The Pissarides Review into the Future of Work and Wellbeing

July 2023

Reframing Automation: a new model for anticipating risks and impacts

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Acknowledgements

This paper was prepared for the Pissarides Review into the Future of Work and Wellbeing, led by Professor Sir Christopher Pissarides (Institute for the Future of Work and London School of Economics). We gratefully acknowledge financial support from the Nuffield Foundation.

The Pissarides Review into the Future of Work and Wellbeing is a collaboration between the Institute for the Future of Work (IFOW), Imperial College London and Warwick Business School. With thanks to Christopher Pissarides (IFOW, LSE), Bertha Rohenkohl (IFOW), Magdalena Soffia (IFOW), Jolene Skordis (UCL) for their valuable comments and input, and Kester Brewin for editorial input.

The idea that we need to ‘reframe automation’ came from Anna Thomas, IFOW Director.

The views expressed herein are those of the author and do not necessarily reflect the views of the Nuffield Foundation, nor those of the Institute for the Future of Work.

Citation

A. Gilbert, *Reframing Automation: a new model for anticipating risks and impacts*, Institute for the Future of Work, July 2023.

DOI: 10.5281/zenodo.8099822

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Abstract

We are living through the greatest technological transition since industrialisation, with automation precipitating major transformations in the nature and experience of work. For policymakers to craft a fairer future of better work through this transition, they need to understand the different impacts that automation can have, and how these impacts structure different types of risk, in different circumstances, for different groups.

In this paper, automation is presented as a process comprising choices made during design, development and deployment of technology. In this regard, while the deployment of technology within firms is most significant, we recognise that aspects of system design which shape impacts are decided before a firm puts them into use.

We argue that, rather than outcomes of technology being predetermined, choices made during each of these stages are conditioned by ideas. Ideas shape what we optimise for, our approach to value creation and, in turn, specific impacts. While there are risks relating to changing access to or availability of work, linked to the conventionally perceived threat of 'displacement', so too can automation affect quality and conditions of work in significant ways, with different outcomes for different groups.

By considering automation as a series of decisions which can lead to different types of work transformation, we aim to identify a wider range of intervention points to steer innovation towards beneficial social outcomes, such as a fairer future through better work. These will be explored in later work within the Pissarides Review.

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1. Why does ‘reframing’ matter?

There is a gap between what has happened and what will happen in the future. This space is shaped by ideas - information which can take form at various scales, ranging from the micro (an algorithmic recommendation) through to the meso (framings, narratives, discourses) and the more macro, such as coherent ideologies. Working across these scales, ideas determine how policymakers allocate resources and create rules. Ideas structure how actors perceive, define, communicate and make their interests actionable (Schmidt, 2008) and therefore, are increasingly recognised as important in economics (Schiller, 2017). Working in and through institutions, ideas can be understood to govern the nature of our societies and are the infrastructures which ultimately determine the success or failure of nation states (Acemoglu, 2012).

Ideas about what technology is, or should do — both for people and to people — also influence the impacts and outcomes it has. Ideas shape choices in design (Binns *et al.*, 2020; Bailey & Barley, 2020) development, (Fenoglio *et al.*, 2022) and deployment. Choices made across these stages are shaped by broader political ideas (Thomas, 1994) and ideological context (Forsythe, 2001; Noble, 1984).

This paper presents a heuristic model of automation to reconfigure and reconstruct ideas about risk arising from technological change.

Deployed with a view to improve job quality, or taking the ‘high road’ automation can and should support redesign of work in ways which improve wellbeing in various ways (Layard and De Neve, 2023).

This piece does not claim to be a comprehensive overview of impacts, or review of all possible benefits, but rather an intervention to restructure and reconstruct mental models of automation risk in light of evidence.

This is seen to be important for decision-makers at different scales:

At the system level, as policymakers and regulators seek to influence design and development of technology to promote responsible adoption.

Automation impacts are not always evenly distributed across demographic groups whether that be gender or ethnicity (Eubanks, 2018) or income and education (Fossen and Sorgner, 2022). In order to shape effective practices of detection, intervention and response, it is therefore important to understand how automation takes different forms, who benefits from these different forms, who is impacted, and how.

Differing types of automation require different forms of intervention and response. Policy can shape how choices in design, development and deployment determine impacts (Aghion *et al.*, 2019; Brownsword et al., 2017).

As firms deploy technology.

Productivity returns from cognitive technologies depend on the relationship between technical and human systems (Shollo *et al.*, 2022). Where firms adopt cognitive technologies without a clear view of how they will create value, they are less successful. Understanding changes to human work arising from different approaches to adoption is also important in evaluating trade-offs between the interests of employers (capital) and workers (labour), particularly as the share of value returned to labour is declining (O'Mahoney et al., 2021).

