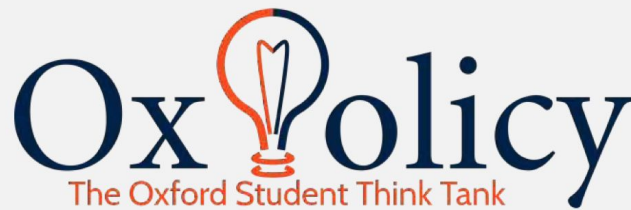


JOBS FOR THE FUTURE

Protecting the Labour Market in the Face of the AI Revolution

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EXECUTIVE SUMMARY

Artificial intelligence (AI) is going to drastically change our society. It has the potential to make a large proportion of jobs redundant, but also offers opportunities to reshape labour markets and improve the quality of work for all. This policy paper analyses the labour market consequences of AI and develops recommendations for policymakers to address these important issues.

Chapter 1 provides the analytical framework for the report and a working definition of artificial intelligence.

Chapter 2 conducts a critical literature review of scholarship on the labour market consequences of automation and AI, evaluating the assumptions behind it and the lessons that can be drawn.

Chapter 3 emphasizes barriers to implementation that may slow down the substitution of AI for human labour.

Chapter 4 develops recommendations for UK policymakers.

KEY LESSONS FROM THE LITERATURE

Our analysis finds that though there is no scholarship concretely addressing the labour market impact of artificial intelligence (rather than automation at large), some **key lessons** can be drawn from the literature:

1. There is a significant potential for substitution of human labour with artificial intelligence.
2. The job creation potential of AI remains unexplored, and may offset (to a degree) the destructive effects of AI.
3. Different groups of workers will be particularly affected in the medium term, in particular low-educated, low-wage workers.
4. AI could have important impacts also on the *quality* of work, rather than only the quantity.

A BRIEF SUMMARY OF OUR RECOMMENDATIONS

A brief summary of our policy recommendations for the UK government is included here. For more detail see 'Our Recommendations' which are included at the end of the section for each particular policy area in Chapter 4.

Assigning Responsibility

The government should:

- Emphasise the need to balance a strategy to develop the artificial intelligence industry in the UK (which the government is already focussed on) with a strategy to build economic resilience in preparation for the greater automation which AI will bring.
- Appoint a special advisor, such as an 'AI tsar', who could provide a better overview of government-wide policy as it relates to AI and drive the development of a comprehensive policy response, which will require coordination across government departments.

Education

The government should:

- Develop a more integrated approach towards STEM education.
- Work towards improving attitudes towards STEM careers on the part of both pupils and parents by embedding careers advice and guidance within STEM classes.
- Realise the full potential of a diverse workforce by addressing inequitable take-up of STEM careers across socio-demographic groups.
- Recognize that a singular focus on STEM does not adequately address development of AI and encourage investment in collaborative and caring skills.

Skills and Retraining

The government should:

- Address information asymmetries about the nature of skills shortages by encouraging employers to innovate and provide their own training programs.
- Ensure that the necessary infrastructure is in place to enable communities to re-orientate themselves away from declining industries towards the growing technology sector.
- Redesign incentive structures for private contractors running retraining programs.
- Shift Universal Credit/benefit sanctions away from short term focus of getting people into work, and focus more on helping them find long term employment.

- Support the development of the Lifelong Learning Fund, with an emphasis on encouraging innovation and variety to accommodate variation in skills shortages (by region and by sector) and learning abilities of participants.

Job Quality

The government should:

- Reconsider its decision, and follow the advice of the Taylor Review in broadening the remit of the Low Pay Commission to include wider consultation and recommendations on how to improve job quality.
- Appoint one government body to collate information on workforce structure, with a view to encouraging workplace practices that give employees more say in their working conditions.
- Pay particular attention to improving job quality in growth sectors such as caring jobs, where human labour will retain a comparative advantage over AI. Currently poor working conditions have created skills shortages in this sector, with many jobs being filled by migrant labour.
- Revisit some of the incentives attached to claiming unemployment support:
- Anticipate the effect of greater transition rates between jobs on pensions and saving for retirement.

Sharing the Gains Fairly

The government should:





- Review the feasibility of a universal basic income scheme, and possibly small-scale pilot schemes to trial the policy of UBI.
- Consider the policy of a 'robot tax', which could provide revenue to invest in education and retraining schemes.

Recommendations

An Overview

A brief summary of policy recommendations are outlined below

Education




-  Improve attitudes to STEM careers by embedding career advice and guidance in classes
-  Address inequitable take-up of STEM careers across socio-demographic groups
-  Encourage investment in collaborative and caring skills
-  Develop an integrated approach to STEM

Skills & Retraining






-  Ensure infrastructure to enable re-orientation towards growing technology.
-  Encourage employers to innovate and provide own training programs
-  Shift universal credit sanctions to focus on helping people find long term employment
-  Support development of a Life Long Learning Fund
-  Redesign incentive structures for private contractors running retraining programs

Fair Gains & Shares



-  Consider the policy of having a robot tax
-  Robot tax can be used to reinvest in education and training
-  Small scale pilot of the universal basic income scheme

Job Quality

-  Follow the advice of the Taylor Review in broadening the remit of the Low Pay Commission to include wider consultation and recommendations on how to improve job quality
-  Improve job quality in the growth sectors such as caring jobs
-  Appoint a single government body to collate information on workforce
-  Revisit some of the incentives attached to claiming unemployment support
-  Anticipate the effect of greater transition rates between jobs on pensions and saving for retirement



Responsibility



-  Appoint an AI Tsar
-  The AI Tsar can provide better overview of government wide policy related to AI
-  The AI Tsar can coordinate among the different departments and provide policy responses.
-  Balance development of AI industries with building economic resilience in preparation for automation

1 WHAT IS AI?

Assumptions and Scope

1.1 Introduction

Artificial intelligence became a recognised term in 1956 (NSTC, 2016). In his 1950 paper “Computing Machinery and Intelligence” Alan Turing famously enquired into whether machines have the ability to think, and how one might test for such a possibility (Ibid.).

While many paradigms exist to describe artificial intelligence, with which many policymakers are familiar, there is lack of clear consensus on a formal definition.

Today, artificial intelligence (AI) is broadly and variously defined in the academic literature and confusion around its precise meaning is further distorted by popular culture. While many paradigms exist to describe artificial intelligence, with which many policymakers are familiar, there is lack of clear consensus on a formal definition. For instance, people will

commonly draw distinctions between weak and strong AI, or ‘stages’ or ‘waves’ of AI. Yet precisely what concept these distinctions are carving up remains unclear. ‘Artificial intelligence’ evokes mixed feelings in the public psyche (Fast and Horvitz, 2016). The more optimistic see it as potentially improving the quality of life for humanity by helping to solve the world’s greatest challenges and inefficiencies. From revolutionising healthcare to boosting the economy, some argue it will provide utility for society. Others are more sceptical, citing potential ramifications of such incredible technology. Whether it’s going beyond our control to actively harming humans, influential personalities from Stephen Hawking to Elon Musk have stressed the revolutionary and existential issues in the field. The frequent politicisation and sensationalism attached to this topic

undoubtedly plays a role in moulding conceptions. The purpose of this chapter is therefore to provide a definitional framework for our study of artificial intelligence, and to define the scope of the report.

1.2 Definition

In assessing the likely labour market consequences of artificial intelligence, our project focuses on a definition of AI as a rational actor, drawing on Russell and Norvig (1998). According to a “rational-acting” definition of AI, computer agents must not only act, but also be able to operate under autonomous control, adapt to change and persist over a long time period. Agents then act to achieve the (expected) optimal outcome. When we speak of an AI agent acting rationally in this context, we are concerned with its ability to perform the best possible action given a set of circumstances. We require it to be able to examine all factors influencing a given situation and then make the “correct” decision, in the sense that it best achieves a certain goal.

In addition, a commonly made distinction is that between strong and weak, or general and narrow AI. Strong or general AI refers to an actor that acts sufficiently rational to perform a wide variety of complex tasks. However, any intelligent system existent today is at most weak AI. For the purposes of this report we consider *narrow* artificial intelligence. We also stipulate a time horizon which we think renders the development of *general* artificial intelligence infeasible.

To clarify, our definition extends from a consideration of the popular paradigms for defining AI in the academic literature. We use a conception of artificial intelligence as a rational actor, where a rational actor is one which employs intelligent strategies to maximally achieve its goals (also known as the ‘rationality as winning’ conception). It is with this definition in mind that we approach the question of scope and settle issues of what properly belongs and does not belong inside the domain of this report.

1.3 Time Horizon

The timespan considered by the literature is immensely varied. Some reports estimate macroscopic impacts over the next 100 years, while others focus simply on questions surrounding what will happen in a particular sector over the next five. Our approach lies somewhere between these two extremes, although it falls more naturally on the

We intend to focus on the near-term impacts of the development of artificial intelligence on technological unemployment through automation, which we define as the next 20 years.

low-sector, near-term approach. We have some credence in the view that a general form of artificial intelligence will be developed within the next fifty years. As such, focus on the near-term impacts of the development of artificial intelligence on technological unemployment (through automation), which we define as the next 20 years.

Geography

This report is a project of OxPolicy, the University of Oxford's student think-tank which focuses on national and international issues with implications for UK policy. As a result, this paper is targeted at UK policymakers and is written in the style of a policy paper. To keep the work within our remit, we look at how the UK government should act, which naturally is best studied by implementing international comparisons and will require an understanding of the global development of the field. Within this report in particular, we will discuss and make recommendations for how policymakers should respond to the labour market impact of automation.

Since the bulk of the literature produced studies the US and UK, we adopt an international but heavily high-income and Western nation analysis. Where feasible and appropriate, we include evidence and policy from a broader range of nations.

Occupations

We propose adopting a cross-sector approach for this report. That is, we will consider the impacts of the development of artificial intelligence on technological unemployment across sectors and occupations. An ideal approach would be to provide a breakdown of literature timelines by sector in this regard, on standard, contemporary definitions of what counts as a primary, secondary and tertiary sector industry (Kenessey, 1987). However, given the various approaches adopted within the literature, a detailed sectoral breakdown cannot be provided. We therefore identify common threads within the literature with regard to sectors or occupations wherever possible.

2 WHAT DO THE EXPERTS SAY?

ASSESSING THE IMPACT OF AI

2.1 Introduction

Artificial intelligence is going to fundamentally transform our society, including the structure of our labour market. The difficulties in predicting the impact of AI due to the current lack of clarity in definition, the unique labour market impacts of AI compared to other types of technological advances and the lack of historical data to analyse for trends means that the assumptions of classical labour market economics may not suffice in predicting future trends and arriving at effective policy making (A brief review of theory and historical thought on the impact of technology on labour markets can be found in the appendix).

The task we set ourselves is therefore to examine existing empirical

Predicting the labour market impact of AI is a significant scholarly challenge due to the current lack of clarity in definition, the unique technological advances AI represents and the lack of historical precedent.

estimations of the labour market impact of AI and critically engage with the varying assumptions underlying them. This leads to a significant scholarly challenge, since a significant proportion of the work done in this area involves a conflation of the technologies underpinning mass-automation and what is properly understood as artificial intelligence. However, as will be detailed in the next section, an analysis of the existing literature is essential in understanding changing labour market dynamics

related to AI. While the literature addresses automation impacts beyond narrow AI, its central premise, like that of our report, is that it will no longer be only manual tasks that are automated, but also cognitive ones requiring rational behaviour. As such, they are extremely relevant to our project.

Several think-tanks and academic researchers have collected and analysed data, arriving at predictions related to job replacement, creation and imbalance and the effect of AI on the labour market. In the next sections, these projections are summarized and analysed for their quality of prediction.

2.2 Presentation of Main Results in the Literature

Whereas ‘automation’ once connoted machines carrying out repetitive tasks in industrial factories, advancements now evoke technologies able to land aircrafts, diagnose disease, and trade stocks. Technological innovation in the workplace was historically considered as complementing human activity, allowing for the outcome of greater goods/services per hour whilst employing the same number of human workers (Ford, 2015). However, with the recent rise of artificial intelligence, there is now an emerging separation of productivity from human labour. This has led to many predictions of an imbalance between replacement and creation, exacerbated by a rapidly growing population. In this section, we briefly summarize the main results of six papers analyzed for this report.

Before presenting a comparative account of the main results, it is important to stress already at this point that none of the reports considered examine exclusively the impact of AI on the labour market, but rather that of “computerization” or a similar concept. This implies the inclusion of jobs that will be automated not because of AI (as defined in chapter I) but related technologies. Largely, it is the replacement of repetitive manual tasks by “non-intelligent” technology that is the current driver of changes to the labour market. However, it is necessary to recognize that in fact, such automation, despite

being “non-intelligent” with basic rule-based capabilities, is the key step in progress to advanced AI (McKinsey Global Institute, 2017). Given the interrelations between the categories, for the purpose of analyzing the labour market impact of technological change, an exclusive focus on AI would be neither implementable nor reasonable. The important point that our report, as well as the papers analyzed, emphasize is that, contrary to previous waves of technological advances, job replacement has moved beyond mere manual jobs to encompass cognitive tasks.

Let us now examine the predictions various reports make on the labour market impact of computerization (for a more thorough analysis of the theoretical concepts employed, see the next section). The reports considered include work by Pearson, Nesta and the Oxford Martin School (Bakshi et al, 2017; hereafter PNO), the McKinsey Global Institute (2017; hereafter MGI), the OECD (Arntz et al, 2016; hereafter OECD), PwC (2017;

Estimated rates of job replacement vary significantly by country and estimation technique.

hereafter PwC), Frey and Osborne (2017; hereafter FO) and the World Economic Forum (2016; hereafter WEF). Estimated rates of job replacement vary significantly by country and estimation technique. The reports consider a range of developed and emerging economies, and use a variety of methods. For convenience, the following

two infographics summarize the main results found in the reports, by replacement rates for different countries and by consequences for different occupations.

CHANGES TO OUTCOMES

By Country

Each report predicts the types of work that would be at risk with automation across different countries and regions in the world. These predictions are summarized below.

The main countries of focus are the UK and the US.

The primary outputs of the models are probabilities of occupations experiencing a rise in workforce share (i.e. increased demand) in 2030 with 'low probability' (less than 30%), 'medium probability' (>50%), and 'high probability' (>70%).

