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To help or to hinder? An examination of how HR policies can support individuals using new technologies in the workplace.

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Executive Summary

This study examines how workplace technologies interact with institutional contexts - particularly employee-centred Human Resource (HR) philosophies - to shape job quality and employee wellbeing. Drawing on survey data from 4,853 UK employees and using regression models, we explore whether HR philosophies can mitigate the adverse effects or amplify the benefits of digital ICTs, AI and machine learning, wearables and robotics.

Findings reveal that good HR environments often enhance the positive links between digital ICTs and flexibility, learning, idea use, and overall quality of life. In contrast, newer technologies often erode job security and may increase repetitive work, even in supportive HR contexts. Our results suggest that while employee-centred HR philosophies amplify benefits from established technologies, they do not yet reliably offset the potentially negative effects of emerging ones.

These findings underscore the importance of aligning the development of HR practices with technological development and provide empirical support for a capability-based, non-deterministic approach to understanding technology's role in the future of work.

1. Introduction

Previous working papers by the authors have examined how the introduction of various technologies is influencing employee wellbeing and job quality, based on an online survey of over 6,000 workers across the UK (Soffia et al., 2024a, 2024b). These studies provide preliminary evidence that while digital ICTs are associated with improved employee quality of life, emerging technologies are linked to reduced wellbeing. Deeper analyses suggest that exposure to ubiquitous digital ICTs correlates with improvements in job quality, particularly around flexibility and discretion, which may explain their positive association with quality of life. In contrast, although emerging technologies deliver some improvements to job quality, their benefits are often offset by increased job insecurity, potentially underpinning the observed decline in health-based quality of life.

The existing literature offers several interpretations of the links between technology exposure, job quality and wellbeing but - perhaps due to the lack of relevant data - tends to focus on direct effects, rarely accounting for organisational context. Focusing exclusively on estimating the direct impacts of technology risks disregarding the role of institutional factors - like human resource approaches, training policies and participation culture - which also influence how technologies affect employees (Nazareno and Schiff, 2021). In their review of the literature, Rohenkohl and Clark (2023) highlight a key gap of existing studies as they often overlook the contextual, socio-technical factors - such as socio-economic environment, existing policy protections, and employers' approach to managing technological change - that shape how workers actually experience automation.

In this paper, we move beyond deterministic views of technological impact and argue that institutional moderators are central to understanding its impact on job and overall life quality. In particular, we examine the role of HR Philosophy - an indicator of employee-centred HR management - as a moderating variable that potentially shapes how technologies affect job quality and wellbeing. Adopting a more sociological and capability-based approach, we hypothesise that the same technology can produce very different outcomes depending on how it is implemented and supported, with different types of HR philosophy acting as enabler or hindrance to the conversion of technological resources into valued outcomes.

Our analysis draws on a large-scale UK workforce survey and focuses on interactions between HR philosophy and four categories of workplace technologies. We assess their combined effects on five indicators of job quality and one measure of health-related quality of life. In doing so, we contribute new evidence on how organisations can support beneficial technological transitions.

The remainder of the paper is structured as follows: Section 2 develops the theoretical background. Section 3 outlines the data, variables, and analytical approach. Section 4 presents the results, and Section 5 discusses their implications in light of the theoretical frameworks. Section 6 offers a conclusion.

2. Theoretical background

Institutional, context- and capability-based approaches to work outcomes

Sociological and institutional theories of work have long emphasised that employment opportunities, job quality, employee wellbeing and, naturally, firm performance outcomes are shaped not only by individual attributes or broader labour market trends, but also by the structures, norms, and cultures embedded within organisations. Firm-level institutions — shared formal and informal rules and values— play a fundamental role in defining how work is organised, experienced day to day, and transformed into valuable outcomes.

According to (Farvaque, 2005, p. 47), this institutionalist perspective is strongly embedded in the capability approach (Sen, 1999, Nussbaum). Sen's argues that the quality of work should be evaluated in terms of the real freedoms individuals have to achieve valued outcomes, and that the institutional environment acts as a critical set of 'conversion factors' that may facilitate or hinder the realisation of such valued outcomes. Studies using the capability framework in the field of work have focused on the role of the organisation's underlying motivation to enhance employees' skills (Leßmann and Bonvin, 2011), training policies (Lambert et al., 2010; Caillaud & Zimmermann, 2011 in Julhe, 2016), voice and representation mechanisms (Bonvin, 2012; De Munck & Ferreras, 2013; Kulkarni, 2010; Leßmann & Bonvin, 2011), organisational culture (Hobson 2011), and managerial styles and HR philosophies (Gürbüz, Van Woerkom, et al., 2022; Lamers et al., 2022; Subramanian et al., 2013) as some of the key organisational-level conversion factors.

In this view, job quality and employee wellbeing are not fixed outcomes, but reflect a dynamic interplay between individual agency and institutional design. Work design theory also provides abundant evidence that workplaces which deliberately promote discretion, learning, flexibility, and voice, are more likely to see improved job quality, employee wellbeing and firm performance outcomes realised (Parker, Morgeson & Johns, 2017). High-performance work systems (HPWS) and high-involvement work practices (HIWPs) exemplify this organisational design. HPWS strategies emphasise employee training, involvement, and autonomy as pathways to both individual wellbeing and organisational performance (Boxall, 2012; De Menezes, Wood & Gelade, 2010). Similarly, HIWPs foster mechanisms for employee input in decision-making, particularly relevant in an era of declining formal representation and traditional voice mechanisms (Marchington & Wilkinson, 2005; Blanchflower & Bryson, 2003; Wilkinson et al., 2020; O'Brady & Doellgast, 2021).

From this perspective, institutional quality is not merely an organisational trait, but a determinant of whether workers adapt to organisational change and experience the full range of intrinsic and extrinsic rewards from work. As Acemoglu and Robinson (2012) argue in their broader theory of inclusive institutions, high-quality governance structures - within firms as well as societies - are central to enabling development and adaptability.