At the individual level, and through institutions which represent workers collectively as they challenge ideas about how automation is changing work.

Different types of automation drive different types of adjustment cost for workers. Recognising the different ways that automation captures value — and makes trade-offs with job quality — could assist workers' ability to understand, shape and negotiate changes to job quality and compensation. This can in turn shape outcomes of adoption, as impacted by the coverage of collective representative organisations (Freeman, 1989).

2. Introducing Automation

There is broad consensus that the best way to examine the risks posed by automation is by looking at the ability of technology to substitute for labour in tasks. Analyses of 'exposure' to automation commonly explore the task composition of a job. This can, in turn, lead to the share of those tasks which are understood to be suitable for technological substitution. Jobs containing a higher concentration of tasks which can be substituted by technology are deemed to be at greater risk.

This is an important route to understanding change, which can be also be mapped across the economy using large datasets. However, such approaches assume several things: a) that the technology can effectively substitute a task b) that it will inevitably be adopted to do so c) that effects are principally on the supply and demand of jobs. Less consideration is given to the impacts on job quality.

In this sense, such models assume outcomes are determined on the basis of how technology is designed, or the claims of its developers as to what it can achieve. However, exploring choices made by firms during the deployment of these tools could reveal a wider range of impacts, by considering effects on neighbouring jobs and broader aspects of work design.

The period of technological change we are currently living through - defined by digitalisation and computing, artificial intelligence (AI) and robotics (and the connectedness of these technologies) means most developments are transformations in information technology ('IT'). Therefore most 'manual' substitution is also relying on data-driven technologies, or advances in cognition.

This is changing the distribution of information, but also the locus of judgement. Automated, data-driven judgement could substitute workers' own judgement about how to conduct their work, or a manager's judgement about workers. It can also be used to mediate the employment relationship, and to initiate and complete market transactions. Such approaches can change demand for skills within jobs, and have a range of other impacts on job quality.

There are opposing views on the likely, aggregate impact of technology adoption. The complementarity thesis generally puts forward an optimistic account: in the long run, digitalisation will reduce routine work and improve job quality, allowing workers to focus on more interesting, rewarding and complex tasks (Bessen, 2015, 2016; Menon *et al.*, 2020). In contrast 'digital Taylorist' accounts suggest work will become more routine and be of a lower quality (Brown et al., 2010; Chang 2010). In practice, different outcomes for different groups are being observed at different speeds; more understanding of how and why is required to create effective interventions and this, in turn, will lead to better understanding of how jobs are polarising not only in terms of income, but also in broader aspects of quality (Lopes and Calapez 2021).

Towards this, this paper presents a series of automation archetypes. Each section contains an explanation and example, how this can capture value for a business and any known economic models or theories; reflections on links to skills, information, or geographically-based frictions (adjustment costs); consideration of the effects on different demographic groups; and reflections as to likely or known impacts on good work principles.

3. Automation archetypes

3.1 Displacement

Automation is widely understood to reflect the ability of technology to ‘replace labor in tasks it was previously engaged in’ (Acemoglu and Restrepo, 2019). This reflects commonly held ideas of automation established during earlier eras of mechanisation.

Displacement: technology is designed or deployed to conduct tasks previously conducted by people, in a way which reduces the demand for labour at the level of an entire job.

Examples:

- Natural language processing displaces transcription jobs
- Chatbots displace customer service operatives
- Driverless cars replace delivery workers
- Manufacturing workers are displaced by assembly line robots

Displacement is the most commonly imagined automation risk. Risk to manual work - typically completed by men - is common in forecasts of disruption (Dickerson et al, 2023). Displacement is commonly presented to show automation as a route not only to productivity gains but also to improve job quality, by removing ‘dull, dirty and dangerous’ work from the economy.

Displacement automation of cognitive rather than manual work has been used to explain the hollowing out of middle-pay jobs from the labour market, as linked to the theory of ‘Routine-Biased Technological Change’ (Autor, Levy Murnane 2003; Goos Manning and Salomons, 2014). This model saw computerisation as suited to undertaking routine tasks, and jobs in the middle-pay range of the labour market most characterised by routine tasks.

By displacing middle-pay jobs, workers enter the labour market and increase competition, putting pressure on wages in lower-income jobs. This may contribute to phenomena such as ‘underemployment’ - which can represent a situation of skills-mismatch, where people are over-qualified for their work; and ‘malemployment’ (Benanav, 2020) whereby oversupply relative to demand for labour puts downward pressure on wages and changes conditions for workers to collectively bargain for given working conditions.