18.7% of US occupations are in the <0.3 category compared to 21.2% in the United Kingdom.

McKinsey

Figures are more conservative compared with other papers:

High risk workers are largest in Germany and Austria (12%) and smallest in Korea and Estonia (6%)

PwC

- Artificial Intelligence was rated by 7% of the respondents on a survey by WEF to be the top driver of change in industries worldwide between 2010-2018.
- The report cites advances in AI, machine learning and natural user interfaces as making it possible to automate knowledge-worker tasks.

Frey and Osborne

Pearson, Nesta and Oxford Martin School

The report looks at automation potential of various countries:

Japan – 55%
India – 52%
China – 51%
United States – 46%
Europe Big 5 – 46%
Rest of world – 50%

OECD

- UK report suggests up to 30% of UK jobs could be automated by early 2030s.
- This is lower than the US where 38% of jobs could be at high risk of automation as well as Germany where 35% jobs are at risk.
- It is higher than Japan where 21% jobs are at risk.

World Economic Forum

Up to 47% of total US employment is in high-risk category over the next two decades.

CHANGES TO OUTCOMES

By Occupation

Each report predicts the types of work that would be at risk with automation across different occupations in the world. These predictions are summarized below.

- Wide variety of jobs are at high risk; metal and plastic workers, financial clerks and other production occupations.
- Impact of automation is predicted to encroach on more cognitively complex occupations.
- Predicted fall in retail sales workers and entertainment attendants is consistent with expansion in digitally provided goods and services.

Pearson, Nesta
and Oxford Martin
School

McKinsey

Most susceptible activities
which account for 51% total
employment and \$2.7 trillion
in wages:

Data collection

Predictable physical
activities

- Automation and digitization are unlikely to destroy large number of jobs.
- However, low qualified workers will bear the brunt of adjustment costs due to automation.

OECD

PwC

Risk is greater in some
sectors:

- Transportation and storage (56%)
 - Manufacturing (46%)
 - Wholesale and retail (44%)
- Risk is lower in other
sectors:
- Health and social work (17%)
- Key factor to differentiate
is education

- Artificial Intelligence responsible for compound growth rate of 1.25% in mobility sector.
- Not a major driver of employment in other areas.

World Economic
Forum

Frey and Osborne

Computerization will
substitute for low-skill and
low-wage jobs.

As is evident, estimates of automation potential vary widely, from a comparatively low 9% estimated by the OECD for the United States, to 47% for the United States estimated in FO. In contrast, predictions by occupation are more homogenous, with most reports agreeing that low-skilled and low-wage workers will be by far the most affected. Some of the variance in predictions is an inherent consequence of the uncertainty surrounding predictions of the labour market impact of AI. However, some portion may also be attributed to the varying theoretical paradigms and assumptions underlying the reports, which we now turn to examining in more detail.

2.3 Conceptualisations of AI in the Reports

Having briefly summarized the main results of the reports, we now critically examine the validity of results in the context of the impact of AI on the labour market. To begin with, this section examines the different ways that AI is conceptualised.

Each report has its own particular definition of artificial intelligence, often broadly conflating the definition with other technological trends such as automation. As such, it is a challenge to identify precisely what assumptions are made about the definitions of different emerging technologies and to classify them, frequently in the absence of sufficiently precise definitions. The technological drivers of automation identified across the literature range through: Machine Learning (ML), Data Mining, Machine Vision, Computational Statistics and Mobile Robotics (MR), as well as more conventional sources such as implementation of software.

Throughout the literature there is a unifying theme that manual, routine tasks are at risk of being replaced by capital. But the understanding of what, exactly, constitutes capital, varies. What precisely labour is being substituted for could be thought variously of as (1) robotics (2) algorithms (3) software (4) digitisation (5) computerisation, depending on the source consulted. The MGI report begins in its executive summary by making reference to robotics, AI and machine learning, referencing a tripartite approximate

classification. Other reports have taken more or less synthesised approaches to

Much of what seems at first to be substantive differences between reports, especially with regards to predicted impact of AI, is due to different definitional frameworks.

conceptualising what kind of capital it exactly is that labour is being substituted for.

Overall, the reports are similar in terms of what they believe the fundamental drivers of automation are.

However, we find that the classification system used by different reports varies wildly. Some reports fail to specify their understanding of AI, and place AI development within a broad approach to technological change. Others underestimate the potential impact of AI by specifying as one sub-division of technological change. Much of what seems at first to be substantive differences between reports, especially with regards to predicted impact of AI, is due to these different definitional frameworks.

Broad Approaches

FO, PNO and the OECD reports take a broad view, terming the object of interest computerisation.

Closely related to digitisation, computerisation captures the thought that computing power is the key driver of automation, which as a description remains value-neutral on what is intelligent computing, and what is not. The OECD report goes further, to divide jobs at risk of computerisation into those that can be “digitised”, and those that can be “automated”. Similarly, both of these subdivisions could include, but are not limited to, AI. Rather than “computerisation”, the PNO and PwC reports tend to refer to “automation”, which includes but is not limited to tasks that could be replaced by AI.

Another approach to classifying the drivers of automation makes reference to ‘emerging digital technologies’. Since the technologies driving anticipated technological unemployment are varied, labour market reports such as McKinsey’s tend to identify any technology which could be understood as disruptive, in other words, one which makes a significant threat to industry incumbents and conventional market conditions. There are significant advantages to this approach. The most straightforward advantage is that it presents a direct benefit to policymakers. As a government official, the pressing motive is to ensure that the labour market impacts of disruptive technologies are handled as efficiently as possible: without significant disruption to the natural rate of unemployment, though frictional unemployment may be permissible in the interests of technological progress.

Underestimating the Scope of AI

The WEF report does not specify its own definition, but surveys different industry leaders on their understanding of the “main technological drivers of change”. Only 7% cite ‘artificial intelligence and machine learning’ as the top driver of change. However, other drivers of change, such as ‘advances in computing power and Big Data’, which are agreed on as more important, arguably provide some overlap with the field of AI development. Thus, not only do the survey responses show varied opinions on whether AI developments are a key driver of technological change; the very design of the survey, and the division of technological change into categories, shows a lack of appreciation of the many areas of technology which could impact on, and be impacted by, AI development.

The most considered conceptualisation of AI is given by FO, who dive into a great deal of granularity, using a classifier algorithm to sort 702 potential occupations in accordance with their degrees of (1) perception and manipulation (2) creative

intelligence and (3) social intelligence. This provides a general basis for assigning a coefficient of computerizability to occupations, without strictly defining what AI is.

But these divisions are academic fields of artificial intelligence, rather than technologies which constitute artificial intelligence. Whilst FO have clear, developed positions on artificial intelligence, it shares a limitation with all the reports, by failing to offer a clear labelling as to which of the drivers of automation, falling under their unifying theme of 'computerisation', precisely qualifies as artificial intelligence.

Different conceptualisations of AI in the reports reflect varying views on the technological drivers of automation. The most polar cases, typifying the spread of the literature, were the MGI report and the PNO report, which both offered a broad perspective on technological change, with this overall theme divided differently in each report. Our survey adds credence to the view that there is no agreed conceptualisation of AI in the literature. Nor has there been a standalone investigation into the direct impact of narrow artificial intelligence, with the effect of AI usually examined as part of a broader set of technological changes.

2.4 Assumptions and Research Methods

The previous section discussed the different ways in which AI is conceptualized in the literature, and argued that there has not been a comprehensive investigation into the specific labour market effects of AI, but rather that the reports use different theoretical paradigms to investigate technological unemployment in varying levels of detail. In this section, we turn to discussing different methodological approaches used in the literature, examining both assumptions underlying different approaches and methods used.

2.4.1 Assumptions in the Literature

Within the literature there are several main assumptions made when calculating the labour market consequences of AI. These centre on the debate between an occupation-based and a task-based approach, the identification of bottlenecks and the transferability of findings across countries.

Main assumptions centre on the debate between an occupation-based and a task-based approach, the identification of bottlenecks and the transferability of findings across countries.

Although we shall be discussing the findings of the WEF report in other parts of this paper, due to their methodology it is difficult to assess the assumptions underlying this paper. The WEF

based their report on survey responses from Chief HR and Chief Strategy Officers from a range of global employers. This means that each survey response will be based on a different individual's set of assumptions, meaning there is not a specific set of assumptions underlying the paper as a whole. Therefore, although it will be discussed in other areas of this paper, the WEF report will not be included in this section.

The reports conducted by MGI, PNO and FO all analyse the labour market consequences in terms of the effects on occupations as a whole. FO analyse the key features of the tasks involved in various occupations and look at how susceptible these were to automation. From this, they draw conclusions as to the potential automatability of various occupations. MGI undertake a similar method, analysing the component activities of each occupation across 46 countries. However, it should be noted that the predictions made by the MGI are not discussed solely in terms of the automatability of entire occupations, despite the fact that this is the starting point of their analysis as they also break activities down into 18 separate capabilities. PNO focus on the changes different occupations would make, as debated by a panel of experts.

However, there are a number of difficulties with taking an occupation-based approach, as highlighted by the OECD report. An occupation-based approach assumes that the entirety of occupations can be automated, rather than just specific tasks within those occupations, whereas, as noted by the OECD report, workers' task structures differ remarkably within occupations. The tasks performed by one person within an occupation could be automatable whereas the tasks performed by someone else of the same occupation may not be as easily. For example, if one considers the occupation of 'shop assistant': It may be that the front of shop work which involves interacting with customers is not automatable, however the task of finding and fetching items from the store room is. Both of these tasks come within the occupation of 'shop assistant' but are not equally mechanisable. This makes conclusions about occupations as a whole more difficult as it is unlikely to be many the whole of which will be fully automatable, particularly within the time-frame we are examining.

Having rejected the occupation-based approach, the OECD focuses instead on a task-based approach. They estimate the relevance of tasks for the automatability of jobs in the US, rather than occupations as a whole. The PwC report then expands on the approach of the OECD through developing their own algorithm for identifying automation risk. PwC also look specifically at the characteristics of tasks which contribute to their automation risk. This is because different tasks will have different barriers to automation, which again highlights how the overall occupation based approach is potentially ineffective.

However, the PNO report points out a number of arguments for why a task based approach could be flawed. They suggest that the unbundling tasks from their occupations could diminish the quality of estimation that one then gets. They claim that particular tasks must be seen within the context of their occupations in order to adequately measure the potential impact of automation. When viewed in isolation from occupations, it may be erroneously assumed that the automation of like tasks has a

similar impact. However, once viewed as part of occupations, similar tasks can have different growth prospects and require different knowledge connected to them. For example, PNO cite the difference in requirements between an insurance sales agent and a solar equipment sales representative. The solar equipment sales representative requires a higher level of technical expertise in order to effectively sell their wares, making it more difficult to automate. By viewing these tasks in isolation, simply as the task 'selling wares', we risk losing important coordinating information that gives occupations their coherence.

Although it is important to view the tasks within their context, generalising across whole occupations is not the best way to do this. As noted by the OECD, many workers within a particular occupation will specialise in tasks that cannot be automated while other tasks will be more automatable. To then state that this occupation is 'automatable' or 'not automatable' does not do justice to the nuance of this difference task automatability. Just as PNO claims that a task based approach loses the subtlety which context gives to the potential automatability of a given task, an occupation based approach loses the impact of task structures for the automatability of an occupation. Given the nature of automation, it seems that automation risk estimations fit a task based approach more naturally than an occupation based approach. Mechanisation occurs on a task by task basis, and so it makes sense for its analysis to reflect this. This is particularly relevant within the time frame we are considering, as although eventually entire occupations may be able to be automated, it is presently more likely that only particular tasks within occupations will be automatable. However, the critiques of the PNO report should be taken into account and therefore, any task based approach should be taken warily, making sure that the tasks are analysed in context.

Automatability Bottlenecks

FO highlight how different tasks will be susceptible to different engineering bottlenecks. These are: perception and manipulation, creative intelligence, and social intelligence. Tasks involving these aspects will be less susceptible to automation than tasks which do not. They then matched these bottlenecks to a number of O*NET variables in order to further define the nature of these bottlenecks.

FO define the perception and manipulation bottleneck as finger dexterity, manual dexterity and working in a cramped work space or awkward positions. Although it may be a while until robots are able to function with the same or higher levels of dexterity as humans, there have been a number of examples which show that there is great progress being made in this area. For example, the Journal of Science Translational Medicine released in 2016 the results of an experiment using a Smart Tissue Autonomous Robot which was used to successfully complete tasks such as the suturing of a cut along the intestinal tissue of pigs (Shademan et al, 2016). This demonstrates that the identified bottleneck of perception and manipulation may not in fact be as much of a bottleneck as FO claim since even surgery, which is often considered to require a level of manual dexterity far above the capabilities of robots, is slowly becoming mechanised.

Creative intelligence is associated with the O*NET variables of originality and fine arts. Unlike perception and manipulation, creativity is often thought to be

one of the most difficult things to mechanise. However, artists and writers alike have been experimenting with the use of robots in creative tasks for decades, as discussed

Even surgery, which is often considered to require a level of manual dexterity far above the capabilities of robots, is slowly becoming mechanised.

by Gayford (2016). For example, Harold Cohen has been using a programme called AARON which has been able to autonomously make pictures since 1973. More recently a programme known as The Painting Fool, made by Simon Colton, has been working towards producing works that can be described as “skillful”, “appreciative” and “imaginative” which Colton defined as the criteria of what would make an artificially intelligent artist. One work produced was a mosaic of images resembling watercolours in response to a Guardian article about Afghanistan. However, the question then arises as to whether or not this could ever truly be called creativity or imagination, or whether the images produced by these programmes are really works attributable to the creativity of the artists Cohen and Colton. In his article in MIT’s Technology Review, Gayford (2016) claims that ‘it is clear that machines can work on this level: they can produce derivative art... But can they do more than that?’. Cohen argues that in order to be as truly creative as artists such as Rembrandt or Picasso, a robot would have to develop a sense of self and “if it doesn’t, it means that machines will never be creative in the same sense that humans are creative” (Ibid.). However, the tasks that we are concerned with will likely not require this level of creativity in automation. Although we may never have a robotic equivalent of Rembrandt, these programmes demonstrate that robots can be creative to a certain extent and could then have the capacity to develop less creatively

complex works such as posters for advertising.

Robots can be creative to a certain extent and could then have the capacity to develop less creatively complex works.

