016)[4] we estimated the proportion of existing jobs that might be of high risk of automation by the 2030s for:

- Each of these 29 countries;
- Different industry sectors;
- Occupations within industries; and
- Workers of different genders, ages and education levels.

We also identify how this process might unfold over the period to the 2030s in three overlapping waves:

1. **Algorithm wave**: focused on automation of simple computational tasks and analysis of structured data in areas like finance, information and communications – this is already well underway.
2. **Augmentation wave**: focused on automation of repeatable tasks such as filling in forms, communicating and exchanging information through dynamic technological support, and statistical analysis of unstructured data in semi-controlled environments such as aerial drones and robots in warehouses – this is also underway, but is likely to come to full maturity in the 2020s.
3. **Autonomy wave**: focused on automation of physical labour and manual dexterity, and problem solving in dynamic real-world situations that require responsive actions, such as in manufacturing and transport (e.g. driverless vehicles) – these technologies are under development already, but may only come to full maturity on an economy-wide scale in the 2030s.

Our estimates are based primarily on the technical feasibility of automation, so in practice the actual extent of automation may be less, due to a variety of economic, legal, regulatory and organisational constraints. Just because something can be automated in theory does not mean it will be economically or politically viable in practice.

[1] *PwC, 'Sizing the prize' (2017): https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html.*

[2] *PwC, 'Workforce of the future' (2017): https://www.pwc.com/gx/en/services/people-organisation/publications/workforce-of-the-future.html.*

[3] *Frey, C.B. and M.A. Osborne (2013), The Future of Employment: How Susceptible are Jobs to Computerisation?, University of Oxford.*

[4] *Arntz, M. T. Gregory and U. Zierahn (2016), 'The risk of automation for jobs in OECD countries: a comparative analysis', OECD Social, Employment and Migration Working Papers No 189.*

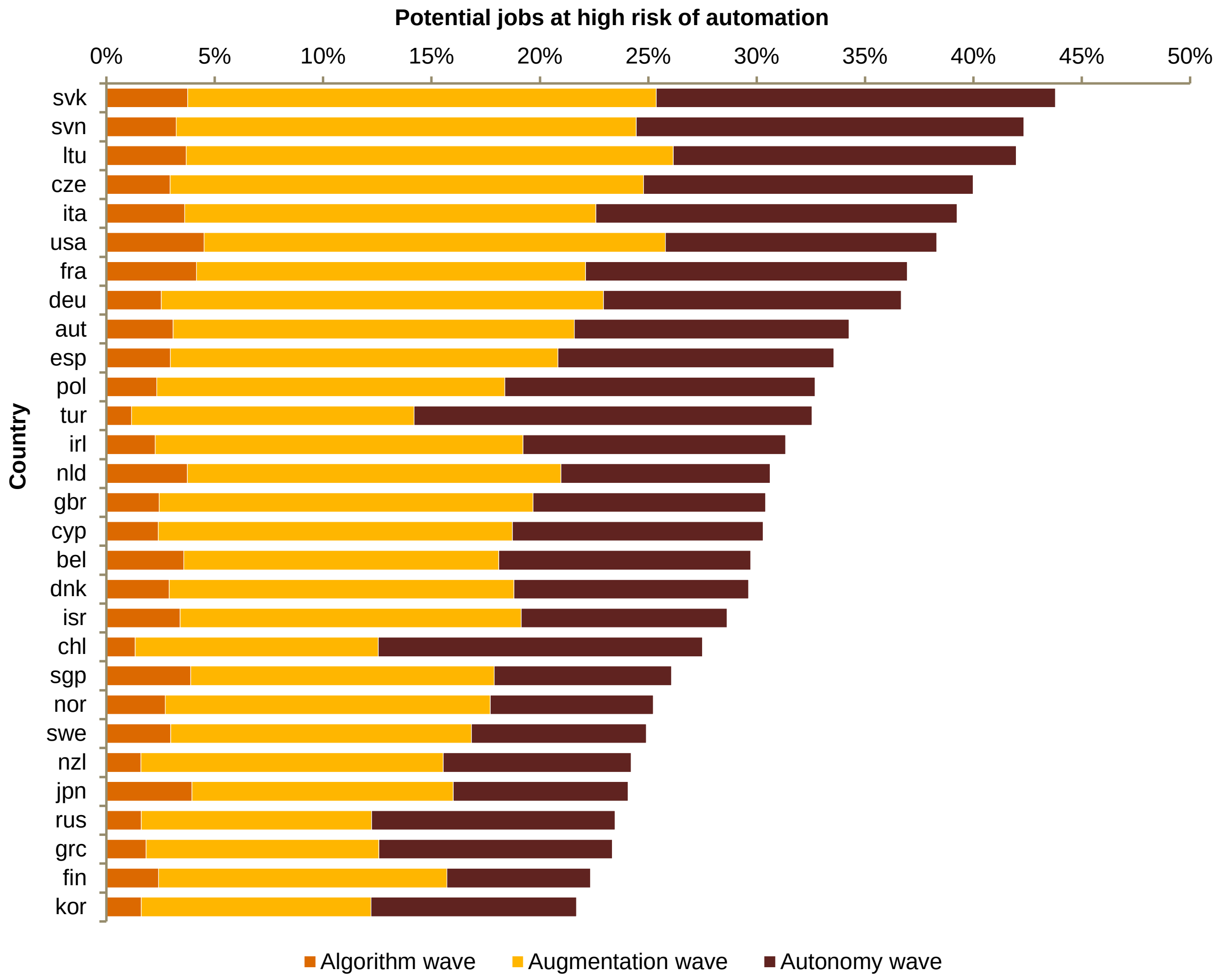
Furthermore, other analysis we have done[5] suggests that any job losses from automation are likely to be broadly offset in the long run by new jobs created as a result of the larger and wealthier economy made possible by these new technologies. We do not believe, contrary to some predictions, that automation will lead to mass technological unemployment by the 2030s any more than it has done in the decades since the digital revolution began.

Nonetheless, automation will disrupt labour markets and it is interesting to look at the estimates we have produced to get an indication of the relative exposure of existing jobs to automation in different countries, industry sectors, and categories of workers. We summarise the key findings in these three areas in turn below.

### Potential impacts by country

As Figure 1.1 shows, the estimated proportion of existing jobs at high risk of automation by the early 2030s varies significantly by country. These estimates range from only around 20-25% in some East Asian and Nordic economies with relatively high average education levels, to over 40% in Eastern European economies where industrial production, which tends to be easier to automate, still accounts for a relatively high share of total employment. Countries like the UK and the US, with services-dominated economies but also relatively long 'tails' of lower skilled workers, could see intermediate levels of automation in the long run.

**Figure 1.1 – Potential job automation rates by country across waves**




*Source: PIAAC data, PwC analysis*

[5] *This modelling was described in our report on the global economic impact of AI here: https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html.*

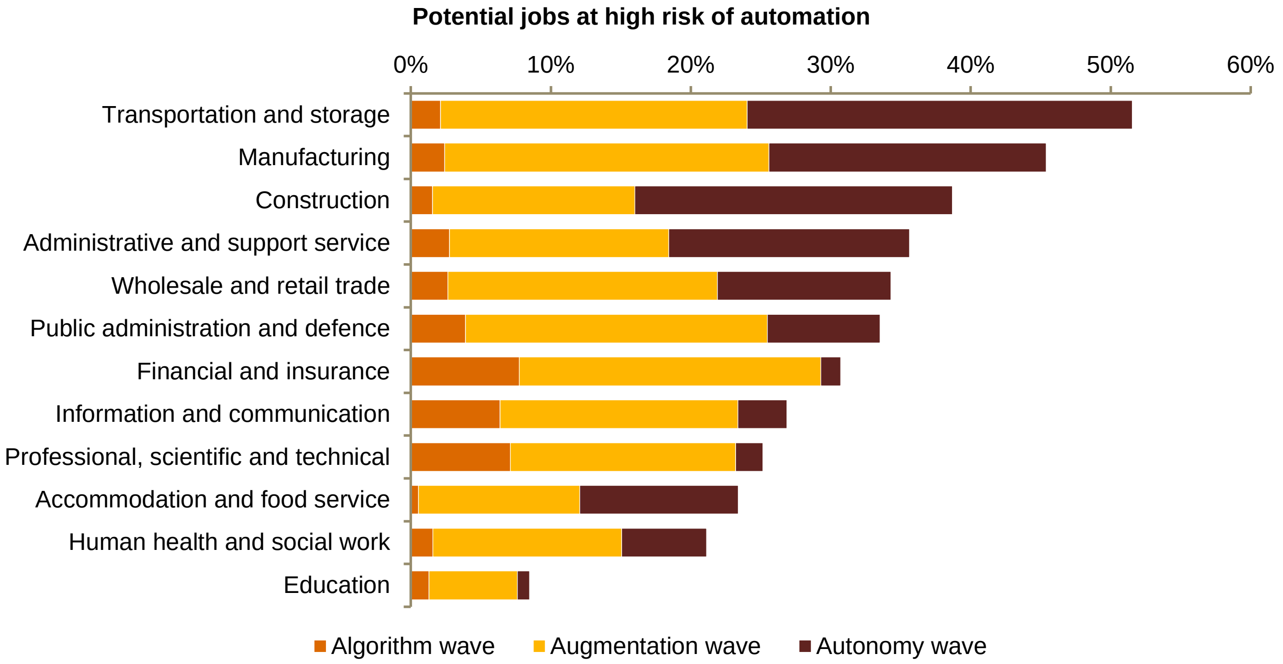
Figure 1.1 also shows how potential automation rates might evolve by country over our three waves of automation. Existing jobs in some countries with relatively low longer term automation rates, such as Japan, may nonetheless be see relatively high automation rates in the shorter term given that algorithmic technologies are already more widely used there.

The opposite is true for a country like Turkey, which may have relatively high exposure to later waves of automation that start to displace manual workers such as drivers and construction workers, but relatively lower exposure in the short term.

### Potential impacts by industry sector

We also see significant variations in potential automation levels between industry sectors, although the pattern here also varies across different waves as Figure 1.2 illustrates.

**Figure 1.2 – Potential rates of job automation by industry across waves**



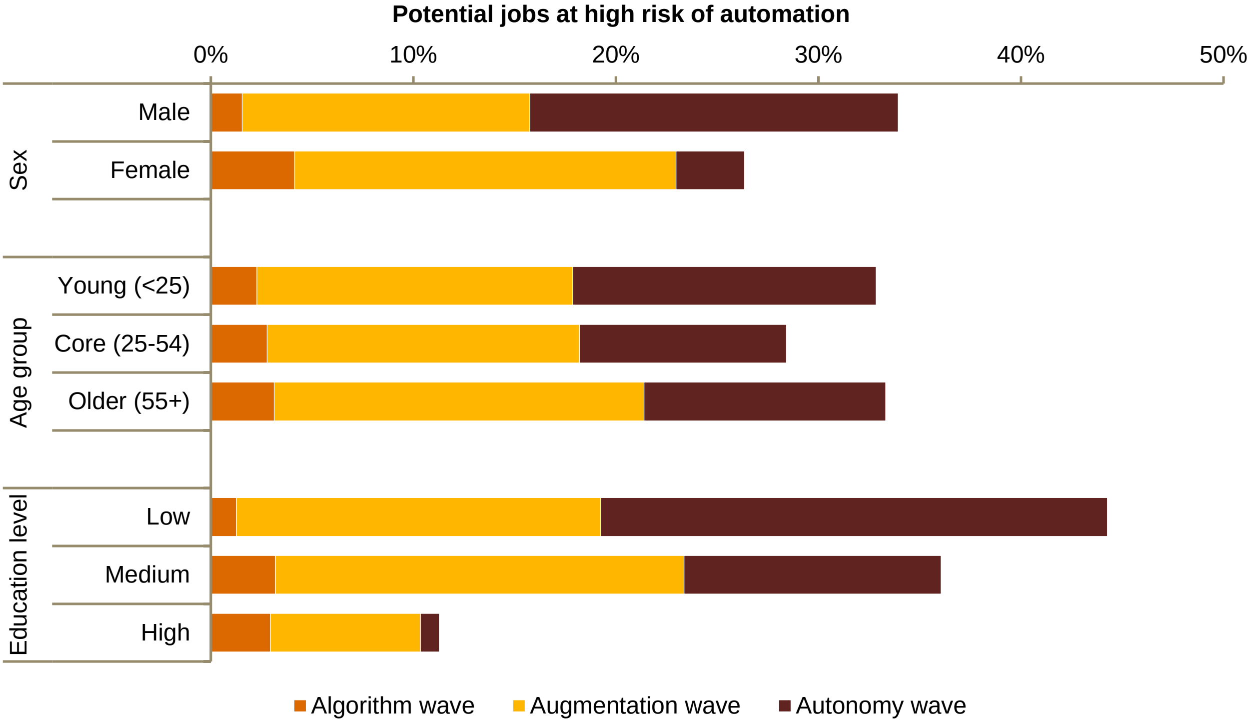

*Source: PIAAC data, PwC analysis*

Transport stands out as a sector with particularly high potential for automation in the longer run as driverless vehicles roll out at scale across economies, but this will be most evident in our third wave of autonomous automation (which may only come to maturity in the 2030s). In the shorter term, sectors such as financial services could be more exposed as algorithms outperform humans in an ever wider range of tasks involving pure data analysis.

### Potential impacts by type of worker

Our analysis also highlights significant differences in the potential impact of automation across types of workers and these will also vary across our three waves of automation as Figure 1.3 shows.

**Figure 1.3 – Potential job automation rates by type of worker across waves**




*Source: PIAAC data, PwC analysis*

The starkest results are those by education level, with much lower potential automation rates on average for highly educated workers with graduate degrees or above, than for those with low to medium education levels. This reflects the greater adaptability of more highly educated workers to technological changes and the fact that they are more likely to be in senior managerial roles that will still be needed to apply human judgement, as well as to design and supervise AI-based systems. Such workers could see their wages increase due to the productivity gains that these new technologies should bring.

Differences are less marked by age group, although some older workers could find it relatively harder to adapt and retrain than younger cohorts. This may apply particularly to less well-educated men as we move into our third wave of autonomous automation in areas like driverless cars and other manual labour that has a relatively high proportion of male workers at present. But female workers could be relatively harder hit in early waves of automation that apply, for example, to clerical roles.

### Implications for public policy

The most obvious implication of our analysis is the need for increased investment in education and skills to help people adapt to technological change throughout their careers. While increased training in digital skills and STEM subjects[6] is one important element in this, it will also require retraining of, for example, truck drivers to take jobs in services sectors where demand is high but automation is less easy due to the importance of social skills and 'the human touch'. Governments, business, trade unions and other organisations (e.g. the NHS and social care providers in the UK) all need to play their part here in helping people to adapt to these new technologies[7]. This will include training and retraining people in softer skills, such as creativity, problem solving and flexibility. On-the-job training will be important here, for example through degree

[6] *Design and other creative skills may also be important here.*

[7] *The recent UK government proposal in its November 2017 Budget for a new National Retraining Scheme involving both business and trade unions is one example here. Further discussion of how people can be helped to adapt to new technologies is contained in our Workforce of the Future report here: https://www.pwc.com/futureworkforce.*

apprenticeships that offer a mix of theoretical study and practical experience, and that are open to a wide range of people (including mature students) to promote social mobility.

In addition, it is important that aggregate demand levels are kept high so as to facilitate the creation of new jobs. One obvious way to do this at present is through increased infrastructure investment (including areas such as housing where this is in short supply as in the UK). Such investment is needed to support longer term growth, but can also create many new jobs in construction and related sectors[8]. Governments can play a key role here both in funding some investment directly and in helping to lever in additional private investment.

It is also important to recognise that concerns about the possible loss of existing jobs should not lead countries to miss out on opportunities to lead the way in developing these new technologies. If governments and businesses in one country do not invest in them, then they will just be developed elsewhere. Unless a country blocks itself off from global trade and investment, which history shows would be extremely damaging economically in the long run, the technologies will still come to all countries over time, so it is better to be at the forefront of this global race.

However, governments do have a key role in making sure that the great potential benefits from AI, robotics and related technologies are shared as broadly as possible across society. As well as investing more in education, training and retraining, and protecting workers rights through appropriate legislation, governments should consider using the tax proceeds from technology-driven growth to strengthen social safety nets for those who lose out from automation.

Universal basic income (UBI) is one idea that has been discussed here. The case for this remains to be proven, but it makes sense for governments to gather evidence from pilot schemes and microsimulation models to inform future decisions on this and other options for sharing the benefits of technology more widely across society. Optimal solutions here may involve combining different ideas (e.g. UBI-type schemes with a degree of conditionality related to working, learning, training, caring or doing some other form of socially valuable activity to qualify for such benefits).

### Implications for business

Our research on AI, robotics and related technologies shows their huge potential to boost productivity and create new and better products and services. There are large benefits to be reaped here by businesses in all sectors, but the phasing of these may vary across different waves of automation (see Table 1.1). Of course, many businesses will need to start investing now for later waves, but they also need to focus on the short-term gains already available through emerging technology and algorithmic methods to enhance data analysis and customer service.

**Table 1.1: Key impacts in the three waves of automation**

| Phase | Description | Tasks impacted | Industries impacted |
|---|---|---|---|
| **Algorithm wave** | Automation of simple computational tasks and analysis of structured data, affecting data-driven sectors such as financial services. | This includes manually conducting mathematical calculations, or using basic software packages and internet searches. Despite increasingly sophisticated machine learning algorithms being available and increasingly commoditised, it is these more fundamental computational job tasks that will be most impacted first. | Data driven sectors like financial and insurance, information and communication, and professional, scientific and technical services. |

[8] *Of course, as our analysis shows, some construction jobs may also be automated in the long run to boost productivity, but if more construction work is undertaken this will also boost the demand for human labour, particularly in the short to medium term.*

| Phase | Description | Tasks impacted | Industries impacted |
|---|---|---|---|
| **Augmentation wave** | Dynamic interaction with technology for clerical support and decision making. Also includes robotic tasks in semi-controlled environments such as moving objects in warehouses. | For example, routine tasks such as filling in forms or exchanging information, which includes the physical transfer of information. It is also likely to see a decreased need for many programming languages as repeatable programmable tasks are increasingly automated, and through machines themselves building and redesigning learning algorithms. | The financial and insurance sector will continue to be highly impacted, along with other sectors with a higher proportion of clerical support, including public and administration, manufacturing, and transport and storage. |
| **Autonomy wave** | Automation of physical labour and manual dexterity, and problem solving in dynamic real-world situations that require responsive actions, such as in transport and manufacturing. | AI and robotics will further automate routine tasks but also those tasks that involve physical labour or manual dexterity. This will include the simulation of adaptive behaviour by autonomous agents. | Sectors like construction, water, sewage and waste management, and transportation and storage with the advent of fully autonomous vehicles and robots. |

*Source: PwC analysis*

Businesses also need to consider now how successive waves of AI-related technologies might further break down barriers to entry in their sector and challenge existing business models. In addition to enhancing existing propositions, it also allows business to offer the same proposition in a more cost effective way, which may be particularly beneficial for small to medium sized businesses and start-ups. This will also create new opportunities for successful businesses to leverage their distinctive competencies in adjacent sectors. Given the fast pace of change, businesses need to be constantly experimenting with new technologies and creating options that they can scale up quickly where successful.