Increasingly, ‘professional’ work has come to be seen at risk of displacement. While RBTC has been understood to impact accountants, or managers who scheduled shifts - which can be conducted by lower complexity algorithms - advances in pattern recognition through Machine Learning have led to professions which require less standardised (or even creative) application of knowledge also being seen as displaceable (Susskind and Susskind, 2015, 2018, Susskind 2023).

Beyond these socio-economic variables shaping displacement effects, forecasts of displacement also highlight uneven consequences for different demographic groups. As occupations and labour markets are stratified by place (Rutherford *et al.*, 2008) and demographic group, so too is risk unevenly distributed, as shown for gender (Roberts *et al.*, 2021), ethnicity (ONS, 2019; Broady *et al.*, 2021) and place (e.g. Crowley and Doran, 2022). There are also politics surrounding the identification of work as befitting of displacement (Resnikoff, 2022) with some demographic groups conceived as 'roboticised' (Bui, 2020). This racialised dimension of automation is also commonly at play with 'faux-automation' (Taylor, 2019) whereby a system is falsely marketed as 'fully automated' when in fact there is a body of labour which is not being well compensated underpinning 'high tech' service delivery. In these cases, it is more common for marginalised groups to be subject to processes whereby the contribution of labour is 'made invisible', presenting issues of equality (Taylor, 2018).

The commonly perceived risk associated with displacement is reduced availability of and access to work, with associated impacts for individuals on pay and wellbeing. Fear of displacement before it is realised can also drive negative effects on wellbeing (see Rohenkohl and Clarke, 2023), highlighting the need for responsible information sharing by employers. Where jobs are displaced entirely, workers may face skills frictions, with skills mismatch either requiring workers to upskill or accept work which does not fully utilise their abilities. This effect is likely to be moderated by geographic friction and the availability of alternative work within a distance that they are happy - or able - to travel.

3.2 Creation

Creation can be linked to technological development where new jobs emerge within the economy which were not previously present, and have the use of new technologies at their core.

Creation: New jobs emerge within the economy which would not have previously existed.

Examples:

- Prompt Engineers using generative AI to create content for a business
- IT Processors
- Data Analysts

In the minds of policymakers, creation is commonly linked to skill-biased models of technological change, i.e. the assumption that technology will in general create better-paid, more interesting work.

Studies which document creation, or jobs significantly altered in their task composition by new technology, have been limited, owing to a focus on task-level change and challenges in identifying the changing constitution of tasks within jobs over time. However, methods to overcome this have been developed (Acemoglu and Restrepo, 2018; 2019) revealing a countervailing force to the employment-eroding effects of task-displacing automation.

Autor (2022) finds that 60% of employment in 2018 in the United States consisted of job titles that did not exist in 1940 (Autor, 2022). However, an analysis of changes in US markets since 1980 found new work predominantly in high-paid professions or low-paid service work. Technologically-linked task or job creation therefore cannot be taken as a countervailing force reducing, or mitigating the polarisation of labour markets. In practice, new jobs heavily shaped by the use of technology may be characterised by any of the following automation types, with associated impacts on quality.

3.3 Augmentation

Augmentation of work reflects choices in the design, development and deployment of technology in ways which lead to a changing demand for manual or cognitive skills within a job. This can reprofile work so as to restructure demand for - and promotion of - human capabilities, depending on the design of a system. Accordingly, the concept of augmentation has recently been broken down into 'high discretion versus low discretion' augmentation (Shollo *et al.*, 2022). High discretion and low discretion augmentation arise as the result of different approaches to design and deployment within the workplace.

High Discretion Augmentation

'High Discretion' Augmentation: technology helps workers to conduct work in ways which improve processes, their experience and, potentially, their productivity.

Examples:

- An architect uses software to model different designs for a building
- A radiographer uses AI to support his analysis of the likelihood that a growth is cancerous
- An assembly worker wears a bionic suit to reduce strain on their body

High discretion augmentation aligns with early theories of the effects of computerisation on the labour market, described as 'skills-biased' automation (Spitz-Oener, 2008). In this process, those with the ability to use technology, commanding it as a tool, see higher compensation in wages (pay). This is assumed to reflect the complementarity of human capabilities with technological one.

High-discretion augmentation could arise through the creation of new, technologically related tasks, which require some human capital contribution to deliver value. Alternatively, a role could be augmented by low-discretion (e.g., routine) tasks being substituted within a role, reducing the share of 'lower value' work. It could also be the result of technology enabling better collaboration between workers (Schuh et al, 2014) augmenting their collective capabilities.
High-discretion augmentation can improve most dimensions of work - ranging from conditions (Gajšek *et al.*, 2020) and learning (Kitsantas *et al.*, 2019) together promoting

dignity (Gilabert 2018); pay (Acemoglu, 2003) equality and autonomy (Romero *et al.*, 2016); support, allowing for increased creativity and collaboration (Siemon *et al.*, 2022); and participation, accelerating new forms of union activity (Irani and Silberman, 2013). Technology-intensive industries and jobs have been found by some studies to have an 'autonomy premium' (Rabensteiner *et al.*, 2022) suggesting there may be a tendency towards high discretion augmentation (see below) in better paid 'tech work'.