The final bottleneck considered by FO is social intelligence. This is defined as social

perceptiveness, negotiation, persuasion and assisting and caring for others. Despite Frey and Osborne’s concern this is also an area with a lot of potential. For example, researchers from the Robotics Research Lab at the University of Southern California have developed an assistive robot, known as Bandit, which helps children with autism learn how to interact with others (Bloudoff-Indelicato, 2017). Maja Matarić, the head

researcher of the team, claims that these robots are able to modulate their responses to situations based on the personality and mood of the patient. If they are able to effectively interact with children and help them develop social skills, robots could then be developed to have the adequate social skills to function within many of the collaborative tasks involved across occupations.

From these examples, we can see that these bottlenecks identified by FO, while likely to remain significant within our timescale, are not inscrutable problems incapable of being overcome. Although robots

Although robots are not yet capable of the highest level of dexterity, creativity or social interaction, it is clear that artificial intelligence is approaching an adequate level within these areas to complete the tasks involved in a number of occupations.

are not yet capable of the highest level of dexterity, creativity or social interaction, it is clear that artificial intelligence is approaching an adequate level within these areas to complete the tasks involved in a number of occupations.

Transferability Across Countries

Both the OECD and PwC reports assume that their findings in the US can be used across different countries. The OECD report takes their findings and extrapolates these out to all OECD countries, assuming that workers with the same task structure face the same automatability risks. The PwC report begins by utilizing the same findings, but includes additional explanatory data. Both the OECD and PwC defend their decision to extrapolate beyond the US by claiming that differences in automatability between the countries originate in differences in task structures or other explanatory variables, instead of fundamental differences between countries that cannot be properly portrayed in their data sets.

However, as noted within the MGI report, it may not be this simple. The McKinsey report models the cost of replacement as an estimation of the percentage of the highest hourly wage for the corresponding activity across all countries. However, the MGI report also notes that the average ‘cohort level growth rates’ may not be reliable. In order to extrapolate one’s finding from one country, such as the US, to all countries, one must both assume that the task structure is the same in similar occupations across different countries and that the wider impact of the automation of certain jobs will be the same.

This does not seem a reasonable assumption to make, especially if one is attempting to extrapolate to countries which have a vastly different infrastructure and spread of industry. In order to better extrapolate across all OECD countries, one may have to conduct research across more OECD countries with varying levels of industry growth and development so that all inferences extrapolated to other countries are made between more similar countries to ensure increased accuracy in inference.

2.4.2 Methodological Approaches

The previous section assessed the methodological approaches of the six reports we analyse with specific reference to how the definition of AI employed by the reports is translated into a defined measure, and whether the assumptions made in this process are reasonable. This section now proceeds to critically investigate the methods of estimation of the impact of AI in the literature, and assess the robustness of various methods.

Three of the reports analysed use the same methodology for developing an indicator for automation. This was first developed in FO, where the authors use US O*NET data, which details key features on occupations as a measurable set of variables, to generate their estimates. Having identified the occupations that correspond to the three engineering bottlenecks identified (discussed above), they employed workshops where they interviewed a group of Machine Learning experts and subjectively hand-labelled 70

different occupations. Having developed this classification, the authors then use a logistic likelihood model to predict the probability of computerisation for the 702 occupations they analyse.

As discussed in the previous section, the OECD paper instead uses a task based approach to examine the potential for automation. However, to estimate this potential they rely on the same automatability indicator that was developed by FO. Their model matches this indicator to US observations in data, and then maps it to OECD countries using data from the Programme for the International Assessment of Adult Competencies (PIAAC). Finally, the PwC paper also uses the indicators developed by Frey and Osborne to predict automatability. Differences in the two estimations can be linked to differing predictive algorithms, where the PwC algorithm is enhanced by linking automatability to the characteristics not just of tasks involved in different jobs, but also the characteristics of the workers doing them.

McKinsey also use an approach that goes beyond analysing occupations, instead identifying component activities of each occupation across 46 countries representing more than 80% of the global economy. These activities were then broken down into 18 capabilities, and the technical potential of each was assessed by developing criteria informed by academic research, internal expertise and industry leaders. The estimation then models automation timelines, considering technical feasibility, solution development, economic feasibility and end-user adoption. To predict technical feasibility, they used interviews with industry leaders and academics, as well as analysing research and technological breakthroughs, trends in publications and patents as a measure of research potential.

The two other research reports considered do not look at the future of work from a perspective exclusively informed by a technological point of view, but rather examine it in relation to different trends. The WEF analysis analyses the impact of the Fourth Industrial Revolution through surveys conducted with Chief HR and Chief Strategy

Officers from a range of global employers. Industry leaders were asked whether they considered AI as one of the biggest challenges, and how they judged its impact to be. PNO use an analysis of trends, using data on key tasks and historical growth patterns for various industries in the US and the UK. The analysis proceeded through debates with panels of experts on changes to different occupations. A machine learning classifier was then used to generate predictions for all occupations, interpreted with

particular attention to discussion from foresight workshops.

The reports employ a large variety of methodologies to estimate the impact of automation, each of which has advantages and disadvantages.

It is evident from the discussion that the reports employ a large variety of methodologies to estimate the impact of automation, each of which has advantages and disadvantages. Of the

six reports discussed, only the analysis discussed by the WEF is survey-based. This approach is subject to various limitations. First, they only survey industry leaders in HR and Strategy. While this can give us meaningful insights from an industry perspective, the perspective is nevertheless limited. Supplementing the analysis with other, such as academic, perspectives would have made the results more robust. Second, the WEF analysis does not rely on a clear conceptual framework of either automation or artificial intelligence. Therefore, it is very difficult to interpret the results of the survey, given that each respondent may have a different conception of artificial intelligence. These two caveats clearly limit the robustness of the results.

In contrast, the other five reports rely, at least partly, on expert assessment of automation potential, and then translate this into some form of statistical analysis. However, this approach is also not without its pitfalls (Pfeiffer and Suphan, 2015). First, experts will usually tend to overestimate the comparative advantage of technologies over workers, particularly in tasks relating to flexibility, power of judgement and

common sense, while underestimating hurdles to implementation. Second, limiting the analysis to quantitative data and simply coding variable into 0 or 1 does not allow for any nuance on the actual implementation of artificial intelligence (see section 3 on barriers), nor on changes to the nature or “quality” of work (see section 2.5). However, while expert assessments therefore may bias the estimation results upwards, predicting automation potential is an area naturally riddled with uncertainty. In order to capture the likelihood of automation, we naturally have to rely on approximations, and expert assessments may be our best way of doing this. It is useful, nevertheless, to keep in mind that the resulting estimates are likely to be upward biased.

Given that they use the same indicator for automation, the difference in estimates in the FO, OECD and PwC studies is due to two factors: (i) the use of occupation-based vs task-based models (ii) differences in predictive algorithms. The issue of task vs occupation-based approaches is discussed in the previous section. This policy brief does not consider the different features of the predictive algorithms used in detail. However, it is likely that the complexity of the PwC algorithm, which also includes individual characteristics of workers to make predictions, makes results more robust.

The advantage of the McKinsey study is that the estimation considers not just their indicator for automation as such, but also criteria such as technical feasibility and economic feasibility. However, predictions on these indicators may not be reliable. Beyond the issue of expert bias discussed above, their estimation of economic growth may not be reliable. This is because they group countries into only two distinct cohorts with predicted growth rates, a measure that cannot account for the complexity of wage growth over time. In addition, their productivity calculations take into account that new jobs will be created, but do not specify what kind of jobs or the potential impact of policy.

Finally, the PNO report is an especially comprehensive investigation into the future of work. For example, they use all 120 O*NET features whereas the FO study only uses

nine skills categories. In addition, they also take into account the impact of changes to the economy other than technological change. Their results are therefore much more detailed than those of other reports, though they are also subject to greater uncertainty.

2.5 Job Creation

The previous sections have pointed out the varying theoretical paradigms underlying the literature, as well as assessing the validity of assumptions and robustness of methods underlying estimates. This final section now addresses the role of job creation, which is not considered in most of the studies, whose object is to estimate rates of job destruction/replacement. In this section we consider why it is important to consider job creation, and ask what predictions we can make about what types of jobs we can expect to be created. Job type can be considered in terms of skill-type, sector, and contract type. The latter in particular can have a significant effect on job quality, and change in this area may lead to concerns about the increasing precarity of work in future.

Why Consider Job Creation?

Experts are right to be concerned that the AI revolution may operate differently from previous waves of automation, especially with respect to the relative rates of job creation and destruction. However, when considering predictions about future rates of automation we should bear the likelihood of job creation in mind. All the reports quite rightly mention the difficulty of predicting patterns of job creation, but this is not a reason to exclude it from our analysis. Limiting job creation to a brief theoretical mention means that it is often passed over when the main conclusions of reports such as those by the OECD and FO are published, and this can feed into sensationalist stories about the destructive economic impacts of technological development. It also discourages policymakers and employers from taking proactive steps to encourage investment and innovation in new technologies (MGI 2017), or to shape the impact of developing AI technologies on job creation.

The range of different predictions of the impact of AI on the job market is partly due to varied assumptions about the extent to which AI will not only replace humans in existing jobs, but will also create new jobs. These could be technology-related jobs

An exclusive focus on job destruction discourages policymakers and employers from taking proactive steps to encourage investment and innovation in new technologies, or to shape the impact of developing AI technologies on job creation.

that do not currently exist, or simply a growth in jobs such as care and education, where humans are likely to retain a comparative advantage. These latter jobs could be paid for by the productivity gains from technological development (OECD, 2016). Some analyses (FO; OECD) focus on the destructive effects of technological developments, considering the possibility of job creation only in their theoretical discussion, not their analysis and predictions.

On the other extreme, some predictions (MGI) base their calculations on the assumption that breakthroughs in artificial intelligence will operate like any other technological development throughout history, with new jobs being created to replace the old ones that are lost to automation. This assumption is more credible when it is accompanied by examples of areas where jobs may be created. Reports published by the MGI and PNO both emphasise the skills where humans are likely to retain a comparative advantage over AI: tasks requiring a high level of interpersonal skills; managing systems or networks of people; and higher-order cognitive skills such as creativity. However the PNO report goes beyond discussion of important skills to consider examples of new occupations which might be created - such as 'green jobs'. Other suggestions come from employers and industry leaders surveyed by the WEF - a common response was an expected growth in specialised sales jobs, as with rapid technological development

comes a need for individuals who can explain the new applications of AI and pitch them to potential clients.

Skills for the Future

There is some debate as to what human skills will remain most in demand - whilst the WEF report emphasises the need for mathematical and engineering skills, FO and PNO predict that there will be a reallocation of jobs towards those requiring creative and social skills, which machines are less able to replicate. This disparity may be partly due to different time scales: as a survey of the views of current employers, the WEF reflects the current and near-future demand for occupational skills, whereas FO are more

concerned with medium term changes in the occupational structure of the labour market.

Previous waves of automation have seen humans displaced by machines in some tasks acquire new skills and take on new jobs, but it may be more difficult to do this in response to AI .

The relative rates of job creation and destruction will have significant impact for the labour market. Previous waves of automation have seen humans displaced by machines

in some tasks acquire new skills and take on new jobs, but it may be more difficult to do this in response to AI (Brynjolfsson and McAfee, 2011; Frey and Osborne, 2017). Since technology now threatens to replace humans in cognitive as well as manual tasks, it will likely become much harder to retrain workers in roles where they can complement rather than compete with new technology. The human skills necessary to work in AI are highly cognitively demanding and take many years to acquire. Thus even if AI is creating jobs, we may worry that the rate at which they can be taken up by humans is much slower than the rate at which existing jobs are automated. It might be more realistic to expect job creation in sectors like education and care, which require a high degree of interpersonal skills, rather than in highly technical fields like computing and engineering.

Meeting the Demand for New Skills

We should also consider that future employment patterns will depend not only on demand for human labour, but also its supply. Artificial intelligence might create demand for highly-skilled workers who can help to develop and work alongside new technologies, but the UK workforce may not have the capacity to meet that need, especially given the UK's much-bemoaned deficiency in STEM education. Again, there are important implications for policy here, in terms of the role of the state and employers in encouraging education, retraining and upskilling. In the World Economic Forum's 2016 survey, employers frequently cited concerns about possible skill shortages in some areas. Firms may increasingly face competition when recruiting for jobs requiring mathematical, engineering or computing skills. Occupational skill shortages may be exacerbated by the trend of population ageing, since older workers tend to be less successful at adapting to new technologies. This feeds into concerns about the effect of automation on inequality, with artificial intelligence replacing humans in some jobs, whilst helping to drive up salaries for a select few highly skilled individuals. This is an obvious opportunity for policy intervention: there is a role for both policymakers and employers to promote education, upskilling and retraining, as will be

discussed in greater detail in later chapters.

There is a role for both policymakers and employers to promote education, upskilling and retraining.

We have already seen how focussing on the possibility of job creation can allow a more proactive policy approach to help mitigate the

disruptive effects of AI on the labour market. Despite the difficulty of making accurate predictions for the net effect of AI on jobs, projections about job creation can still be used to make useful proactive policy decisions. This is particularly important because

along with job creation comes concerns about the quality of new jobs that are created (Taylor, 2017).

Job Quality

Some studies which do consider job creation as well as job losses frequently raise concerns about growing inequality and labour market dualisation (PNO, 2017; Taylor, 2017). Whilst jobs involving physical activity are most at risk of automation, AI also threatens to replace humans in many more highly-paid jobs such as those involving data collection and processing (PNO, 2017). Typically high-skilled, well-paid jobs are likely to remain in areas such as management, and predictions such as those from the WEF predict that job growth will be concentrated in high-skilled areas, but, as discussed above (Sections 2.5.1 and 2.5.4), the rate at which such high-skilled new jobs can be created and filled is uncertain. The other area of job creation, in human services such as the care sector, is one where low pay and low job security is common (Hewko et al, 2016).

Job quality is not just about the type of work, but the stability of employment. The rapid rate of technological development means that in the 21st century we can no longer expect to follow a traditional linear career path, retaining the same job, or working for the same company, throughout our working life (IPPR, 2015). Technological development enables greater flexibility in work practices, with work being less limited to the traditional workplace and working hours (Störmer et al, 2014). It also gives greater opportunity for those who are self-employed to take on project work from a wider range of clients, as they are less limited by geographical factors. But with flexibility comes uncertainty, and greater risk. Even if new jobs are created to offset job losses from automation, greater labour market churn brings a risk of greater instability for many workers.

