The Pissarides Review into the Future of Work and Wellbeing

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What do we know about automation at work and workers' wellbeing?

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Abstract

Automation technologies are reshaping work, which has complex impacts on the wellbeing of workers. This paper reviews the literature on the impact of automation technologies on subjective wellbeing.

We explore (i) automation risk, (ii) expectations of automation and (iii) technology adoption, analysing their effects on job and life satisfaction. Taken together, the findings are mixed and depend on technology type. Studies reveal variation across different occupations and industries. While negative consequences of automation are commonly studied, our review uncovers potential for both positive and negative effects on wellbeing. We suggest future research directions to delve deeper into this complex relationship.

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1. Introduction

Rapid technological advances and evolving working practices are profoundly changing the world of work. One prominent aspect of this transformation is the introduction of automation technologies in the workplace, which have complex direct and indirect impacts on work activities and on the wellbeing of workers. These arise from changes in tasks, uncertainties in the availability of resources and redesign of work processes.

An emerging literature investigates the consequences of automation and technological change in labour markets and beyond, considering both positive and negative impacts. However, while extensive research has been done on the impact of new automation technologies on employment levels, productivity and wages[1], little is known about their influence on workers' wellbeing. As a large body of research on wellbeing demonstrates, increased economic performance does not automatically translate into higher wellbeing for people and the relationship between economic outcomes and people's wellbeing is remarkably complex (Clark *et al*., 2008, 2018; Layard, 2011). Despite the existence of a substantial body of research exploring these complex relationships, the literature examining how new technologies shape workers' experiences and wellbeing remains fragmented and incomplete.

In this paper, we review this literature with a view to identifying common themes and gaps and facilitate future research. Section 2 introduces the concepts of subjective wellbeing and automation, as we use them in this paper. In section 3 we provide a brief overview of some early research on the impact of automation at work. Section 4 discusses the literature on the relationship between quantitative indicators of automation risk and wellbeing. In section 5, we examine this question from the workers' perspective, investigating the link between workers' expectations about automation and their wellbeing. Section 6 discusses studies on the adoption of automation technologies and wellbeing. In section 7 we briefly deviate from our central theme of subjective wellbeing and consider the impact of automation on objective wellbeing and other related outcomes. Finally, in section 8 we conclude and reflect on potential directions for future research.

2. Definitions

2.1 Wellbeing

Our focus is on workers' subjective wellbeing. The main elements of subjective wellbeing are life satisfaction, the presence of positive and negative moods and assessments of having purpose and meaning in life (e.g., see the recent review by Nikolova & Graham, 2022). This approach recognises the idea that wellbeing is the overarching good (Layard & De Neve, 2023) and that individuals are the best judges of how their own lives are going, providing a complementary measure to other outcomes, such as income, health, skills, social connections and environmental quality (OECD, 2013, p.29).

Traditionally, wellbeing has been defined through hedonic and eudaimonic perspectives. The hedonic approach considers wellbeing in terms of near-term pleasure or happiness - that is, emotional wellbeing - while the eudaimonic approach views it as the longer-term realisation of human potential (Deci & Ryan, 2008; Frijters, 2021; Kahneman & Deaton, 2010; Ryan & Deci, 2001). More recently, subjective wellbeing has been conceptualised as having three separate but related dimensions, namely, 1) affective subjective wellbeing, referring to feelings that are usually related to short-term circumstances, 2) evaluative wellbeing, referring to a judgement of one's overall life and circumstances, including capabilities, means and long-term opportunities and 3) the eudaimonic dimension related to life purpose and the process of living well in aspects such as competence, autonomy, personal growth and relatedness (Nikolova & Graham, 2022).

These three dimensions of wellbeing are often assessed simultaneously through self-reported evaluations in large-scale surveys. The concept of happiness as 'life satisfaction' emerges from the evaluative conceptualisation of wellbeing, which many studies adopt when examining the wellbeing of workers[2]. Following a bottom-up approach, key elements of life satisfaction include work life, health, family and leisure and self-worth. Of course, work is a significant part of life and thus an important activity contributing to one's overall wellbeing, far beyond the income that it generates. Research shows that happiness with working life is closely linked to employment and pay but extends beyond them to encompass job satisfaction, career satisfaction, the perception of doing meaningful work and work-related stress (see e.g. Cassar & Meier, 2018; Layard, 2011; Nikolova & Cnossen, 2020).

While life satisfaction and job satisfaction are sometimes used interchangeably in research as measures of subjective wellbeing, many studies focus solely on the job satisfaction of workers, rather than their overall life satisfaction. Although these two measures are often correlated, focussing solely on job satisfaction may not completely capture the broader relationship to life satisfaction[3]. Life satisfaction is influenced by job satisfaction and vice versa, with the nature of this relationship being moderated by various individual factors including age, sex, job level, marital status, as well as the norms and expectations that workers may have (Erdogan *et al*., 2012; Nikolova & Cnossen, 2020; Nikolova & Graham, 2022). Additionally, it is important to note that both life satisfaction and job satisfaction are measures of subjective wellbeing, and that they may not align well with objective measures of wellbeing. For instance, workers might report high job satisfaction while working at jobs that are very stressful or have low pay. The relationship between subjective and objective measures of wellbeing is complex and influenced by various factors that are often unmeasured (De Neve *et al*., 2013).