These outcomes are highly desirable and should be the focus of innovation. However, such benefits are not evenly distributed. Research suggests that access to highly paid tech jobs is racialised, and gendered (Young, Wajcman and Sprejer, 2021). This contributes to issues in the design of new technology, which exacerbate wider equality impacts (Benjamin, 2020). Further, research suggests technology is more commonly designed to positively augment those in jobs already characterised by higher wages and levels of education (Menon *et al.*, 2020). These effects can also arise in deployment, as negotiation shapes ideas about contribution. Research has shown that the professions, when subject to automation impacts, are well equipped to engage in 'boundary work' - using language and framing as ideas about the changing contribution of humans to outcomes are negotiated (Faulconbridge *et al.*, 2023). This could mean that outcomes of exposure vary between workers with the same level of 'objective' exposure risk, but hold different skills in articulation. Both of these effects could mean deeper polarisation of learning and autonomy at work (Kwok, 2020) with effects which go beyond the workplace, to impact wider civic behaviour (Lopes, Lagoa and Calapez 2014). How the value of a worker is estimated or how workers come to be rewarded reflects a variety of factors (Pitts, 2020).

Low Discretion Augmentation

AI has been described as holding the capacity to 'reduce the cognitive load' of workers by delimiting their choice environment (Shollo *et al.*, 2022).

'Low Discretion' Augmentation: technology is designed and deployed to reduce the required discretion and skills composition of work.

Examples:

- Route instructions for taxi drivers on major platforms reduce the need for detailed place knowledge
- A factory worker is required to follow a single method for conducting their work, taking pictures to confirm compliance with a set method

Theories of 'effort-biased' automation (Green 2000; 2001; 2004 Guy and Skott 2005, Skott and Guy 2007) define work 'effort' by the ability of workers to deliver work which is discretionary, i.e. that which is not directly outlined, coded and specified by management. Such processes, if successful, reduce the human capital (experience and skills) required for jobs, and so allow labour to be contracted at a cheaper rate. If there is a good supply of this lower-skilled workforce, this process could reduce skills frictions and adjustment costs for the employer. However, if low-discretion augmentation occurs to jobs and workers remain in these positions, they could experience social and psychological wellbeing costs as the result of a skills-mismatch, where they are not able to fulfil their capabilities.

Managerial approaches to the deployment of technology in the service of reducing discretion reflect 'one best method' approaches to management, developed during Taylorism (Pruijt, 2003) and drive the routinisation of work (Burgess and Connell, 2020) rather than promoting autonomy or creativity. Studies of changes to work in the UK suggest there has been a decline in task discretion since the 1990s (Gallie, Felstead and Green, 2004) and this has known consequences for wellbeing (Green, 2004).

Some technology developers are explicit about their objective to reduce discretion of workers. This is seen to deliver value by reducing scope for errors. But it can also deliver savings by reducing the requirement for experience. This seeks to overcome 'Polanyi's paradox' (Polanyi, 1966) which suggests that we each know more than we can tell. This private, or tacit knowledge, restricts the extent to which work can be codified and can be substituted. Some algorithmic management tools offer this tacit knowledge elicitation as part of their package of workplace change (Gilbert and Thomas, 2021). However, for these processes to work, there needs to be a socio-technical lens during deployment; deriving methods from extensive data collection is unlikely to work (Fenoglio *et al.*, 2022).

Generative AI is now seen as holding the potential to disrupt creative work, which has long been deemed inherently human and with greater capacity to be intrinsically rewarding. Generative AI can augment creative workers. Yet, various instances suggest that approaches to deployment can drive 'low discretion' augmentation, substituting core decision-making aspects of work but not entirely displacing the requirement for labour, leaving only lower quality work. A prime example of this is encapsulated in the Hollywood script-writers struggle (live at the time of writing). First-version scripts commonly command a higher rate than subsequent editorial work of a first draft which receives a lower rate.