Organisational moderators in the context of technological change

These institutional dynamics need renewed attention in the context of accelerating adoption of modern workplace technologies, including generative AI, robotics, wearables and algorithmic management (Hayton, Stuart, Costa). While many studies attempt to forecast the imminent impacts of such technologies on job displacement or, equally, rush to ensure that technological innovation will bring nothing else but prosperity for those who remain in work, a growing literature cautions against technological determinism. Deterministic accounts posit that technology exerts a direct, uniform influence on work outcomes, from job quality to employee wellbeing and organisational performance. However, such views overlook the contextual nature of technological change.

Against such determinism, it has been argued that the impact of technology is always mediated by organisational and institutional choices. For instance, Boyd and Holton (2018) caution that the actual effects of robotics and AI are slower, more uneven, and more embedded in institutional structures than commonly assumed. Joyce et al. (2023) similarly argue that digital technologies reshape work through social processes, not mechanical causation. Rather than seeing technology as a force unto itself, these scholars direct attention to how it is embedded within existing power dynamics, management ideologies, and workplace regimes.

In the same line, others point to the idea that a single technology can serve various different purposes, with different implications for job quality and wellbeing, depending on how it is designed, implemented, and governed (Gilbert 2023, 2024). In particular, Parker and Grote (2019: p. 1174) remark: "the same technology could have different effects on work design depending on whether, for example, a human-centred approach to technology development and deployment is adopted, the skill levels of current workers, the organizational strategy and design, and so on. Organizations can thus actively make choices to improve the effect of technology on work design, and hence on important outcomes." For example, Lamers et al. (2021) draw in the capability approach to emphasise the role of organisational context in determining whether algorithmic management tools can both support worker autonomy and dignity through enhancing feedback loops in high-trust settings, or reinforce surveillance and control in low-trust environments. Thus, the question is not whether technologies have effects, but how organisational and institutional factors condition these effects.

Parker and Grote (2019) identify several such moderators, including institutional regimes, management ideologies, and pre-existing work practices. These factors shape how technologies are deployed and experienced in real-world settings. Recent qualitative evidence supports this view: for example, Yu-Liu et al (in Pissarides and Thomas 2025) document how collaborative deployment of robotic tools - where workers had input into programming and task design - led to increased worker engagement and productivity.

The central role of HR philosophy

Within the existing future of work literature, three sets of organisational factors have emerged as particularly salient in moderating the effects of technology: voice mechanisms, training practices, and HR philosophy.

Voice mechanisms, including trade unions and consultative bodies, play a long-recognised role in shaping job quality. Beyond negotiating wages and hours, these structures influence how organisational change is introduced and how risk is distributed. Where worker voice is strong, transitions are more likely to be negotiated rather than imposed. Studies show that in sectors with robust representation, technological change tends to produce less polarising effects (Doellgast & Wagner, 2022; Kornelakis et al., 2022; Lloyd & Payne, 2019). Traditional collective bargaining structures - such as trade unions - have been shown to buffer workers against wage stagnation and job insecurity under automation (Berg et al., 2023; Rabensteiner & Guschanski, 2022).

Training policies is another vital component. Technological transitions require new skills, but also the time and space for workers to integrate these into their routines. Training provided through high-involvement approaches has been linked to improved worker outcomes and smoother transitions (Boxall, 2012; De Menezes et al., 2010). Haepp (2021) shows that training moderates the relationship between automation and wellbeing, particularly when it is inclusive and forward-looking. As noted by Pissarides and Thomas (2025), co-determined training strategies - involving both managers and employees - create feedback loops that enhance learning, motivation, and job clarity.

The third variable, HR philosophy, can be considered as encompassing various organisational features including approaches to voice and training, as well as more individually defined managerial or leadership styles. HR philosophy refers to an organisation's overarching values or strategic orientation towards managing human resources - whether it is employee-centred and the workforce seen as an asset to be invested in, or efficiency-centred and employees seen as costs to be minimised (Lepak et al., 2007). As such, HR philosophy can reflect and reinforce other organisational practices concerning training and voice. It captures not just isolated policies, but the broader strategic posture of the organisation. Firms that adopt employee-centred HR philosophies tend to invest more in workforce development, wellbeing, and long-term employment relationships.

Despite its conceptual importance, there is limited empirical research examining how HR philosophy moderates the relationship between technology adoption and job quality or wellbeing. Most existing studies focus on its associations with firm-level outcomes such as performance or retention (e.g., Bloom et al., 2015), rather than worker-level experiences. A partial exception is Hayton (2024), who found that high-involvement HRM practices amplified the positive effects of firm-level technology adoption on anticipated improvements to job quality - measured through employer expectations around pay, hours, meaningfulness, development opportunities, and participation. However, these outcomes were proxies and based on managerial perceptions. Other research has provided qualitative evidence from case studies and focus groups, highlighting the potential of employee-centred HR practices to shape how workers experience emerging technologies (Pissarides and Thomas 2025), but such findings remain context-specific and difficult to generalise.

By contrast, relatively more attention has been paid to how HR philosophy, practices, and the HR profession itself are being transformed by new technologies—particularly algorithmic tools used in recruitment, performance management, or scheduling. This literature emphasises the bi-directional nature of the relationship between HR and technology, suggesting that digital systems can reshape HR roles and strategies as much as HR frameworks shape how technology is used (Sidhu et al., 2024; Sapta et al., 2021, https://journals.sagepub.com/doi/10.1177/0008125619867910,).

Contributions of this study

Our study builds in this emerging evidence and contributes to knowledge around the interplay of technology and HR philosophy in various ways.

First, it focuses on HR philosophy as a potential organisational moderator. In our previous work (Soffia et al., 2024a, 2024b), we found strong positive associations between employee-centred HR philosophy and multiple job quality outcomes, as well as with quality of life. This justifies our choice of HR philosophy as the focal moderator. Moreover, our interest on this organisational variable lies on the fact that it is a domain where employers retain agency and can design concrete interventions, especially against declining training provision and forms of representation like unions in the UK context.