Individuals also need to be more entrepreneurial, taking responsibility for their lifelong learning and seeking to generate their own intellectual property and start new businesses. Much of the automation of the future may be driven by these new businesses replacing or challenging established companies that find it harder to change.

At the same time, as we have argued in previous reports[9], businesses and other employers need to adopt a responsible approach to AI, both as regards their customers (e.g. as regards data privacy) and their workers (e.g. helping them to develop the skills they need to prosper in an age of increasing automation and rapid technological change).

By acting in this way[10], businesses and governments can help to maximise the benefits of AI and robotics while minimising as far as possible the negative impacts of these disruptive technologies.

[9] *See our website for more details on Responsible AI: https://www.pwc.co.uk/services/audit-assurance/risk-assurance/services/technology-risk/technology-risk-insights/accelerating-innovation-through-responsible-ai/responsible-ai-framework.html.*

[10] *For more on this, see the following G20 Policy Insights paper by various PwC authors: http://www.g20-insights.org/policy_briefs/accelerating-labour-market-transformation/.*

# 2. Introduction

The potential for disruption to labour markets due to advances in technology is not a new phenomenon. Most famously, the Luddite protest movement of the early 19th century was a backlash by skilled handloom weavers against the mechanisation of the British textile industry that emerged as part of the Industrial Revolution (including the Jacquard loom, which with its punch card system was in some respects a forerunner of the modern computer). But, in the long run, not only were there still many (if, on average, less skilled) jobs in the new textile factories but, more important, the productivity gains from mechanisation created huge new wealth. This in turn generated many more jobs across the UK economy in the long run than were initially lost in the traditional handloom weaving industry.

The standard economic view for most of the last two centuries has therefore been that the Luddites were wrong about the long-term benefits of the new technologies, even if they were right about the short-term impact on their personal livelihoods. Anyone putting such arguments against new technologies has generally been dismissed as believing in the 'Luddite fallacy'.

However, over the past few years, fears of technology-driven job losses have re-emerged with advances in 'smart automation' – the combination of AI, robotics and other digital technologies that is already producing innovations like driverless cars and trucks, intelligent virtual assistants like Siri, Alexa and Cortana, and Japanese healthcare robots.

While traditional machines, including fixed location industrial robots, replaced our muscles (and those of other animals like horses and oxen), these new smart machines have the potential to replace our minds and to move around freely in the world driven by a combination of advanced sensors, GPS tracking systems and deep learning - if not now, then probably within the next decade or two. Will this just have the same effects as past technological leaps – short term disruption more than offset by long term economic gains? Or is this something more fundamental in terms of taking humans out of the loop not just in manufacturing and routine service sector jobs, but more broadly across the economy? What exactly will humans have to offer employers if smart machines can perform all or most of their essential tasks better in the future[11]? In short, has the 'Luddite fallacy' finally come true?

This debate was given added urgency in 2013 when researchers at Oxford University (Frey and Osborne, 2013) estimated that around 47% of total US employment had a 'high risk of computerisation' over the next couple of decades – i.e. by the early 2030s.

However, there are also dissenting voices. Notably, Arntz, Gregory and Zierahn (OECD, 2016) re-examined the research by Frey and Osborne and, using an extensive new OECD data set, came up with a much lower estimate that only around 10% of jobs were under a 'high risk[12] of computerisation'. This is based on the reasoning that any predictions of job automation should consider the specific tasks that are involved in each job rather than the occupation as a whole[13].

In an earlier article in March 2017[14] we produced our own analysis of the potential effect of automation on jobs with a focus on the UK. Using a more refined version of the OECD methodology, we concluded that up to 30% of UK jobs could be impacted by automation by the 2030s. We also produced high level comparisons suggesting somewhat lower potential automation rates in Japan and somewhat higher rates in Germany and the US.

[11] *Martin Ford, The Rise of the Robots (Oneworld Publications, 2015) is one particularly influential example of an author setting out this argument in detail. Calum Chace (The Economic Singularity, 2016) also discusses these issues in depth.*

[12] *In both studies, this is defined as an estimated probability of 70% or more. For comparability, we adopt the same definition of 'high risk' in this report.*

[13] *The importance of looking at tasks is also emphasised by Autor (2015).*

[14] *'Will robots steal our jobs?' PwC UK Economic Outlook, March 2017, available here: https://www.pwc.co.uk/economic-services/ukeo/pwcukeo-section-4-automation-march-2017-v2.pdf.*

At the same time, we also emphasised that various economic, legal and regulatory and organisational factors mean that these potential risks may not lead to actual job displacement. In some cases, it would alter the nature of jobs significantly, but not displace humans entirely.

Furthermore, we emphasised that there were likely to be broadly offsetting job gains from the new technologies, provided that the income and wealth gains from these advances were recycled into the economy. This qualitative judgement was backed up by later detailed quantitative modelling[15] that concluded that the net long term job impact of automation would be likely to be neutral or even slightly positive[16]. This will, however, require both business and governments to provide support to workers affected by these technological advances to retrain and start new careers.

In this paper, we extend our March 2017 analysis of jobs at potential risk of automation to a much wider set of countries, using the OECD's PIAAC database for 29 countries (27 from the OECD, plus Singapore and Russia). In total, this covers the jobs of over 200,000 workers and so provides a much larger dataset to explore potential impacts of automation by country, sector and type of worker. The additional data also allows us to provide a more robust analysis of the factors causing automation risk to vary across countries and sectors.

We also identify how this process might unfold over the period to the 2030s in three overlapping waves:

1. **Algorithm wave**: focused on automation of simple computational tasks and analysis of structured data in areas like finance, information and communications – this is already well underway.
2. **Augmentation wave**: focused on automation of repeatable tasks such as filling in forms, communicating and exchanging information through dynamic technological support, and statistical analysis of unstructured data in semi-controlled environments such as aerial drones and robots in warehouses – this is also underway, but is likely to come to full maturity in the 2020s.
3. **Autonomy wave**: focused on automation of physical labour and manual dexterity, and problem solving in dynamic real-world situations that require responsive actions, such as in manufacturing and transport (e.g. driverless vehicles) – these technologies are under development already, but may only come to full maturity on an economy-wide scale in the 2030s.

### Report structure

The discussion in the rest of this report is structured as follows:

- **Section 3 –** How do potential automation rates vary by country?
- **Section 4 –** Which industry sectors could see the highest levels of automation?
- **Section 5 –** Which occupations could see the highest rates of automation?
- **Section 6 –** Why does the potential rate of job automation vary by type of worker?
- **Section 7 –** What are the public policy implications?
- **Section 8 –** Implications for business – constraints, opportunities and responsibilities.

Further details of the methodology behind our analysis are contained in a technical annex at the end of this report, together with references to the studies cited.

[15] *This modelling was described in our report on the global impact of AI here: https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html.*

[16] *Other reports such as ZEW (2016) and Acemoglu and Restrepo (2016) also highlights the job creating potential of these new technologies. However, an empirical study for the US manufacturing sector by Acemoglu and Restrepo (2017) found a net negative impact on employment from industrial robots, so this remains an active area of debate.*

# 3. How do potential automation rates vary by country?

**Key findings**

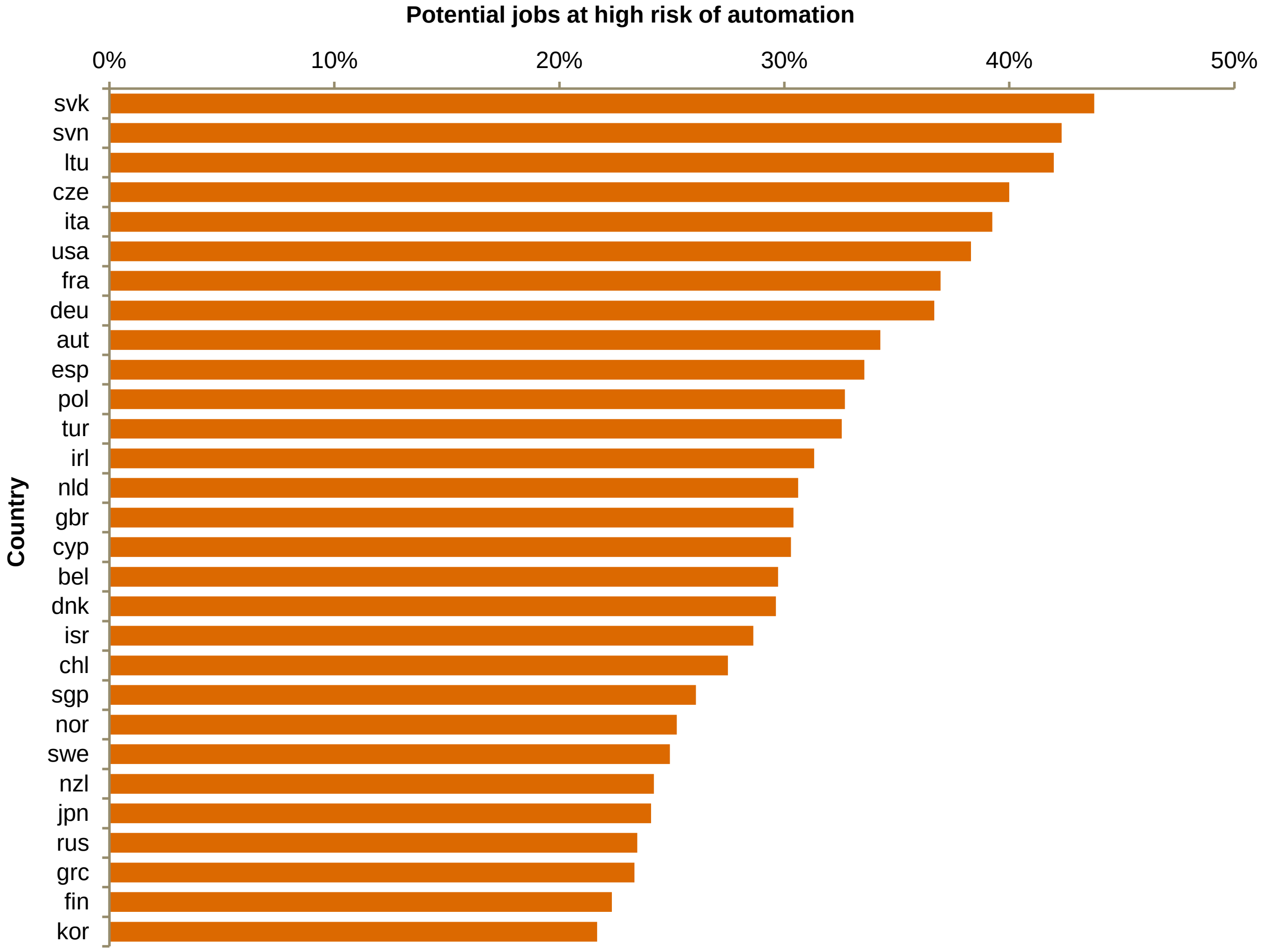
- The estimated share of existing jobs that could potentially be automated by the 2030s varies widely across countries from only around 22% in Finland and South Korea to up to 44% in Slovakia.
- Countries with similar labour market performances and economic structures have broadly similar levels of potential automation. Four broad country groups emerge: a) Industrial economies with relatively inflexible labour markets, which could see the highest automation rates; b) Services-dominated economies such as the US and the UK with long tail of lower skilled workers and intermediate levels of potential automation; c) Nordic countries with high employment rates and skill levels and relatively low levels of potential automation; and d) East Asian nations with high levels of technological advancement and education, which could see high short term automation rates in some sectors but lower longer term impacts.
- Industry structure is important as Eastern European countries, for example, tend to have relatively high shares of employment in sectors such as manufacturing and transport that are projected to be relatively easy to automate looking ahead to the 2030s.
- Automation rates also differ across countries because ways of working differ. In particular, workers in countries such as Singapore and South Korea with more stringent educational requirements have greater protection against automation in the long run. This is also true (particularly in Europe) for countries with higher levels of education spending as a percentage of GDP.
- Country automation levels will evolve over time – jobs in more technologically advanced nations like Japan and South Korea may be at immediate risk as computational tasks are automated in the first algorithmic wave. But workers in these nations could eventually face lower risks in the later waves of automation that displace manual jobs and could have a greater impact on workers in other countries with lower average skill levels and/or large manufacturing bases.

## 3.1. Estimated potential automation rates across countries

The methodology for estimating potential future automation rates that we previously developed[17] was refined and applied across the set of 29 countries for which OECD PIAAC data are publicly available (27 from the OECD plus Singapore and Russia). This revealed a range of estimates across countries for the share of existing jobs with potential high rates of automation by the 2030s, as shown in Figure 3.1. Notably some Eastern European countries such as Slovakia (44%) and Slovenia (42%) face relatively high potential automation rates, whilst Nordic countries such as Finland (22%) and Asian countries such as South Korea (22%) have relatively lower shares of existing jobs that are potentially automatable.

[17] *PwC (2017), UK Economic Outlook: Will robots steal our jobs? Available here: https://www.pwc.co.uk/economic-services/ukeo/pwcukeo-section-4-automation-march-2017-v2.pdf.*

**Figure 3.1 – Potential rates of job automation by country**




*Source: PIAAC data, PwC analysis*

## 3.2. The relative impact of industry composition and job automatability

The overall automation rate estimates in Figure 3.1 reflect two key factors:

1. The share of employment in each country across industry sectors; and
2. The relative automatability of jobs in each country on a sector by sector basis.

As a result of differences in labour market structures, education and skills levels, and government polices across the countries, the relative impact of these two components varies between countries (see Figure 3.2), which gives rise to differences in estimated automation levels. Looking at Figure 3.2, we can distinguish four broad country groups:

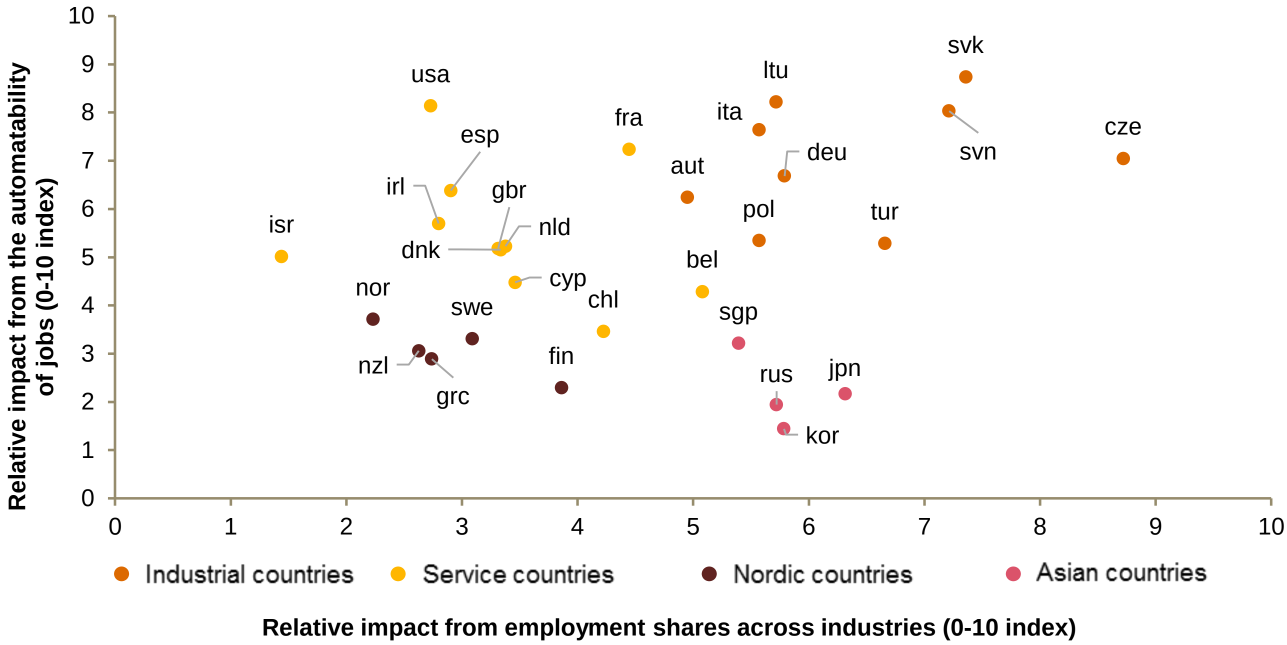
**Industrial economies** – for example, Germany, Slovakia and Italy, which could see relatively higher automation rates in the long run. These countries are typically characterised by jobs that are relatively more automatable and (relative to the OECD average) more concentrated in industry sectors with higher potential automation rates (as discussed further in Section 4 below).

**Services-dominated economies** – for example, the US, UK, France and the Netherlands, which have jobs that are on average relatively more automatable based on their characteristics, but also a greater concentration on services sectors that tend to be less automatable on average than industrial sectors.

**Asian countries** – for example, Japan, South Korea, Singapore and Russia, which have jobs that are relatively less automatable overall but with relatively high concentrations of employment in industrial sectors with relatively high potential automation rates.

**Nordic countries** – for example Finland, Sweden and Norway (in addition to New Zealand and Greece outside this region). These countries have jobs that are on average relatively less automatable and in industry sectors with relatively lower potential automation rates.

**Figure 3.2 – Potential impact across countries by employment shares and automatability of jobs**




*Source: PIAAC data, PwC analysis*

There are also some relationships here between estimated automation risks in different countries and their performances on PwC's labour market indices – the Young Workers Index (YWI)[18], the Women in Work Index (WWI)[19] and the Golden Age Index (GAI) for older workers[20]. European countries such as Slovakia, Slovenia, Czech Republic and Italy have repeatedly appeared towards the bottom or lower middle of the rankings on all of these labour market indices. This indicates relatively higher NEET (not in education, employment or training) rates for younger people and lower engagement of women and older people in the workforce. Similarly, New Zealand and Israel, along with the Nordic countries, have been high performers on all of our indices due to relatively high employment rates and education and skill levels across all major demographic groups.