Yet, in work which combines cognitive and physical tasks, another paradox pulls in tension with Polanyi's, impacting the relevance and application of these principles. Moravec's Paradox (Moravec, 1988) reflects the fact that: 'it is comparatively easy to make computers exhibit adult level performance on intelligence tests… and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility' (Moravec, 1988 p 15). While robotics has significantly advanced since Moravec made these comments, patent analysis from just 2020 suggested firms were still assuming (and producing) the longevity of this principle (Delfanti and Frey, 2021) with product design by market leaders in AI still positioning humans as central to work processes, but functioning as the 'sensing appendage' of machines. However, robotics is developing at pace, and sensor-motory capacities have advanced significantly in the last two years.

In practice, an experienced worker can consciously or unconsciously programme instructions about work methods into a system. This information can then be used by an employer to replace them with those who have less experience by instructing these workers on how to conduct tasks in real-time, through task-based guidance rather than general formal education (Gilbert and Thomas, 2021). Real-time instruction, via app, could also undermine the ability of workers to collectively organise and effectively disrupt through withdrawing their labour.

This can be considered as 'pre-automation', whereby as much of a role as is possible - including aspects of judgement (cognition) are automated, until such time technology permits full displacement (Vertesi *et al.*, 2020). As a consequence, rather than tasks or whole jobs being substituted, jobs can become reconstituted and downgraded in terms of job quality while workers remain in role, resulting in their discretion and agency becoming progressively delimited. Such transformations of work could negatively impact autonomy, dignity and learning. If successfully used to replace experienced or formally educated workers with those who are less experienced, this could also impact pay. However, routinisation has been found to positively impact job quality in some cases, and even increase creativity and proactiveness (Ohly and Sonnentag 2006).

Both low-discretion augmentation and intensification (see next) are important to consider in light of evidence that routinisation of work is increasing across professions, despite declining shares of 'routine work' (Bisello *et al.*, 2019). In this context, workers can be required to 'upskill' to work with new digital tools, while also coming to spend more time on repetitive and standardised tasks (Cedefop, 2023). This means that a more critical lens is needed to evaluate uncritical claims of 'digital upskilling' and recognise where there may be a general reduction in autonomy or discretion at work, despite the need for new knowledge relating to specific tools.

The prevalence of this automation impact for different groups of workers is difficult to detect at the aggregate, labour market scale. However, increased routinisation of work - including in the professions - is indicative of this trend. This raises questions about what makes for good work and the role of promoting human capabilities.

3.4. Intensification

Intensification is commonly understood to reflect an imbalance between job demands and job control, from the perspective of a worker. This theory is well established in psychology to understand how work shapes wellbeing (Van der Doef *et al.*, 1999).

Intensification: Technology is designed, developed or deployed to support increased density of tasks. This generates value by increasing the output and activity of humans.

Examples:
- A worker who is algorithmically managed is set a task delivery rate of 95%, with 5% rest time
- A consultant undertakes meetings via telepresence (see below) and, as a result, more meetings are possible throughout the day.

Intensification has been linked to automation through various theories of 'effort-biased' automation (Green 2000; 2001; 2004 Guy and Skott 2005, Skott and Guy 2007). These either see automation as increasing marginal productivity by increased effort of workers, rather than technological functionality. These variably define 'effort' as related to the work which is discretionary, i.e. that which is not directly outlined, coded and specified by management. Intensification at work (Chesley, 2014) has been linked directly to the phenomenon of algorithmic management (Lager *et al.*, 2021) and remote work (see telepresence below) (Kelliher and Anderson, 2010).

Intensification can be driven by technology design, development or deployment and be the result of an overestimation of displacement effects (linking intensification to low-discretion automation). Accurately predicting how labour-saving a technology will be (a choice made during deployment) is difficult and ultimately political as it relates to the intensity of others who remain in work and the impacts on their roles. Displacement effects or the potential of a tool may be consciously overestimated where management does not understand frontline processes or are prioritising savings over job quality. When displacement benefits are over-assumed, adjacent roles can see work 'transferred'. This has been described as 'heteromation' of work for others who remain in work in adjacent roles (Ekbia and Nardi, 2014; Dholakia and Firat, 2019). This can apply to work across pay or skill ranges, for instance as checkout assistants are required to staff tills and help customers to manage self-service checkouts, increasing the task-density of work (Gilbert and Thomas, 2021) or public servants (who have seen welfare allocation processes automated by robotic process automation) dealing with only the most complex cases, requiring human review - leading to intensification of their work (see below, also Zhu and Kanjanamekanant 2023).

Intensification can also play out in different ways in different professions and for different demographic groups, reflecting the ability to 'push back' among groups who hold less power (Harvey, 1995). As technological acceleration changes requirements for work, older workers can experience a greater burden (Mauno *et al.*, 2019). Some have theorised that algorithmic 'nudges' can lead to an intensification of work for those in specific types of work - notably the gig economy (Yeung, 2017). By linking speed of performance to contract security, or distracting workers from hazards, systems can lead workers to take health and safety risks (Christie and Ward, 2019).