Second, our analysis is unique in examining a varied set of job quality indicators - including autonomy, learning opportunities, repetitiveness, flexibility, and job security - rather than focusing solely on wages or job quantity. Moreover, we explore whether these dimensions are reflected in higher-value outcomes such as health-related quality of life, providing a more complete picture of how individual experiences of technology interplay with institutional environments.

Third, by using large-scale, employee-level data, we overcome some of the limitations of prior research that has relied on firm-level reports or sector-specific case studies. This allows for a more generalisable understanding of how HR philosophy conditions technological outcomes across industries and regions.

All in all, we contribute with empirically grounded insights into how firms can concretely take actions to support individuals using new technologies in the workplace.

3. Methodology

Data

We conducted an online survey of adults aged 18 and above, currently in paid work, and residing in the United Kingdom, from 22 May to 30 June 2023. The survey aimed to explore how exposure to technology influences wellbeing and job quality, and the exposure to technology was broadly defined and interpreted by participants. To promote a consistent understanding of technology, the survey provided examples of various technological tools and systems. While this approach did not isolate the effects of specific technologies, it ensured a comprehensive examination of how technology affects diverse aspects of work processes.

The survey employed a robust sampling strategy to represent the UK's working adult population. Key demographic factors, such as age, gender, education level, employment type (employed and self-employed), and geographic region, were considered. Additionally, to address recruitment challenges—such as underrepresentation of individuals with no academic qualifications, self-employed workers, and older adults (over 65) in Northern Ireland—post-fieldwork weighting was applied using the Labour Force Survey data. This ensured the final weighted sample accurately reflected the working population of the UK.

The current analysis uses data from 4853 employees with complete responses across all variables of interest. Ethical approval for the study was obtained from the Humanities and Social Science Research Ethics Committee (HSSREC) at the University of Warwick, UK.

Measurements

Job quality and wellbeing

The analysis in this study focused on six key variables, chosen to measure perceived job quality within the workplace and workers' overall wellbeing. Five job quality and one wellbeing variable served as the dependent variables in the analysis:

- ***Workplace flexibility.*** *This examined whether employees experienced changes in their ability to work flexibly in terms of location due to technology.*
- ***Learning opportunities at workplace.*** *This variable measured whether employees perceived a change in their opportunities for learning at work due to technology.*
- ***Idea use.*** *This variable measured the extent of autonomy in the decision-making process and the application of employees' own ideas.*
- ***Unrepetitive work.*** *This captured the extent to which technology reduced the proportion of repetitive tasks in employees' roles.*
- ***Job security.*** *This variable gauged workers' perception of job insecurity related to the introduction of technology, by asking them about their perceived likelihood of becoming unemployed within the next 6 months.*
- ***Quality of life.*** *Quality of life was assessed using the UK's EQ-5D-3L value set. This measure is a continuous variable where a value of 1 represents a full health state; a value of 0 represents a state equivalent to death; negative values indicate health states perceived as worse than death.*

For the first five job quality variables, responses were collected using a 5-point ordinal scale: “increased a lot,” “increased a little,” “not changed,” “decreased a little,” and “decreased a lot.” From this, we created a 3-category ordinal scale to capture changes in job quality outcomes: Better, Unchanged, and Worse.

For the first three job quality variables - workplace flexibility, learning opportunities, and idea use - the Better category included “increased a lot” and “increased a little”; Unchanged included “not changed”; and Worse included “decreased a little” and “decreased a lot.”

For the last two job quality variables, a reversal of categories was done due to the nature of these outcomes being negatively framed. Job security was originally measured as the perceived likelihood of becoming unemployed within the next six months. Therefore, Better included “decreased a lot” and “decreased a little”; Unchanged included “not changed”; and Worse included “increased a little” and “increased a lot.” This variable illustrated each employee’s forecast of their future employment and was not a measure of the labour market.

For unrepetitive work, which was originally framed as the share of repetitive tasks, the same reversal procedure was applied. This recoding ensured that, for all variables, the Better category consistently reflected improvements in job quality.

In short, higher values on the ordinal scales of these variables are always favourable. These variables allowed for a nuanced exploration of how technology influences various dimensions of job quality and worker wellbeing.

Technology exposure

Exposure to technologies are measured through 5-scale ordinal variables, ranged from 1 (“never”) to 5 (“always”). Study participants were asked their perceived degree of interaction with four types of technologies in their workplace, including:

- ***Digital information or communication technologies*** *(for example computers, laptops, tablets, and smartphones, real-time messaging tools, as well as other devices that connect to the internet)*
- ***Wearable and remote sensing technologies*** *(for example, CCTV cameras, proximity cards, fitness trackers, smartwatches, smart glasses, GPS devices, and other sensors that gather data)*
- ***Software technologies using artificial intelligence (AI) and machine learning (ML)*** *(for example, advanced data analysis and programming software, text mining, natural language processing, speech recognition, image recognition, biometrics, decision management, touchscreen ordering, self-checkouts)*
- ***Automated tools, equipment, machines and robotic technologies*** *(for example, autonomous robots, self-driving vehicles, drones, handheld monitors or scanners, measuring and diagnostic devices or robots, 3D printers, lasers, CT scans, smart whiteboards, and other technologies that can automate physical processes).*

This measure of technology exposure has the advantage of capturing more than the actual displacement of whole jobs by automation and to focus on the more nuanced levels at which human workforce interacts with technological systems.

As Parker & Grote (2019) assert, “it is most likely that tasks will be automated, not whole jobs, such that much work will entail an intense interaction between humans and self-learning autonomous technology”.