Workers' subjective wellbeing is an important outcome of interest for research and policy, as it relates to other outcomes for individuals and firms, and overall productivity. For example, high job satisfaction is associated with lower rates of staff quitting (Clark, 2001; Green, 2010) and higher productivity and workplace performance (Bryson *et al*., 2017; De Neve *et al*., 2019; Judge *et al*., 2001). At the other end of the scale, worried and unhappy workers may experience low motivation and work engagement (Inuwa, 2016; Lyubomirsky *et al*., 2005), which can lead to mental stress and anxiety and have negative implications for workers' long-term performance (Bliese *et al*., 2017; Faragher *et al*., 2013). However, making use of subjective wellbeing indicators is not without limitations. A caveat is that such indicators, such as job satisfaction and life satisfaction, are usually self-reported and therefore may be subject to influences from unobserved variables that researchers are unable to account for.

While this review primarily focuses on subjective wellbeing, we note that there is a body of literature that investigates the impact of automation on workers by examining objective measures of wellbeing. For example, some studies use clinical tools derived from psychiatry to determine the mental health of respondents. These tools range from established clinical tools for the diagnosis of major depressive disorders or generalised anxiety disorders, through to simple subjective questions of self-reported mental health or the number of recent days where poor mental health has been experienced. Beyond mental health, other studies use self-reported measures of overall health status or use county-level or city-level aggregate measures of the physical and mental health status of populations as proxies. We provide a brief overview of this literature in section 7.

2.2 Automation

We adopt here a broad definition of automation at work, referring to the introduction of new technologies in the workplace and how they are changing the way jobs are designed. We narrow our focus to the impacts of automation in the more recent period of technological change, which has been often described as the fourth industrial revolution. This includes (but is not limited to) breakthroughs in digital technologies, data and connectivity, advanced robotics, analytics, Artificial Intelligence (AI) and advanced engineering.

The potential impacts of automation are diverse and extend well beyond the substitution of jobs by automation technologies. Automation technologies influence both the context and content of work. Nazareno & Schiff (2021) present a conceptual framework that outlines how automation technologies can impact worker wellbeing. We adapted this framework in Figure 1 to provide a foundation for discussing the current state of the literature on the topic. In addition to the elements illustrated, we note that the impact of automation on wellbeing is not predetermined but is sensitive to the context in which automation technologies are diffused and adopted, including the firm, industry and social and policy environment.

To structure our review, we have identified three main ways in which automation has been conceptualised in the existing literature.

First, one strand of literature focuses on objective measures of the potential risk of automation within industries or occupations and examines its relationship with individual or aggregate measures of subjective wellbeing. This work often draws upon the estimates developed by Frey & Osborne (2017) regarding the probability of jobs being fully automated through advances in computerisation. More recently, research has linked these probabilities to wellbeing outcomes.

A second strand of literature explores workers' own perceptions about future automation and how these perceptions are related to their wellbeing. This line of research investigates workers' anticipated impacts of automation and examines how these affect their current wellbeing.

A third strand of studies examines the 'real world' adoption and implementation of automation technologies in the workplace and its impact on employee wellbeing. Research on the adoption of automation in the workplace is highly context-specific and often focuses on the introduction of these technologies as replacing existing technologies or as complementary tools.

After providing a brief overview of the early work on the relationship between automation and wellbeing, our review of the current literature begins by examining the connection between automation risk and worker wellbeing (section 4). We then delve into what is known about the role of workers' expectations and perceptions regarding future automation and their effects on wellbeing (section 5). Next, we summarise the findings regarding the impact of the adoption of automation technologies on wellbeing in specific contexts (section 6). Finally, we briefly discuss the literature that examines objective wellbeing (section 7).

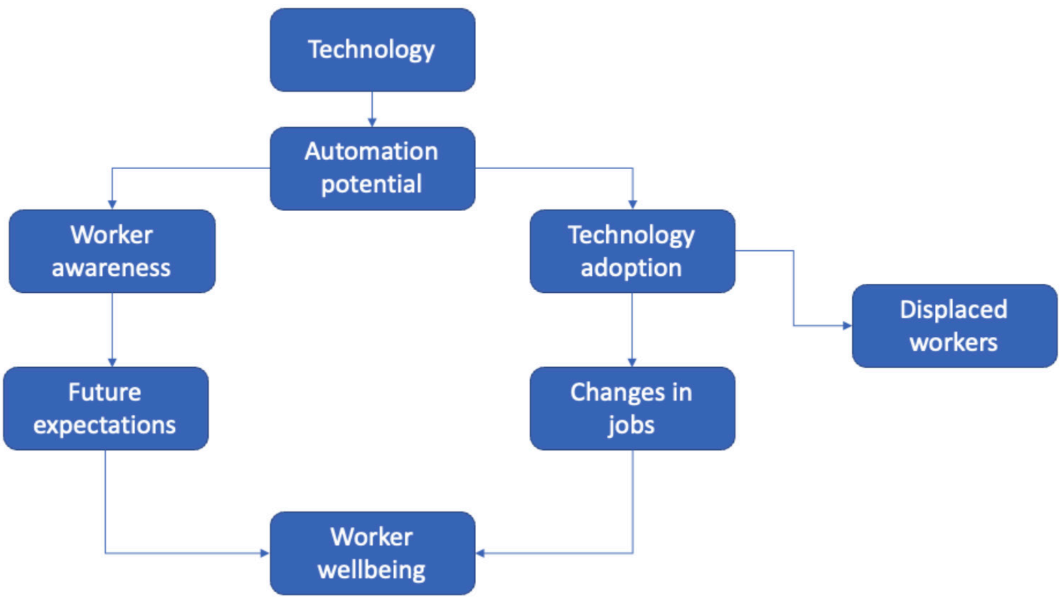

Figure 1 – Framework of the impact of automation technologies on wellbeing
Source: Figure adapted from Nazareno & Schiff (2021).