## 3.3. Factors related to estimated automation levels

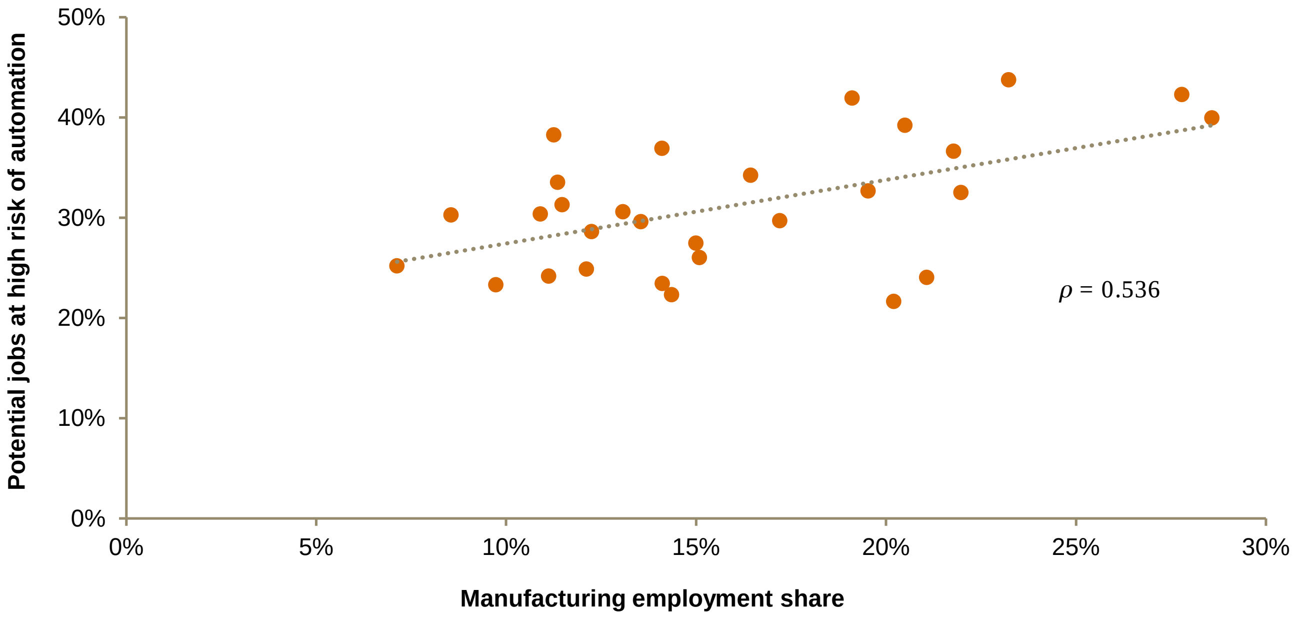
Countries that have an increased concentration of labour in more industrial sectors, rather than in the service sectors, tend to have higher potential automation rates (other things being equal). For example, countries with a higher share of employment in the manufacturing sector such as Czech Republic (29%) and Slovenia (28%) are estimated to have an increased potential job automation rate, see Figure 3.3. These jobs are characterised by a greater proportion of manual or routine work that is typically more susceptible to automation (as discussed further in Section 4 below).

[18] *PwC (2017), Young Workers Index: The $1.2 trillion prize from empowering young workers in an age of automation. Available here: https://www.pwc.co.uk/services/economics-policy/insights/young-workers-index.html.*

[19] *PwC (2017), Women in Work Index: Closing the gender pay gap. Available here: https://www.pwc.co.uk/services/economics-policy/insights/women-in-work-index.html.*

[20] *PwC (2017), Golden Age Index: The potential $2 trillion prize from longer working lives. Available here: https://www.pwc.co.uk/services/economics-policy/insights/golden-age-index.html.*

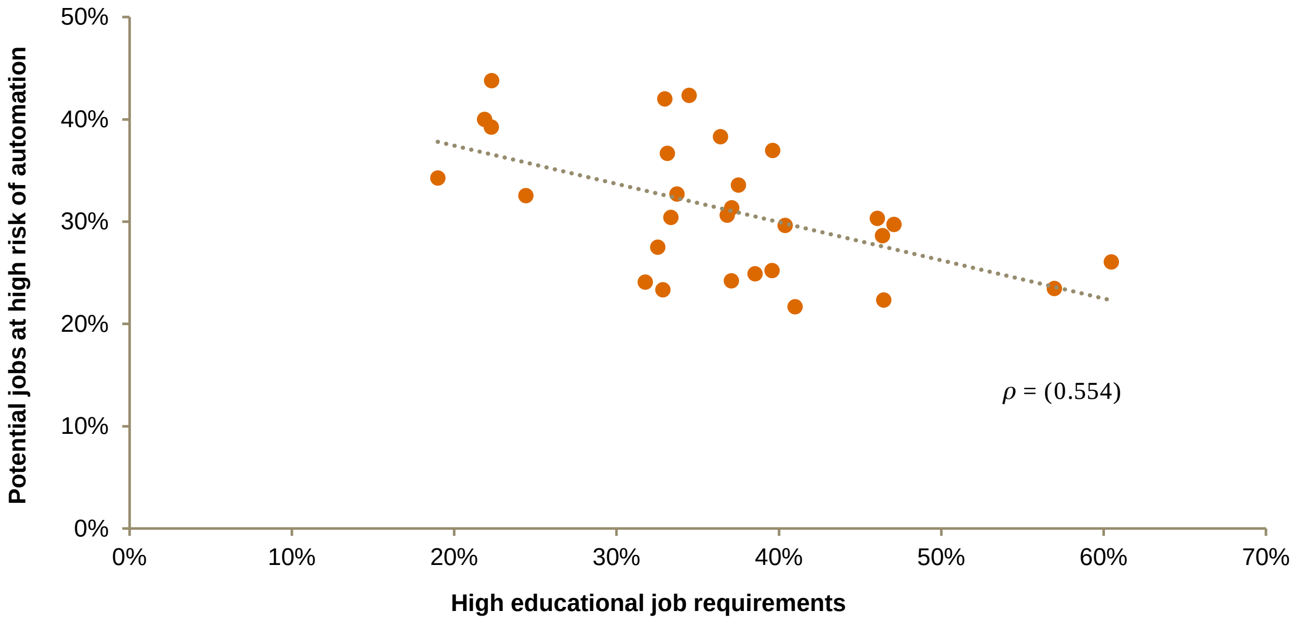
**Figure 3.3 – Relative impact from employment shares across industries e.g. manufacturing**




*Source: PIAAC data, PwC analysis*

The relative impact from the automatability of jobs is instead dependent on a wider range of determinants, such as the level of training, education, and skills required for those jobs. For example, countries with a higher proportion of labour employed in jobs with a high level of educational requirements, such as Singapore (60%) and Russia (57%), are estimated to have lower potential automation rates (see Figure 3.4). Notably, this is a stronger effect than the proportion of labour with high education levels alone (e.g. degree-level, correlation ($r$) = -0.35 vs. $r$ = -0.55 for high educational job requirements).

**Figure 3.4 – Relative impact from the automatability of jobs e.g. educational job requirements**

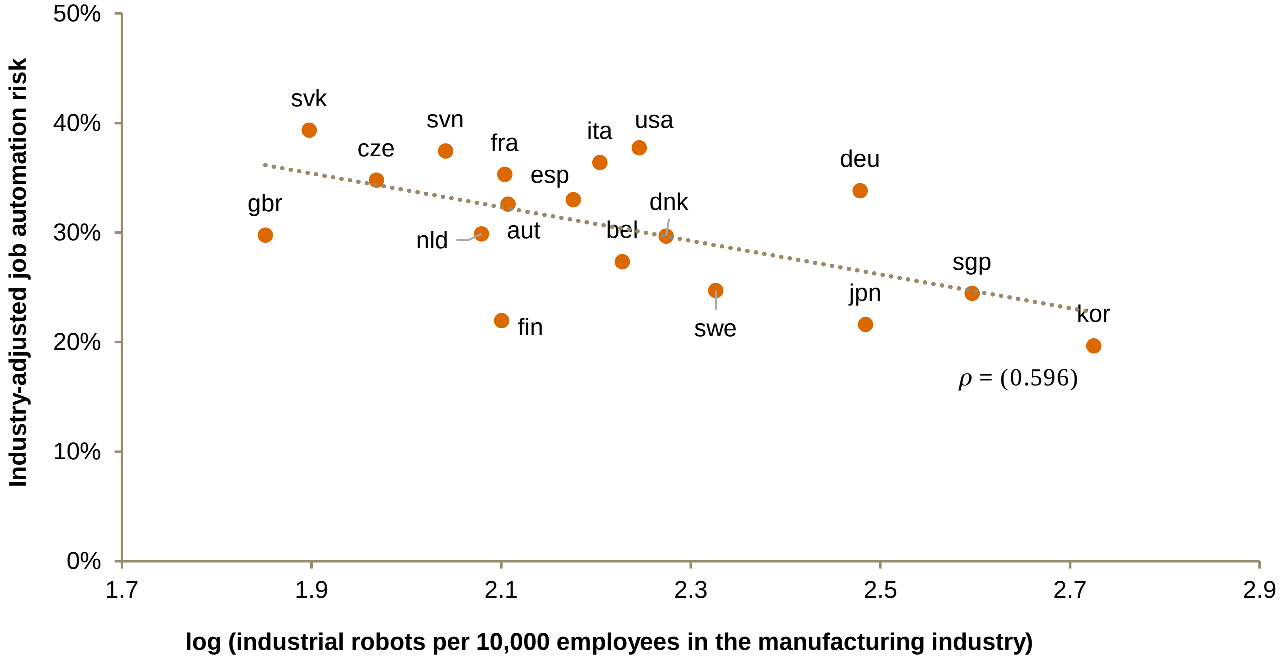



*Source: UNDP HDI data, PwC analysis*

Furthermore, for European countries there are strong negative correlations between the potential share of existing jobs at high risk of automation and country education metrics, such as government expenditure on education as a percentage of GDP (r=-0.77) and pupil-t0-teacher ratios in primary school (r=0.53)[21]. This relationship is not so strong for Asian countries that have proportionally lower education spend and higher pupil-to-teacher ratios than in Europe. However, these Asian countries nonetheless achieve high educational outcomes, notably for STEM subjects, so the underlying negative relationship between high education and low automatability also holds here even if different metrics need to be used to show this relationship in Asia.

In addition to the share of employment and automatability of jobs, one other factor that may impact Asian countries more is the current technological level and the extent to which job automation has already taken place, which is also an important factor in future automation rates. Figure 3.5 shows a negative correlation between the potential jobs at high risk of automation, adjusted to account for industry composition, against the density of industrial robots in the country[22]. This suggests that workforces in more technologically advanced countries such as Japan, South Korea and Singapore that are increasingly working alongside robots have already adjusted to automation to some degree and so may be at lower future risk. Instead they may be well placed to reap the benefits of automation in terms of higher productivity and real wages.

**Figure 3.5 – Relationship between density of industrial robots and industry-adjusted job automation rates**




*Source: International Federation of Robots, PwC analysis*

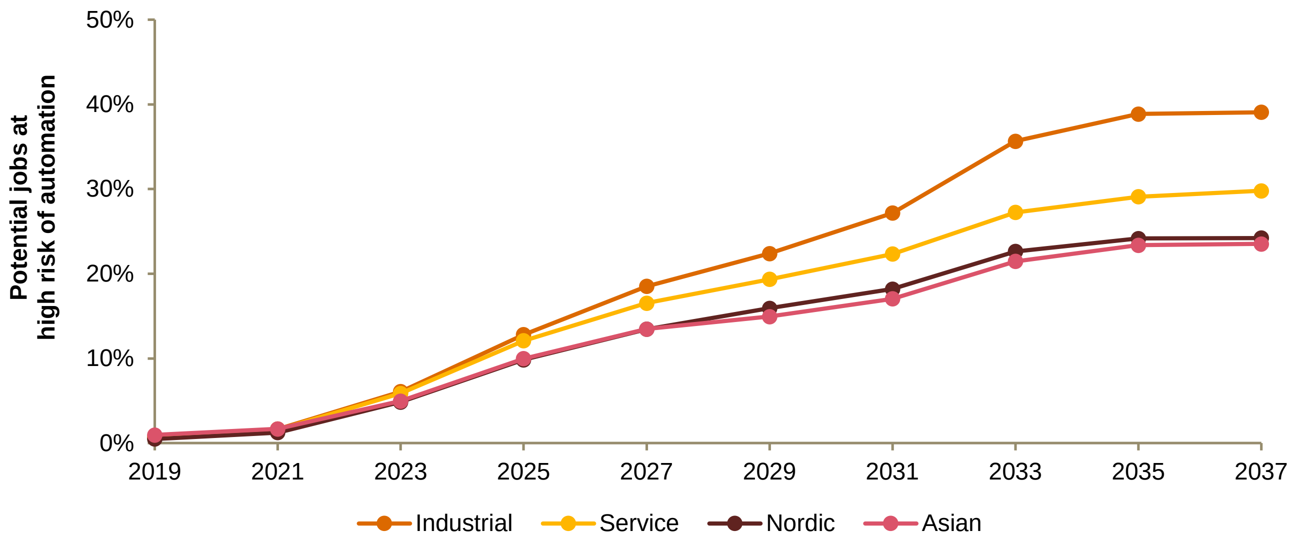
[21] *Data sourced from the United Nations Development Programme. Government expenditure on education (% of GDP 2010-2014); Pupil-to-teacher ratio (2010-2014).*

[22] *International Federation of Robotics – https://ifr.org/ifr-press-releases/news/world-robotics-report-2016.*

## *3.4. Impact on countries over time – the three waves of automation*

The impact of the automation process is expected to vary over-time as automation encroaches on increasingly human-like capabilities, as illustrated in Figure 3.6 for the four country groups we discussed earlier in this section. On average across the 29 countries covered, the share of jobs at potential high risk of automation is estimated to be around 3% by the early 2020s, but this rises to around 20% by the late 2020s, and around 30% by the mid-2030s. The precise timings shown in Figure 3.6 (and subsequent charts of this kind in the report) are subject to many uncertainties, but give some indication of how automation might have its effect on different groups of countries over time.

**Figure 3.6 – Potential impact of job automation over-time across the four country groups**




*Source: PIAAC data, PwC analysis*

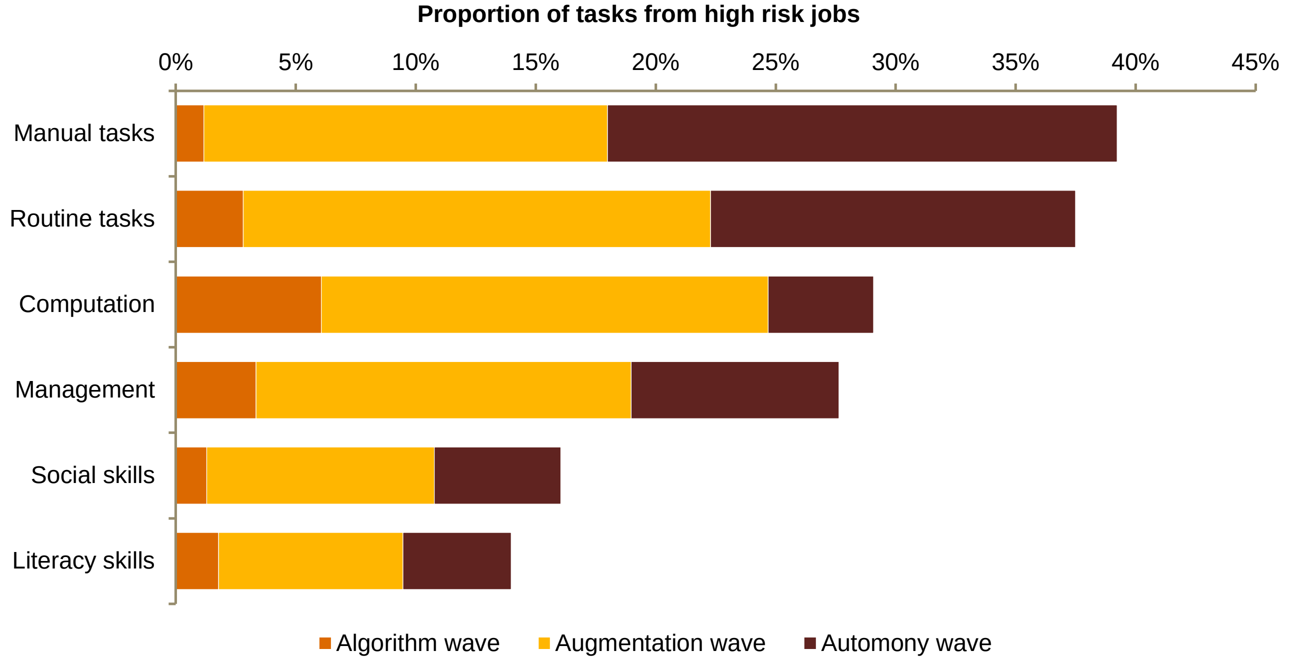
As mentioned in the introduction, this automation process can be characterised as involving three overlapping waves, which we refer to as: 1) an Algorithm wave, 2) an Augmentation wave, and 3) and Autonomy wave.

**Algorithm wave** – The first wave of automation, which is already well underway, is primarily an automation of simple computational tasks and analysis of structured data (see Figure 3.7). This includes manually conducting mathematical calculations, or using basic software packages and internet searches. Increasingly sophisticated applications for processing big data and running machine learning algorithms are available to the market and being commoditised. However, it is these more fundamental computational job tasks that will be most impacted first.

**Augmentation wave** – The second wave of automation is expected to involve a more dynamic change to how many job tasks are conducted, in particular those that are routine and repeatable. For example, routine tasks such as filling in forms or exchanging information, which includes the physical transfer of information, will increasingly be augmented by technology. It is also likely to see a decreased need for many programming languages as repeatable programmable tasks are increasingly automated, and through machines themselves building and redesigning learning algorithms. This will also involve further advances in robotics, although generally these will not be fully autonomous during this period but will operate with the assistance of human workers and augment their capabilities. The impacts of this second wave are expected to emerge on an economy-wide scale during the course of the 2020s.

**Autonomy wave** – The third wave of automation is one of autonomous AI and robotics that will further automate routine tasks but also those tasks that involve physical labour or manual dexterity. Problem solving will increasingly extend from analytical modelling of structured data to problem solving in dynamic real-world situations that also requires responsive actions to be taken. This will include the simulation of adaptive behaviour by autonomous agents, such as in factories or in transport. The full impacts of this third wave are only expected to emerge on an economy-wide scale in the 2030s, even though some of these technologies are already being piloted now.

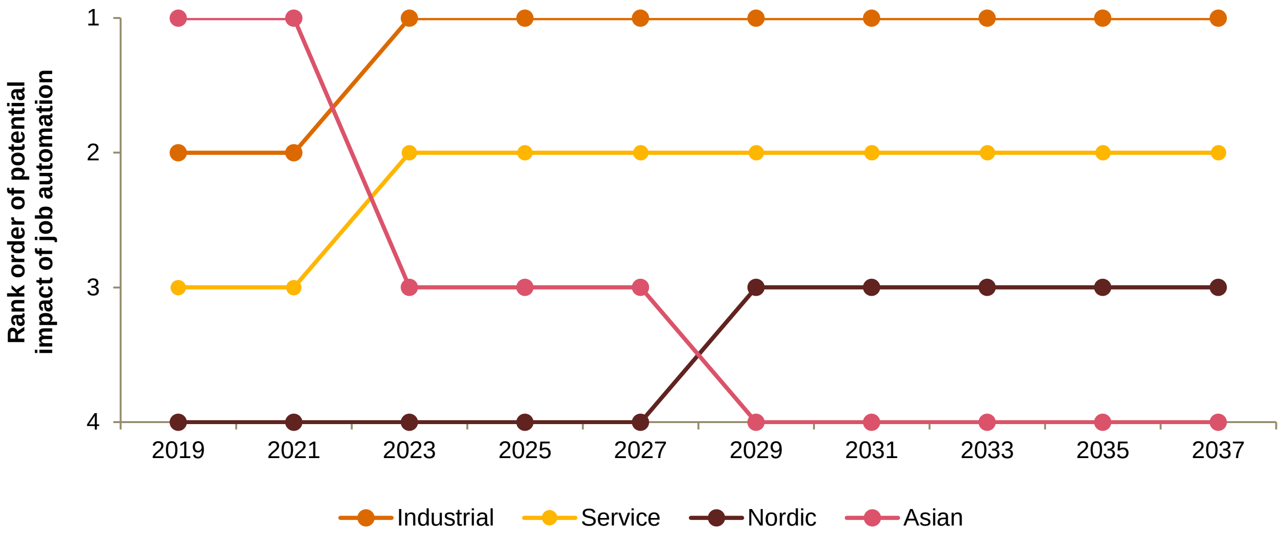
**Figure 3.7 – Task automation across the three waves**




*Source: PIAAC data, PwC analysis*

As these three waves play out, different regions of the world are expected to see relatively greater impacts at different points in time, as illustrated in Figure 3.8. For example, a greater impact is expected in Asian countries at first as the Algorithm wave predominates. However, both industrial and services-dominated economies are then expected to face greater impacts in the longer term as the Augmentation and Autonomy waves ripple through economies.