Shaping Change: The Effect of Labour Market Institutions

Despite uncertainties, we should not shy away from trying to predict rates of job creation as well as job destruction. Although it is extremely difficult to envision the form and timescale of future developments in AI, it may be easier to predict how the labour market will respond to those changes, since, as the PNO report points out, there is considerable persistence in the occupational and skills composition of the workforce, which enables us to make some predictions. Labour markets operate following not only laws and regulations but also deeply-embedded social norms and cultural conventions, and this path-dependence means that the pace of labour market change may be much slower, and more predictable, than the rate of technological development. As such, there are substantial employment adjustment costs, even in the face of major changes such as the arrival of new and disruptive technologies (Pierson, 2004; PNO, 2017). Thus, even though it is hard to predict how technology will change, it is perhaps easier to predict how it will be implemented.

2.6 Conclusion

In this chapter, we have considered a variety of reports about the labour market impact of automation, and considered what these can tell us about the ways in which AI will change the structure of labour markets. The approaches used in estimations of job replacement vary wildly, as do the results of such estimations. This report cannot claim to have identified a “correct” estimate of the labour market consequences of AI. Rather, we have discussed different theoretical paradigms and assumptions underlying the literature, and the different ways in which the reports can be useful for the purpose of our research. There are no estimations that singularly address the labour market impact of AI, rather the reports focus on the overall effect of “computerisation”. With the exception of the WEF survey, which focussed on a survey of HR experts, methodologies used are reasonably robust and there are arguments for and against the assumptions

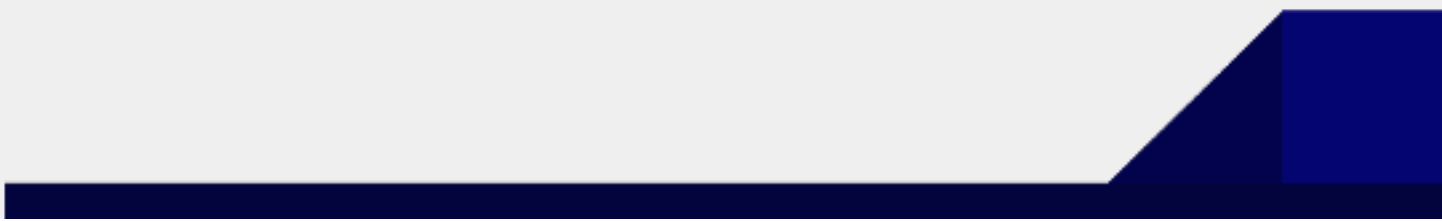
underlying the reports as to how best to capture the impact of AI. In particular, given the continuing advances in technological development outlined above, the literature makes relatively prudent assumptions as to the extent of jobs that may feasibly be automated in the near future. Particularly crucial was the distinction between an occupation-based and a task-based approach. While the OECD estimation, using a task-based approach, argued that automation potential was lower than previously found, the PwC study using the same methodology but a more refined predictive algorithm found that an occupation-based approach may overestimate the extent of automation, but not as severely as suggested by the OECD. On balance, the evidence therefore does suggest that automation has the potential to disrupt labour markets by displacing a significantly large number of jobs. However, it remains to be further explored how differences in automation potential can be best investigated, given the difficulties associated with extrapolating results across countries. This remains a promising avenue for further research.

Moreover, while the FO report inspired much of the recent research on automation, in particular the OECD and PwC reports, estimations of these three reports are limited to rates of job replacement. In contrast, the PNO and McKinsey reports use particularly detailed methodologies that address not just rates of job replacement, but also attempt to model broader influences on the economy as well as rates of job creation.

We can therefore see that while no one report can be identified as the “best”, we can place them on a spectrum as to their level of detail and robustness of methods. While we cannot, naturally, identify a concrete number specifying the impact of AI on the labour market, some common conclusions emerge.

1. Technological progress, and in particular replacement of cognitive tasks as can be achieved through AI, will have a major disruptive effect on labour markets, replacing a significant proportion of jobs. While we conclude that, given our preference for a task-based approach, cautious estimates may be more appropriate, these estimates still indicate significant amounts of labour market disruption.
2. We can identify differentiating factors that will determine which workers will be particularly affected. In particular, low-skill and low-wage jobs may be most affected in the short run, though certain white collar jobs will also be affected.
3. A focus on only the employment impact of automation is too narrow - it is likely to not only have impacts on job replacement, but also the ways in which we work, introducing greater flexibility and opportunity into labour markets.
4. While the literature focuses on the disruptive effect of AI, job creation effects may also be significant, and could potentially offset job destruction effects.

The infographic below summarizes our conclusions.



Major Conclusions



Major labour market disruption will happen via replacement of cognitive tasks.

JOBS IN DANGER

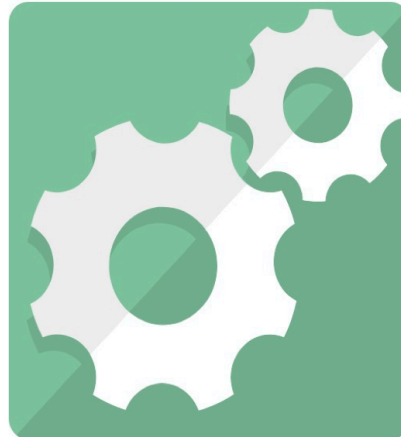


Low skill and low-wage jobs will be more affected in the short term.



Certain white-collar jobs are likely to be affected.

Automation will have a myriad of impacts outside of employment.



Greater flexibility and job opportunities are also likely to occur thereby changing the way we work.



JOB CREATION

While only job destruction is mostly discussed, job creation is significant and can offset the effects of job destruction

powered by

3 WHAT DO PEOPLE THINK?

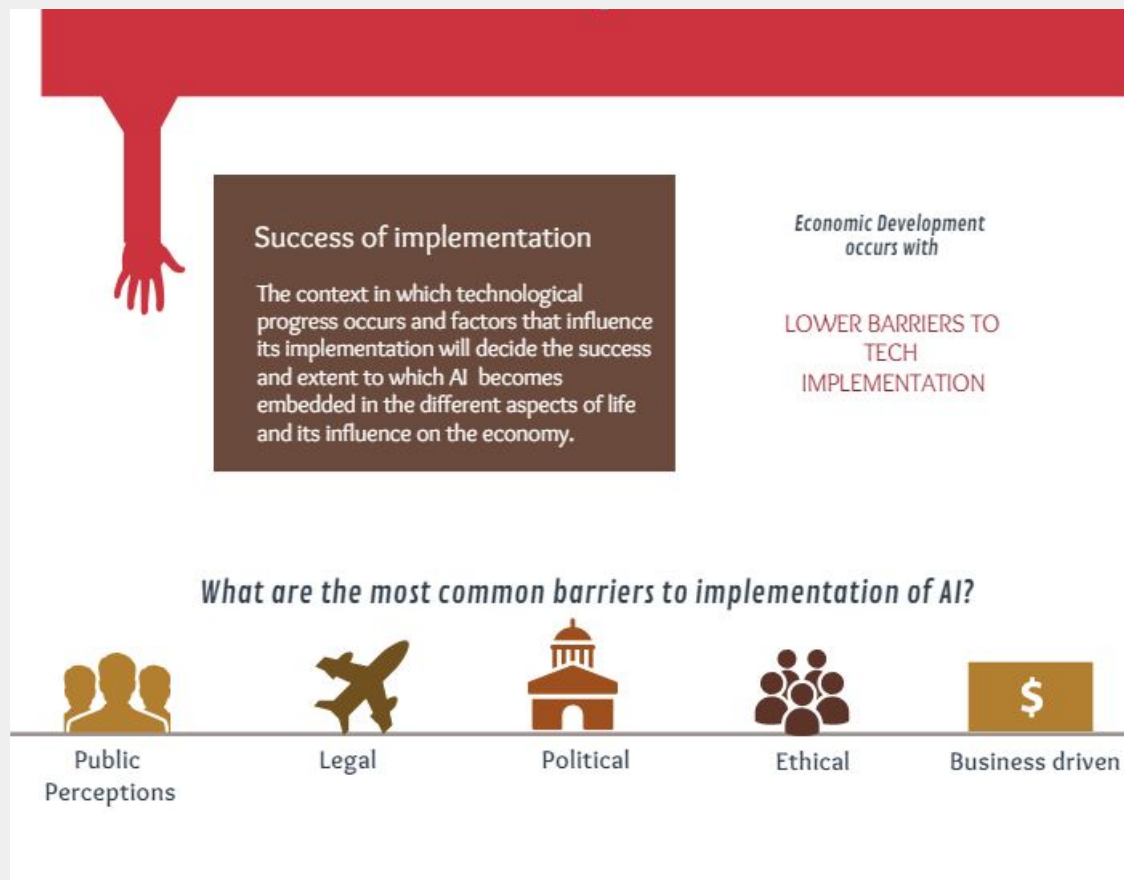
BARRIERS TO IMPLEMENTATION

3.1 Introduction

An issue that is not explicitly considered in estimations of the labour market impact of AI are barriers to implementation of AI. While a certain number of jobs may be “automatable”, actual implementation may not take place as quickly as may be possible, due to economic, political and regulatory constraints. This chapter now considers these factors in more detail. Barriers to the rapid and industry-wide implementation of artificial intelligence arise from three main sources; political barriers, barriers due to public perception and business driven barriers.

Historically, economists have correlated economic development with lower barriers to implementation of technology. Such barriers have always taken the forms of regulatory and legal constraints, threat of violence, outright sabotage or worker strikes (Parente and Prescott, 2001). Other barriers have also included the investment that needs to be made to advance the technology as well as the technology in and of itself.

This chapter will discuss the main barriers to entry within the political, socio-economic and technological sphere. We aim to establish the extent to which these barriers are currently present and theorize as to in how far they may persist in the medium term.



3.2 Political Barriers to Implementation

Internationally, there has so far been minimal political resistance to the implementation of AI as the technology is nascent. The current general stance of countries is focused less on resistance but more on how it will help populations, and what is needed to mitigate risks. However, there are several aspects of AI that may bring about political resistance in the future.

The composition of the workforce varies by area, and thus the impact of AI on the labour market will be different in different regions. For example, the proportion of individual skills required in Dover, Kent would not mirror that of Canary Wharf, London. The effect of technological advancements on labour markets is also heterogeneous, as

illustrated by the 19th century rise in the productivity of lower-skilled workers relative to that of higher-skilled workers. As Chapter 2 of this paper has shown, low-skill labour will initially be the most significant area of job replacement following the introduction of AI. With differing impacts and clashing interests, political representatives of different areas will have contrasting opinions on AI.

Distribution of wealth is a topic commonly utilised by politicians: the notion of AI serving the elite rather than all parts of the socioeconomic spectrum can be expected to be employed in rhetoric. In a recent publication, the Oxford Martin School (Frey et al, 2018) examined whether groups in the labour market that have perceived negative outcomes in response to technological change are more likely to opt for a radical political change. They found a relationship between electoral districts exposure to automation and their share of voters supporting Donald Trump in the 2016 Presidential Election – ‘victims of the Computer Revolution leading to a rage against machines.’ Such anxiety manifesting

at the level of policy formulation may hinder implementation.

Autonomous machines create a host of ethical issues that have the power to polarise political debate.

Autonomous machines also create a host of ethical issues that have the power to polarise political debate.

One of the most sensitive areas is public safety – more specifically, how technologies will formulate decisions in life or death situations. A commonly cited hypothetical scenario is the case of self-driving cars. With studies showing cars can be modelled to make decisions based on human behaviour (Sütfeld et al, 2017) the contention still stands regarding which moral values should be included in the guidelines for machine behaviour.

Security holds extraordinary weight in the realm of politics, and AI has posed many related questions. A report released by American think tank RAND (Osoba and Wesler, 2017) articulates the public concern of artificial intelligence having unexpected and

systemic effects. Additionally, it is argued reliance on agents increases the risk of diminished resilience. The accusation of compromising public safety is frequently implanted in polemics, and may influence policy commitments.

3.3 Public Perception as a Barrier to Implementation

From dramatised news articles to influential figures such as Elon Musk and Mark Zuckerberg displaying clashing opinions, mixed public perception of AI is expected. Our infographic summarizes some recent studies' findings on the public perception of AI, which are elaborated on in more detail below.

Public Perceptions about AI

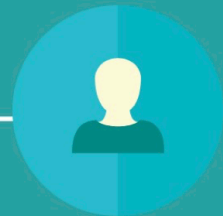
Attitudes depend on circumstances and application of AI technology.

TOP CONCERNS



Young survey respondents (18-44) are more enthusiastic than older consumers (44+).

Only 38% of Britons say they don't trust AI.



Non-academic concerns include privatization of AI, lack of regulation, control of expertise in the hands of few.

powered by

 **PIKTOCHART**

To better gauge the public psyche and its feelings around AI, Google has recently launched PAIR - the People and AI Research Initiative. From the list of studies it has published it is clear the overall feeling is AI will allow society to become better; prospects such as more efficient healthcare and automobile traffic are an attractive thought (ARM, 2017). It should be noted these studies found differences between demographics. For example, Asian respondents were the most bullish about the positive effect of AI in the future, while Europeans were the least optimistic. Young survey respondents (18-44) also showed more optimism than older consumers (44+). When it comes to gender, there were no significant differences. The Royal Society's (2017) public dialogue on machine learning also found that the public does not have a single view on such technology. Attitudes, positive or negative, depend on the circumstances or application in which it is being used. Nearly 38% of Britons have said they do not trust AI, while of the other 62%:

- 40% trusted AI to recommend personal entertainment
- 25% trusted automated sales processes
- 16% trusted medical diagnostics that only relied on AI

Top concerns include data security (30%), errors made and the resultant loss of productivity (40%), loss of control over data (41%), and loss of jobs (30%). The British respondents were more likely to never want to use AI (20%) than their American counterparts (10%). Some of the larger concerns reported in non-academic articles include the rapid falling of AI into private hands, the lack of regulation, and the control of expertise and wealth in the hands of a few.