3. Early contributions

The impact of technological change on the lives of workers has for centuries been a subject of research and popular and political debate, spanning multiple industrial revolutions in agriculture, manufacturing, heavy industry and — more recently — offices and the service sector. Autor (2015) and Acemoglu & Restrepo (2019) provide historical perspectives on the impacts of automation on labour markets. The prevailing historical viewpoint, as expressed in these articles, suggests that while automation technologies may lead to task substitution within occupations, they also created new or augmented roles. This is exemplified by the finding that 60% of employment in 2018 in the United States consisted of job titles that did not exist in 1940 (Autor, 2022). Contemporary accounts often present a more pessimistic view of automation as leading to job substitution and subsequent unemployment, while the passage of time emphasises the capacity of labour markets to adapt — and often thrive — because of automation technologies.

Historical perspectives specifically examining the impact of automation technologies on worker wellbeing are limited. Shepard (1977) reviewed the relationship between automation technologies and job satisfaction in the 1950s, 60s and 70s, focusing on the increased use of automation in manufacturing industries. In some respects, the review by Shepard shares similarity to many studies from the more recent literature discussed in this paper. It identifies consensus regarding the impact of technology on the nature of work, but disagreement on the extent to which this translates into changes in job satisfaction. Similarly, a later review on the introduction of computing technologies in the workplace and its effect on job satisfaction finds "a mass of contradictory findings" (Attewell & Rule, 1984). Opinions were divided between computerisation as either 'deskilling' or 'upgrading' the workforce. Nevertheless, workforce surveys generally perceived computerisation in a more positive light, highlighting improvements in job satisfaction for those in employment in computerised occupations. Yet, relying solely on workplace surveys exposes a major limitation of the study of technology adoption in the workplace: the authors typically interview employees after the introduction of technologies at work, and thus fail to capture the experiences of those who have been displaced or have chosen to leave their jobs, potentially introducing a selection bias towards a more positive perception of automation technologies.

While the concept of wellbeing has been the subject of philosophical debate for centuries, efforts to collect data on happiness and quantify subjective wellbeing on a large scale have intensified in the last forty years, and particularly since the turn of the millennium (Clark, 2018; OECD, 2013). Disagreements about how to measure wellbeing, happiness and life satisfaction have resulted in various approaches to assessing subjective wellbeing, and dissensus persists to the present day. Notable advances in the application of subjective wellbeing in economics — and as a tool for policy analysis — occurred between 2008 and 2012. This period saw the formation of the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz *et al*., 2009), the publication of the first World Happiness Report (Helliwell *et al*., 2012) and the first collection of subjective wellbeing data in a nationally representative survey by the Office for National Statistics in the United Kingdom (Allin & Hand, 2017). Collectively, these efforts have led to an increased focus on subjective wellbeing in recent empirical research, aiming to understand its correlates and determinants, including the relationship between subjective wellbeing and work, which is extensively discussed in this review.

4. Measures of automation risk and worker wellbeing

The concern over the potential job destruction and widespread unemployment resulting from technological advances is not a new phenomenon. However, the advances in robotics and artificial intelligence in recent decades has reignited the debate surrounding an imminent wave of job destruction. Various studies have predicted that many jobs are at high risk of being automated, with workers in low-skilled routine jobs and lower levels of education being particularly vulnerable (Arntz *et al*., 2016; Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). Nevertheless, higher skilled workers are not immune to the impact, especially with the progress in AI applications that can now handle increasingly complex tasks requiring higher cognitive discretion and creativity (Felten *et al*., 2019; Tolan *et al*., 2021; Webb, 2020).

While there has been growing interest in measuring automation risk in the past decade, the progress in examining its impact on worker outcomes has been uneven. The seminal paper by Frey & Osborne (2013, 2017) was the first to distinguish between jobs with high and low probability of computerisation, sparking a series of studies focused on measuring automation risk and predicting its consequences for economic outcomes, including unemployment and wages. More recently, researchers have started investigating the relationship between automation risk and other outcomes, including life satisfaction, job satisfaction and mental health. It is worth noting that automation risk serves as a forward-looking indicator for the technical feasibility of implementing automation technologies, rather than a measure of automation that is economically feasible or that has already occurred, a point we will revisit later.

The evidence regarding the links between automation risk and subjective wellbeing is limited and results from this literature are mixed. Lordan & Stringer (2022) conducted a recent study that was the first to examine the connection between automation risk and life satisfaction (as opposed to job satisfaction or mental health)[4]. Analysing panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, the authors find that working in a job with higher automation risk - defined as a job with a high proportion of routine tasks - is associated with lower life satisfaction for workers in certain industries like retail and public administration. However, the overall result was not significant for the entire sample, suggesting that the relationship between automation risk and wellbeing may be restricted to specific occupations or industries, or to the specific demographic groups that populate these occupations. The study highlighted age and gender differences, with younger workers (aged 15-39) and women in retail experiencing the strongest negative associations. Furthermore, the estimates vary according to education levels, with stronger negative correlations observed for workers with low levels of education.

Several studies have examined the relationship between automation risk and job satisfaction, with most finding a small negative association, not always statistically significant. Gorny & Woodard (2020) conducted a cross-country analysis investigating the relationship between automation risk and job satisfaction in the US and some countries in Europe. They use the automation risk measures at the occupation level developed by Frey and Osborne, as well as task-based measures of automation risk from subsequent studies (Arntz *et al*., 2016). Overall, the authors report a negative correlation between automation risk and job satisfaction in most countries[5]. Interestingly, when controlling for variables that capture workers' fear of job loss or their feelings of job security, the estimated coefficients remain unaffected, which suggests that these factors are not influencing the relationship observed. Workers were also asked if they find their jobs meaningful. When accounting for this, the negative association between automation risk and job satisfaction almost disappears. These results suggest that it is the nature of highly automatable jobs, characterised by high monotonicity and low perceived meaning, that primarily drives the negative impact on job satisfaction, rather than an increased fear of job displacement, as proposed by other studies.