**Figure 3.8 – The rank order of potential impact over-time across the four country groups**




*Source: PIAAC data, PwC analysis*

In Table 3.1 below we set out estimates of how the proportion of jobs at risk of automation in different countries might evolve over the three waves.

**Table 3.1 – Estimated share of jobs at potential high risk of automation across countries for each of the three waves: Algorithm wave, Augmentation eave and Autonomy wave**

| Country | Algorithm wave (%) | Augmentation wave (%) | Autonomy wave (%) |
|---|---|---|---|
| Slovakia | 4 | 25 | 44 |
| Slovenia | 3 | 24 | 42 |
| Lithuania | 4 | 26 | 42 |
| Czech Republic | 3 | 25 | 40 |
| Italy | 4 | 23 | 39 |
| USA | 5 | 26 | 38 |
| France | 4 | 22 | 37 |
| Germany | 3 | 23 | 37 |
| Austria | 3 | 22 | 34 |
| Spain | 3 | 21 | 34 |
| Poland | 2 | 18 | 33 |
| Turkey | 1 | 14 | 33 |
| Ireland | 2 | 19 | 31 |
| Netherlands | 4 | 21 | 31 |
| UK | 2 | 20 | 30 |
| Cyprus | 2 | 19 | 30 |
| Belgium | 4 | 18 | 30 |
| Denmark | 3 | 19 | 30 |
| Israel | 3 | 19 | 29 |
| Chile | 1 | 13 | 27 |
| Singapore | 4 | 18 | 26 |
| Norway | 3 | 18 | 25 |
| Sweden | 3 | 17 | 25 |
| New Zealand | 2 | 16 | 24 |
| Japan | 4 | 16 | 24 |
| Russia | 2 | 12 | 23 |
| Greece | 2 | 13 | 23 |
| Finland | 2 | 16 | 22 |
| South Korea | 2 | 12 | 22 |

*Note: figures shown are cumulative so those in the final column include the estimated impacts from all three waves of automation.*

*Source: PIAAC data, PwC analysis*

## 3.5. Two important caveats – constraints on automation and new job creation

When considering these and other results in this report, however, it is important to bear in mind, first, that there could be a variety of economic, legal and regulatory and organisational constraints that mean that automation does not proceed as fast as projected here. We discuss these constraints further in Section 8 below.

Second, we also believe that new technologies like AI and robotics will create many new jobs. Some of these new jobs will relate directly to these new technologies, but most will just result from the general boost to productivity, incomes and wealth that these technologies will bring. As these additional incomes are spent, this will generate additional demand for labour and so new jobs, as such technologies have done throughout history.

Our other research[23] suggests that the net long term effect on employment in advanced economies like the US and the EU may be broadly neutral, although it is harder to quantify new job creation than it is to estimate the proportion of existing jobs at risk of automation (precisely because those jobs exist now and we therefore know a lot about their characteristics). We can, however, gain some more insight into potential areas of job losses and gains by considering how automatability varies by industry sector, which is the subject of the next section of this report.

[23] PwC (2018), *The macroeconomic impact of artificial intelligence*

# 4. Which industry sectors could see the highest rates of automation?

**Key findings**

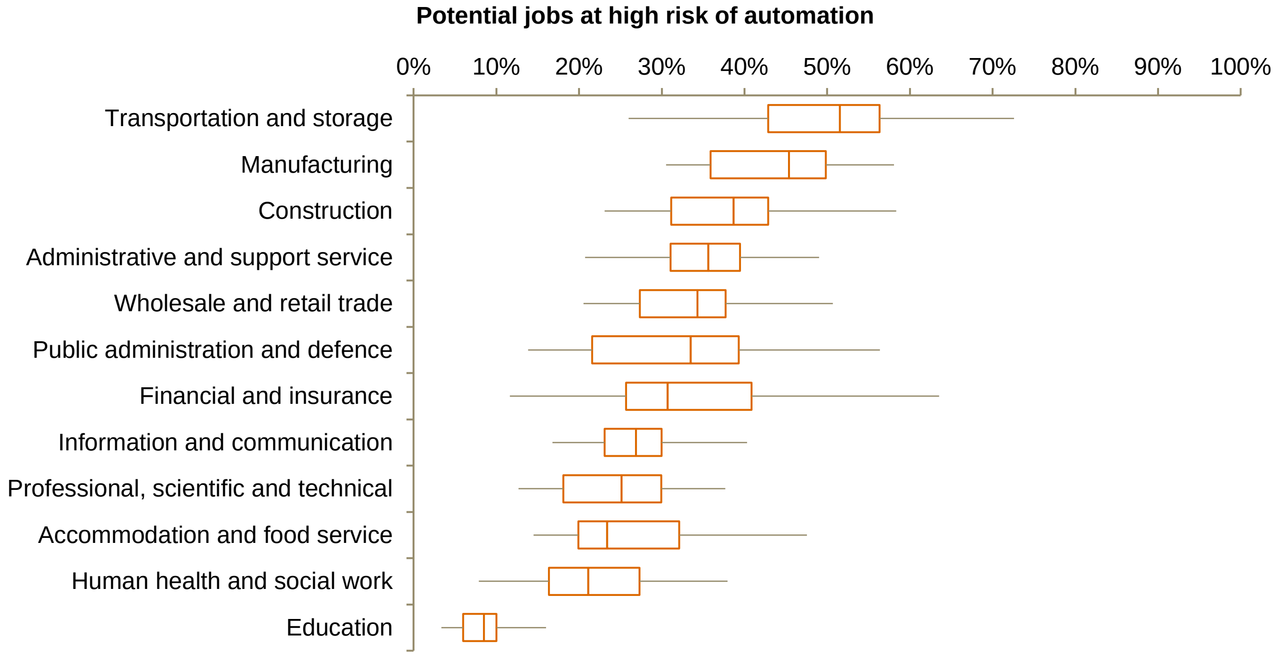
- Potential automation risk varies widely across industry sectors. Transportation and storage and manufacturing are estimated to have the highest share of existing jobs that could potentially be automated by the 2030s at around 52% and 45% respectively. Human health and education are the major sectors with the lowest estimated future automation rates, and corresponding potential for net job gains in the long run.
- Industries are likely to follow different paths of automation over time – data-driven industries such as financial services and information management will be most affected in the short term as algorithmic technologies are developed. In the longer run, the advent of driverless vehicles and other types of autonomous machines will impact sectors such as transport and construction.
- An industry's task composition and educational requirements are the primary drivers behind its automatability. Industries where large number of workers are engaged in relatively routine tasks are likely to see more automation. Less automatable sectors have a greater proportion of time spent on social and literacy-based tasks, and also have higher average educational requirements.

## 4.1. Total automation rates across industries

The estimated share of existing jobs with potential high rates of automation varies widely across industry sectors, from a median across countries of 52% for transportation and storage to just 8% for the education sector (see Figure 4.1 – error bars in this and other similar charts in this report show the variation across countries in our estimates of potential automation rates by industry).

However, in terms of absolute numbers of jobs that could be automated, the greatest impact might be felt in the manufacturing sector (with an estimated automatability of 45%) as this has a median employment share across countries of 14%, as compared to only 5% in transport and storage. The wholesale and retail trade sector has a moderately high automatability estimate at 34% (with a median employment share of 14%), whilst health and social work has relatively lower potential automatability at 21% (with a median employment share of 11%).

**Figure 4.1 –Share of jobs with potential high automation rates by industry**




*Source: PIAAC data, PwC analysis*

The fact that automatability in a given industry sector varies across countries is illustrated by the more detailed figures in Table 4.1 for five of the largest sectors by employment.

**Table 4.1. Share of jobs with potential high automation rates for the top 5 industries by employment share, across countries.**

| Country | Manufacturing (%) | Wholesale and retail trade (%) | Human health and social work (%) | Education (%) | Construction (%) |
|---|---|---|---|---|---|
| Slovakia | 58 | 43 | 34 | 14 | 42 |
| Slovenia | 57 | 35 | 31 | 13 | 53 |
| Lithuania | 55 | 39 | 27 | 26 | 58 |
| Czech Republic | 55 | 33 | 38 | 10 | 36 |
| Italy | 55 | 35 | 29 | 17 | 44 |
| USA | 53 | 51 | 28 | 12 | 34 |
| France | 53 | 41 | 29 | 17 | 41 |
| Germany | 49 | 43 | 24 | 9 | 39 |
| Austria | 48 | 37 | 26 | 9 | 51 |
| Spain | 45 | 35 | 26 | 8 | 42 |
| Poland | 50 | 31 | 21 | 9 | 48 |
| Turkey | 45 | 26 | 36 | 8 | 40 |
| Ireland | 50 | 39 | 17 | 7 | 33 |
| Netherlands | 46 | 35 | 24 | 8 | 36 |
| UK | 45 | 42 | 18 | 8 | 23 |
| Cyprus | 38 | 35 | 14 | 6 | 42 |
| Belgium | 45 | 28 | 19 | 10 | 43 |
| Denmark | 46 | 33 | 17 | 9 | 44 |
| Israel | 42 | 34 | 14 | 8 | 42 |
| Chile | 32 | 27 | 23 | 13 | 29 |
| Singapore | 33 | 38 | 19 | 9 | 26 |
| Norway | 33 | 34 | 16 | 6 | 35 |
| Sweden | 45 | 26 | 22 | 4 | 28 |
| New Zealand | 36 | 32 | 16 | 6 | 23 |
| Japan | 32 | 27 | 10 | 6 | 29 |
| Russia | 33 | 21 | 8 | 5 | 45 |
| Greece | 35 | 23 | 20 | 3 | 25 |
| Finland | 41 | 22 | 9 | 4 | 35 |
| South Korea | 31 | 24 | 12 | 6 | 31 |
| **Employment share (median)** | **14.4** | **13.7** | **10.7** | **8.7** | **7.6** |

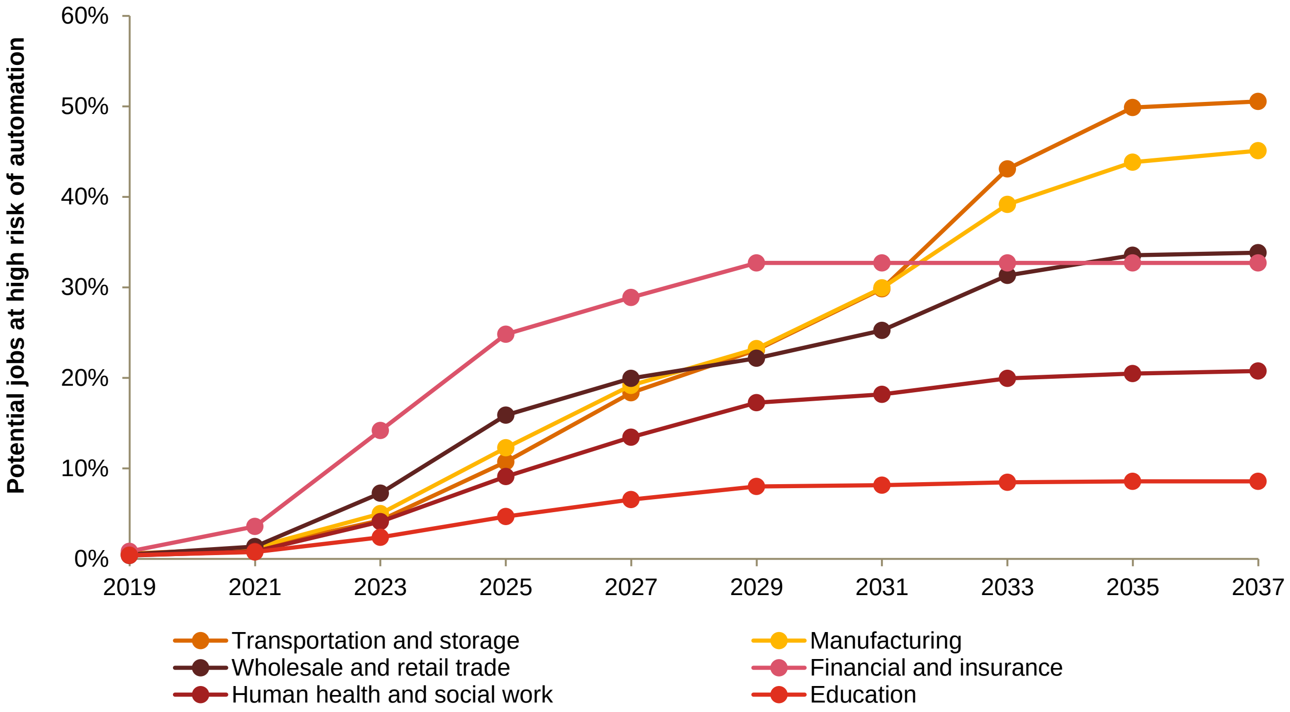
*Source: PIAAC data, PwC analysis*

As the colour coding in the table shows, there are some clear common patterns across countries between those with high automatability (red colour) and low automatability (green colour), but also some differences between countries within sectors.

## *4.2. Impact on industries over time*

The automation process is also expected to affect industries differently over time, as shown in Figure 4.2. For example, the financial and insurance sector has the highest share of existing jobs at potential high risk of automation in the Algorithm wave at 8%, but then peaks at just over 30% in the early 2030s as we move into the Autonomy wave. In contrast, the transport and storage and manufacturing sectors have lower potential automation rates in the Algorithm wave, but this picks up to higher levels by the time of the Autonomy wave in the 2030s (by which time use of driverless vehicles is likely to become more widespread across the economy).

**Figure 4.2 – Potential impact of job automation over time across industry sectors**

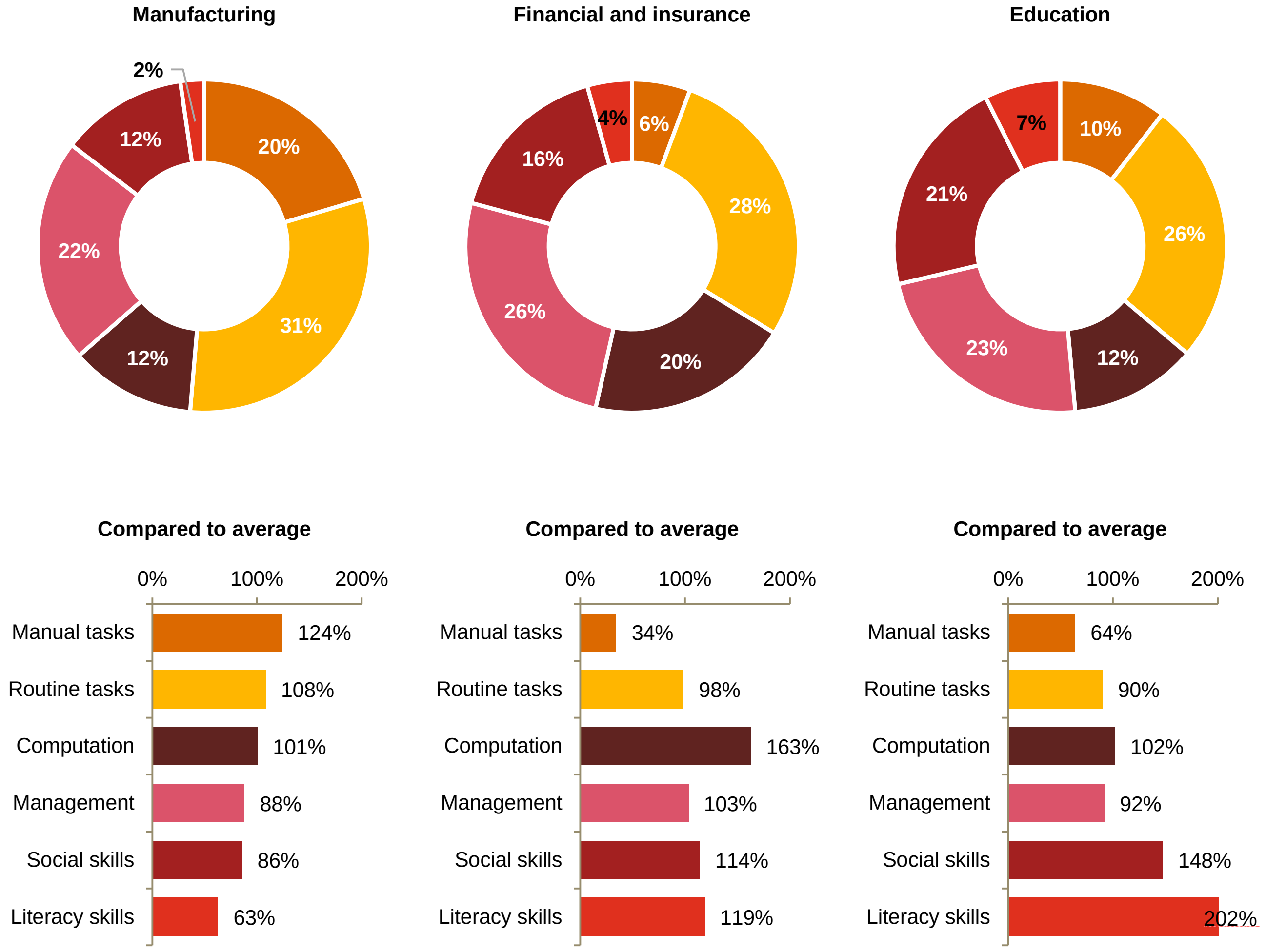



*Source: PIAAC data, PwC analysis*

## 4.3. Drivers of differences between industries

One of the main drivers of a sector being potentially more automatable is the composition of tasks involved in jobs in that sector. Workers in sectors such as manufacturing and transport and storage spend a larger proportion of their time engaged in manual tasks and in conducting simple administrative and routine tasks, as shown in the left hand pane of Figure 4.3 for manufacturing. In the long term these tasks are most likely to be automated by machines that are increasingly able to replace human labour, and carry out tasks at much higher speed and levels of accuracy and efficiency.