3.4 Legal Barriers to Implementation

Human conduct, and sometimes the machines that humans use, are governed by law. However, if a system gains a high-degree of autonomy through AI, who is then responsible for any laws violated? Such legal conundrums pose as a potential barrier to implementation, as a clear plan of action needs to be formulated for when something goes wrong (House of Commons Science and Technology Committee, 2016). One of the big challenges AI researchers are tackling is reinforcement learning: grading systems are created and the AI must determine the best course of action in order to

If a system gains a high-degree of autonomy through AI, who is then responsible for any laws violated?

achieve a high score, consolidating the most rational plan of action. However, it has been shown AI models are capable of finding varying methods to achieve positive results. (Jeon et al, 2018) For example, an AI-controlled

traffic signal may learn it is more efficient to change the light one second earlier than previously done. What if this leads to more drivers running the light and causes more accidents? It had traditionally been held a legal system would only find liability where the developer was negligent or could foresee harm. A New York state case in 2007 (Wu, 2010) did not find the defendant liable where a robotic loading system injured a worker, because it was found the manufacturer had complied with regulations. In reinforcement learning, there is no fault by humans and no way of foreseeing such an injury, so traditional tort law would declare the developer is not liable. Seeing as it is unlikely AI will be given personhood and hauled into court, the law will need to adapt to this technological change in the near future.

3.5 Business Driven Barriers to Implementation

Even though most businesses are eager to invest in emerging technologies, several barriers to implementation exist. Within organizations, barriers appears to take several forms. A recent study by technology market research firm Vanson Bourne and Teradata (2017) found that key barriers within the organization include the lack of an IT infrastructure, lack of access to talent and a lack of budget for implementation.

Most AI implementation strategies in many industries are in the earliest development stages across industries. Any confusion seems to arise from the lack of expertise in understanding which form of AI is best suited for an enterprise. The Vanson Bourne study which surveyed decision makers from organizations of revenue more than \$50M a year indicated that senior executives seem to feel the lack of an IT infrastructure that will support the growth of their enterprise in AI.

In most cases, companies tend to rely on existing technology leaders within the company framework to assist with the implementation, however, expertise in the implementation is still in its nascent phase. The PwC Digital IQ study (2017) indicated that every functional area of a business now invests in technology that is outside of the sphere of control by the CIO, effectively resulting in a leadership conflict that hampers investment in AI.

The same survey also highlighted the shortage of AI brainpower and talent: Only 20% of the interviewed executives felt their organizations had the skills necessary to succeed with AI. Furthermore, only 43% of companies had a team for dedicated digital innovation. Finally, employee fear of change, cited by 54% of respondents as a top barrier of implementation, especially in the financial services. A recent report by EY (2017) also noted that 56% of respondents reported that the lack of AI experts is the greatest barrier to more widespread implementation. Moreover, organizations are

concerned with the lack of diversity of available talent, keeping in mind that gender diversity can influence biases that the machine learns.

The internal barriers to AI implementation are further complicated by barriers from policies and regulation as well as the impact on customer expectation. One such external barrier appears to be stakeholder buy-in. An EY report (2017) found that 33% of respondents cited stakeholder buy-in as a barrier to AI implementation.

3.6 Ethical Barriers to Implementation

As AI becomes more capable and begins transforming our lives, and as development and implementation outpaces our ability to govern the technology, key ethical questions arise and act as barriers to further implementation.

The global economy runs on compensation for contribution to it. Most companies compensate for hourly work, and as AI cuts down the need for human workforce, individuals with ownership get a larger distribution of the wealth. Start-up founders take a large portion of the economic surplus. The question of how to share the gains from technological progress fairly is therefore key for policymakers.

Furthermore, AI is capable of large monetary returns to companies and economies precisely because it uses previous data to learn. This means that AI relies on data that is not necessarily bias free. For instance, a recent case study showed that Northpointe's software used to predict future criminals showed racial bias (Angwin et al, 2016). As such, the issue of keeping emerging technologies as bias-free as possible will be central in order to ensure safe implementation.

3.7 Conclusion

A host of issues may slow down the process of job replacement via automation as it was laid out in the previous chapter. However, as businesses adapt to changing technological capabilities and the implementation of AI becomes ever cheaper to implement, the substitution of capital for labour is likely to become profitable for businesses. Rather, political, ethical and legal barriers are likely to pose more of an impediment for AI in the medium run. This means that it may take much longer for jobs to actually be replaced than would be feasible technologically. While these barriers may reasonably be expected to slow down the process of automation, however, we do not expect them to halt the process entirely. This is why it is essential for policymakers to address the impact of AI on jobs and the economy. We now develop a set of policy recommendations, focusing on the areas of labour market and educational policy.

4 WHAT SHOULD WE DO?

POLICY RECOMMENDATIONS

4.1 Introduction

Current government policy has identified artificial intelligence and related technologies as a potentially fast-growing sector of the UK economy, and a government-commissioned independent report published in October 2017 focussed its recommendations on how best to encourage growth of the AI industry in the UK (Hall and Pesenti, 2017). We applaud this proactive approach to technological change, noting in particular the assessment of the Centre for Public Impact that the UK is a policy leader when it comes to considering how AI can be used to transform the delivery of government services (CPI, 2017). However, we also note that when it comes to preparing for the socioeconomic impact of AI on the labour market, a coordinated government strategy is notably lacking.

We will argue that the focus on AI as simply another emerging industry, with policy

When it comes to preparing for the socioeconomic impact of AI on the labour market, a coordinated government strategy is notably lacking.

recommendations centred around how the UK can gain a comparative advantage in that industry, is too narrow. In particular, it diverts attention from the question of how government policy can be used to mediate the effects of the labour market disruption which AI will inevitably bring. The government is right to identify that the AI revolution brings opportunity for significant technical advancement, but a desire to place the UK at

the forefront of such innovation should not come at the expense of protecting the wellbeing of those whose jobs AI might replace.

Furthermore, if AI is to be integrated further into our workplaces and homes, there is a need for a level of trust in this technology. To maintain this trust, government will not only have to consider regulation and safety concerns, but also be seen to be acting to ensure that the economic benefits of AI implementation are felt across the economy, and not just by a narrow section of society - those who develop and invest in these new technologies.

Overview

Clearly there is a role for government policy to support development of AI (encouraging investment), and implement precautionary legislation (ensuring safety). However for the purposes of this report we will focus on government policy which affects the labour market impact of AI. This will include re-evaluating existing government policy, such as education, training, and unemployment support, as well as considering completely new policy responses, such as a robot tax and universal basic income.

We will conclude this chapter with recommendations for some key steps the government should take - considering the political feasibility as well as the efficacy of our recommended policies.

Current Government Policy

A government-commissioned independent review, *Growing the Artificial Intelligence Industry in the UK* (Hall and Pesenti, 2017), tended to treat AI like any other technological development, seeing the AI industry as an economic opportunity, and centring its proposed policy responses around promoting the UK as an industry leader, for example by promoting educational initiatives which could supplement AI innovation. It did consider the implications of AI in terms of data confidentiality and protecting personal

information, but in economic terms the impact of AI has so far tended to be seen through rose-tinted spectacles, with little attention paid to its potentially deeply disruptive economic impact.

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Throughout this chapter we set out our policy recommendations in bold. These are discussed in detail within each section and summarised at the end of each section. For an overview of these

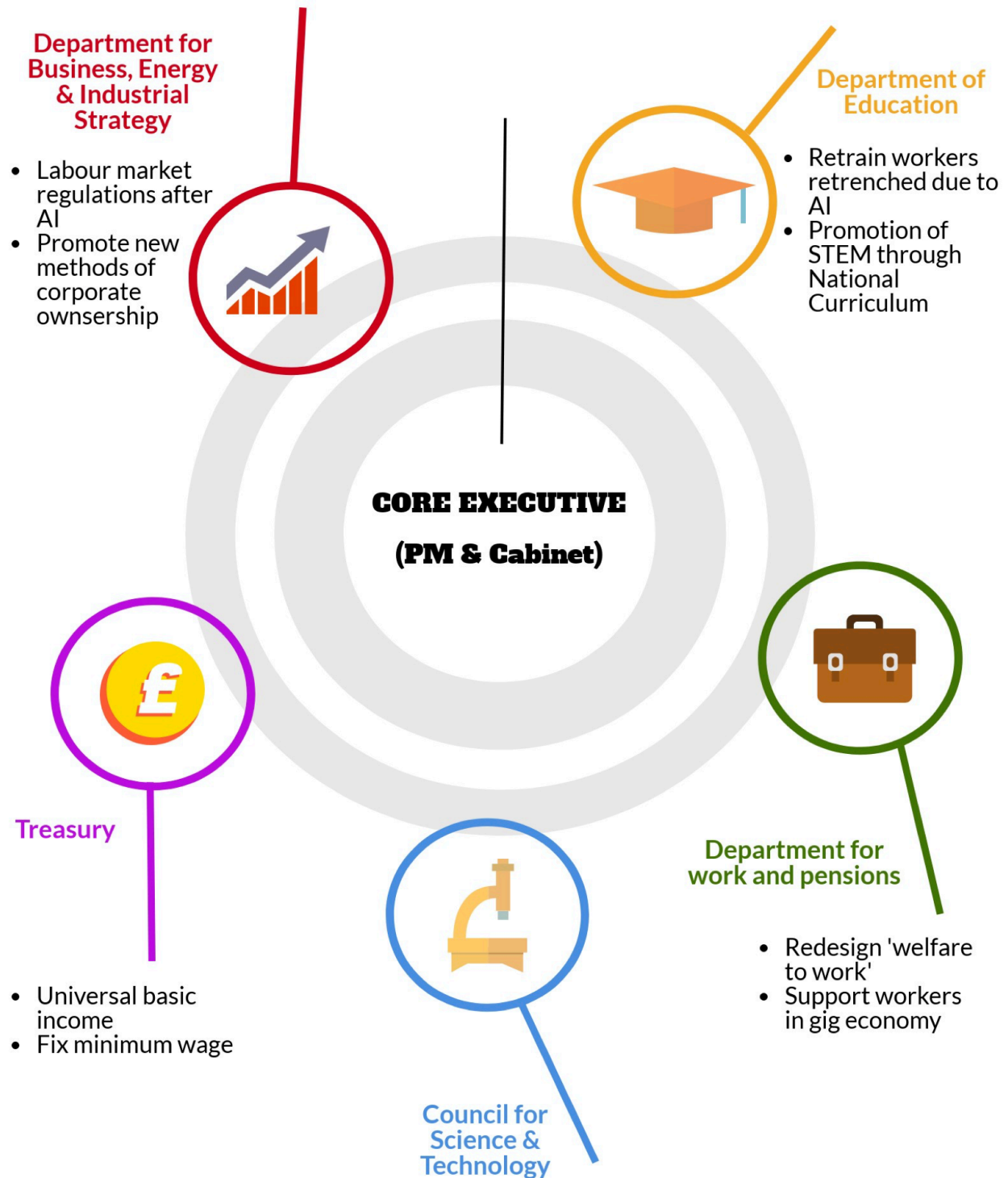
recommendations see the chapter's conclusion (Section 4.7) and the executive summary.

4.2 Assigning Responsibility

An effective policy response to AI developments would require a coordinated policy across many different government departments. This will make any government strategy on AI difficult to plan and implement.

Currently there are many different government departments, and non-departmental bodies, with responsibilities for areas of policy relative to the labour market impact of AI.

Government bodies influencing AI legislation in the UK



For example:

- The Treasury's power and influence means that its views on AI would be critical in shaping the government's response. In particular, radical new policy responses such as a universal basic income are unlikely to be considered without the backing of the Treasury, which would likely play a large role in deciding how to fund such scheme. In addition, decisions on taxation which could either incentivise AI innovation or disincentivise its implementation would come from the Treasury.
- The Department for Education would shape policy responses focussed on education and retraining. It has the power to make crucial decisions such as whether to focus the national curriculum around STEM subjects, hoping to create a new generation of technically able workers to help service AI technology, or to boost creative and interpersonal skills and focus on developing human talent in areas where AI lags behind. It also has control over retraining programmes which could be targeted at helping those whose jobs have been lost to automation.
 - Since education is a devolved policy area, the response here may vary significantly between the constituent nations of the UK.
 - The Education Funding and Skills Agency (created following a merger of two agencies in 2017) is responsible for the funding of education for pupils aged 5-16 education; education and training for those aged 16-19; apprenticeships and adult education; and managing school building programmes (all in England).
- The Department for Business, Energy and Industrial Strategy (BEIS) has a remit which encompasses policy responses such as encouraging investment and innovation in AI, or promoting new models of corporate ownership, so that the productivity gains from new technologies are shared more easily. It also has

some influence over labour market regulation such as minimum wage setting and enforcement.

- The Department for Work and Pensions (DWP) has a role to play in considering how the benefit system can support people in what is likely to be an increasingly volatile and disrupted labour market.
 - A key consideration in this area is whether the current popularity of welfare conditionality is helping or hindering labour market adaptation to automation. Welfare policies aimed at incentivising people to find a job as soon as possible may force people to take jobs which may not be in their long-term interest, or best suited to their skillset. Coordination is needed here with the Department for Education, as in some cases it would be preferable for people to embark on training programmes which would better protect them against the structural changes in employment patterns, rather than to take the first available job, which may soon be lost to AI.
 - The DWP has been slow to react to rapidly-changing employment types enabled by technological development. The rise of the gig economy and of self-employment means that policies such as National Insurance, which relies partly on employer contributions, or Universal Credit's system of monthly payments, are increasingly outdated. Coordination is needed here with the Department for Business, Energy and Industrial Strategy, which would have a role to play in any new employment legislation to insulate workers from these changes in employment patterns.

- Other departments, such as Health and Transport, would also likely be significantly affected by AI developments, although they have a smaller role to play in terms of shaping an overall policy response to AI-induced labour market change.

In addition to these departments, there are of course the devolved administrations in Scotland, Wales and Northern Ireland, as well as a whole range of non-departmental bodies which would be involved in a government AI strategy. These include:

- Sponsored by the Department for Business, Energy and Industrial Strategy:
 - The Low Pay Commission: an independent, non-departmental body that advises the government about the National Living Wage and the National Minimum Wage.
 - Science and Technology Facilities Council: coordinates research on some of the most significant challenges facing society, such as future energy needs, monitoring and understanding climate change, and global security. Offers grants and support in particle physics, astronomy and nuclear physics.
 - Innovate UK (formerly the Technology Strategy Board): focusing on business, works alongside companies to enable and support innovation
 - The Council for Science and Technology (CST) advises the Prime Minister on science and technology policy issues.
- The UK Commission for Employment and Skills was another non-departmental advisory body, providing advice on skills strategy to various departments (Education, BIS, DWP). It closed in March 2017.