Another study by Nazareno & Schiff (2021) investigates five hypotheses arising from the conceptual framework mentioned earlier, using the automation risk estimates from Frey and Osborne and data on wellbeing from the General Social Survey for the United States. They report a small, non-significant relationship between automation risk and job satisfaction after controlling for other job-related characteristics including workload, autonomy and work conditions. However, the study also considers the impact on some objective measures and finds that high automation risk is associated with less job stress but worse overall health.

The research on the relationship between automation risk and subjective wellbeing is still in its early stages and definitive conclusions are yet to be reached. While the measures of automation risk have been around for more than a decade, the investigation of their links to subjective wellbeing has only recently gained attention.

One limitation of existing studies is their reliance on existing measures of automation risk rather than direct measures of technology usage at work. The measures of automation risk serve as proxies for automation, rather than direct measures of technology usage at work. These measures represent the potential technical feasibility of automating certain tasks or occupations based on the current available technology, but they may not fully capture people's actual experiences of automation. Workers in the same occupation may have varied experiences following the introduction of automation technologies. The socio-economic environment, the policy environment and how much protection it affords to workers, and how employers manage the deployment process and transition to new technologies, are important influences on workers' response to the new technologies. Unfortunately, large-scale surveys used to assess the impact of automation on worker wellbeing are unable to account for these important sources of variation across the workforce.

The mixed results in the literature may also arise from a series of methodological choices that limit the ability to draw stronger conclusions. One central concern is the lack of consensus on the best way to measure automation risk. The widely used Frey and Osborne approach focuses on the probability of whole occupations being fully automated (or not) by computers, but it may not be applicable to other technologies or to impacts beyond labour substitution[6]. While most studies reviewed here employ the Frey and Osborne measures, a few use alternative measures, making it difficult to compare results across studies. Among the exceptions, Lordan & Stringer (2022) use a measure of specialisation in routine tasks developed by Autor & Dorn (2013), and Nazareno & Schiff (2021) use a similar measure based on Autor *et al*. (2003) as a check for robustness[7]. Emerging research proposes alternative ways of measuring automation risk and exposure that consider a broader range of technologies, such as AI and software, and aim to capture effects beyond the substitution of human labour (e.g. Brynjolfsson *et al*., 2018; Felten *et al*., 2019; Webb, 2020). However, these measures have not yet been applied to studying the links to wellbeing. This lack of consensus on foundational aspects, including measuring the degree of automation risk, poses further challenges in examining the relationship between automation and wellbeing.

Another issue relates to how researchers deal with estimation concerns related to endogeneity and selection bias in these studies. There may be reverse causality, with job satisfaction affecting individuals' perceptions of automation risk. For example, workers who are already dissatisfied with their jobs may be more likely to perceive higher automation risk due to under-performance related to their unhappiness at work. Failing to account for this could lead to upward biased estimates. Additionally, there may be systematic differences between workers in highly automatable occupations and those in non-automatable occupations. Workers who are more satisfied with their jobs may be more likely to remain in their current positions, while those who are less satisfied may leave the workforce or search for other jobs. Some studies acknowledge these concerns and employ econometric techniques like fixed effect models or propensity score matching to address them. However, residual biases may still persist due to unobserved time-varying factors. Further tests are needed to better understand the implications of these methodological issues and their impact on the estimates that we have reviewed here.

5. Expectations, fears of automation and wellbeing

The next strand of literature that we review examines the impact of workers' expectations, fears and concerns about automation on wellbeing. Exposure to new technologies in local labour markets can lead to increased uncertainty among workers which, in turn, can directly affect their wellbeing. The form and extent to which wellbeing is affected may depend on several factors, including the worker's knowledge about new technologies and past waves of automation, as well as the social environment, institutions and policy landscape. Many factors influence the formation of such expectations, and they may arise from uncertainty about the future rather than an immediate risk of job loss. Even so, the introduction of uncertainty about future job prospects and financial conditions can lower current life and job satisfaction.

Recent data from the European Skills and Jobs Survey 2022 (ESJS2), a representative survey of more than 45,000 workers from 27 EU countries, Norway and Iceland, shows that, on average, 35% of workers have great or moderate concern that new digital or computer technologies will soon replace their main job or part of it (Cedefop, 2022). As expected, there is considerable variation across countries. Countries in the south of Europe generally have a higher proportion of concerned workers, with Spain having the highest proportion at 65%. While the European survey does not include data for the UK, a recent study by Innocenti & Golin (2022) surveyed more than 15,000 workers in 16 countries and reported that around 18% of UK workers fear automation. Among all countries surveyed, the authors find that, on average, 30% of workers are concerned about losing their jobs in the next 5 years because their tasks would be replaced by machines or computers. The results suggest that workers' fears seem to be lower in the UK than in other European countries.

The cross-country evidence suggests that the widespread fear of automation is a global phenomenon. In 2021, a Price Waterhouse Coopers survey[8] conducted in 19 countries revealed that, on average, 45% of respondents were worried that automation is putting at risk the jobs 'of people like me'. Similarly, evidence from a representative sample of almost 4,300 US workers by Golin & Rauh (2022) reveals that 35% of workers fear displacement through technology. The authors also measure the perceived automation risk by asking respondents, "On a scale of 0-100%, how likely do you think it is that you might lose your job/not find a job due to automation, robots and artificial intelligence within the next 10 years?". They find that around 40% of workers have a perceived automation risk of more than 50%. Younger and less educated workers have a higher perceived automation risk, which also varies considerably by occupation. Another recent survey revealed that workers in the US and parts of Asia feel insecure about their jobs because of robots, even in industries where robots are not currently being used (Yam *et al.*, 2022).