**Figure 4.3 – Task composition for manufacturing, financial and insurance, and education sectors.**




*Source: PIAAC data, PwC analysis*

However, as noted above, industries follow different paths of automation over time, and data-driven industries such as the financial and insurance sector (and others such as the 'information and communication' and the 'professional, scientific and technical' sectors) may be most automatable in the short term. Workers in these sectors typically spend a disproportionately larger amount of their time engaged in simple computational tasks (see middle panel of Figure 4.3 for finance/insurance).

In contrast, relatively low automatability sectors such as human health and social work, and education (see right hand panel in Figure 4.3) have more focus on social skills, empathy and creativity, which are more difficult to directly replace by a machine even allowing for potential technological advances over the next 10-20 years.

## 4.4. Which sectors are likely to see the largest jobs gains?

We mentioned above that our previous research suggests that, at the macroeconomic level, the job losses from automation are likely to be broadly offset by job gains arising from new technologies like AI and robotics. This will include some totally new jobs in areas relating specifically to these technologies, which will be relatively highly skilled and highly paid, but probably relatively small in number based on past experience[24].

However, the largest job gains will be in sectors where these new technologies boost demand, either directly or indirectly, through increasing income and wealth. As these additional incomes are spent on goods and services, so this will generate increased demand for labour. It is difficult to put precise numbers on what kind of jobs these will be, but we would anticipate them being concentrated in non-tradable service sectors such as health and education that a richer, and older, society is likely to demand more of, and which are less readily automatable according to our analysis. In the case of education, the increased demand with an ageing population and rapid technological change may not be from the young but rather from older people wanting to retrain for new careers later in life, or just to study for personal fulfilment in retirement. While some of this could be delivered digitally, there is still likely to be strong demand for human teachers, coaches and mentors to help guide people through this process (whether in person or online). As average incomes grow, there will also be increased demand for a range of other jobs providing personal services (e.g. cleaning, household chores and repairs, personal trainers and shoppers, and the digital platforms providing these services).

In addition, the government should benefit from increased tax revenues from the higher incomes and profits that these new technologies will generate. These additional tax revenues could fund higher public spending on health and education to support additional jobs in these areas, but could also be directed into increased investment in infrastructure, which would both support the supply side of the economy and create new jobs in construction and related sectors. While construction may well be more automatable than health or education by the 2030s, we would still expect there to do be considerable human employment in this sector on supervisory jobs and those that require multi-tasking and flexibility rather following set routines.

The public policy implications are discussed further in Section 7 below. Before that, however, we look in the next section at how different occupations may be affected by automation.

[24] *As discussed, for example, in Frey and Hawksworth (PwC, 2015)*

# 5. Which occupations could see the highest rates of automation?

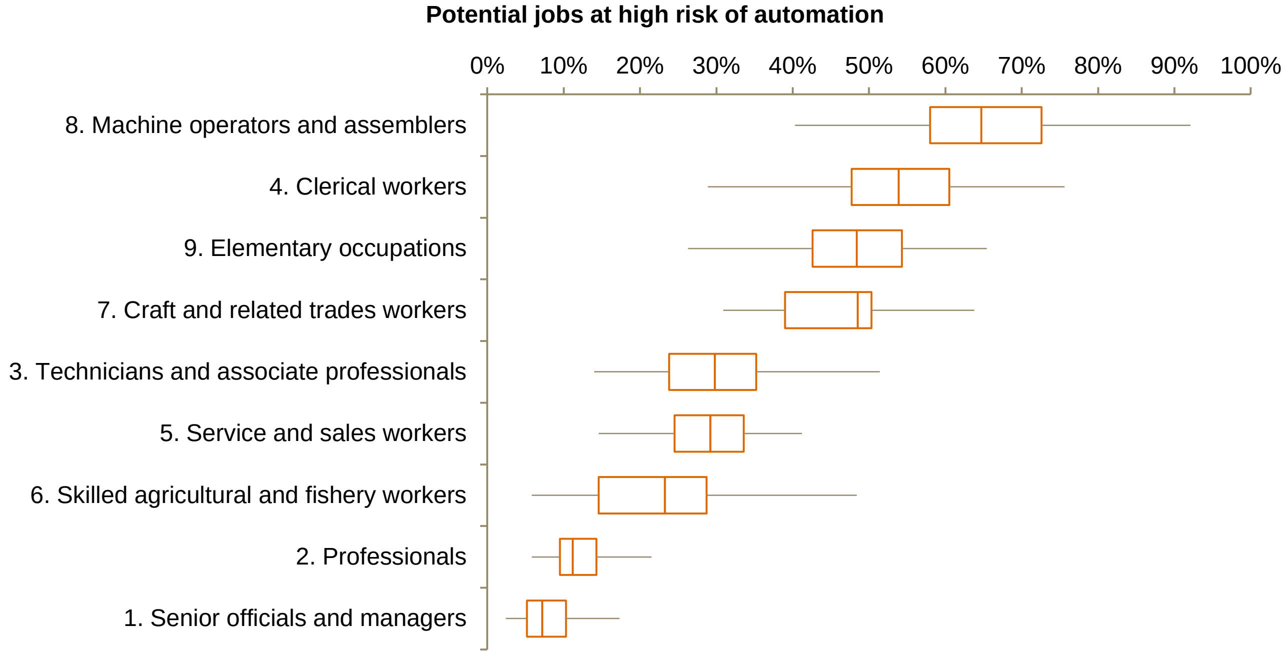
**Key findings**

- Potential automation rates vary widely by occupation – machine operators and assemblers could face a risk of over 60% by the 2030s, while professionals, senior officials and senior managers may face only around a 10% risk of automation. These variations stem from the different kinds of tasks performed in different occupations and their varied educational requirements.
- Workers in different occupations are likely to be impacted differently over time – technicians and clerical workers could be most heavily affected in the algorithmic and augmentation waves where machines overtake humans in firstly simple computational tasks and eventually routine, information processing tasks. However, in the longer run, machine operators and assemblers may be the most exposed to automation.
- Occupations typically vary more in their automatability than industries, which reflects the fact that they are typically more concentrated in their task composition than industries. However, a given occupation could see different automation rates in different industries and countries depending on factors such as the average education level of workers, and the practices of labour division and specialisation from country to country.

## 5.1. Total automation risk across occupation categories

In addition to the overall impact on industries, potential rates of automation also vary across occupational categories. For example, our estimates suggest a median long run automation rate of up to around 64% for machine operators and assemblers, as compared to a median rate of just 6% for senior officials and senior managers (see Figure 5.1). Machine operators and assemblers are most over-represented in the transportation and storage sector, accounting for on average 43% of the employment in that sector, followed by 20% for the manufacturing sector.

**Figure 5.1 – Share of jobs with potential high rates of automation by industry**

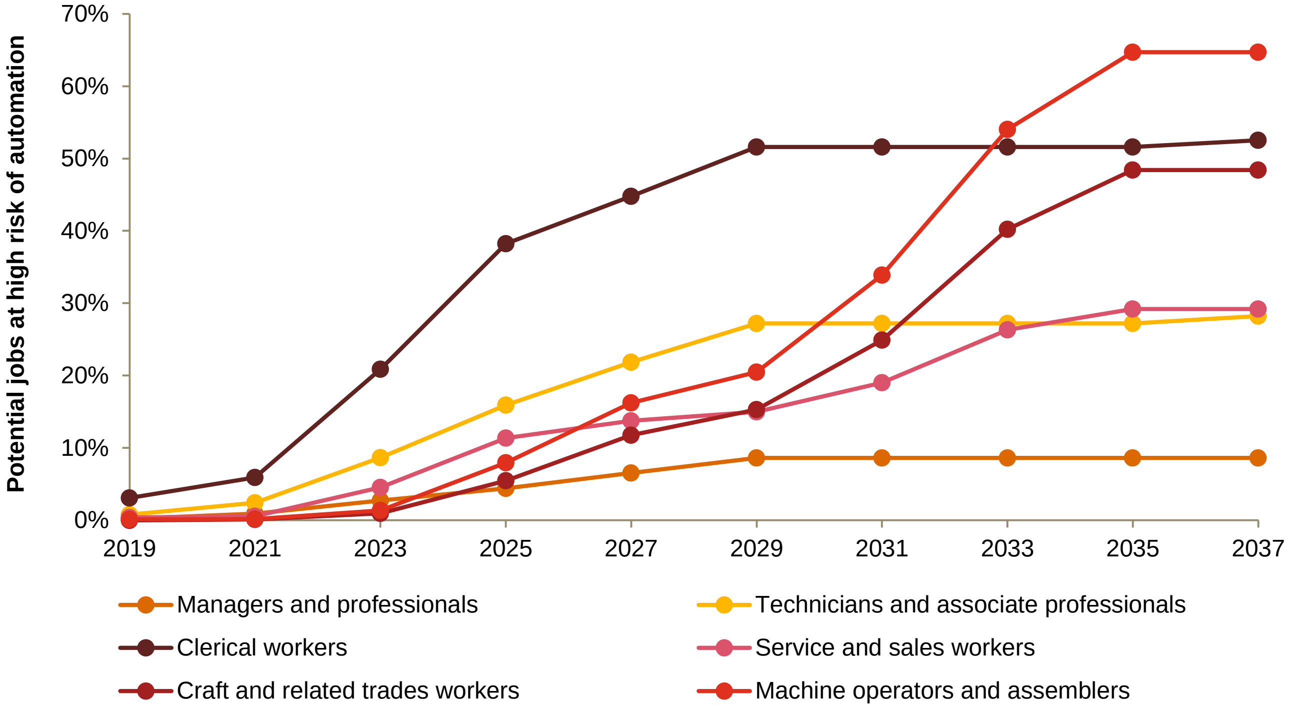



*Source: PIAAC data, PwC analysis*

## 5.2. Impact over time by occupation

The impact of the automation process shows notable differences between occupations over time (see Figure 5.2). In particular, clerical workers are estimated to face the highest potential impacts in the short to medium term. This includes: general and keyboard clerks, customer services clerks, numerical and material recording clerks, and other clerical support workers. The proportion of these clerical jobs at potential high risk of automation is estimated at 10% in the Algorithm wave, rising sharply to 49% in the Augmentation wave of the 2020s (but with only a slight further rise to 54% in the Autonomy wave of the 2030s, which would hit other occupations such as machine operators and assemblers more).

**Figure 5.2 – Potential impact of job automation over time across occupational categories**

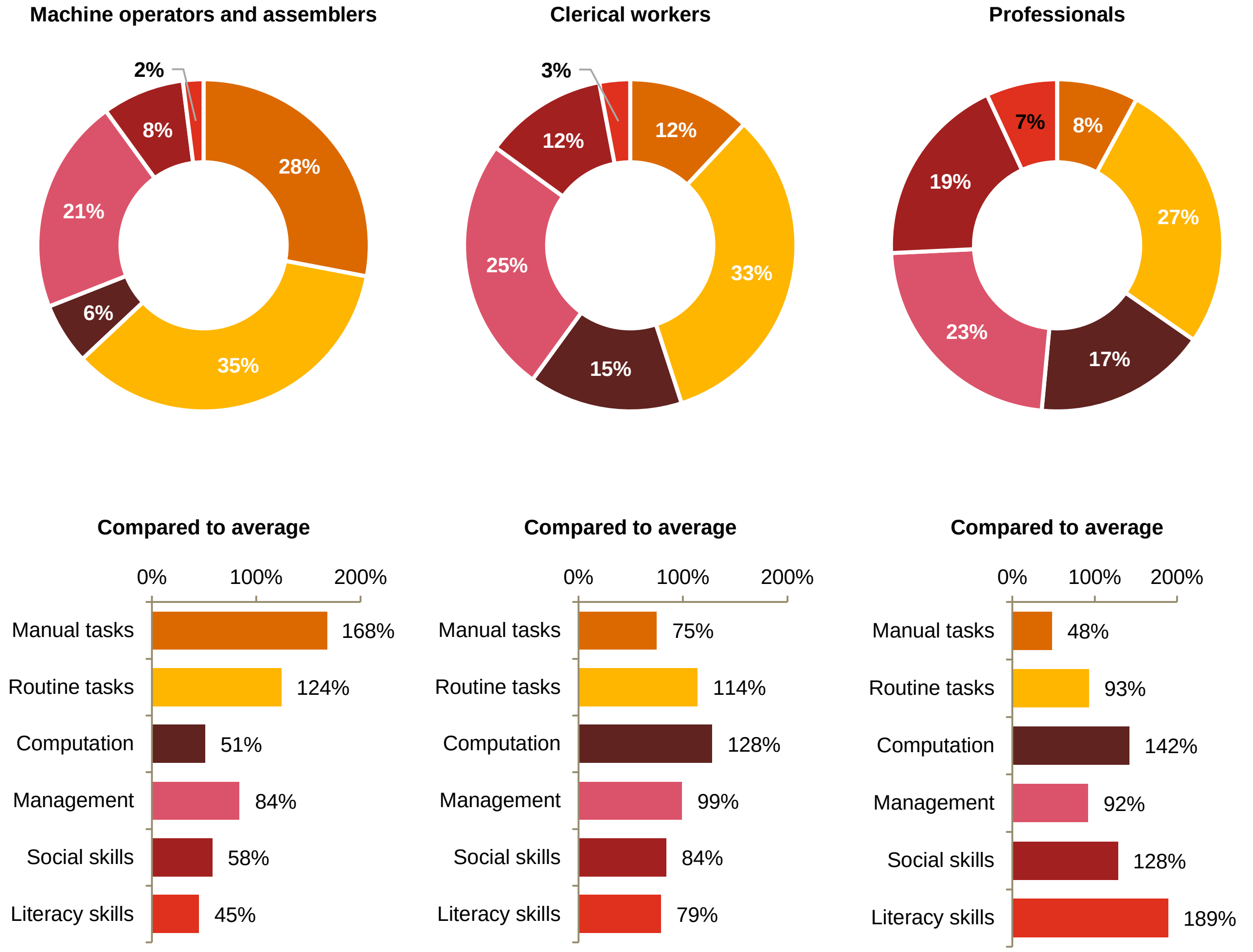



*Source: PIAAC data, PwC analysis*

## 5.3. Drivers of differences between occupations

The estimated differences in potential automation rates across occupational categories is much greater than across industries. For example, machine operators and assemblers have a long run estimated automation rate that is over 10 percentage points greater than the most automatable industry during the Autonomy wave (which is the transportation and storage sector). For these workers, the tasks conducted are primarily manual and routine tasks, which account for approximately two-thirds of their working activity (see left hand panel in Figure 5.3). This concentration of labour into this particular set of tasks makes their work more automatable.

**Figure 5.3 – Task composition for machine operators and assemblers, clerical workers and professionals**




*Source: PIAAC data, PwC analysis*

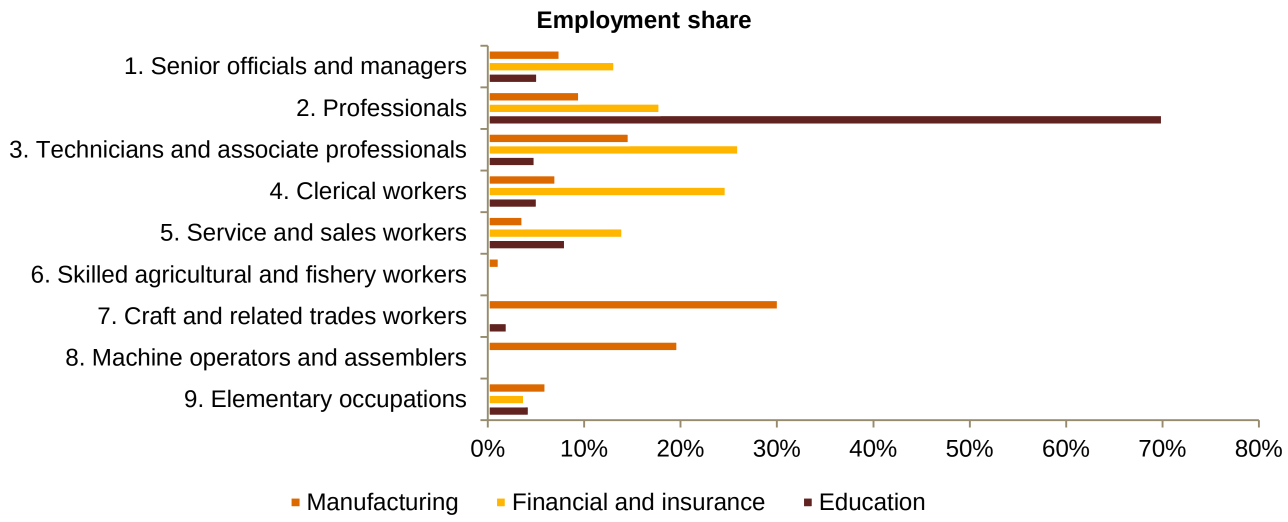
Clerical workers, likewise, could face much higher automation rates in the Algorithm and Augmentation waves than the most automatable industry in that period (the financial and insurance sector). These clerical workers inherently undertake work that is most characteristic of the Augmentation wave – routine processes, simpler computational tasks and exchanging information.

Professionals, as well as senior officials and senior managers, are estimated to be at the lowest risk of automation throughout the three waves. They are more likely to be engaged in social skills, literacy skills and more complex computational tasks that are less automatable (see right hand panel in Figure 5.3). They also tend to be relatively highly educated and this will help them to adapt to new waves of technology so as to remain complementary to machines, rather than being replaced by them. The nature of their work may change significantly over time (as it did previously with the advent of personal computers and later the internet), but they are less likely to find themselves displaced entirely by autonomous machines than a driver, factory worker or clerk.

## 5.4. Composition of industries by occupational category

The share of employment across occupations varies between industry sectors, which accounts for some of the variation in the overall estimated rate of automation by sector. For example, machine operators and assemblers typically account for around 20% of occupations in the manufacturing sector, but are negligible in both the financial and insurance and education sectors (see Figure 5.4). Instead, the financial and insurance sector is over-represented in clerical workers (25%) and associate professionals (26%), whereas education sector staff are primarily teaching professionals (70%).