HR Philosophy

HR Philosophy is 3-item scale measuring workers' perceptions about Human Resources management, adapted from Lepak et al (2007) and used in Hayton et al. (2023). Participants were asked their level of agreement with three statements (alpha = 0.87):[1]

- *'We take care of our workforce, no matter what business challenges we face';*
- *'We invest heavily in our employees because we know that they determine the success of our business'; and,*
- *'We maintain a long-term commitment to the growth and well-being of our employees'.*

The average scale is reversed score and ranges from 0 (representing maximum efficiency-centrality) to 4 (representing maximum employee-centrality).

Other institutional factors

Other institutional factors included as controls are:

- ***Formally Recognised and Independent Structures*** *(FRIS) measures whether employees have access to independent mechanisms of support, such as trade unions, staff associations, or employee forums.*
- ***Internal Consultative and Participative Structures*** *(ICPS) examines the availability of internal participatory mechanisms, such as work councils or joint consultative committees, which facilitate dialogue and collaboration within the organisation.*
- ***Employer Training*** *captures whether employees have undergone formal or passive training programmes provided by their employer.*
- ***Self-Training*** *assesses informal or self-initiated training efforts.*

To ensure reliable results, we also control for socio-economic and demographic controls, including gender, age, ethnicity, marital status, number of dependent children, education, skill level (based on SOC2020 sub-major groups), level of pay, job tenure, sector of employment and rural urban classification. Table 1 presents the summary of descriptive statistics.

Analytical approach

We aim to investigate how institutional variables moderate impacts of digital technology on wellbeing and perceived job quality. We first estimate the following regression equations for quality of life:

$$1) \qquad QoL_i = \beta_0 + T_i\Gamma_1 + I_i\Gamma_2 + X_i\Gamma_3 + I_i \cdot T_i\Gamma_4 + \epsilon_i$$

where QoL_i is the EQ-5D-3L quality of life of individual i, T_i is a vector that includes our four variables of technology exposure, I_i is a vector that includes our five institutional variables, X_i is a vector includes various socioeconomic and demographic characteristics as controls, and Γ_i denotes the error term. The Quality of Life variable, derived from the UK's EQ-5D-3L value set, is inherently capped at 1 for individuals reporting a full health state. This ceiling effect poses a challenge in distinguishing differences in utility among healthy individuals, potentially introducing censoring bias in the analysis. Such bias arises because the scale

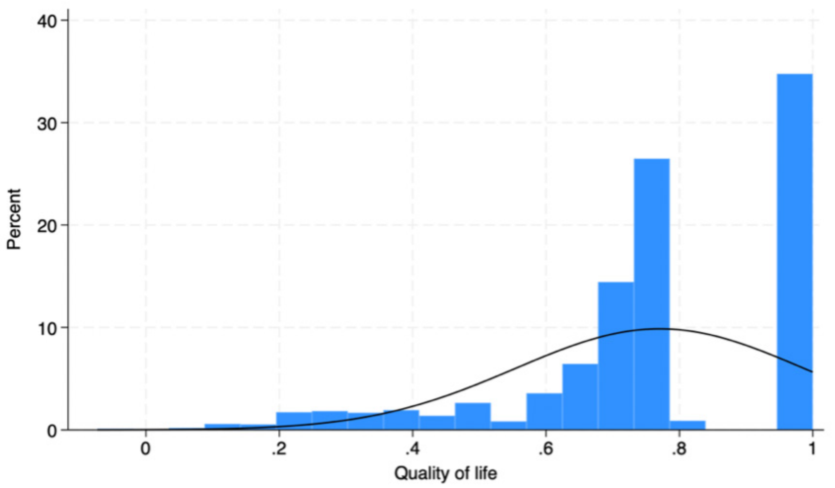
1 Of note, this scale is not measuring practices as intended by the organisation, but rather as perceived by individual employees. The gap between both reports is well established in the literature, and it is often explained by eligibility issues (i.e. not everyone in an organisation might access to wellbeing and development resources), by unintended variance in the application of organisational policies, or simply by biased perceptions of individuals vis a vis the intended practices (Jiang et al., 2017; Meijerink et al., 2016; Piening et al., 2014). However, the experience of HR practices as reported by workers is considered valid and a potential mediator between technological deployment and worker wellbeing.

does not allow for variation beyond the upper limit, which can lead to an underestimation of the true variability in quality of life across respondents.

As illustrated in Figure 1, the histogram of the Quality of Life variable shows a notable clustering at the maximum value, providing clear evidence of this censoring bias. To address this issue, we employed a Tobit model, which is specifically designed to handle censored data. The Tobit model accounts for the fact that some values of the dependent variable are limited by an upper threshold, allowing for a more accurate estimation of the relationships between the independent variables and Quality of Life.

This methodological adjustment ensures that our analysis provides robust and consistent insights into the impact of technology on Quality of Life, correcting for the potential censoring bias imposed by the nature of the EQ-5D-3L measure.

Figure 1 - Histogram of Quality of Life variable



Regarding perceived job quality variables, we employed ordered logistic regression, given our ordinal response variables. Preliminary assumption checks for ordered logistic regressions have been performed in our previous reports, which provided suggestive evidence to the reliability of our results. The generic form of such regressions is:

2) $$P(JQ_i > j) = \frac{exp(\beta_0 + T_i\Gamma_1 + I_i\Gamma_2 + X_i\Gamma_3 + I_i \cdot T_i\Gamma_4 + \epsilon_i)}{1 + exp(\beta_0 + T_i\Gamma_1 + I_i\Gamma_2 + X_i\Gamma_3 + I_i \cdot T_i\Gamma_4 + \epsilon_i)}$$

where JQ_i is the level of perceived job quality of individual *i*. As mentioned, all of our perceived job quality variables are 3-scale ordinal variables (Worse, Unchanged and Better). We controlled for the same variables as in the QoL model.

4. Results

Descriptive analysis

We begin by reporting descriptive statistics for the relevant study variables (see Table 1 in Appendix A). The mean quality of life recorded in our sample was 0.77 (SD 0.22), which was significantly lower than the UK general population benchmark reported by Jenssen et al. (2019) of 0.86 ($t = -28.77$, $p < 0.05$). Only 13% and 16% of participants reported improvements in job security and task variety, respectively. A 38% recorded improved opportunities to use their own ideas, 47% said flexibility to choose their work location had improved, and more than half (57%) reported improved opportunities to learn new things due to technology.