Having such fears, worries and expectations about automation can have negative implications for workers' life and job satisfaction. The prospect of unemployment or reduced work tasks introduces a great deal of uncertainty around future job prospects and financial conditions. Using data from the Eurobarometer survey, Hinks (2021) finds that having a fear of robots is correlated with lower life satisfaction across 25 countries of the European Union. In this study, fear of robots is measured by respondents' perceptions, attitudes and use of autonomous systems, including robots, driverless cars and civil drones.

In studies that rely on self-reported wellbeing and self-reported expectations about automation, there is a concern that these subjective reports could be affected by unobserved individual factors such as ability, risk attitudes and personality traits. In order to address this endogeneity concern, a rapidly growing literature employs an objective measure of technology adoption - often the adoption of industrial robots - as an instrument for workers' fears of being replaced by technology[9]. This research makes an important advancement over previous studies, as it goes beyond correlational associations and provides a better methodology to isolate the impact of perceptions and identify causality[10]. The results from this literature suggest a negative impact of fears of automation on life and job satisfaction.

Evidence from the Eurobarometer survey shows that between 32-44% of workers report having a fear of being replaced, varying by country. Using historic robot adoption as an instrument for workers' anticipations about future automation, Schwabe estimates the impact of anticipations about replacement of the current job by robots and AI on workers' life satisfaction (H. Schwabe, unpublished). The study reveals that the direction of association between fear of automation and wellbeing depends on various individual factors, such as age and education levels. Specifically, younger workers experience a negative effect on life satisfaction, while for older workers a positive relationship is observed. The author suggests that this could be related to a learning effect whereby younger workers, with limited exposure to past automation and a longer time horizon to consider, are more fearful about the increasing prevalence of technology. On the other hand, older workers, having already witnessed previous waves and benefits from automation may be better equipped to evaluate its potential displacement impacts. There is a possibility that the older workers who have chosen to stay in the workforce and have continued working in highly automatable jobs after previous waves of automation are part of a selected group that hold more favourable views of new technologies. In contrast, younger workers may have not undergone the same self-selection process yet.

Similarly, using data from the Working Life Barometer survey 2016-2019 in Norway, Schwabe and Castellacci (2020) show that the fear of possible future replacement negatively affects job satisfaction. The authors find that automation in industrial firms (instrumented by the introduction of industrial robots) has made 40% of workers fear that their work might eventually be replaced by machines. Additionally, they find that the effect varies across workers of different skills. The overall negative effect is driven by low-skilled workers, whose jobs involve routine tasks that are highly automatable, resulting in a stronger fear of replacement.

It is worth noting that most of the studies providing improved causal estimates on the relationship between automation and individual outcomes rely on robot adoption data provided by the International Federation of Robots (IFR). While this dataset contains information on the aggregate stock of robots at the national level, an assumption is needed to allocate robots to regional labour markets. Typically, this is done by following the approach by Acemoglu & Restrepo (2020b), which assigns the increase in the stock of robots by sector using the employment distribution at the start of the analysis period. However, it is important to acknowledge that robot adoption may be influenced by other sector-specific factors and so not reflect the actual robot exposure of the surveyed workers.

It is not a given that the relationship between anticipated impacts of technology and wellbeing is unidirectional. Wellbeing at work can also influence attitudes towards new technologies. In a survey-based study with blue-collar workers, Hampel *et al*. (2022) find that attitudes towards the introduction of new technologies are themselves likely driven by workers' current perceptions of their work, desired work characteristics and feelings of job dissatisfaction. Workers who are more enthusiastic about technology were more willing to accept high work demands associated with digital technologies, while those with lower levels of work enrichment', particularly low autonomy, were more fearful of job loss.

Shifting the focus from the data on robots to broader technological change, Makridis & Han (2021) quantify the effects of technology on employee life satisfaction and empowerment[11]. The authors adopt a broader definition of technological change based on the growth in the net stock of intellectual property (IP) and linked it to individual outcomes from the Gallup daily poll of US residents. The study finds that technological change is positively associated with a significant increase in current and future life satisfaction and in the probability of individuals reporting empowerment. Interestingly, the effects on wellbeing are stronger in workplaces with more directive managers. The authors argue that structured management might play a crucial role in facilitating employees' experimentation and adaptation as their jobs change. However, they also find that increases in technology growth have a weaker effect on life satisfaction in trusting working places. While this may seem counterintuitive, the authors suggest that it is possible that more trusting workplaces are less well equipped to handle certain forms of sudden technological change.

The direction of the findings of the literature examining the impact of fear of displacement depends on the conceptualisation of automation or technology being examined. Recent literature focusing primarily on robot adoption typically suggests that the negative effect on wellbeing occurs through feelings of job insecurity generated by fear and concerns about their introduction at work. Extensive research has demonstrated that feelings of job insecurity have strong negative effects beyond the labour market, affecting the psychological well-being and health of employees (e.g. De Witte *et al*., 2016; Lepinteur, 2021; Rohde *et al*., 2016; Smith *et al*., 2013).

Broader issues concerning data availability present challenges in estimating the effect of automation on overall wellbeing. All existing studies default to using data on current workers, limiting their survey to employed respondents. In other words, they focus on people who have not been displaced by the adoption of new technologies or who have managed to return to work by the time the survey was conducted. If the displaced workers are the ones who experience more negative feelings related to automation and for whom the impact on wellbeing is stronger, researchers might be missing important information about the impact of automation on wellbeing and potentially underestimating the magnitude of these effects due to this selection bias. Further research is needed to extend these surveys and explore the impact on the wellbeing of individuals who are displaced or who do not re-enter the workforce.