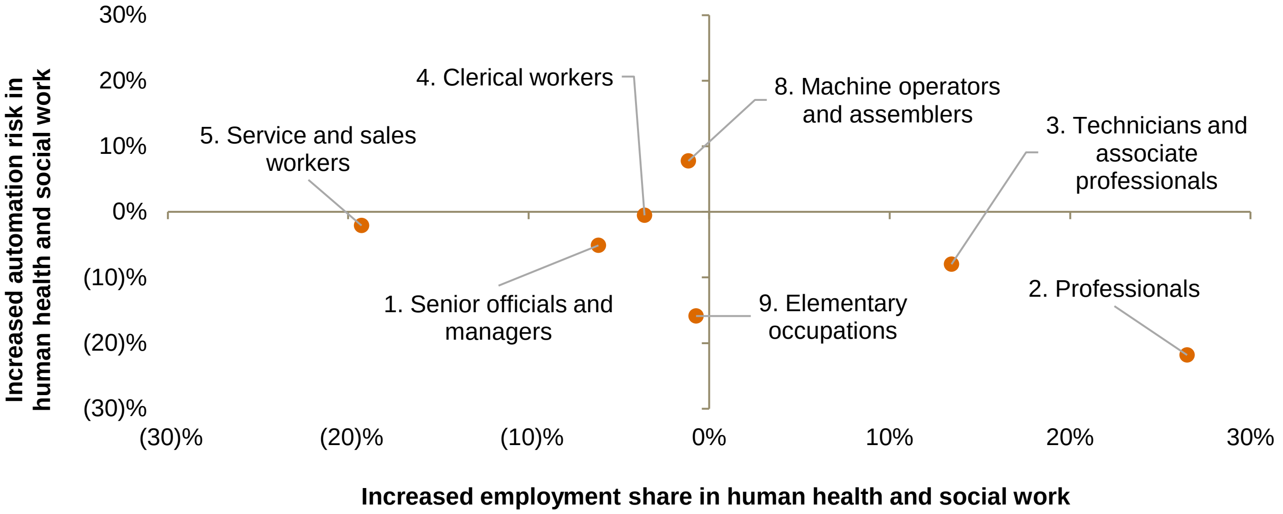
**Figure 5.4 – Employment share across occupations**




*Source: PIAAC data, PwC analysis*

However, not all occupations are the same across different industry sectors. For example, professionals and associate professionals are not only over-represented in the health and social work sector (31% and 24%) compared to the wholesale and retail trade sector (5% and 10%), but also have a significantly lower estimated risk of automation (Figure 5.5). In contrast, service and sales workers are over-represented in the wholesale and retail trade sector relative to the health sector (46% vs. 27%), but face a roughly equivalent risk of automation in the two sectors.

**Figure 5.5 – Potential impact of job automation by occupation: Human health and social work vs. wholesale and retail trade**




*Source: PIAAC data, PwC analysis*

These sectoral and occupational variations are driven by differences in ways of working such as the educational requirements of jobs and the characteristics of the workers employed. In the next section, we look in more detail at how different types of workers may be affected by automation.

# 6. Why does the potential rate of job automation vary by type of worker?

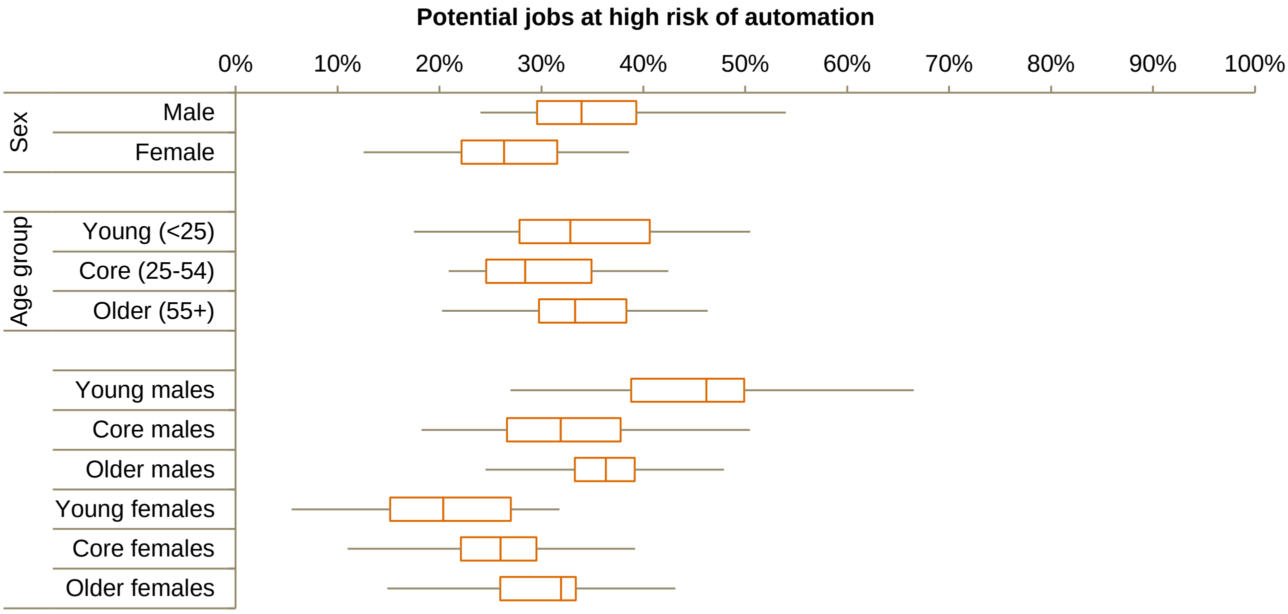
**Key findings**

- Potential automation risk varies significantly across different types of workers. Males may face a higher automation risk (34%) than females (26%) in the long run because they are more likely to be employed in manual-task-focused sectors such as manufacturing (13%) and transportation and storage (6%). In comparison, female employment in these sectors is relatively lower as women tend to be more concentrated in sectors such as education and health requiring more personal and social skills that tend to be less automatable.
- Automation risk is prevalent for all age groups, but the differences are less marked. Despite the risks facing some young workers, they are potentially well positioned to capitalise on the new opportunities from digital technologies if they can acquire relevant training. Similarly, older workers also need to equip themselves with a skillset that complements the digital workplaces of future.
- On average, males with low levels of education face the highest long term risk of automation of over 50%. For both genders and across all age groups, highly educated workers consistently have lower automation risks in the long run. This reflects the fact that their roles involve skills of supervision and intellectual reasoning that will still be needed alongside AI-based systems. Higher levels of education also allow workers flexibility to move around different occupations and industries and thus potentially escape automation risks.
- Different worker types are impacted differently over time by successive automation waves – highly educated women performing clerical tasks and highly educated men in analytical jobs could, for example, be relatively vulnerable in the short term. But, eventually, less educated men may face the highest risks as autonomous machines are deployed that are capable of independently performing manual tasks such as driving, as well as many factory and warehouse jobs that currently employ a higher proportion of men than women.

## 6.1. Total automation risk across workers

The estimated share of existing jobs at high risk of automation by the 2030s is greater for male workers, with a median automation rate estimate across countries of 34%, as compared to 26% for female workers (see Figure 6.1). This is primarily because male workers are typically over-represented in highly automatable sectors such as transportation and storage, manufacturing and construction, whereas female workers are typically over-represented in the health and social work and education sectors that have relatively low estimated future automation rates (see Figure 6.2).

**Figure 6.1 – Share of jobs with potential high rates of automation by gender and age group**

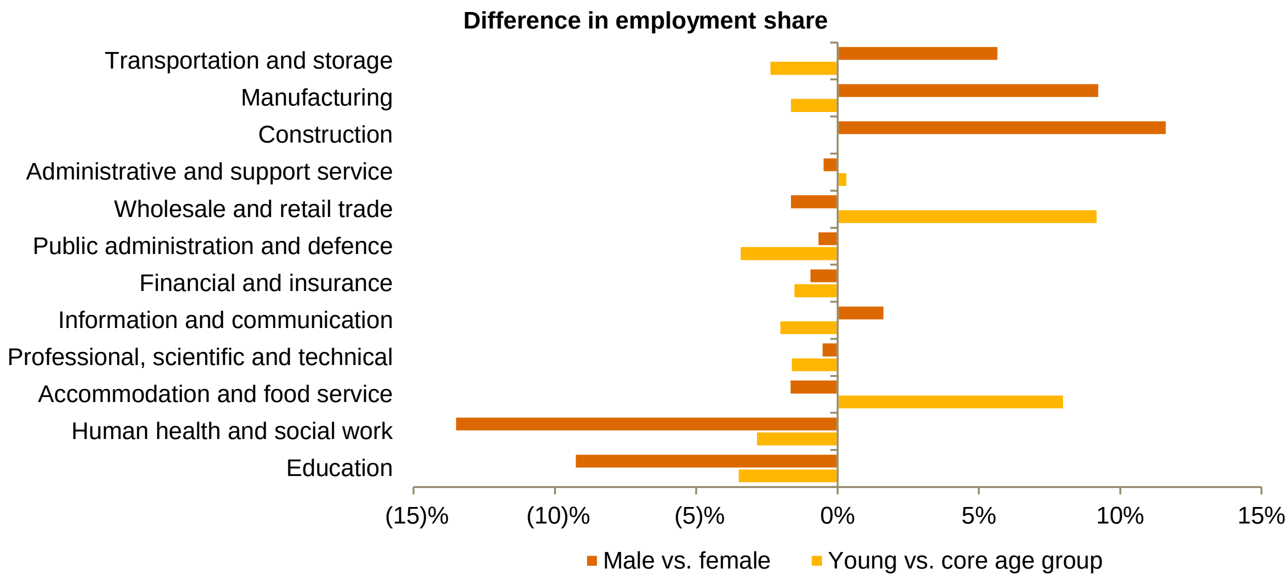



*Source: PIAAC data, PwC analysis*

Overall, as Figure 6.1 shows, there is not much difference in the potential rate of automation between age groups. There is, however, a notably greater potential rate of automation for young males (46%) than for young females (20%). For both males and females there is a greater representation of young workers (less than 25 years old) in the wholesale and retail trade, and accommodation and food service sectors, as shown in Figure 6.2. However, across industry sectors young males are broadly represented to the same extent as core and older males, and young females are broadly represented to the same extent as core and older females.

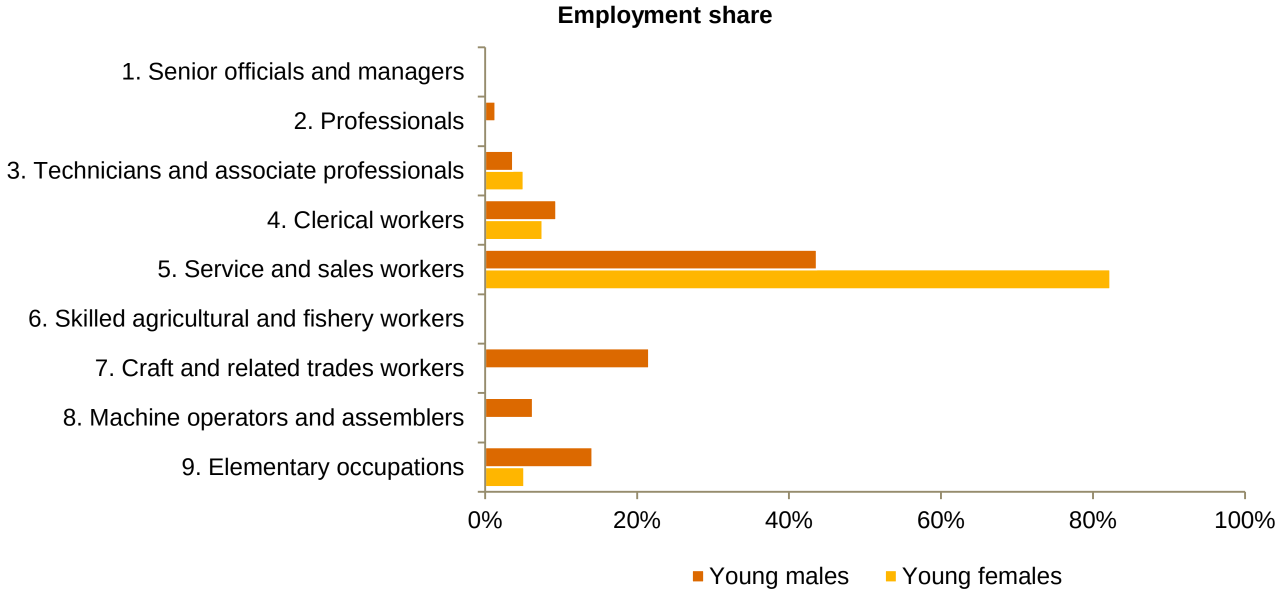
Instead it appears that young male and young female workers differ in the type of jobs they do within industries. For example, in the wholesale and retail trade sector, young males are more likely to be craft and related trades workers than young females (22% vs. ~0%), whereas young females are more likely to be service and sales workers (82% to 44%), as shown in Figure 6.3.

**Figure 6.2 – Difference in employment shares across industries by sex and age group**




*Source: PIAAC data, PwC analysis*

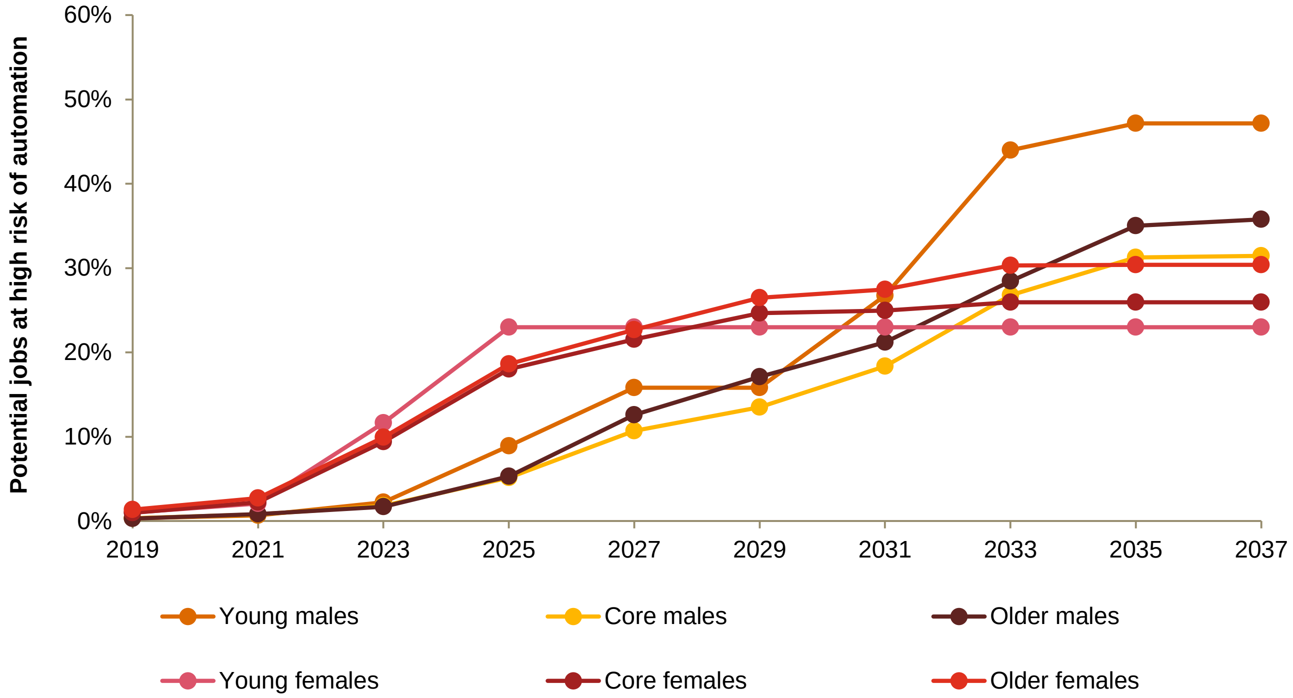
**Figure 6.3 –Employment shares across occupations in the wholesale and retail trade sector**




*Source: PIAAC data, PwC analysis*

However, across the waves, female workers of all ages could be impacted more heavily at first, with an increased potential rate of automation during the Algorithm and Augmentation waves (see Figure 6.4). This is primarily driven by a greater proportion of women employed as clerical workers across industries.

**Figure 6.4 – Potential impact of job automation over time across workers by age groups**

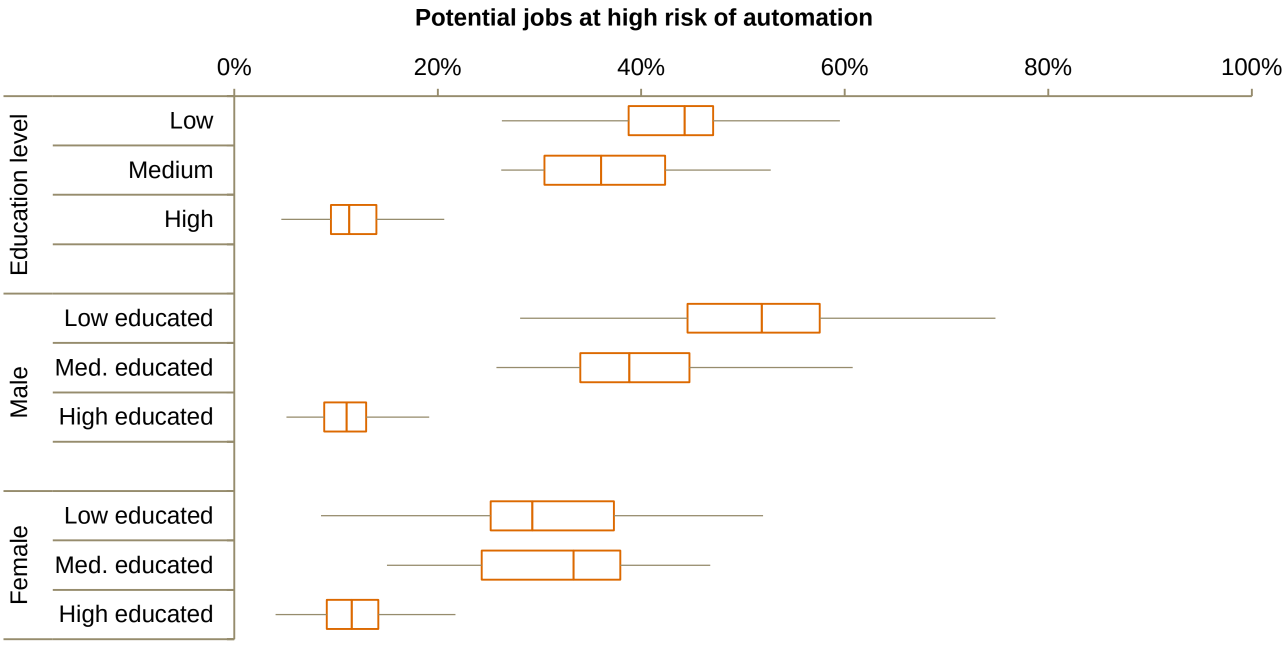



*Source: PIAAC data, PwC analysis*

## 6.2. Potential automation rates by education level

The greatest difference in the share of jobs with potential high rates of automation relates to the education levels of workers. Those with low levels of education (e.g. GCSE level equivalent or lower in the UK) and medium levels of education have notably higher estimated median automation rates across countries (44% and 36% respectively), compared to those with higher levels of education, such as university graduates (11%), as shown in Figure 6.5. Workers with high education levels are over-represented in the professional, scientific and technical, and education sectors (see Figure 6.6), which tend to be less automatable on average.