Learning from Abroad: United Arab Emirates

The United Arab Emirates (UAE) has carved into its government the Ministry of Cabinet Affairs and the Future. Within this, a Minister of State for Artificial Intelligence is responsible for monitoring different sectors of the economy and their readiness for future change, and considering how AI implementation will vary by sector. The 'UAE Strategy for AI', launched in October 2017, was the first of its kind in the region, and consolidated the country's commitment to a government which will rely on various future services, sectors, and infrastructure projects (UAE Government, 2018). Some of the main aims include using an integrated smart digital system that can overcome challenges and provide quick efficient solutions (e.g., through the employment of AI) and making the UAE the first in the field of AI investments in various sectors.

As with the UK, the focus of the UAE's strategy is more concerned with developing the country's AI industry, and integrating AI with government services than with mitigating the socioeconomic impact of AI. However, the structure of the UAE's economy is very different from the UK, meaning that following the kind of AI strategy embraced by the UAE is risky for the UK. The UAE economy currently provides work for a large population of migrant workers, who would likely simply return home if displaced by AI, thus reducing the labour market impact of AI implementation. The UK can learn from the UAE in terms of integrating roles concerned with AI into the structure of government, but it should also differentiate itself, by creating an AI strategy which places greater importance on anticipating the labour market impact of AI-enhanced automation.

Our Recommendations

The government needs a coordinated response to the labour market disruptions that AI will bring. The scale of the AI revolution means there is a need for a coordinating figure, or body, who can draw together the many different actors crucial to an effective policy response. Up until now, the the UK Government has lacked any kind of coherent strategy on AI.

The scale of the AI revolution means there is a need for a coordinating figure, or body, who can draw together the many different actors crucial to an effective policy response.

There has already been some acknowledgement of this. In March 2018 a new Office for

Artificial Intelligence was created as a joint unit between the Department for Digital, Culture, Media and Sport (DCMS), and the Department for Business, Energy and Industrial Strategy (BEIS). This will work alongside two other newly-created bodies, an industry-led AI Council and the Centre for Data Ethics (DCMS, 2018). However, as with the 2017 Growing the Artificial Intelligence Industry in the UK report, the focus of these units are on encouraging the growth and implementation of AI technologies, rather than preparing for the socio-economic impact of their implementation.

Whilst the appointment of a House of Lords Select Committee on Artificial Intelligence in June 2017 is an encouraging sign that Parliament is considering broader issues of structural change, its remit, to consider the economic, ethical and social implications of advances in artificial intelligence, and to make recommendations, makes it an area of discussion rather than a source of policy innovation. The committee process means that there is still a need for an actor within government to champion policy recommendations developed and coordinate their implementation.

Whilst there is of course value to the deliberative process of a parliamentary committee, more rapid action is needed, given the rapid pace of technological and economic change. For this reason, we propose **the appointment of an individual within the Cabinet Office, who has the ear of the Prime Minister and can build a network of contacts across Whitehall, to establish better communication and coordination over how different government departments are reacting to the challenge of AI** - and indeed, to discover whether they are even giving consideration to the issue. The best way to do this might be to appoint a Special Advisor, or 'AI tsar', who could be independent of any particular department, and thus avoid being captured by one particular department's views on AI.

4.3 Education and Training

Technological progress is changing skills demand in national economies. As our analysis has shown, it is low-skilled, low-educated workers in particular who will suffer

Policymakers should respond by emphasizing STEM skills in national education, but also by furthering the development of creative and soft skills where humans are, in the medium term, expected to remain superior to AI.

disproportionately from the effects of artificial intelligence on the labour market. Investment in skills needs to be both proactive, furthering development of in-demand skills, and reactive, enabling retraining of those "left behind" by technological change. This

section focuses on proactive skills building. Policymakers should respond in two ways: first, as has been commonly argued, by emphasizing STEM skills in national education, but second, and as importantly, furthering the development of creative and soft skills where humans are, in the medium term, expected to remain superior to AI.

In the UK, the government response to changing skills demand as a result of technological progress has been largely focused on the development of STEM skills. as outlined in the STEM Strategy (Department for Education, 2011) and the Industrial Strategy (HM Government, 2017). It is commendable that the UK government has acknowledged the challenges related to AI and has taken action to address the need for STEM skills more proactively. Government policy emphasizes business taking the lead in promoting STEM education, through business focus groups, scholarships and the development of regional links. However, the strategies also include schools- and university-based measures, such as increasing the focus on mathematics and sciences, emphasizing enquiry-based learning, flexibilizing education pathways and continuing professional training. We applaud the government for making a sustained commitment towards increasing STEM education, including an additional £406m to be spent on investment in maths, technical and digital education, as well as for an approach that integrates STEM policy across business, education and training. However, there are several areas in which the UK STEM strategy needs to be improved if it is to lead to the skills development necessary for mediating the labour market impact of AI. This section outlines critical points for improvement.

Importantly, a more concentrated effort must be made to change perceptions of STEM careers in both students and parents, a factor that has been shown to be essential in take-up of STEM subjects at A-Level and beyond. This is especially important for groups traditionally underrepresented in STEM education, such as women and ethnic minorities. Given the high level of specialization in the British education system, which requires students to specialize in a highly limited number of subjects, **we recommend embedding STEM careers guidance within STEM subjects early as an especially effective way of emphasizing the usefulness of taking up STEM subjects** (Reiss and Mujtaba, 2017).

Second, it is imperative to take an integrated approach across subjects and create cohesive structures of teaching and learning. Significantly, technology and engineering are important aspects of the STEM curriculum that should not be sidelined (Kennedy and Odell, 2014). This is especially important not just in the context of encouraging STEM education but also ensuring computer literacy for all. However, just as important is the avoidance of inequitable discipline preferences, where take-up of STEM skills is proactively encouraged at the expense of other important elements of learning (English, 2017). As emphasized throughout this report, creative and collaborative skills are increasingly important as these are areas in which individuals, in the medium term, will still “have an edge” over AI. **Efforts should thus be made to integrate the arts into stem approaches and bridge interdisciplinary gaps. Further, collaborative and creativity-building approaches to teaching should be explored and integrated into the curriculum.**

Finally, to maintain competitiveness in the face of AI development, greater efforts should be taken to ensure that the full diversity of talent in the UK population is utilised. In addition to ethical issues associated with lack of diversity, there is a strong business case to be made for increasing diversity in take-up of both STEM education and STEM-oriented careers. This business case for diversity has been recognized by the government in the Lord Davies Review on Women on Boards (2011) and the Baroness McGregor-Smith Review on Race in the Workplace (2017). However, an orientation towards increasing diversity in take-up of STEM is lacking in the government’s industrial strategy, especially with regard to ethnic diversity. It is thus imperative that STEM education strategies more explicitly address socio-demographic gaps and differential access across groups, including of course gender but also other categories less prominent in the public discourse, such as ethnic minorities (Royal Academy of Engineering, 2017). *The UK’s demographic diversity should be a source of innovation and economic strength, but currently socio-demographic barriers to success in education*

means that many individuals fail to realise their full potential. While initiatives to encourage STEM education in under-represented groups exist, more coordination and governmental oversight is necessary in order to truly make an impact. **We recommend that initiatives consider not only the school level but also other transitions, such as that from school into work. In addition, funding and opportunity gaps across geographic areas and schools need to be more consciously addressed.**

The UK government response to changing skills demand has largely focused on STEM education. While a recognition of the need to develop these skills in the face of technological progress is commendable, this approach sorely neglects other types of skills likely to be increasingly in demand as AI is introduced in the labour market, such as collaborative and caring skills, where humans have a comparative advantage. While the introduction of robots and AI into caring labour is certainly feasible within the medium to long-term (Erikson and Salzman-Erikson, 2016), public opposition is likely to hinder these developments for some time. We can see this by looking at the example of Japan, where the introduction of robots in the caring industry due to rising demand has been largely unsuccessful due to public opposition (Hurst, 2017). Demand for caring skills is only expected to increase given aging populations, falling fertility and rising female labour force participation. **The low social status that is often accorded to care work needs to be addressed both through monetary means, such as living wages and opportunities for career progression, and increased societal recognition, for instance through community awards (JRF, 2014).**

Learning from Abroad: United States

In the United States, IBM (2016) offered a policy advice document to the White House Office of Science and Technology. In the document, IBM point towards universities in America crafting new AI curricula, which harnesses the wealth of expertise housed in leading firms to offer faculty members. Firms can also offer students access to cloud platforms with AI-based services from image recognition to machine learning. However, most of these courses and platforms would require programming skills and advanced mathematics as prerequisites. Thus, introducing 'coding' as a mandatory High School subject was a mission Barack Obama described as a necessity (Smith, 2016). The UK government must focus on revising the curriculum delivered by state-sponsored education, if the UK is to stand as chance of being a global technological leader.

Our Recommendations

We recommend that the government:

1. **Develop a more integrated approach to STEM education by:**
 - a. **Devoting more resources to the teaching of technical and digital skills.**
 - b. **Encouraging the teaching of other disciplinary approaches alongside STEM.**
 - c. **Developing more creative and collaborative methods of teaching.**
2. **Work towards improving attitudes towards STEM careers on the part of both pupils and parents by embedding careers advice and guidance within STEM classes.**

3. Address inequitable take-up of STEM careers across socio-demographic groups by:
 - a. Closing funding gaps across geographic areas and schools.
 - b. Developing awareness initiatives for disadvantaged groups at both the school level and the period of career transition after university.
4. Recognize that a singular focus on STEM does not adequately address development of AI and encourage investment in collaborative and caring skills through:
 - a. Improved regulation of care work.
 - b. Living wages for carers.
 - c. Social recognition initiatives directed at care workers, such as community awards.

4.4 Job Quality

As highlighted in Chapter 2 (Section 2.5), the labour market disruption caused by AI raises concerns over job quality. Government has a role to play in smoothing what are likely to be increasingly frequent transitions between jobs, and rethinking aspects of a social security system which was conceived of at a time where people's occupation tended to remain the same throughout their working life.

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Since the turn of the century, unemployment support and other welfare payments in many OECD countries have seen increased conditions attached to them (Dwyer, 2010). In the UK, for example, claimants of Job Seekers' Allowance have had to meet conditions such as regular Job Centre attendance, completion of interview training, and submission of a certain number of job applications per week, in order to qualify for financial support. In the face of increased labour market churn brought about by AI, such policies of welfare conditionality, which focus on reducing unemployment by incentivising people to look for work, may not be the most effective solution.

Increased use of sanctions for those not meeting conditions attached to benefits is associated with increased poor quality unemployment, characterised by low earnings and instability (Arni et al., 2009). The conditions necessary to qualify for unemployment support are increasingly time-consuming, and a focus on encouraging those in unemployment to enter more long term education and retraining programmes might prove a more sustainable solution (see Section 4.5 for more on skills and retraining). Stringent conditions attached to claiming benefits are likely to become less effective as the skillset of the workforce becomes increasingly mismatched with the available jobs. The rise of the 'low pay, no pay' cycle, as people re-enter the labour market for a short time before becoming unemployed again, creates uncertainty and stress for workers and is economically inefficient (Thompson, 2015). Thus **we recommend that the government revisit some of the incentives attached to claiming unemployment support, with less of a focus towards short term re-entry into the labour market, and a greater emphasis on finding long-term employment, even if it means a longer period of transition, during which individuals may be reliant on income support.**

Increasing rates of transition between jobs will also require a rethink of a wide range of government policy. For countries like the United States, where a large proportion of the population receive health insurance through their employer, it will mean increased uncertainty over access to healthcare. In the UK the government **needs to anticipate the**

effect of greater transition rates on pensions: not only will fewer people be working for the same employer (and thus paying into a company pension scheme) for a long period; the greater uncertainty in the labour market may force people to spend some of their retirement savings to support themselves when transitioning between jobs.

Finally, improvement in communications technology, and the drive for humans to remain competitive against increasingly competent AI alternatives, is likely to lead to more flexible working patterns - as has already been observed with the rise of the gig economy. Increasing numbers of people may be working in non-traditional forms of employment, outside the remit of traditional labour market protections - for example, self-employed workers may be earning far less than the minimum wage.

As discussed in Section 4.3 (Education and Training), care work is a key sector where

Given the growing demand for caring skills, a system where a large amount of such labour is provided by migrants is not likely to be sustainable in the long term.

humans are likely to remain competitive in the face of AI development. Hence, measures need to be taken in order to increase the supply of care labour. In particular, this requires the improvement of the working conditions of care

workers. Better government regulation is needed to protect this workforce, for instance through national Health Care Assistant registries (Hewko et al, 2015). This is especially important for home health care workers who are especially exposed to lower job stability, hours and wages.

Many of these issues regarding job quality, in particularly those linked to the rise in self-employment, were discussed in the independent Taylor Review of Modern Working Practices published in July 2017. The UK government's announcement in December that its response to the Review would be postponed suggested that, either the issue of

quality is not high on the policy agenda, or that there is lack of agreement over what form such a response should take. The eventual response, issued in February 2018 in the form of the government's *Good Work* report (HM Government, 2018) did make some promising steps towards addressing the challenges of changing work conditions. Steps have been made to pay greater attention to job quality, with the drawing up, in the Government's 2017 Industrial Strategy, of a set of measures against which to evaluate job quality. In particular, we applaud the attention which the Government's *Good Work* report gives to employee engagement. There is growing evidence that greater control over work conditions and environment not only reduce workers' stress levels and improves their health outcomes (Eurofound, 2010) but also their job performance (Surowiecki, 2004) and productivity (Taylor, 2017). Encouraging worker engagement could allow humans to develop comparative advantage over AI, as humans may be better able to think creatively about ways to innovate improve workplace practices in order to improve productivity - or at least, they may be better able to communicate such suggestions to employers.