Intensification is advertised as an economic function of some algorithmic management technologies, claiming to reduce non-productive time ('NPT'). However, these design choices can only be realised through the application of these tools by firms during employment. 'Metricisation' - whereby work and performance are measured by quantitative indicators - is enabled by the greater use of algorithmic systems at work, and can intensify work (Willis *et al.*, 2018). Metricisation is known to be a significant driver of wellbeing harms, both through changes to individual self-perception and behaviours (Moore, 2017) impacts on relationships between people (Danaher *et al.*, 2018) driving workplace competition (Steffen, 2019), and changes to support. By influencing the time, location or sequencing of work, intensification can also significantly impact autonomy (Breaugh 1985).

Metricisation (evaluating and measuring what counts as work by proxy indicators) becomes extended in algorithmic management, through associated choices about organisational design, and penalty and reward for performance against these metrics (Ulbricht and Yeung, 2022; Eyert *et al.*, 2022, Gilbert and Thomas, 2021). Algorithmic management can change and regulate workers by first representing work performance through a set of data points or indicators; setting a standard for the delivery of these, and then upholding these standards through positive reinforcement and rewards (such as access to hours, pay, recognition via status or ratings tables, shaping dignity) or negative reinforcement (such as removed access to promotion, hours or contract termination) (Kellogg and Valentine, 2020). In this sense, both job and organisational redesign are intertwined with technological functionality.

Work which is subject to low discretion augmentation and intensification may also be experienced as 'routinised'. Research has demonstrated that the use of IT can drive routinisation even in 'high skill' roles (Petrakaki and Kornelakis, 2020). A meaningful distinction between augmentation and intensification has not yet been resolved from an economic viewpoint. This may reflect challenges around the detection of different impacts and, potentially, also normative assumptions in regards to acceptable trade-offs between job quality and productivity. It could also reflect poor interdisciplinarity and the absence of good firm-level data on adoption.

3.5 Telepresence

The detachment of work from place is a growing trend (Felstead and Henske, 2020) with COVID-19 accelerating the development of patents for technology which support remote work (Bloom *et al.*, 2021).

Telepresence: Technology is designed and deployed to enable a user's perceptual, cognitive or psychomotor capabilities into a distant environment (Draper *et al.*, 2020)

Examples:

- A civil servant conducts their work remotely, no longer required to live in central London
- A technician in Vietnam controls a robot in a warehouse in America
- A surgeon conducts surgery in an adjacent room via a remote controlled robot

Teleworking, defined as work performed at home or a satellite office (Shin *et al.*, 2000), has accelerated following recent improvements in enabling or supportive technologies, and access to home-based broadband connections. This has clear implications for the geography of work in ways which vary by role and sector (Crowley and Doran, 2020).

Telepresence can create economic gains for firms in various ways. The first is by exploiting wage differences by region. An early impact of computerisation was the ability to offshore work, with firms capitalising on lower rates of pay in the global south (Thite, 2010) a trend which has been amplified and taken new forms through the rise of internet-enabled platform work (Lehdonvirta *et al.*, 2019). Varying degrees of compensation for the same work by country were long normalised as acceptable business practice. However, as information about these practices has become more prevalent, it has been challenged and become a corporate reputational risk, particularly in the tech sector, where high-paid jobs in the global north are supported by 'ghost workers'. The concept refers to those who conduct work which is perceived to be automated, with the human contribution not recognised. These workers are generally contracted to do piecework, in lower-income countries, with poor compensation (Gray and Suri, 2019) reflecting aforementioned 'faux-automation'. However, beyond issues of pay are wider risks to wellbeing arising from the nature of this work - which can, for instance, involve redacting hateful and unacceptable content.

The most commonly imagined form of telepresence is the professional, desk-based 'remote worker'. This has allowed businesses to continue to operate during crisis events by overcoming geographic frictions. Telepresence can reduce non-productive time within working hours (spent on travel) and save on office expenditures, depending on support packages offered to workers for home-based working. It is a very small select group of this more empowered workforce who are afforded the freedom over locality such that they can selectively offshore themselves, working as 'digital nomads' (Nash *et al.*, 2018; Nichols, 2022).

In contrast to computer-based remote working, workstation telepresence (human-telerobot compliance, whereby a human operator projects his/her body image and behavioural skills to control a robot remotely) is being used to overcome Moravec's paradox, with offshored labour guiding remotely operated warehouse robots in the US (Delfanti, 2022). Such workstation telepresence is also arising within workplaces in the UK.