**Figure 6.5 – Share of jobs with potential high rates of automation by gender and education level**

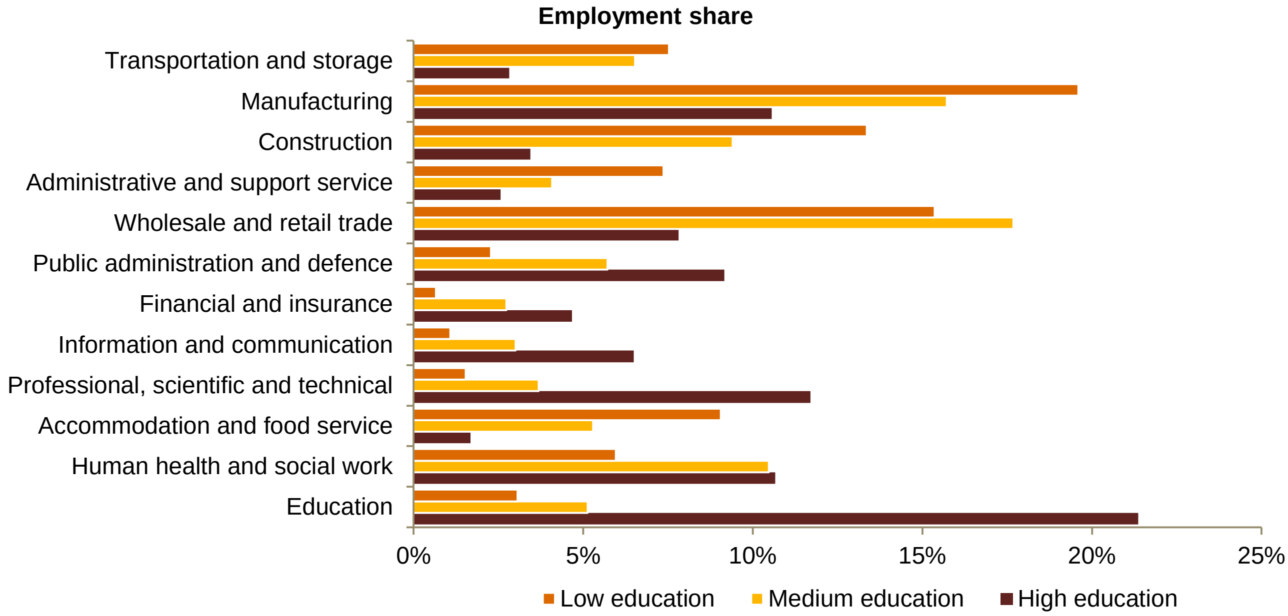



*Source: PIAAC data, PwC analysis*

Males and females with high education levels have similar estimated rates of automation in the long run (11% and 12% respectively). Highly educated male workers are more likely to be employed in the information and communications sector (males: 9% vs. females: 4%), whereas highly educated female workers are more likely to be employed in education (females: 29% vs. males: 14%).

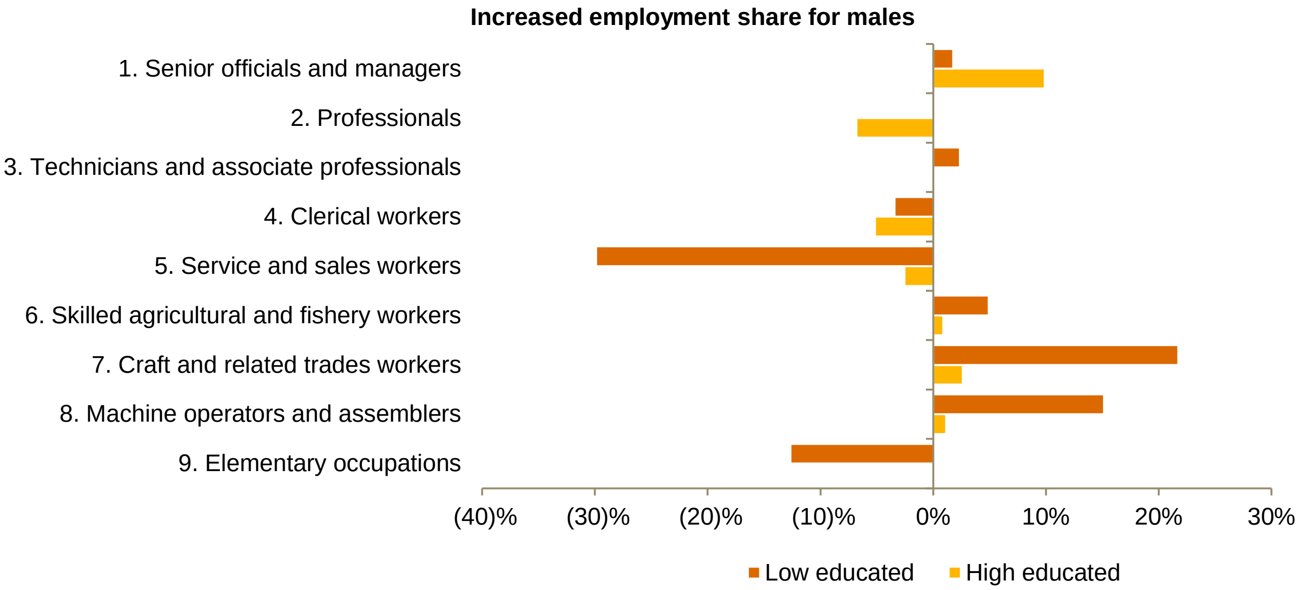
In contrast, for workers with only a low level of education there is a notable difference between males and females. Men with low education levels face an increased estimated risk of automation (52%) compared to low educated women (29%). The greatest difference is between the type of occupations, with low educated male workers over-represented as craft and related trades workers and machine operators and assemblers, whereas low educated female workers are over-represented as service and sales workers and in elementary occupations, such as cleaners and helpers (see Figure 6.6). Notably, male and female workers with high education levels also show a greater similarity in their employment shares across occupations.

**Figure 6.6 – Employment shares across industries for workers across education levels**




*Source: PIAAC data, PwC analysis*

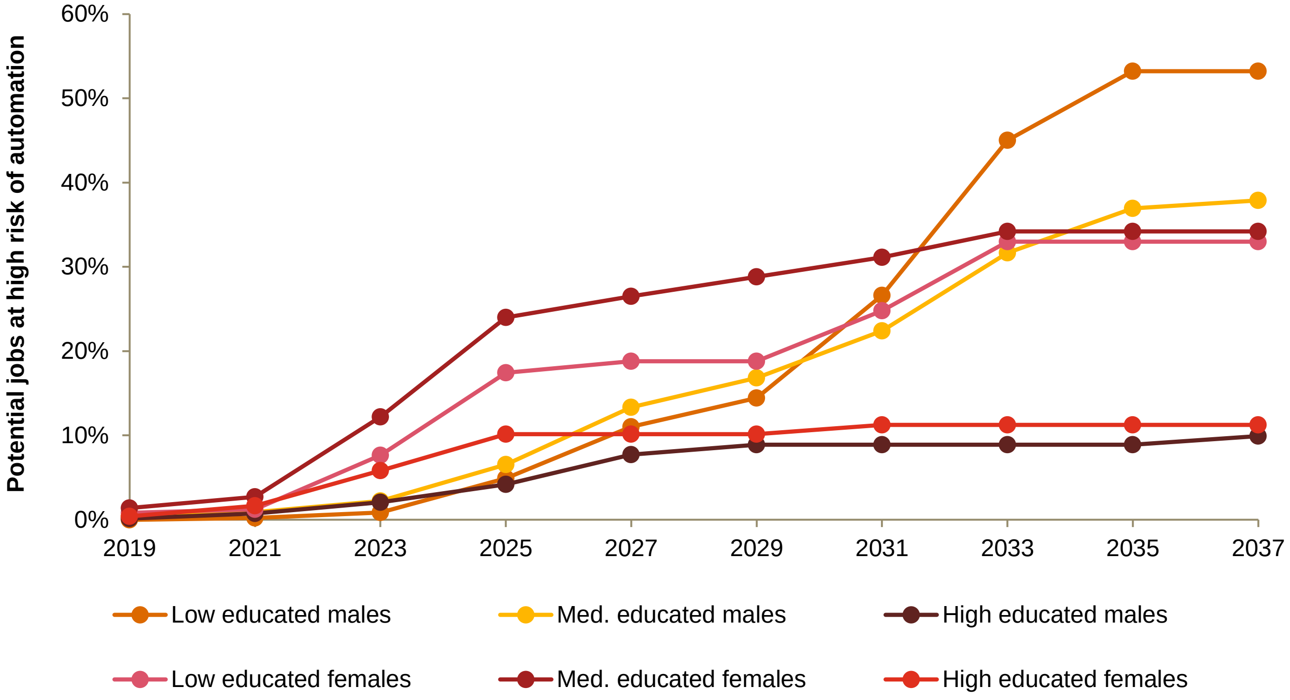
**Figure 6.7 – Difference in employment shares across occupations for males vs. females**




*Source: PIAAC data, PwC analysis*

Over time the education level of workers also plays a striking role, as Figure 6.8 shows. Low and medium educated male workers are least impacted in the Algorithm wave, as computational tasks typically forms a smaller proportion of their daily activity. However, by the end of Augmentation wave, the potential jobs at high risk of automation are comparable between male and female workers with either a low or medium education. In the final Autonomy wave, low educated males are expected to be at a much greater risk as manual and routine tasks (including driving) become more heavily automated across the economy.

**Figure 6.8 – Potential impact of job automation over time across workers by education level**




*Source: PIAAC data, PwC analysis*

The results described in this section are averages across all countries in our sample, and there are some variations by country as the detailed estimates in Table 6.1 show. However, the broad patterns seen by gender, age and education appear to be reasonably consistent across countries.

**Table 6.1. Share of jobs with potential high rates of automation by worker characteristics, across countries**

| Country | Sex | | Age group | | | Education level | | |
|---|---|---|---|---|---|---|---|---|
| | Female (%) | Male (%) | Young (%) | Core (%) | Older (%) | Low (%) | Medium (%) | High (%) |
| Slovakia | 39 | 48 | 47 | 42 | 46 | 54 | 53 | 18 |
| Slovenia | 35 | 49 | 50 | 41 | 45 | 63 | 47 | 13 |
| Lithuania | 30 | 55 | 50 | 40 | 43 | 57 | 50 | 21 |
| Czech Republic | 38 | 42 | 40 | 38 | 45 | 51 | 47 | 11 |
| Italy | 32 | 44 | 42 | 39 | 39 | 45 | 43 | 16 |
| USA | 37 | 39 | 39 | 37 | 40 | 47 | 46 | 21 |
| France | 32 | 41 | 42 | 35 | 40 | 51 | 41 | 14 |
| Germany | 34 | 39 | 44 | 35 | 36 | 48 | 43 | 10 |
| Austria | 32 | 37 | 41 | 32 | 36 | 46 | 36 | 21 |
| Spain | 28 | 39 | 33 | 34 | 32 | 44 | 39 | 14 |
| Poland | 24 | 39 | 35 | 30 | 38 | 49 | 42 | 14 |
| Turkey | 19 | 36 | 41 | 30 | 35 | 38 | 35 | 7 |
| Ireland | 27 | 35 | 30 | 31 | 33 | 38 | 39 | 11 |
| Netherlands | 28 | 33 | 34 | 28 | 34 | 47 | 36 | 10 |
| UK | 26 | 34 | 32 | 28 | 36 | 47 | 35 | 12 |
| Cyprus | 27 | 33 | 28 | 30 | 32 | 38 | 38 | 12 |

| Country | Sex | | Age group | | | Education level | | |
|---|---|---|---|---|---|---|---|---|
| | Female (%) | Male (%) | Young (%) | Core (%) | Older (%) | Low (%) | Medium (%) | High (%) |
| **Belgium** | 23 | 36 | 39 | 27 | 33 | 45 | 33 | 10 |
| **Denmark** | 26 | 33 | 26 | 27 | 36 | 41 | 33 | 10 |
| **Israel** | 26 | 31 | 35 | 26 | 31 | 44 | 36 | 13 |
| **Chile** | 21 | 32 | 28 | 27 | 29 | 35 | 29 | 5 |
| **Singapore** | 28 | 24 | 24 | 23 | 33 | 46 | 30 | 10 |
| **Norway** | 22 | 28 | 26 | 22 | 31 | 40 | 31 | 9 |
| **Sweden** | 20 | 30 | 25 | 22 | 30 | 40 | 28 | 7 |
| **New Zealand** | 23 | 25 | 31 | 22 | 26 | 39 | 29 | 11 |
| **Japan** | 22 | 25 | 30 | 25 | 21 | 31 | 28 | 12 |
| **Russia** | 13 | 33 | 21 | 22 | 28 | 39 | 31 | 11 |
| **Greece** | 18 | 27 | 19 | 25 | 20 | 24 | 30 | 10 |
| **Finland** | 16 | 29 | 17 | 21 | 26 | 39 | 27 | 6 |
| **South Korea** | 18 | 24 | 30 | 21 | 20 | 24 | 26 | 9 |

*Source: PIAAC data, PwC analysis*

The fact that potential automation rates vary widely across different types of workers immediately raises the prospect that, even if new technologies like AI and robotics are good for the economy as a whole, there could be important distributional effects. This in turn raises issues for public policy, as discussed in the next section of this report.

# 7. What are the public policy implications?

Major new technologies always raise important public policy issues and the same is true for AI and robotics. It is beyond the scope of this report to consider all of these in detail, but we provide an overview here of three key areas:

- **Boosting education and skills levels** to help people of all ages to adjust to new technologies;
- **Supporting job creation through government investment** that can also help to lever in private investment, notably in areas like infrastructure and housing; and
- **Enhancing social safety nets** to support those who may find it difficult to adjust to new technologies.

## 7.1. Education and skills

Our analysis above has highlighted the key role of education as a driver of potential automation risk. More educated and skilled workers will, on average, be better able to adjust to new technologies and benefit from the higher real wages these will bring by boosting productivity. Less well educated workers will generally bear more of the costs of automation, potentially widening further existing income and wealth inequalities. Increasing their adaptability and skills will be critical to enabling these groups to share in the gains from new technologies and work more effectively with them[25].

Government, working with employers and education providers, should therefore invest more in the types of education and training that will be most useful to people in this increasingly automated world. Exactly how to identify the skills that will be required and develop the training is much more complex of course – for many people, this will involve an increased focus on vocational training[26] that is constantly updated over their working lives to stay one step ahead of the robots. It will also require more focus on STEM subjects (science, technology, engineering and mathematics) where countries like the US and the UK tend to lag behind leading nations such as South Korea, Japan, Singapore and indeed India and China to an increasing degree.

There also needs to be better matching of workers to the new opportunities that will arise in an increasingly digital economy. This will require effective programmes of retraining for older workers as well as help with job search. Of course, workers also need to take personal responsibility for their lifelong learning and career development, but governments and businesses need to support them in achieving these goals.

## 7.2. Job creation through increased public and private investment

Additional investment in education and skills will only be fully effective, however, if there are jobs available for people to do. This will require running the economy at a sufficient level of aggregate demand to maintain high employment levels.

Governments can help with this by investing more in areas like housing and infrastructure that are beneficial to the longer term productivity of the economy, but will also help to create jobs that cannot be fully automated. The exact nature of the desirable investment will vary from country to country – in the UK, for example, a severe shortage of housing supply would suggest that housebuilding would be one priority, as the government has recognised. Improvements in transport infrastructure are also much needed in the UK, but also in countries such as the US and across much of Europe. In emerging economies, construction of power plants and extension of communications networks may also be priorities. Governments may not be able to fund all of these projects,

[25] *For more on these issues, see this recent PwC report on human value in the digital age: https://www.pwc.nl/en/publicaties/human-value-in-the-digital-age.html.*

[26] *An area where the UK lags well behind countries like Germany as highlighted in our 2017 Young Workers Index report, which is available here: http://www.pwc.co.uk/services/economics-policy/insights/young-workers-index.html.*

but they can help to lever in private funds through providing some government funding and/or government guarantees for private sector borrowing.

Central and local government bodies also need to support digital sectors that can generate new jobs, for example through place-based strategies[27] focused on university research centres, science parks and other enablers of business growth. This place-based approach is, for example, one of the key themes in the UK government's new industrial strategy[28] and its wider devolution agenda. It also involves extending the latest digital infrastructure beyond the major urban centres to facilitate small digital start-ups in other parts of the country. Similar approaches are likely to be appropriate in other advanced economies, though the details will vary across countries.

## *7.3. Enhancing social safety nets*

To the extent that new technologies boost productivity, income and wealth, they should also boost tax revenues[29]. As well as being invested in education, skills and infrastructure as described above, there could also be a case for spending more on stronger social safety nets for those not able to easily adapt to new automation technologies.

This could be done by extending existing social security benefits, but more radical solutions include the idea of a universal basic income (UBI). This is an old idea[30], but it has gained traction in Silicon Valley and elsewhere in recent years as a potential way to maintain the incomes of those who lose out from automation and (to be hard headed about it) whose consumption is important to keep the economy going. The problem with UBI schemes, however, is that they involve paying a lot of public money to many people who do not need it, as well as those that do. As such the danger is that such schemes are either unaffordable or destroy incentives to work and generate wealth, or they need to be set too low to provide an effective safety net.

Nonetheless, we are now seeing practical trials of UBI schemes in a number of countries around the world including Finland, the Netherlands, some US and Canadian states, India and Brazil. The details of these schemes vary considerably, and it is beyond the scope of this report to review them in depth, but it seems likely that more pilot schemes of this kind will emerge around the world and that they will come on to the policy agenda in countries such as the UK as well. While UBI in its pure form may not be politically or economically attractive, some variants on it might be if they involve a greater degree of conditionality (e.g. requiring some form of paid or voluntary work, education and training, family caring responsibilities or similar activities to qualify for payments). Some aspects of the idea, such as providing a universal lifelong learning fund for each person that they could draw down when they needed it, might also be worth considering further even if a full UBI scheme is rejected.

For the moment, the first priority may be to gather an evidence base on the different options through pilot schemes, detailed financial modelling and other studies. The optimal solutions will also vary by country depending on local political, economic and social circumstances. But the broader question of how to deal with possible widening income gaps arising in part from increased automation seems unlikely to go away.

[27] *For more on place-based strategies in the UK context, see also our 2017 Good Growth for Cities report: https://www.pwc.co.uk/industries/government-public-sector/good-growth.html.*

[28] *https://www.gov.uk/government/topical-events/the-uks-industrial-strategy.*

[29] *Another idea here is the suggestion of Bill Gates to tax robots where these displace human labour. However, it is not clear that such a specific tax on investment in robots would be economically efficient. Other labour-saving technologies do not face such specific taxes, so why single robots out for such treatment and potentially lose productivity gains from such innovation and investment?*

[30] *For more details on the history of the UBI idea and its pros and cons see Guy Standing, Basic Income: And How We Can Make It Happen (Pelican Introductions, 2017).*

# 8. Implications for business: constraints, opportunities and responsibilities

Much of this report has focused on the potential impacts of automation for existing jobs, but we should not forget the huge potential benefits that technologies like AI and robotics can offer to the economy and to business. In an earlier study, we estimated that additional investment in these technologies, over and above current baseline levels, could contribute as much as 14% to global GDP by 2030 (or around 10% to UK GDP)[31].

From a business perspective, another recent PwC survey[32] found that 52% of CEOs worldwide are already exploring the benefits of machines and humans working together. Automation opens up a range of opportunities for businesses. Directly, this includes the ability to collect, store and analyse data at a scale and speed that will allow firms to drive cost efficiencies and improve the quantity and quality of their products. Indirectly, businesses across the economy could benefit from increases in demand created by higher productivity growth and the positive spill-over effects of industry wide digitisation.