The government's focus on improving employee engagement is a positive step, as it is not only likely to improve people's wellbeing in the workplace, it may also help to strengthen an area in which humans have a comparative advantage over AI. The Taylor Review recommended that the government enforce stricter obligations on employers to report statistics about their workforce structure, such as the number of requests by workers to move from zero-hours to fixed term contracts, and the rate at which such requests are approved. The Government argues that its recent Non-Financial Reporting Directive already covers this. Only time will tell if this claim will bear up, but for the present we recommend that the **information on workforce structure should be collated by one government body**, rather than hidden amongst a range of information released by companies in line with the Non-Financial Reporting Directive. Employer interest-groups, such as the TUC, would likely be willing to work with a government body like the Low Pay Commission (LPC), to collate this information. **Better monitoring of the**

workforce structure is needed if the government is going to follow up on its commitment to increase employee's control over their work conditions.

Whilst there are some good initiatives suggested in the Government's *Good Work* report, the overall approach is not promising, championing the UK's achievements of low unemployment rate and labour market flexibility without giving full consideration to the realities underlying this - increasingly precarious, unpredictable and often low-paid work for many people, with the rise of the gig economy shifting risks away from employers and onto individuals (Standing, 2011). The Government continues to view labour market flexibility as an unqualified good. **A less partial approach is needed, particularly as the rise of AI-driven automation may drive the interests of employers and workers further apart, with employers being incentivised to replace human workers with AI.**

It is disappointing that the Government did not accept the Taylor Review's recommendation of widening the remit of the Low Pay Commission (LPC) to

An approach to policy making that does not view labour market flexibility exclusively as an unqualified good is necessary.

include recommendations on how to improve quality of work in the UK. The Government has chosen to keep the responsibility for such considerations within BEIS and sector-specific teams in other government departments, which is likely to result in less independence of thought and innovation than giving the responsibility to an independent body like the LPC - as well as exacerbating the problem of diffuse responsibility discussed above (Section 4.2). We recommend that the government reconsider its decision, and follow the advice of the Taylor Review in **broadening the remit of the Low Pay Commission to include wider consultation and recommendations on how to improve job quality.**

Our Recommendations

We recommend that the government:

1. Revisit some of the incentives attached to claiming unemployment support:
 - a. Less focus on short term re-entry into the labour market, and a greater emphasis on finding long-term employment, even if it means a longer period of transition during which individuals may be reliant on income support.
2. Anticipate the effect of greater transition rates between jobs on pensions and saving for retirement:
 - a. Specific recommendations in this area go beyond the remit of this report, but there is room for further research here.
3. Reconsider its decision, and follow the advice of the Taylor Review in broadening the remit of the Low Pay Commission to include wider consultation and recommendations on how to improve job quality. In particular:
 - a. Information on workforce structure should be collated by one government body with a view to encouraging workplace practices that give employees more say in their working conditions.
4. Pay particular attention to improving job quality in growth sectors such as caring jobs, where human labour will retain a comparative advantage over AI.
 - a. Currently poor working conditions have created skills shortages in this sector, with many jobs being filled by migrant labour.

4.5 Skills and Retraining

The rapid rate of innovation in artificial intelligence technology means that the “creative destruction” effect which technology has had on the labour market since the industrial revolution is likely to happen more rapidly, and often in unpredictable ways. With people increasingly changing jobs halfway through their career, and also retiring later, there will be an increasing need for people to retrain and acquire new skills throughout their lives.

With people increasingly changing jobs halfway through their career, and also retiring later, there will be an increasing need for people to retrain and acquire new skills throughout their lives.

With this in mind, the UK Government has introduced a new £40 million Lifelong Learning Fund. It admits that is ‘a starting point’ (HM Government, 2018) and will mainly be directed at pilot programmes to examine which retraining programmes work best.

The experimental, evidence-based approach of pilot schemes is a good idea, but we recommend that **the Government should have a concrete plan to step up this funding in the short-medium term.** The £40 million allocated to the Lifelong Learning Fund is dwarfed by the overall projected government spending for 2017-18 of £87bn (HM Treasury, 2017). Human capital investments can take a long time, especially if they involve significant adjustments, such as by retraining manual workers in digital skills like computer coding, and thus this is an area of policy where the government cannot afford to delay, especially given longstanding concerns about UK productivity.

The UK Government also announced a National Retraining Scheme, targeted at adult learning and retraining. This ‘will be driven by a new National Retraining Partnership – the coming together of the government, business and unions to help set the strategic direction of the scheme and oversee its implementation’ (HM Government, 2018: 55).

‘The scheme will include a set of sector focused and employer-driven initiatives to target immediate skills shortages in key sectors. There will be £64m for schemes in the digital and construction sectors.’ Whilst this sectoral focus is important, the government should consider that, as already discussed, interpersonal skills are likely to be the area where humans retain a comparative advantage over AI. Thus, as already discussed with respect to education (see Section 4.3), it should broaden its sectoral focus to include areas like the creative industries and the care sector.

When designing training programmes to help those displaced by AI find employment in new sectors, an appreciation for variations within the labour force is key. A ‘one-size fits all’ approach will be inadequate when it comes to skills and retraining programmes. Particular issues which policymakers should consider are variations in occupational mobility of labour; varying levels of human capital within the workforce; and varying duration of unemployment.

Occupational labour immobilities refer to the ease with which skills from one industry can be redeployed in another sector. The labour market impact of AI depends not only on the relative rates of job destruction and creation, but also how easy it is for those who are displaced by AI to find new employment in expanding sectors. We cannot assume that it is possible to, for example, retrain every unemployed taxi driver as a computer programmer.

This is a particular challenge with respect to AI, since it is likely to replace human labour not in terms of entire *jobs*, but in terms of particular tasks within jobs (See Chapter 2). Therefore having transferable skills is of limited use in finding employment if artificial intelligence also has those skills. *Different levels of human capital within the workforce* mean that some workers will have skills which are easier to translate into new jobs than others, and some workers will have a greater aptitude for learning the new skills necessary to find employment in an AI-enhanced economy.

A further barrier to addressing these skills shortages is that the government may have limited information as to the current skills base of the workforce, and the current skills shortages of different sectors - information which is crucial to planning retraining programmes. A key critique of the Wolf Report into vocational training education (2011) was the inefficiency which arose from the government attempting to exert excessive control over this policy area. One possible solution, as recommended by an LSE report (LSE Growth Commission, 2017) is for government to devolve more of the skills budget to employers, who have better access to information about what skills gaps there are in the workforce. Employers could be incentivised to do this through **measures such as tax breaks for employers running who run training programmes for their employees.**

This is particularly problematic in the UK context of an ageing population, combined with rising retirement ages. It is not feasible to assume that large numbers of workers in their 50s and 60s who lose jobs to AI can simply take early retirement, yet this elder demographic may find it particularly hard to adapt to working in roles alongside new technologies. For example, those aged 75 and over are much less familiar with the internet, with 40% reporting internet use in the last 3 months, compared to 99% for 16-34 year-olds (ONS, 2017).

It is not feasible to assume that large numbers of workers in their 50s and 60s who lose jobs to AI can simply take early retirement, yet this elder demographic may find it particularly hard to adapt to working in roles alongside new technologies.

There are huge economic gains to be realised here, as many older people are keen to carry on working into retirement, but identify lack of technical training as a key barrier (Lee et al., 2010). **Retraining programmes will need to take account of a wide range of technological expertise amongst participants.**

Differing duration of unemployment. It is easy for retraining programmes to focus on participants for whom it is easier to find a new job, or devote fewer resources to participants for whom it will be harder to find a job. These practices, known as ‘cream-skimming’ and ‘parking’, are problematic when retraining programmes are contracted out to private companies (Finn, 2011). This leads to a growing divide between the short-term and long-term unemployed, with the latter being far less likely to find a new job (Krueger et al, 2014).

Long-term unemployment is particularly problematic not only because of its negative impact on mental health (Karsten and Moser, 2009), but also because of the risk of hysteresis. This is the process by which, the longer someone is unemployed, the more their skills become outdated, and the harder it becomes to return to work. This rate at which skills become outdated is likely to increase with the rate of technological innovation, and so **the government needs to increase its focus on targeting the long-term unemployed. We recommend that the government revisit the targets it sets private providers of training programmes, and add conditions stipulating that a certain proportion of training programmes should be targeted specifically at the long-term unemployed.** Such programmes might be funded by reducing the number of places on standard retraining programmes. This would reduce ‘cream-skimming’ without negatively impacting the number of unemployed finding work, since many of the easier-to-retrain workers, who had previously found work after completing retraining programmes, are likely to find new employment anyway.

Finally, the Government should also consider how the current incentive structure of its welfare system of Universal Credit impacts on the choices and opportunities for retraining amongst adults who lose their jobs to automation. Recommendations for less stringent conditions on unemployment assistance have already been discussed with respect to job quality (Section 4.4), but this is also relevant when considering how to update workers’ skills to adapt to the changing labour market. This is particularly

relevant to the issue of skills and retraining, since some of the technical skills necessary to make labour competitive in an economy where the role of AI is growing may take a long-time to acquire. The current welfare-to-work policy is not always supportive of such long-term human capital investments - for example, the Help to Work Scheme for the long-term unemployed, introduced in 2014, which requires claimants to attend the Job Centre every day, or to participate in a Community Volunteering Programme, are unlikely to be compatible with the kind of long-term skills-investments necessary for workers to adapt to a drastically-changing economy (Dar, 2016). **We therefore recommend that the incentive structures of the government's welfare to work policy be adjusted, with a focus on finding long-term employment rather than speedy re-entry to labour market, which might only propel workers into short-term jobs which are also on the verge of automation.**

Learning from Abroad: United States

Allowing for greater diversity in skills and retraining programmes can drive innovation, for example by allowing employers to experiment with online training programmes and other ways of using new technologies to fill skills vacancies. However, the government needs to ensure that the necessary infrastructure is in place to give retraining initiatives the best chance of success.

Pioneering initiatives in Eastern Kentucky have been retraining former workers in the coal mining industry in computer coding. This simultaneously combats the problem of high unemployment due to the decline of the coal industry and skills shortages faced by the growing tech industry. With 600,000 US tech vacancies unfilled each year, this leads to many jobs being outsourced abroad. However, there is room for improvement: poor broadband coverage in rural areas has put-off new businesses, who might otherwise be attracted by the newly-reskilled workforce (Rosenblum, 2017).

Our Recommendations

We recommend that the government:

1. Address information asymmetries about the nature of skills shortages by:
 - a. Using tax breaks to incentivise employers to run their own training programmes.
2. Ensure that the necessary infrastructure is in place to enable communities to re-orientate themselves away from declining industries towards the growing technology sector:
 - a. This can start with ensuring quality broadband coverage across the UK.
3. Redesign incentive structures for private contractors running retraining programs:
 - a. Incentives should ensure that programs help those long-term unemployed who are likely to be suffering most from skills atrophy/hysteresis.
 - b. Incentives should stop contractors from 'cream-skimming' those who would likely have found a new job anyway, and prevent the 'parking' of those at risk of long-term unemployment.
4. Shift Universal Credit/ benefit sanctions away from short term focus of getting people into work, and more focus on helping them find long term employment:
 - a. More care should be taken over matching people to appropriate training programmes, rather than blanket rules that everyone has to attend training programmes to be eligible to claim.

5. We commend the pilot schemes under the Lifelong Learning Fund, and recommend an emphasis within this on encouraging innovation to accommodate the range of different challenges when it comes to skills shortages, for example, varying needs by:

- a. Region,
- b. Sector, and
- c. Demographic group.

4.6 Sharing the Gains Fairly

As highlighted in Chapter 2, it is likely that the areas in which jobs will be retained in the face of widespread automation are areas with high levels of technical skill where humans will maintain a comparative advantage over AI. This means that the negative changes due to widespread automation will disproportionately affect those on low incomes, and with a lower level of education, as these are the people who are likely to be in the lower skilled, easily automatable areas of the job sector. Therefore, schemes

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must be in place to help spread out both the gains from automation and the negative effects.

Some argue that this will be done naturally with limited input from the government as the widespread automation, whilst destroying some jobs, will create

others. For example, the WEF found that a common response amongst industry professionals surveyed was that there was an expected growth in specialised sales jobs.

PNO and McKinsey also both predicted that there would be an increase in jobs which involve tasks requiring a high level of interpersonal skills such as managing systems or networks of people, as well as jobs requiring higher-order cognitive skills such as creativity. However, this does not help our above issue as this suggests that the job creation will be within highly skilled, technical jobs which usually require a high level of education, therefore still leaving the less well educated jobless.

The first suggestion for how to tackle this is some form of taxation. Bill Gates has been an advocate of this suggestion saying 'right now, the human worker who does \$50,000 worth of work in a factory, that income is taxed and you get income tax, social security tax and all those things. If a robot comes in to do the same thing, you'd think that we'd tax the robot at a similar level' (McGoogan, 2017). A robot tax would slow the rate of transition to a largely automated economy and would provide revenue to aid financial adjustment. However, this is precisely the reason why many industry professionals are unenthusiastic about the prospect of a robot tax (Kaminska, 2017). It would slow the rate of transition, thus slowing the rate at which businesses reach peak automated efficiency. As the uptake would be slower, it would also slow the rate of innovation. Although it may not be in the businesses interests from a profit maximising point of view, from a more societal, economic point of view a slow transition may be necessary in order to prevent widespread unemployment and inequality (Shiller, 2016).

The most obvious way to slow this rate of transition would be a robot tax. However, the implementation of a robot tax is not straightforward. The ambiguity of the term 'robot' makes it difficult to formulate an effective robot tax. To add to this slowing the rate of transition may not completely solve the problems stated above. A tax does not help the fact that those in low skilled jobs will become unemployed and the subsequent jobs created will be in highly skilled job sectors, it merely means this process may happen over a number of decades rather than over a number of years. Therefore, although a robot tax may be effective if it could be worked out how to properly formulate it, it must

be implemented in combination with other schemes in order to combat the route problems caused by widespread automation.

As noted above one of the problems caused by widespread automation is the fact that there is a disparity in education levels between those losing their jobs and what is required for the jobs created. This is added to by the fact that predictions suggest that one of the sectors that is likely to see an increase in job creation is in sectors like education and care as these require a high degree of interpersonal skills. There is the possibility that a large proportion of the jobs created are likely to be in completely different sectors to those where jobs are being lost. In order to overcome these problems one can invest in retraining programmes and accessibility to further education as outlined in sections 4.3 and

4.5. However, retraining could take a while and in all likelihood would be unpaid. This is problematic for individuals who are coming from previously lower paying jobs as they may not have the

Even if the governmental funds were available to invest in retraining programmes, such retraining is simply not a viable option for many of the individuals losing their jobs.

funds to pay their way through re-education and support themselves whilst retraining. This means that even if the governmental funds were available to invest in these programmes (although this itself is problematic) then retraining is simply not a viable option for many of the individuals losing their jobs.