ONS data show that, in February 2022, almost half of those who worked from home in some capacity reported that it improved wellbeing (47%). However, the opportunity to work remotely is unevenly distributed by demographic group, including gender (McKinsey 2020) and community of place (Mutebi and Hobbs, 2022). ONS statistics also find that opportunity is stratified by grade, with managers and supervisors more likely to work from home sometimes or always, compared to non-managers and non-supervisors (ONS, 2022). People with higher qualifications are more likely to do some work remotely than people with no or lower qualifications. Employers of higher-educated workers were found to have more trust in remote workers (Bartik *et al.*, 2020). However, as recent research by Microsoft notes, there is now a widespread 'productivity paranoia' - whereby employees from across sectors are working increased hours from home, often citing burnout - but managers are concerned about worker contribution (Microsoft, 2022). The productivity returns of remote working are mixed (Galanti *et al.*, 2021).

While teleworking is associated with higher organisational commitment, job satisfaction and job-related wellbeing, these benefits have been found to come at the expense of work intensification, and an inability to switch off (Felstead and Henske, 2021) with consequences which can go beyond work. Managerial imperatives to standardise processes increased during COVID-19, as workers were not trusted without increased instruction and oversight, driving the routinisation (by prescription) of formerly high discretion work (Marta *et al.*, 2020).

Telepresence is also increasingly used to extend managerial oversight in the form of 'surveillance'. Terms like 'augmenting' and 'complementary' are often used to market systems which are essentially providing a surveillance function (Klinova, 2022). Surveillance as an extension of managerial control is associated with a series of deleterious effects on job quality - particularly autonomy (Katzenbach and Ulbricht 2019) dignity (Lamers *et al.*, 2022) and participation (Benlian *et al.*, 2022; Wood 2021), undermining rights within the workplace (Duggan *et al.*, 2020; Del Castillo *et al.*, 2022). However, these outcomes are contingent: designed and deployed in accordance with good human resource management philosophies, it can also improve workplace wellbeing through improving safety (Chamorro-Premuzic, 2020) and autonomy (Meijerink and Bondarouk, 2023).

While advantages for equality have been championed (allowing parents more flexibility to navigate working commitments and home life) in practice remote work has been shown to entrench existing tendencies in the gendered burden of domestic labour (Chung *et al.*, 2021). Social inequalities need to be addressed for their various root causes, and rarely have a 'technical fix'.

3.6 Matching

As outlined above, cognitive technologies substitute for human judgement by processing information. Increasingly, this functionality is used to play an intermediary role in markets, mediating transactions between agents. This can be understood as a form of 'matching'.

Matching: information processing capabilities of technology are harnessed to reduce frictions in processes of pairing (worker to job, or task).

Examples:

- Hiring: AI is increasingly used in recruitment, to identify a good 'match' between applicants and jobs
- Dynamic pricing: Self-employed workers can be given different rates for jobs where a matching algorithm exploits wage elasticities on the basis of supply
- Delivery: data analytics ensure rapid matching of labour demand and supply by matching drivers with riders for a platform based taxi service

In practice, matching reflects machine learning's capabilities in rapid analysis of data, and the development of predictive analytics (the core competency of machine learning) in parallel with other functionalities (e.g., automated decision-making, recommendations). It therefore can substitute human cognition (e.g., the taxi rank coordinator becomes and algorithm) to offer value creation - but also enables new business models which capture other forms of value and have different types of impact.

Matching was considered for its potential to entirely 're-wire' labour markets, but scepticism remained about the ability of these tools to fully devise what made for a good match (Autor, 2017). The use of AI in hiring (predicting who will be a good match in a new job) has become highly prevalent. This allows for significant labour-saving in terms of human resource management functions in recruitment. This has been explicitly outlined as a strategy to improve performance and reduce frictions in hiring, with a variety of tools ranging in complexity now available. However, as is recognised in a range of places, this presents significant risks to equality.

Matching can be deployed to entirely restructure business processes (Brynjolfsson *et al.* 2018), with subsequent effects on jobs and the quality of work. There are a number of businesses that have established 'new' models on the basis of predictive analytics - notably, platform businesses in logistics and delivery (Deliveroo, Uber, Amazon). Deployed in the service of platform business models, matching can collapse geographic frictions - matching labour demand and supply - more seamlessly. While geographic fractions can be removed by matching, as work is decoupled from the workplace, employers can make the case for ‘outsourcing’ of work as workers are expected to own their own means of production (be that a laptop for a creative, or a car for an Uber driver). This can offload capital costs from ‘the firm’ to individuals. The move to treating workers as individual contractors will plausibly accelerate and take new forms, impacting cognitive work, post-Covid (Erickson and Norlander, 2021). ‘Superstar’ business models (Autor *et al.*, 2022) that - as their principal model of ‘innovation’ - harness algorithmic management to ‘match’ independent contractors to jobs through algorithms, save up to 30% by removing outlay on standardised employment protections (Rolf *et al.*, 2022). Beyond this, matching can be used to exploit wage elasticities and offer ‘dynamic prices’ which reflect the (alleged) supply of labour at any time. Research has demonstrated that this drives racial discrimination (Dubal, 2020).