## 8.1. What constraints will need to be overcome to realise benefits for business?

Of course, these gains will not come automatically or easily. There will be a variety of technological, economic, legal and regulatory, and social constraints to be overcome to realise such benefits. For example:

- **Technological constraints:** For any benefits from automation to materialise, it first has to be technically feasible to adopt the technology in practice. This goes beyond just developing the technology in a lab. It has to be integrated and adapted into solutions before it can be deployed in a real world business situation. Different countries have different rates of technological advancement and thus will have different speeds of automation. For instance, some developing countries may not have the basic communications infrastructure needed to implement new technologies[33]. On the other hand, some businesses in advanced economies may have legacy systems that are well developed, but do not mesh easily with new techniques like AI.
- **Economic constraints:** Technology must have a business case for being adopted. In many companies, the upfront cost of advanced automation technologies such as AI and robotics may make this a significantly higher risk option than just expanding by using additional labour, particularly where this is relatively flexible and/or low cost. Over time, the relative cost of AI and robotics should come down as with other digital technologies in the past, perhaps at a significant rate, but the exact timetable for this is not clear.
- **Legal and regulatory constraints:** Data is fundamental to the functioning of AI. Businesses wishing to adopt AI and related technologies will therefore need to deal with a range of data regulation issues such as protection of individual data rights and privacy, incomplete data collection leading to learning mishaps, and misuse of data sharing platforms. Machine optimisation rules also need to be regulated to prevent biases in the insights that are generated using data. Besides tech firms involved in developing AI, there may also be a need to rethink the existing regulatory structures in other industries involved in deploying AI. For instance, in the case of driverless cars, regulations on accident liabilities will need to be rethought and potentially redesigned to determine who among the human vehicle owner/driver, the car manufacturer, the provider of software, or some other supplier should bear or share responsibility for any accidents.

---

*[31] PwC, 'Sizing the prize' (2017): https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html*
*[32] PwC Global CEO survey (2018): https://www.pwc.com/gx/en/ceo-agenda/ceosurvey/2017/gx/talent.html*
*[33] Although some emerging economies, notably China, may be ahead of many high income countries in their mobile telecommunications and digital infrastructure due in part to having installed this more recently.*

- **Social constraints:** Individuals may not be willing to have robots or other smart machines replace humans for all of their day-to-day interactions, especially for risky fields such as health provision or driving. Societal concerns can be raised with regards to the potential rise in inequality as a result of automation as tech companies and highly educated workers gain at the expense of other workers. Acceptance of AI by society will occur when people are convinced of its advantages over humans in particular applications and history suggests that this can be a long process.

Eventually, we can expect that all or most of these issues will be resolved, as with past waves of new technology since the Industrial Revolution. But the timing of this is uncertain and will vary from country to country and case to case. This means that actual job displacement of workers by automation may not reach the potential levels indicated by our analysis, but also that the economic and business benefits of AI and robotics may take longer to come through than hoped. In the long run, we would expect a significant proportion of these benefits to be realised given the potential power of these technologies, but it is unlikely to be a smooth or easy process.

In the remainder of this section we look at some of the potential benefits of automation in relation to company supply chains and also discuss potential applications to healthcare as a specific example where public attitudes will be important to the speed of uptake of AI and robotics. Finally, we consider what business needs to do to help its workforce adapt to these technologies and, more generally, to adopt a responsible approach to AI.

## *8.2. AI's impact on company value chains*

Analysis in our 2017 Sizing the Prize report showed that firm productivity – how much a company can produce using a given level of inputs – could be significantly boosted by AI technologies in many different ways. There are applications for AI across the whole value chain. These will often take the form of software, systems and machines that augment or assist the workforce and, in the process, make them more efficient and allow them to concentrate on higher value activities. But, in some cases, such technology could eventually replace some or all human workers altogether (although there will often be an intermediate stage first where humans work alongside machines – and in some cases this may be better than either working alone[34])

Table 8.1 below outlines the impact that AI can have at each stage of a firm's value chain and illustrates specific examples across various industry sectors.

**Table 8.1 – Applications and the impact of AI on productivity along the value chain**

| Value chain element | Impact of AI | Examples |
|---|---|---|
| **Strategy, business model, products and services**<br>The 'brains' of a company's operations, decision making about offerings, pricing and go-to-market strategy. | Reduces the risk, time and capital expended in the process of moving from strategy to execution. | • Simulating market conditions for production forecasts and pricing strategy.<br>• Creating digital mock-ups of product features based on historically successful features/user preferences. |
| **R&D and innovation**<br>Discovery of new information and trends. | Reducing the runway required before insights are generated. | • Drug repositioning – scanning scientific and clinical research data to identify other uses for drugs already approved. |
| **Purchasing and production**<br>Sourcing raw materials and manufacturing. | More output or better quality output using fewer resources. | • Robotics automating assembly lines.<br>• On-demand manufacturing: adjusting to produce goods based on order specifics or turning on/off autonomously. |

[34] *As discussed further, for example, in a recent PwC report on human value in a digital age: https://www.pwc.nl/en/publicaties/human-value-in-the-digital-age.html.*

| Value chain element | Impact of AI | Examples |
|---|---|---|
| **Supply chain and logistics**<br>Getting production resources from A to B and getting the final product to the customer. | Reducing the time and resources required in these processes. | • Auto-ordering raw materials based on sales patterns and known lead/production times.<br>• Routing emergency vehicles to hospitals based on case criticality, staffing, expertise, traffic and patient load. |
| **Marketing, sales and customer service**<br>Increasing customer engagement and conversion of customers. | Reducing the information asymmetry between producer and consumer and tailoring messaging accordingly. | • Personalised recommendations of products and services.<br>• AI chatbot customer service agents.<br>• Call centre sales practice monitoring. |
| **Enabling functions (finance, IT, risk)**<br>Back-office supporting activities. | Reducing costs and reducing risks including with better planning and forecasting. | • Adverse event monitoring in pharmaceuticals (trends in doctor visits, social media reporting etc.). |

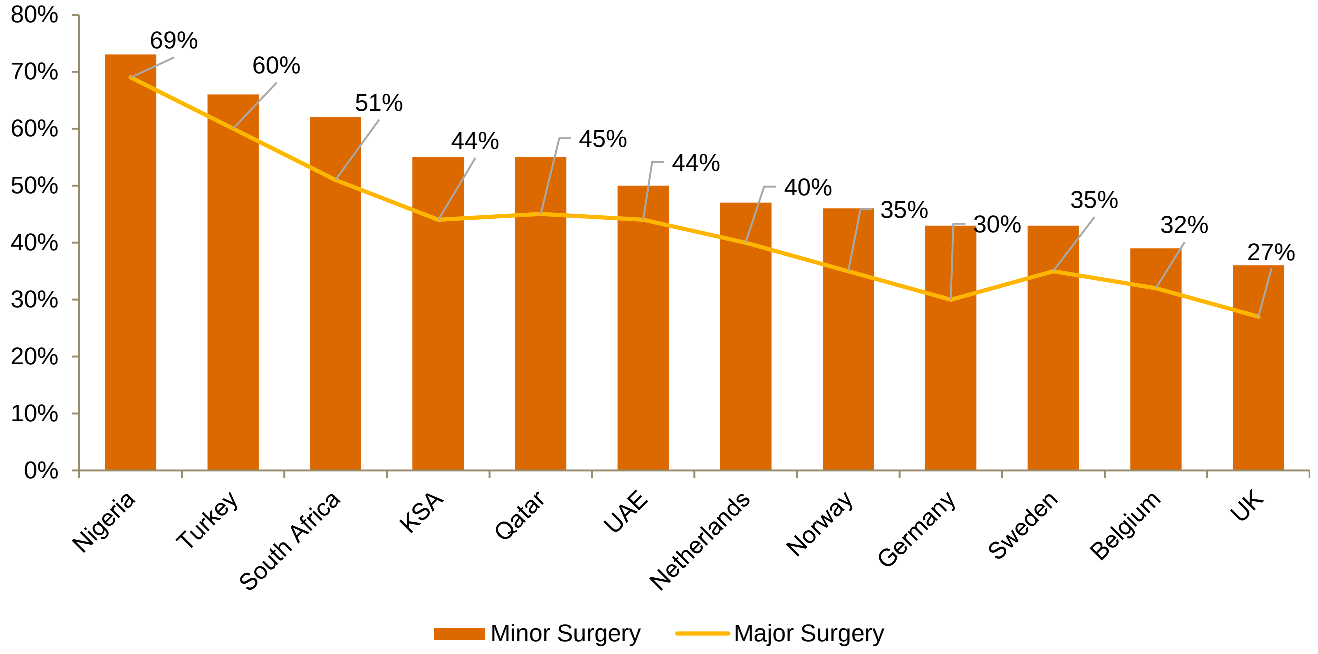
*Source: PwC analysis in 'Sizing the Prize' report on AI (June 2017)*

## 8.3. AI and healthcare provision

Besides their impact on purely commercial activities, PwC's previous analysis shows the opportunities that exist for AI in public services such as health and social care provision. Robotics and AI will help to increase the focus on preventative care and aim to transform every aspect of the medical ecosystem, including but not limited to early detection, diagnosis, decision making, treatment and end of life care.

In a recent international poll of 12,000 people commissioned by PwC[35], the majority of respondents in countries such as Turkey, Nigeria and South Africa were willing to embrace AI and robots as part of their health care and even surgery, although the numbers were lower in the UK (see Figure 8.1).

**Figure 8.1 – Willingness to have surgery performed by robots**




[35] *https://www.pwc.com/gx/en/industries/healthcare/publications/ai-robotics-new-health.html.*

As we discussed in Section 4 above, this does not mean that doctors, nurses and other workers will disappear from the health service. With ageing populations across most advanced economies, demand for health and social care services will only continue to increase over the coming decades. This is likely to require both more human workers and greater use of AI, robotics and other advanced technologies to complement and boost the productivity of these human workers. Countries like Japan with relatively rapidly ageing populations are already leading the way here in their healthcare sectors.

## *8.4. Businesses need to help workers retrain and adapt to new technologies*

Businesses should also seek to use AI and robotics in a responsible way[36]. This includes encouraging continued innovation and research, but at the same time developing policies that protect customer data and help workers and institutions adapt to the new demands posed by these technologies. This will include reconfiguring training programs to help workers acquire both the digital and softer skills which will be demanded in the new age, replacing legacy processes and systems with those that are more suited to handle newer technologies, and also temporary support for those that lose out from the impact of automation. As discussed in the previous section, this has to be coupled with nationwide policies by the government to ease the transition process for workers displaced by automation.

## *8.5. Conclusion*

This section has illustrated some of the potential benefits of AI and related technologies for business and society more generally, but also some of the constraints that need to be overcome and the responsibilities this involves for business.

As we have argued in past sections of this report, AI and robotics will be disruptive for labour markets and some jobs will be displaced or fundamentally changed in nature. But many new jobs will also be created and the long term net effect should be positive for the economy as a whole. Business and government need to work together to help people through the transition to this brighter future and ensure that as many people as possible share in the benefits from these new technologies.

[36] *See our Responsible AI website for more details: https://www.pwc.co.uk/services/audit-assurance/risk-assurance/services/technology-risk/technology-risk-insights/accelerating-innovation-through-responsible-ai.html*

# Annex – technical methodology

The methodology used in this study builds on previous research by Frey and Osborne (2013)[37], Arntz, Gregory and Zierahn (2016)[38] and our previous research on this topic in PwC's UK Economic Outlook (March 2017)[39].

In the original study by Frey and Osborne (hereafter 'FO') a sample of occupations taken from O*NET, an online service developed for the US Department of Labor, were hand-labelled by machine learning experts at Oxford University as strictly automatable or not automatable. Using a standardised set of features of an occupation, FO were then able to use a machine learning algorithm to generate a 'probability of computerisation' across US jobs, but crucially they generated only one prediction per occupation.

Using the same outputs from the FO study, Arntz, Gregory and Zierahn (hereafter 'AGZ') conducted their analyses on the OECD Programme for the International Assessment of Adult Competencies ('PIAAC') database, which includes more detailed data on the characteristics of both particular jobs and the individuals doing them than was available to FO. This allows a critical distinction that it is not whole occupations that will be replaced by computers, algorithms and robots, but only particular tasks that are conducted as part of that occupation. Furthermore, this allows for the fact that the same occupation may be more or less susceptible to automation in different workplaces.

The PwC automation rate algorithm developed in our earlier study (PwC, March 2017) involved first taking the labels from the FO study and replicating the methodology from the AGZ study using the PIAAC dataset. The methodology was then enhanced using additional data and a refined automation-rate prediction algorithm. This model was initially trained on PIAAC data for the UK, US, Germany and Japan, but then extended to over 200,000 workers across 29 countries in the present study. This much larger sample size gives increased confidence in our estimates of the relative automatability of jobs in different industry sectors and across different types of workers (e.g. by age, gender or education level).

As a further extension in the present study, the initial set of labels, seeded from the study by FO, were simulated across a range of scenarios that varied the automation-rate estimates associated with both tasks and occupations. Feedback from computable general equilibrium (CGE) modelling of the economic impact of AI[40] then allowed predictions for the potential jobs at high risk of automation to vary over a projected timeframe from 2018-2037. This formed the basis for the analysis of automation waves over time in the present study. However, it should be emphasised that this is only intended to give a broad indication of how automation might roll out across economies over time; our results should not be interpreted as precise point estimates for particular future years.

[37] *Frey, C.B. and M.A. Osborne (2013), The Future of Employment: How Susceptible are Jobs to Computerization?, University of Oxford.*

[38] *Arntz, M. T. Gregory and U. Zierahn (2016), 'The risk of automation for jobs in OECD countries: a comparative analysis', OECD Social, Employment and Migration Working Papers No 189.*

[39] *'Will robots steal our jobs?' PwC UK Economic Outlook, March 2017, available here: https://www.pwc.co.uk/economic-services/ukeo/pwcukeo-section-4-automation-march-2017-v2.pdf.*

[40] *PwC (2017), Sizing the Prize: What's the real value of AI for your business and how can you capitalise? Available here: https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf.*

# References


Acemoglu, D. and P. Restrepo (2016), 'The race between machine and man: implications of technology for growth, factor shares and employment', NBER Working Paper no. 22252.

Acemoglu, D. and P. Restrepo (2017), 'Robots and jobs: evidence from US labour markets', NBER Working Paper no. 23285.

Arntz, M. T. Gregory and U. Zierahn (2016), 'The risk of automation for jobs in OECD countries: a comparative analysis', OECD Social, Employment and Migration Working Papers No 189.

Autor, D. H. (2015), 'Why are there still so many jobs? The history and future of workplace automation', *Journal of Economic Perspectives, 29(3), pp.3-30*.

Chace, C (2016), *The Economic Singularity*: Artificial intelligence and the death of capitalism, The Three Cs.

Ford, M. (2015), *The Rise of the Robots*, Oneworld Publications.

Frey, C.B. and M.A. Osborne (2013), 'The Future of Employment: How Susceptible are Jobs to Computerisation?' University of Oxford.

Frey, C.B. and J. Hawksworth (2015), 'New job creation in the UK: which regions will gain the most from the digital revolution?', *PwC UK Economic Outlook*, March 2015. Available from: http://www.pwc.co.uk/assets/pdf/ukeo-regional-march-2015.pdf

PwC (2017), *UK Economic Outlook*: Will robots steal out jobs? Available here: https://www.pwc.co.uk/economic-services/ukeo/pwc-uk-economic-outlook-full-report-march-2017-v2.pdf

PwC (2017), *Young Workers Index: The $1.2 trillion prize from empowering young workers in an age of automation*. Available here: https://www.pwc.co.uk/services/economics-policy/insights/young-workers-index.html

PwC (2017), *Golden Age Index:* The potential $2 trillion prize from longer working lives. Available here: https://www.pwc.co.uk/services/economics-policy/insights/golden-age-index.html

PwC (2017), Human value in the digital age. Available here: https://www.pwc.nl/en/publicaties/human-value-in-the-digital-age.html

PwC (2017), *Sizing the Prize: What's the real value of AI for your business and how can you capitalise?* Available here: https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf

PwC (2017), *Workforce of the future: the competing forces shaping 2030*. Available here: https://www.pwc.com/gx/en/services/people-organisation/workforce-of-the-future/workforce-of-the-future-the-competing-forces-shaping-2030-pwc.pdf

PwC (2017), *Workforce of the future:* detailed survey results. Available here: https://www.pwc.com/gx/en/services/people-organisation/workforce-of-the-future/workforce-of-future-appendix.pdf

PwC (2017), *Responsible artificial intelligence study: Accelerating Innovation*. Available here: https://www.pwc.co.uk/audit-assurance/assets/pdf/responsible-artifical-intelligence.pdf

PwC (2017), Women in Work Index: Closing the gender pay gap. Available here: https://www.pwc.co.uk/services/economics-policy/insights/women-in-work-index.html

PwC (2017), *G20 Insights: Accelerating Labour Market Transformation*. Available here: http://www.g20-insights.org/policy_briefs/accelerating-labour-market-transformation/

PwC (2018), Global CEO Survey. Available here: https://www.pwc.com/gx/en/ceo-agenda/ceosurvey/2018/gx.html

Standing, G. (2017), *Basic Income: And How We Can Make It Happen*, Pelican Introductions.

ZEW (2016): *Racing with or against the machine? Evidence from Europe:* http://ftp.zew.de/pub/zew-docs/dp/dp16053.pdf

# Authors, contacts and services

This report was written by John Hawksworth, Richard Berriman and Saloni Goel. Additional research assistance was provided by Nick Parlett, Robyn Foyster, and Pearl Ho.

For more information on the report, please contact:

**John Hawksworth**
*Chief Economist*

E: john.c.hawksworth@pwc.com

**Richard Berriman**
*Senior Manager – AI Team*

E: richard.berriman@pwc.com

Many thanks to the many other PwC experts who contributed helpful comments or inputs, including Euan Cameron, Rob McCargow, Nick Jones, Jonathan Gillham, Justine Brown and Anita Hagen.

### PwC's economics services

Our Economics practice's consulting services combine strategic analysis of macroeconomic and microeconomic trends with strong quantitative techniques across all industry sectors and public policy analysis. Further details of our services can be found on our website at: http://www.pwc.co.uk/economics-policy/index.jhtml

And please see our Economics in Business blog page to read our insights on current economic developments and their implications for governments and business: http://pwc.blogs.com/economics_in_business/

### PwC's AI services

Our AI team supports our clients to navigate emerging technology, build AI-enabled solutions that underpin business strategy, and are disrupting our own firm through changes that AI brings to the business.

For queries about our AI practice, please contact Euan Cameron:

**Euan Cameron**
*Partner – UK AI Leader*

E: euan.cameron@pwc.com

### Intelligent Digital

Intelligent Digital is PwC's approach to balancing business understanding with technology innovation and human insight to help solve our client's important problems.

To learn more about our Intelligent Digital approach visit http://pwc.co.uk/intelligentdigital/

180123-184242-RB-OS