A final suggestion for how to tackle these problems is by implementing a universal basic income (UBI). Robert Skidelsky argues that a UBI that grew in line with productivity “would ensure the benefits of automation were shared by the many, not just the few” (Skidelsky, 2016). He argues that as widespread automation makes the workplace more precarious, a UBI can guarantee the basic income previously provided by work and

welfare. UBI will both provide a safety net for those who become unemployed due to the automation of their jobs. This continual provision of income will then allow them to be supported whilst undergoing retraining schemes. It also allows individuals to become more flexible in the way in which they work. Skidelsky notes that technological innovation will cause per capita income to rise as automation is bound to increase profits, and therefore people will need to work less to satisfy their needs. IPPR (2015) research also suggests that the rapid rate of technological development may mean that we can no longer expect to follow a traditional linear career path, with work becoming more sporadic, and people moving between jobs and companies more frequently than in previous centuries. Both these observations suggest that the way people work, and therefore their income, will become more sporadic. UBI would protect people while their working income is no longer a constant flow. This is a suggestion that has been advocated by both the left and right as it both ensures a basic welfare provision across society, but is also more efficient and more equitable than traditional welfare systems, meaning it is able to reduce bureaucracy. This means it could provide a bipartisan response to the changes caused through automation. However, the obvious difficulty with this suggestion is that to provide everyone with a universal basic income is expensive. Even though UBI would save money as it would streamline the current welfare system and therefore cut out costly administration, it is unlikely that the savings made here would cover the costs of widespread UBI implementation.

Learning from Abroad: South Korea

South Korea have implemented what is being called a robot tax within their new tax policy at the end of 2017 (McGoogan, 2017). The government is limiting tax incentives it previously gave for investments in automated machines. However, it could be argued that this is not strictly a robot tax as it is simply the reversal of tax breaks previously given. It is also difficult to see whether this will have the results the South Korean Government hopes, that of making up for income taxes lost from workers, as it is only a year into implementation.

Learning from Abroad: UBI Trials

Europe

UBI has long been suggested as a response to inequality in countries across the world, however it has been more seriously considered in recent years as it seems that it can provide a good answer to the changing working environment. For example, Dalia Research (2016) found that 68% of people across all EU member states would “definitely or probably” vote in favour of some form of UBI. This general public support has led a number of European countries to investigate trials into the feasibility of UBI, with plans for trials within the UK having also been announced by the Scottish Government (Brooks, 2017), although the exact details of this are yet to be released. Despite this apparent general support across Europe, in a 2016 referendum in Sweden 75% of voters rejected a basic income of £1980 in part because it would have meant increasing welfare spending from 19.4% to around a third of the country’s GDP. Alternatively, Finland have begun a two-year, nationwide pilot UBI scheme (Henley, 2017). From 1st January 2017 2000 unemployed Finns aged 25-28 will receive a guaranteed sum of £475. This income will replace any existing social benefits they

receive and will continue to be paid even if they find work. The experiment having been completed at the end of 2018, results should become available at the end of 2019.

Canada

Although it is too early to tell whether UBI would be a success from the Finnish trial, we can get some idea from a scheme run in Dauphin, Manitoba in 1974 (Kassam, 2016; Kassam, 2017). Dauphin was a small farming town of about 10,000. Over the course of 4 years, 1000 residents took part in a pilot scheme run by both the federal and provincial government. Participants received a stipend of about 60% of Canada's poverty threshold which translates to around C\$16,000 a year in today's dollars for a single person. For every dollar participants earned from other income sources, 50 cents were scaled back from the monthly payment. Research found that over the four years the only changes to the residents' working habits were that new mothers took longer maternity leaves and teenage boys were more likely to stay in school for longer. Instead of becoming an alternative income source as opposed to working, it was found that the income became a source of stability, protecting residents from financial ruin in the case of sudden illness, disability or unpredictable economic events. The basic income also appeared to reduce hospitalisations, injuries and mental health issues. Although this trial occurred on a much smaller scale, it does show that UBI schemes could be effective in solving the problems associated with widespread automation. It would provide an effective buffer for individuals who end up having more sporadic work patterns.

Our Recommendations

Although UBI would be quite a radical response, it is clear that if effectively implemented it has the potential to combat many of the negative labour market impacts of widespread automation. In order to increase feasibility it could be implemented in combination with some form of robot tax the revenues which could be plugged into the universal basic income funding.

We recommend a review of the feasibility of a universal basic income scheme, taking into account the money saved from a streamlined welfare system and potential reduction in healthcare requirements as demonstrated in Dauphin. If the results of this are positive, **small-scale pilot schemes could be explored to trial the policy of UBI.**

If even trials of a universal basic income are unfeasible, **the idea of a robot tax should still be considered, which could provide revenue to invest in education and retraining schemes.**

We recommend that the government:

- 1. Review the feasibility of a universal basic income scheme.**
 - a. In addition to the pilot schemes already being planned in four local authorities in Scotland, trials should be considered at a local level in other nations of the UK.**
- 2. Consider the possibility of a robot tax, which could:**
 - a. Smooth the disruption caused by automation, and**
 - b. Provide revenue to re-invest in education and retraining schemes.**

4.7 Conclusion

The UK's current policy response to the development of artificial intelligence is conspicuous in its absence:

- In education policy there is a renewed focus on promoting STEM subjects and technical skills, but no appreciation for the comparative advantage humans may retain over AI when it comes to creative and interpersonal skills, which is reflected in their neglect in many school curriculums.
- Retraining programmes for those who may lose jobs to AI-enhance automation are underdeveloped and underfunded.
- Beyond the commissioning of the independent Taylor review into modern working practices, there has been no consideration for how AI will alter the nature of employment, and no regulation to protect workers who may be increasingly vulnerable to competition from AI in the “gig economy”.
- Nor has there been consideration for the possible impact on the income distribution (between owners of technology and those vulnerable to job loss). This will require critical reflection on the structure of the tax and benefit system.
- To the extent that AI has figured on the government agenda, there has been a focus on encouraging investment in developing technologies to ensure that the UK is at the forefront of the AI revolution. Whilst this is an admirable goal, government policy needs to consider the wider impact of AI development on the labour market (and thus on society), and to develop a proactive policy response.





As such, we have compiled a variety of policy recommendations, summarized in the infographic below, as well as compiled in the executive summary, in order for the UK labour market to better meet the challenges posed by AI.

Recommendations

An Overview

A brief summary of policy recommendations are outlined below

Education




-  Improve attitudes to STEM careers by embedding career advice and guidance in classes
-  Address inequitable take-up of STEM careers across socio-demographic groups
-  Encourage investment in collaborative and caring skills
-  Develop an integrated approach to STEM

Skills & Retraining






-  Ensure infrastructure to enable re-orientation towards growing technology.
-  Encourage employers to innovate and provide own training programs
-  Shift universal credit sanctions to focus on helping people find long term employment
-  Support development of a Life Long Learning Fund
-  Redesign incentive structures for private contractors running retraining programs

Fair Gains & Shares



-  Consider the policy of having a robot tax
-  Robot tax can be used to reinvest in education and training
-  Small scale pilot of the universal basic income scheme

Job Quality

-  Follow the advice of the Taylor Review in broadening the remit of the Low Pay Commission to include wider consultation and recommendations on how to improve job quality
-  Improve job quality in the growth sectors such as caring jobs
-  Appoint a single government body to collate information on workforce
-  Revisit some of the incentives attached to claiming unemployment support
-  Anticipate the effect of greater transition rates between jobs on pensions and saving for retirement



Responsibility



-  Appoint an AI Tsar
-  The AI Tsar can provide better overview of government wide policy related to AI
-  The AI Tsar can coordinate among the different departments and provide policy responses.
-  Balance development of AI industries with building economic resilience in preparation for automation

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APPENDIX

A.1 Technology and the Labour Market: Theory and Historical Thought

This section briefly reviews how labour economics predicts the effect of technological progress on the labour market, and argue that traditional models may not be adequate to accurately capture the effect of AI on labour markets.

A.1.1 Technological Progress and Labour Economics: A Brief Summary

Let us first review the role of technological progress in economic theory (Acemoglu, 2016). In the classical macroeconomic model, aggregate production is a function of the available stocks of capital and labour. Under this model, if the capital stock is a maintained constant, then aggregate production is dependent on the variable input; labour. The level of employment is established by the demand for and supply for labour. The demand for labour from profit-maximizing firms depends on the revenue that they earn.

The demand for labour is assumed to be inversely related to the real wage. For profit maximising businesses, labour will only be hired up to the point where the marginal product of labour, defined as the change in output that results from the employment of one additional worker, is equal to the real wage. Therefore, as real wages increase, demand for labour will decrease.

The supply of labour on the other hand is determined by the response of 'utility maximising individuals' to the level of the real wage. An increase in real wage has two effects:

1. Income effect: With a higher wage, individuals need to spend fewer hours working to maintain the same standard of living, and so can work fewer hours, leading to a reduction in labour supply.
2. Substitution effect: A higher real wage increases the opportunity cost of taking leisure time, causing individuals to substitute leisure for consumption, leading to an increase in labour supply.

The overall effect on the labour market is the sum of the two above effects. In a competitive market, without government intervention and trade unions, real wage levels will equilibrate to labour supply and demand.

The classic view is that technology augments and complements certain type of skills is captured by the following aggregate production function (Acemoglu, 2016):

Aggregate production $F(A_L L, A_H H)$

where (A_L) and (A_H) represent technology, which boosts the quantity of a good which each type of worker is able to produce. Classical economic models assume that advances in technology affect the supply curve, thereby shifting it. Technological improvements are thought to increase productivity, thereby driving supply of a good up, and its prices down. This will remain the case until there is a change in demand. This model was the basis of the predictions made for skill-biased technological change i.e. technology will become progressively skill biased.

A.1.2 Technological Progress and Labour Markets: A Historical Overview

Having briefly summarised the classical view on the impact of technology on the labour market, we now turn to reviewing the effects it has had historically. Technology is an important source of economic progress, but it also remains the greatest source of disruption for the labour market. Aversion to the “creative destruction” of technological progress has been present since the industrial revolution but came into academic

consciousness when John Maynard Keynes postulated his technological unemployment theory, predicting that “our discovery of means of economising the use of labour [is] outrunning the pace at which we can find new uses for labour” (Keynes, 1930). The need to protect workers from losing their jobs due to new and improved technology has since been a concern for government.

Historically, there have been various schools of thought concerning the effect of automation on labour market economics. These can be broadly classified into two main categories; those that see AI and automation as a threat and those that see it as an opportunity.

The school of thought that subscribes to the more optimistic outlook, seeing AI as an opportunity, maintains that automation and subsequently AI will have a positive impact due to what is known as the productivity effect. As automation increases efficiency and productivity, there will be an increase in demand for labour in other jobs and industries. It has been noted for example that with increases in automation and the resulting increase in efficiency, the demand for human labour has also increased in the banking industry. A modern example of this is the paradox of increased bank tellers even as the number of ATMs increased. Relieving tellers of the mundane tasks has allowed banks to provide more customer care, thus increasing their profitability (The Economist, 2016).

A second school of thought maintains that by directly displacing employees from tasks they were previously performing, automation and then subsequently AI is a direct threat to the labour market. Since the industrial revolution in the 18th century, prominent economists have postulated that while automation is good at increasing productivity, the addition of technology would leave the population redundant and deteriorate the conditions of the labourer. An example of this that has seeped into popular consciousness is that of the Luddites, the group of 18th century British weavers who, in a time of abject poverty due to a century of economic upheaval and widespread

unemployment, smashed up the textile machinery which they saw as the cause of their unemployment.

Typically, short term effects, especially negative ones, are dissociated from long term effects of the advance of technology. The displacement from employment, argued economists such as Sir James Steurt, would be temporary, but the increase in productivity would be permanent and therefore the most worthwhile outcome. This seems to be the trend reflected by historical evidence; while in the short run displacement of labour seems to dominate, in the long run, market and societies seem to adapt to these automation jolts and the productivity effect takes over.

A.1.3 The Limitations of the Classical View in Predicting the Impact of AI

Historically, opinion has diverged on the likely consequences of technological change for labour markets. However, an examination of historical data as well as a consideration of specific issues with AI leads us to question the adequacy of the classical model for predicting the labour market impact of AI.

Firstly, the historical data demonstrates that the labour market impact of technological progress diverges from classical predictions. While the model assumes that all technological progress increases all wages (albeit at different rates) historical data disputes this (Acemoglu, 2016). In addition, there has been no uniform increase in demand for high-wage workers as expected, especially after the 1980's i.e. highly skilled workers are no more in demand than pre-rise of technology (Acemoglu and Autor, 2011). Finally, there has been a polarization of employment but not of wages (Autor and Dorn, 2013).

In addition, despite the arrival of the computer age, the evidence suggest that we see the effects of computers everywhere but in productivity statistics, as first described by Robert Solow in 1987. Even as the productivity of computer and automation-producing industries increases, there has been little or no corresponding increases in productivity

and output in manufacturing industries that have increasingly used computers more heavily.

Moreover, we should consider that historical evidence can only take us so far – the impact of advances in AI is likely to differ vastly from previous technological progress. The McKinsey Global Institute estimates that the disruption of computer driven automation and subsequently of AI is occurring at a scale of 300 times that and ten times faster than the industrial revolution. In addition, rising evidence that both blue-collar and white-collar jobs will be affected, and that both routine and non-routine cognitive tasks are at risk, means that the skills-based predictions of classical labour economics cannot fully describe the labour market impact of artificial intelligence.

Another novel aspect of the changes to labour market dynamics with the implementation of AI is the type of job creation that is predicted to occur. For instance, jobs that are predicted to be created include jobs that will complement the AI that is being implemented, requiring labourers with technical skills that can complement the tasks undertaken by AI. Examples of the skills needed include function support and training provided by humans to increase efficiency of the AI programs in place through programing and higher cognitive order data science, but also filling skill gaps in more customer facing tasks that require a more 'human touch'. The other aspect is the creation of completely new jobs brought about by automating mundane tasks, allowing humans to move to tasks that require higher cognitive functioning. This of course will see the destruction of both low-skilled and high-skilled jobs, but is predicted to affect low-skilled workers more.