Finally, although most studies have focused on workers' fears of potential displacement, it is important to consider that the introduction of new technologies could also create positive expectations around future opportunities and job conditions. If individuals perceive ongoing technological changes as signs of future economic growth and the emergence of better, more meaningful jobs assisted by technology, automation could have a positive impact on wellbeing. Future research should explore the possibility of positive expectations and how wellbeing at work can also influence the formation of these expectations.

6. Adoption of automation technologies in the workplace and worker wellbeing

Until this point, the discussion has been about the relationship between workers' wellbeing and automation risk and expectations around automation. In this section, we shift our attention to research that has explored the impact of automation technologies that have already been adopted.

The existing research on the impact of widespread internet use in the workplace on worker wellbeing has yielded mixed results[12]. Studies have shown that internet use at work increases job satisfaction by improving access to data and information, creating new activities and simplifying interactions and communication with colleagues and superiors. Castellacci & Viñas-Bardolet (2019) and Martin & Omrani (2015) found evidence of this in their analysis of data from the European Working Conditions Survey for 16 countries. Bolli & Pusterla (2022) conducted a case study of Swiss professional education and training students and graduates, revealing a positive relationship between work digitalisation and increased job satisfaction. The authors suggest this positive effect is generally driven by increases in productivity and the perceived 'interestingness' of work, which offset the smaller negative effects of increased time pressure and decline in work-life balance. However, there are also potential risks associated with changes in time use and increased stress, which could result in lower job satisfaction (Castellacci & Tveito, 2018). Castellacci & Tveito (2018) note that personal characteristics such as psychological functioning (life purpose, self-realisation), capabilities and framing conditions can help explain why internet use has varying wellbeing effects across demographic groups and work situations.

Most of the existing literature on the direct link between technology adoption and wellbeing is based on evidence from small-scale surveys. In a recent paper, Haepp (2021) examines the relationship between the adoption of new technologies and employee wellbeing in medium and large-scale private sector firms, using the German Linked Personnel Panel survey. The overall findings indicate no significant effect of technology adoption on different measures of wellbeing, including employee job satisfaction. However, the study found that workers who felt their existing skills were rendered redundant by new technologies and lacked the skills to take advantage of them experienced lower job satisfaction. This suggests that the impact of new technologies on worker wellbeing is not uniform and can be influenced by worker-perceived skill gaps. Consequently, negative impacts on wellbeing may depend on the context of technology adoption and effective training programmes. Firms that adopt technology collaboratively and provide comprehensive training programmes may be able to offset the negative impact on their workers' wellbeing.

Through a series of interviews with direct or indirect users of robotics, AI and automation, Bhargava *et al*. (2021) explore their perceptions on job security, job satisfaction and employability. The participants reported benefits from the use of these technologies in their professional and personal lives, emphasising better use of their time and skills, as low-value, routine and menial tasks are phased out. Respondents also expressed the views that human touch and soft skills are irreplaceable and cannot be replicated by technology.

However, the authors also note that many participants lacked knowledge about how some of these technologies work in practice and their role as end-users, perceiving them as 'a black box'. This suggests that the perceived impact of automation technologies on workers may be limited by their awareness of technologies being implemented. For example, customer-facing workers in the retail sector maybe be unaffected by the introduction of automated processes to support 'back office' accounting functions , but the same technologies may alter the work of employees in the finance department, who are also unaware of them

While these survey-based studies offer valuable insights specific to their respective contexts, it is important to consider the challenges of comparing across studies and drawing general conclusions. These studies typically rely on small samples, use varying definitions of technologies and examine different measures of wellbeing. Moreover, most of these studies establish conditional correlations, as researchers face difficulties in fully addressing potential issues of endogeneity and reverse causality. Like the studies discussed earlier, these workplace surveys and case studies may also be affected by sample selection bias, as they often exclude individuals who have been displaced or have not returned to work, limiting our understanding of the impact on the entire initial workforce.

7. Beyond subjective measures of wellbeing

Beyond subjective wellbeing, there is also research exploring the association between risk of and fear of automation and mental health indicators. Studies in this category indicate that individuals working in jobs with higher risk of automation are more likely to experience mental health issues. Blasco *et al*. (2022), using individual level data from the French Working Conditions Survey, find that workers in automatable jobs are more likely to experience anxiety or depression, which they attribute to increased feelings of job insecurity. Similar findings are reported by Patel *et al*. (2018) for the United States. Linking the General Social Survey (GSS) and the Frey and Osborne automation probabilities, the authors find that higher automation risk is associated with higher levels of job insecurity and poorer general health. Abeliansky & Beulmann (2019) use robot adoption data from the IFR to investigate how robot intensity in different manufacturing sectors affects the mental health of workers in Germany. They find that increased robot intensity is associated with lower mental health, driven by fears of job insecurity and of worse economic conditions in the future. Brougham & Haar (2018) find that workers who believe that new technologies, such as AI, robots and algorithms, can replace their jobs report higher levels of depression, while Vieitez *et al*. (2001) reports a link to increased anxiety among manufacturing workers. As discussed previously, it is important to note that studying the links between self-reported expectations and mental health indicators can be challenging due to unobserved factors that may influence both variables of interest, potentially biassing the estimates.

Furthermore, several studies make use of objective measurable indicators of wellbeing, instead of the subjective measures that we have been discussing. Objective measures suffer less from biases due to idiosyncratic factors like moods and perceptions, but they are much narrower than the subjective measures, which capture whole life feelings. Objective measures make use of data on such health-related issues such as depression, hospitalisations, and other observed responses, such as absenteeism.