The average level of employee-centred HR philosophy reported by participants was relatively high and equivalent to 2.45 (SD 1.01). Another important set of organisational factors for our study are training and worker representation. Three-quarters of respondents had gone through formal or passive training (employer-provided) during their current job, and 62% had undertaken other informal types of training (self-provided). A similar proportion (58%) reported they had access to formally recognised and independent structures to express their views about work, while only 16% said they had access to other informal consultative channels.

Unsurprisingly, the level of exposure to Digital ICTs was high, with 82% of participants using this type of technology at least sometimes on a typical work week. Exposure to emergent technologies was considerably lower, ranging from 34% in the case of wearables, to 41% in the case of robotics, with 37% reporting exposure to AI and Machine Learning

The median employee was 43 years old. The sample was evenly split between men and women; 88% identified themselves as White, 6% identified as Asian or Asian British, 3.8% as Black, Black British, Caribbean or African and another 3% as Mixed, multiple or other ethnic group. About three-quarters of the sample had a qualification level at or above A-levels, and more than half (56%) had an occupational skill level of 3 or higher (inclusive of some technical and professional occupations). Over 50% received an annual salary between £20,300 (approximately equivalent to the National Living Wage set from April 2023) and £35,100 (which is close to the £34,963 median gross annual earnings for full-time employees in the same year; ONS, 2024). The majority of employees had been in their current job for three years or more, typically in the Commerce and Hospitality, Administrative and Support Services, Health and Education sectors. More than half of the sample lived in predominantly urban areas, including London.

Main effects of technologies on job and life quality

Before examining the moderating role of institutional factors, we estimated the main, or unconditional, effects of four workplace technologies on employees' job quality and overall quality of life, assuming these effects are constant across different HR environments.

Table 2 (in Appendix A) reports marginal effects from ordered logistic regressions (Models 1 to 5) and a tobit regression for quality of life (Model 6), with 95% confidence intervals.

Figures 2 - 7 visualise these main effects through predicted probabilities.