While legal classification of these workers is disputed and has led to new classifications (Fendrick, 2018), transition to these models is happening at pace across sectors (Prassl, 2018), raising questions for changing conditions of work. Workers in such situations across the economy have been classified as ‘under-employed’ - a concept framed by the ILO as ‘disguised unemployment’, or ‘underemployment’ - reflecting the growing number of individuals who find themselves neither unemployed nor fully employed (Benanav, 2019). Flexibility in matching the demand and supply of labour can create savings for firms by reducing outlay on unnecessary labour. However, it also contributes to the reduced labour share (Autor *et al.*, 2020).

Approaches to deployment can also reduce access to management, with consequences for and visible accountability surrounding employment decisions. This can create and exacerbate information asymmetries, reducing an individual’s ability to contest and challenge the fairness of employment-related decisions (Iamiceli, 2019). A recent survey of gig workers suggested 65% were anxious regarding their future pay, 54% about having less say over how their job is done, and 53% about it becoming more difficult for them to use their skills (Wood, 2023).

Research suggests that a third of platform workers have a mismatch between the lower-skilled tasks they perform and their high level of education/skills (Pesole *et al.*, 2018). This may reflect the racial segmentation of labour markets (Bhattacharyya, 2018) upheld by institutions - be that ideas about the worth of some persons, or formal rules (such as mutual recognition of skills for migrants) constraining the agency of persons within a labour market (Peck, 1989).

Matching relies on the ability of machine learning to predict future outcomes on the basis of historic patterns of behaviour and resource. This has been repeatedly demonstrated to present issues of equality (Binns *et al.*, 2020). However, such matching processes, as used in hiring, have also been deployed to predict propensity to unionise (Newman, 2017), impacting the potential for participation in determining working conditions and reducing the power of labour to determine fair pay.

4. Conclusions

Automation can take various forms, depending on choices made during design, development and deployment. These different forms of automation are associated with different benefits - or impacts - for specific demographic groups, geographic communities and socio-economic strata, with wider consequences for work and society.

Risks associated with automation are generally profiled by models which consider the share of tasks within jobs which can be substituted by technology. Higher risk jobs are those in which a higher share of tasks can be substituted, potentially allowing entire displacement of a role. This displacement effect is popularly considered to also be the main route to securing or producing new value by adoption.

However, as this work demonstrates, when automation is viewed holistically in the context of its deployment — above the level of tasks — transformations not only to access, but also to terms conditions and changes in quality of work can arise. This means that jobs which may have a small risk score by share of tasks that are substituted could also see significant transformation.

Evidence suggests that UK policymakers have conventionally understood risks emerging from technology to be the displacement of workers (job loss) and what is here described as 'high discretion augmentation' (popularly described as 'upskilling') (Carstensen, 2022). However, for transition to deliver a fairer future of better work, broader risks will also need to be managed.

AI has been defined as 'a rational agent seeking to maximise a form of reward' (Kasy, 2023). As we head into this automated future, we need to consider what we are optimising for, and who is rewarded by our approach.

This work has been prepared as part of the Pissarides Review into Work and Wellbeing, and informs an institutional analysis to be conducted across England, Scotland and Wales. The heuristic of automation presented here will be used to evaluate how concepts and models of risks among policymakers shape AI regulation.

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The Pissarides Review into the Future of Work and Wellbeing

Automation technologies are transforming work, society and the economy in the UK in ways comparable to the Industrial Revolution. The adoption of these technologies has accelerated through the COVID-19 pandemic, and the impact of automation is unevenly distributed, with a disproportionate impact on demographic groups in lower pay jobs.

The Pissarides Review into the Future of Work and Wellbeing will research the impacts of automation on work and wellbeing, and analyse how these are differently distributed between socio-demographic groups and geographical communities in the UK.

For more information on the Review, visit: pissaridesreview.ifow.org

If you have a professional or research interest in the subject of the impact of automation technologies on work and wellbeing and have insights to share, please contact Abby Gilbert, Director of Praxis at the Institute for the Future of Work at abby@ifow.org

If you are a member of the press and have an enquiry or would like to receive new press releases by email, please email Kester Brewin, Senior Communications Manager at the Institute for the Future of Work at kester@ifow.org