As new technologies enter the workplace and replace less interactive and routine intensive tasks, there is potential for them to increase the meaningfulness of work, namely, the sense of doing something useful. Well-designed and well-implemented systems can reduce demands and alleviate cognitively taxing work, freeing workers to focus on more engaging tasks (Johnson *et al*. 2020). Engaging in meaningful work can lead to increased job satisfaction and worker wellbeing (Rothausen & Henderson, 2019). In this light, recent research has explored how the adoption of advanced robots can enhance or diminish the meaningfulness of work. Smids *et al*. (2020) propose a conceptual framework for examining five key aspects of meaningful work, all of which are key for motivation and human flourishing at work, highlighting the risks and opportunities associated with the introduction of robots. Existing empirical work suggests that the risks often outweigh the benefits when it comes to the adoption of industrial robots[13]. Nikolova *et al*. (2022) show that in a sample of 20 European countries, robotisation has a negative impact on work meaningfulness, autonomy, competence and relatedness, deteriorating the opportunities for workers to derive meaning and self-determination from their work . Antón *et al*. (2020)

also report a negative impact on work quality, specifically in terms of an increase of work intensity (although they find no significant impact on skills and discretion).

The broader consequences of automation on workers' mental and physical health of workers are not yet fully understood. At a time of increasing workplace stress and work-related mental health issues (e.g. Kniffin *et al*., 2021), the use of new technologies in the workplace may further exacerbate these problems. Emerging research on 'technostress' — a state of stress associated with excessive technology use (Singh *et al*., 2022) — has highlighted potential negative impacts such as increased stress, overload, mental exhaustion and burnout (Johnson *et al*., 2020). Researchers now understand that work factors such as poor job design, high job demand, low job control and high effort–reward imbalances tend to be associated with a greater risk of developing common mental health conditions (Harvey *et al*., 2017), and the introduction of automation technologies can influence these factors either positively or negatively. Therefore, there is still much uncertainty surrounding the potential impact of automation technologies on general worker wellbeing.

Much of what is known about the recent implementation of novel technologies in the workplace is based on earlier innovations such as ICT and the internet. The increased use of ICT and email was found to be associated with higher levels of employee strain and distress due to intensification of work (Barley *et al*., 2011; Chesley, 2014). Additionally, the widespread use of internet and increased screen time have been linked to sedentary workplace behaviour (Owen *et al*., 2011; Waters *et al*., 2016) and an increased likelihood of developing physical health problems such as diabetes, cardiovascular disease, musculoskeletal disorders and obesity (Horton *et al*., 2018). However, evidence regarding the impact of novel automation technologies like AI and advanced robotics on worker wellbeing is limited.

New technologies can also present opportunities for improving health outcomes. For example, it has been suggested that automation plays an important role in improving safety at the workplace. One area where evidence is more prominent is the adoption of robots to undertake physically demanding tasks or operations in dangerous environments. Gunadi & Ryu (2021) show that robot intensity in manufacturing is positively related to the health of low-skilled workers in the US. By substituting repetitive manual tasks, robots allow workers to transition to occupations with lower intensity of physical tasks, resulting in overall health improvements. In a related study, Gihleb *et al*. (2022) show that increased robot exposure is associated with a reduction in work-related injuries, which in turn can contribute to a reduction of mental health issues related to such injuries. These benefits, however, represent a reduction in workplace accidents or longer-term physical harms of manual labour primarily in manufacturing industries and may not translate into generalised improvements in employee physical and mental health across different sectors and occupations.

In addition to individual experiences of work, technology can also affect the quality of interpersonal relationships and the social capital within organisations. The rise of remote working, accelerated by the COVID-19 pandemic, has brought about significant changes in working relationships, and some of these changes are expected to persist. Remote and hybrid work have become the new normal for many workers, creating new forms of working relationships in which colleagues may never meet face to face. These changes in themselves may significantly alter worker wellbeing. Growing evidence suggests the effects of remote work are not felt uniformly across workers, varying with age, gender, education, childcare responsibilities and the living environment (e.g. Schifano *et al*., 2021; Singh *et al*., 2022). The disruption to existing working relationships may also influence the reception and acceptance of new automation technologies, though the extent and nature of these effects remain unanswered questions that require further exploration.

8. Conclusions

Automation technologies are rapidly transforming the world of work, but their impact on worker wellbeing is not yet well understood. In this section, we recapitulate the main findings of this literature review and discuss implications for future research.

Studies focusing on the relationship between risk of automation and subjective wellbeing generally indicate a negative relation between job satisfaction and high automation risk. However, the magnitude of these effects tends to be small, and estimates are not always statistically significant. So far, only one recent study has looked at life satisfaction, as opposed to job satisfaction, finding similar results for employees in certain industries such as retail and public administration. This approach assesses present wellbeing against the potential risk of automation, measured by the technical feasibility of automating tasks and jobs. However, there is a lack of consensus about how to adequately measure automation risk and most studies (implicitly) assume that the main effect of automation technologies is to replace human labour. Further research needs to explore potential impacts of automation beyond labour substitution and to incorporate new technologies in the measurement of automation risk.

Fear of displacement by automation technologies is a significant concern, particularly for those in jobs at higher automation risk, although not exclusively. In the absence of an effective objective measure of automation risk or technology adoption, it is difficult to determine the extent to which anticipated impacts materialise. Nevertheless, evidence from the literature suggests that both life and job satisfaction are, on average, lower among workers who fear automation. Most studies on this topic rely on surveys of workers that ask respondents about their fear of automation in terms of job displacement. For example, the Eurobarometer, one of the largest surveys examining these fears, asks workers, "Do you think your current job could be done by a robot or artificial intelligence in the future?". To date, little attention has been given to eliciting expectations about other ways automation could change jobs, including potential positive impacts and expectations. While this limits our ability to draw broader conclusions about the impact of emerging technologies and the overall effects of automation on wellbeing, it also suggests various avenues for extending surveys and research to encompass these diverse impacts.