Figure 2 - Workplace flexibility

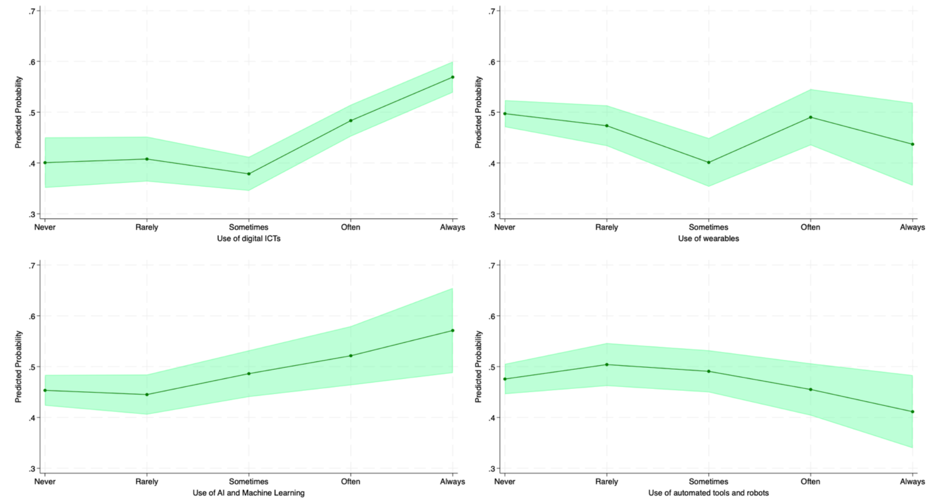


Figure 3 - Learning opportunities

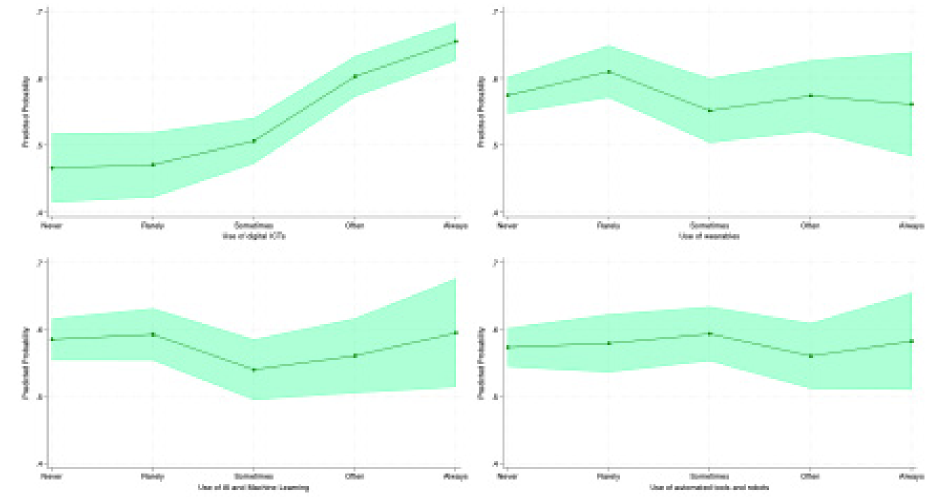


Figure 4 - Use of own ideas

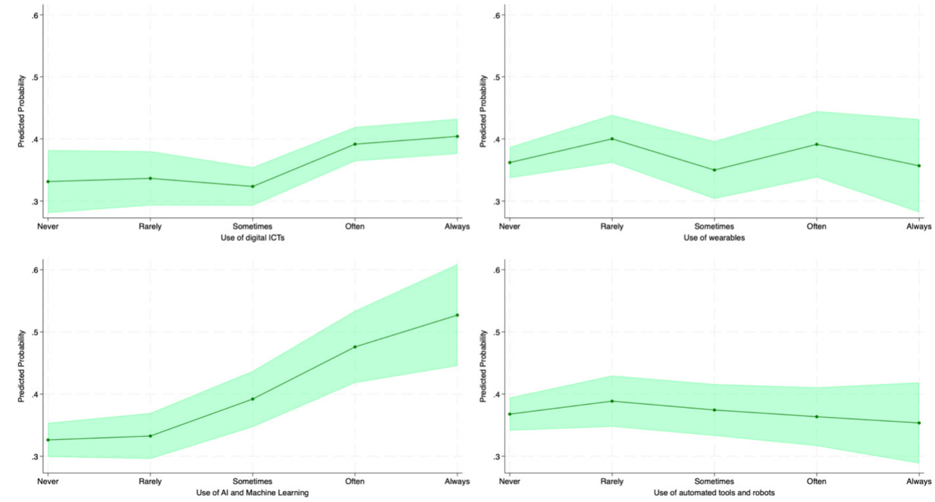


Figure 5 - Unrepetitive work

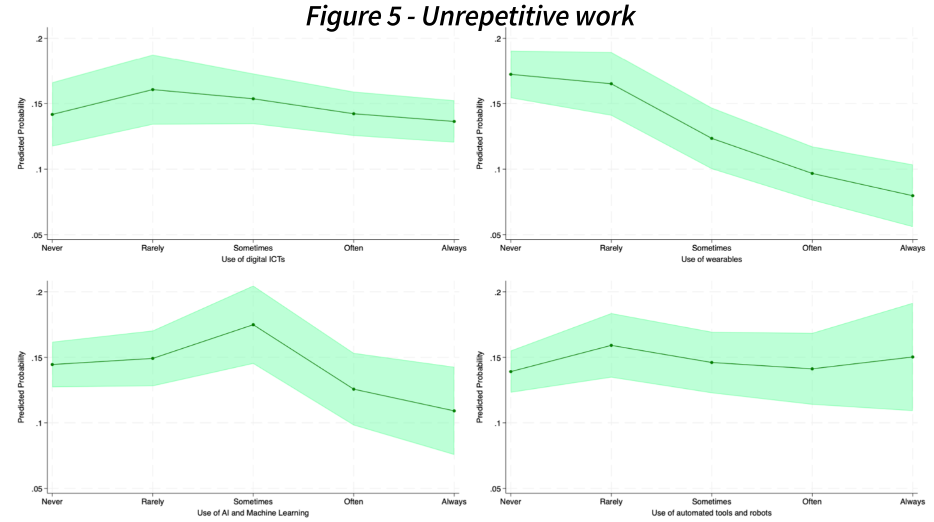


Figure 6 - Job security

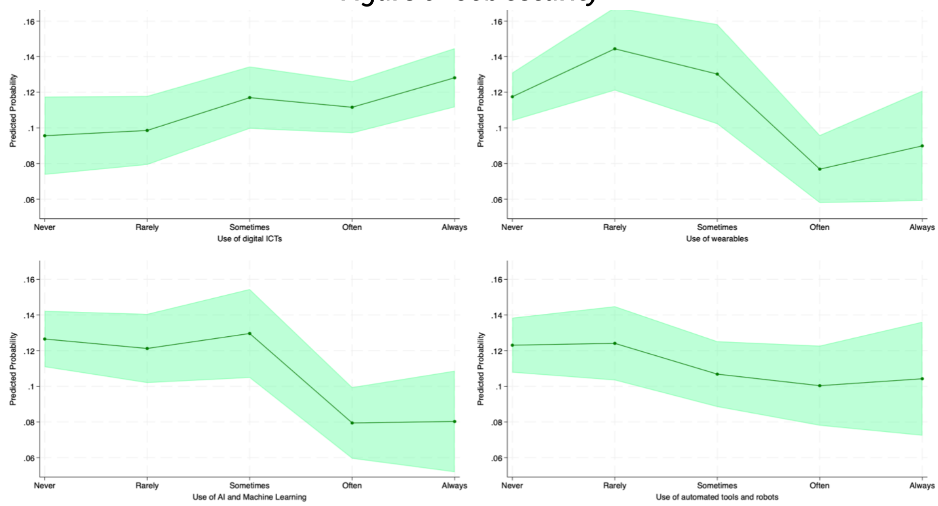
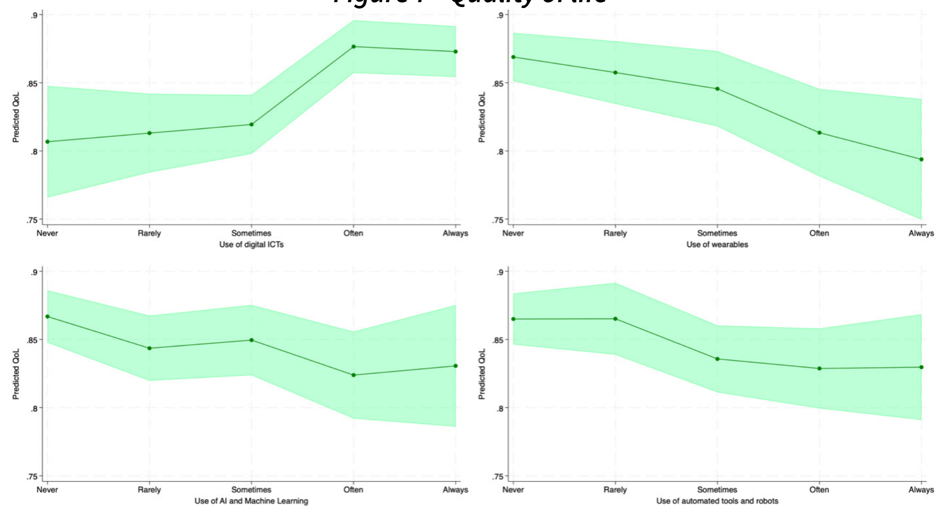


Figure 7 - Quality of life



Digital ICTs show consistently positive associations with multiple job quality indicators – including flexibility, learning opportunities, idea use, and job security – as well as with overall quality of life. In contrast, wearables are linked to more negative outcomes: moderate exposure is associated with increased task repetitiveness, lower job security and reduced quality of life. AI and machine learning technologies are positively associated with flexibility and idea use, but are also linked to a deterioration in job security and quality of life. Robotic technologies show weaker associations overall, though moderate exposure correlates with a slight decline in predicted life quality.