Throughout the reviewed literature, there may be issues with systematic biases affecting subjective wellbeing measures and measures of fears of automation, which could introduce uncertainty about the reported results. Workplace surveys on attitudes towards automation technologies necessarily exclude workers who have been displaced as a result of automation, which could lead to an underestimation of the negative impact. In addition, very little is known about the impact of automation on different types of workers, such as individuals who have been displaced or unable to return to work. Further research should examine the impact on individuals who are no longer employed, identify distributional impacts and determine the groups most likely to be vulnerable or affected, in order to understand the broader societal impact of automation technologies.

The evidence regarding the impact of recent 'real world' implementations of automation technologies on wellbeing is mixed. Some technologies have been shown to increase job satisfaction for certain workers, with findings indicating that this is likely mediated by more engaging work. However, these gains can be sometimes offset by the intensification of work, increased stress and time pressure. Overall, the impact of automation on wellbeing appears to be highly context dependent and influenced by factors such as skill requirements and the design of work.

Our review suggests that automation can have both positive and negative effects on workers' wellbeing, with most studies finding negative impacts on life and job satisfaction. Ultimately, the magnitude and direction of the relationships observed seems to depend on what technologies are being studied, assumptions related to the nature of changes to work brought by technology (e.g. substituting or complementing human labour etc.), whether technologies are changing central tasks of a job or marginal tasks, and who is expected to be affected by these changes and who is surveyed by researchers.

Lastly, it is worth noting that with all the recent rapid developments in technology, researchers often aim to examine the potential impact of nascent changes that may be happening on a small scale or still in progress, making it challenging to observe substantial effects and to generalise findings. In previous waves of automation, as highlighted by Autor (2015), Polanyi's paradox limited the extent to which automation technologies could take over entire occupations. Instead, specific tasks were automated, with new tasks emerging for workers to complement the new technology. The developments in machine learning and AI may reverse Polanyi's paradox[14] as algorithms may learn the rules required to perform tasks without the need for human intervention. Whether the impact of the ongoing wave of automation is different from that of previous waves remains to be seen. One way to advance this line of empirical research would be to collect better large-scale data on the adoption of AI, robots and other advanced automation technologies. Current empirical research relies heavily on data provided by the IFR, while adoption of other types of technology is less well understood. A useful contribution in this regard would be the collection of large-scale data on technology adoption at the firm level, especially when this can be matched to worker data. Some early attempts in this direction have been made, e.g. Acemoglu *et al*. (2022).

In conclusion, although as more evidence is gathered there is much more to be learned, the available evidence suggests that automation technologies have the potential to improve worker wellbeing, primarily by increasing job satisfaction. However, it is important to note that this improvement is neither universal nor inevitable, nor does it always translate into more life satisfaction. Instead, to ensure successful adoption from the perspective of enhancement of worker wellbeing, it is essential to carefully assess how work is transformed by technology, the effects on job design and job quality and how these changes are being perceived and felt by the workers themselves. This also includes gaining a better understanding of the conditions and opportunities given to individuals to adapt their roles or skills, as well as the circumstances of those who do not benefit or are negatively impacted by new technologies. A more comprehensive approach that takes these factors into account will contribute to a better integration of technologies in a way that improves the overall wellbeing of workers.

Endnotes

1 For example, see Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2020; Bloom et al., 2014; Brynjolfsson et al., 2018; Brynjolfsson & McAfee, 2014; Goldin & Katz, 2010. Autor (2022) also provides a comprehensive review of the evolution of economic thinking on the labour market impacts of technological change.

2 Life satisfaction is typically elicited by asking people general questions such as 'how satisfied are you with your life as a whole?', in which respondents usually place their answer on a points scale.

3 From the workers' perspective, the UK Health and Employment Review project has identified that of all factors evaluated within the review, self-reported job satisfaction emerged as having the strongest link with general wellbeing. For a review on job satisfaction and health outcomes, see Faragher et al. (2013).

4 Other studies examining the relationship between automation risk and mental health also report a negative relationship (e.g. Abeliansky & Beulmann, 2019; Patel et al., 2018).

5 Although this cannot be generalised. The authors note that adapting the different automation risk measures to different datasets for the countries analysed resulted in a varying degree of accuracy in this analysis.

6 The method for assessing which occupations can be fully automated, which relied on the opinions of experts, has been later criticised for its lack of transparency (Wolters, 2020).

7 In another study examining the relationship of automation risk and mental health outcomes, Blasco et al. (2022) create their own measure of automation risk at the individual level, taking into account the share of workers executing repetitive tasks which can be monitored easily and executed by following direct instructions.

8 https://www.pwc.com/gx/en/issues/upskilling/hopes-and-fears.html

9 This identification strategy relies on the assumption that historic robot exposure influences wellbeing through workers' anticipations of possible future displacement.

10 The aforementioned US study by Golin & Rauh (2022) is also able to address endogeneity concerns by using a different experimental approach, although they focus on the relationship between workers' perceived automation risk and preferences for redistribution and intentions to join a union, and not impacts on wellbeing.

11 In this context, empowerment means employees' perception of using their strengths and carrying out their tasks.

12 See Castellacci & Tveito (2018) for a detailed review of this near ubiquitous technological transformation to working life.

13 These five aspects of meaningful work are: the pursuit of a purpose, social relationships, exercising skills and self-development, self-esteem and recognition and autonomy (Smids et al., 2020).

14 "We know more than we can tell" - the idea that machines can only be trained to replicate actions that can be explicitly programmed leaves some seemingly simple tasks resistant to automation (Polanyi, 1966).

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