In terms of institutional context, the HR philosophy variable shows strong baseline associations with job quality: more employee-centred HR approaches are positively linked to flexibility, learning, idea use, and job security, though not to repetition. HR philosophy also contributes significantly to overall quality of life, with a regression coefficient of B = 0.028 (95% CI: 0.022–0.035), reinforcing its broad relevance for work-related outcomes.

Links between technologies and job and life quality across types of HR philosophy

Having established the direct association between the various technologies and changes in job characteristics as well as on employees' quality of life, we now examine whether these associations are contingent to different HR policies. To do this, we calculated and plotted predicted probabilities of declaring positive job quality outcomes (e.g. more workplace flexibility), as well as the predicted Quality of Life scores, for both good and poor HR philosophy scenarios (with all other variables held at their means). We defined low/poor levels of HR philosophy as those at the 25th percentile of the HR index (score = 1.25), and high/good levels as those at the 75th percentile (score = 3.00).

Figures 8 - 13 show interaction plots for the association between different technologies and better workplace flexibility by type of HR philosophy.

Figure 8 - Workplace flexibility

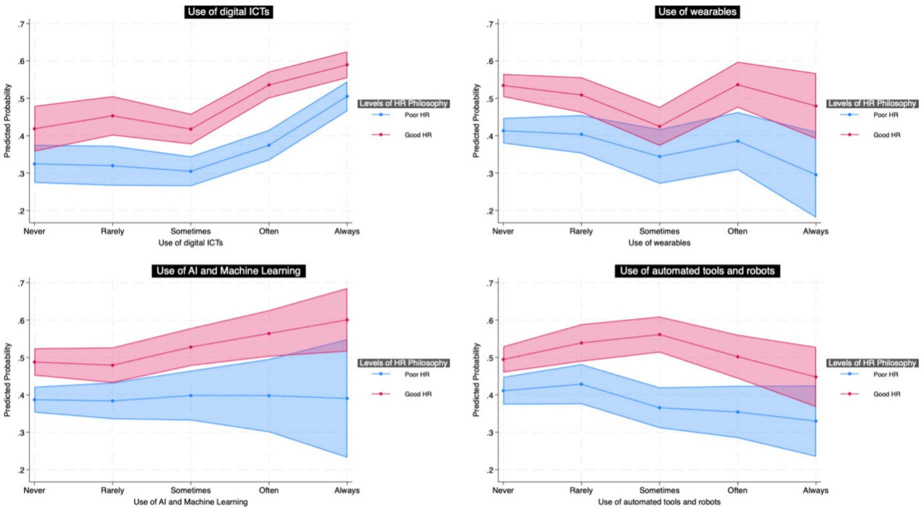


Figure 9 - Learning opportunities

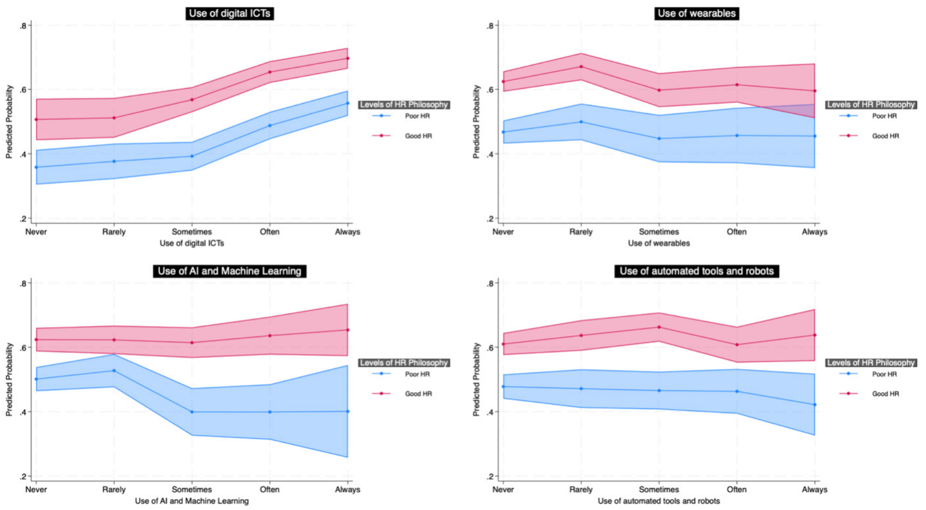


Figure 10 - Use of own ideas

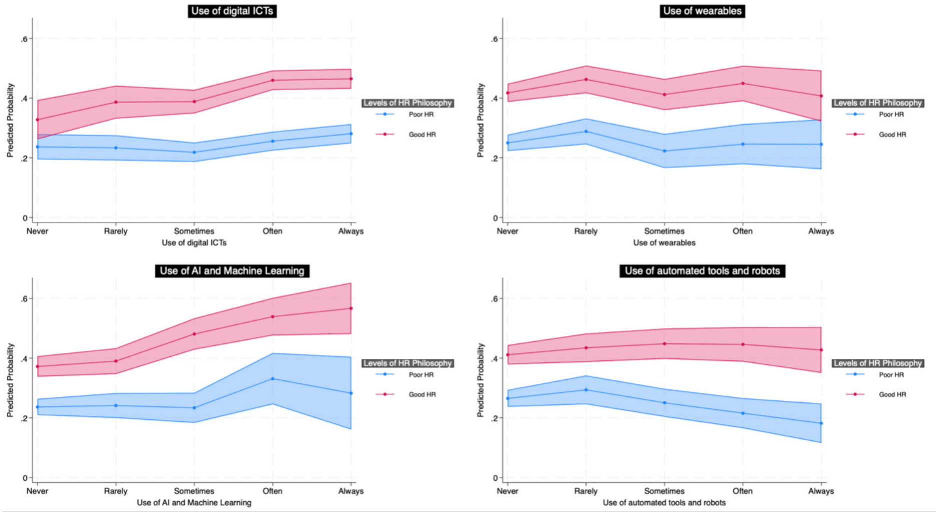


Figure 11 - Unrepetitive work

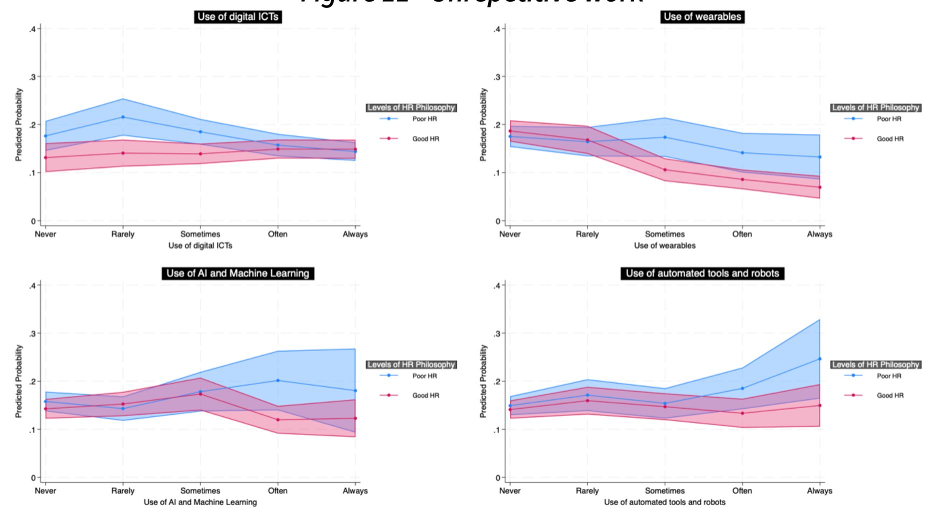


Figure 12 - Job security

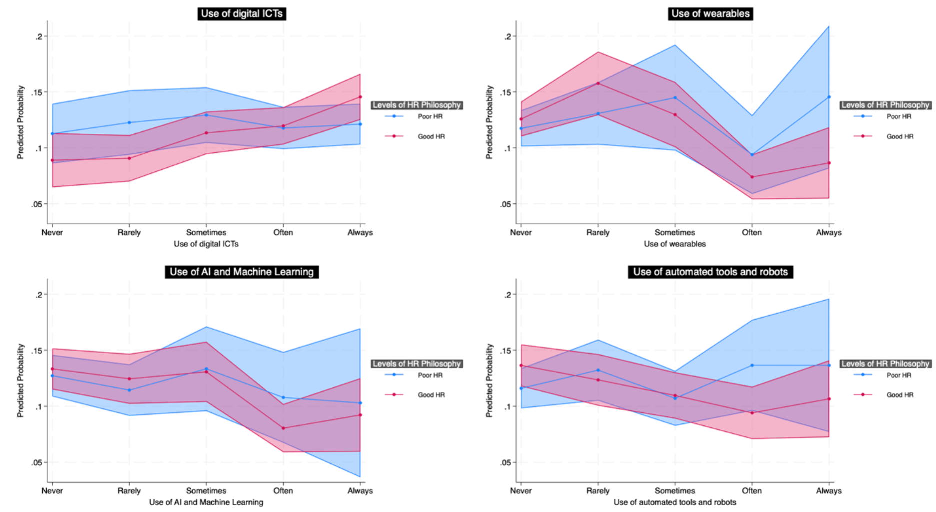


Figure 13 - Quality of life

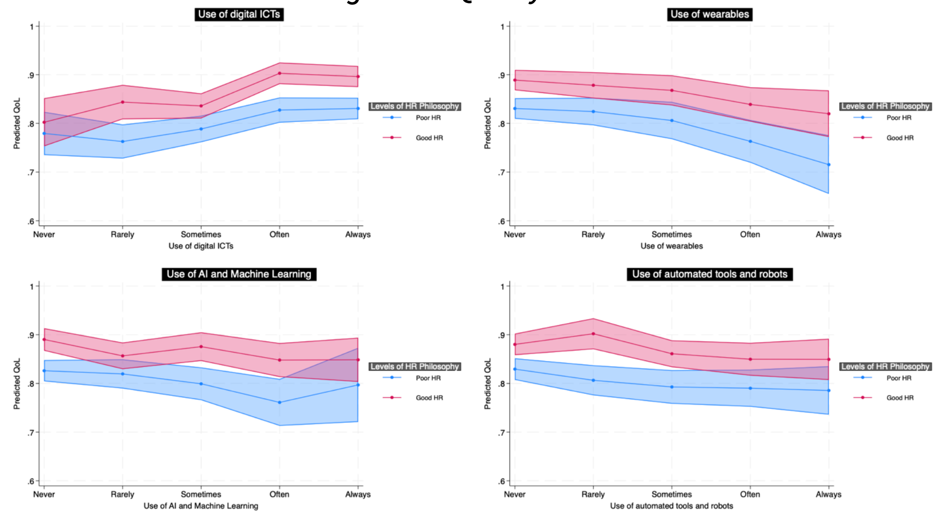


Figure 8 presents four plots illustrating the association of each technology with better workplace flexibility across good (red) and poor (blue) HR philosophy. Each plot includes 95% confidence intervals for the predicted probabilities. Overlapping confidence intervals may suggest that the differences between predicted probabilities was not statistically significant at 5% significance level.

The plot indicates a positive association between exposure to digital ICTs and flexibility across both types of HR philosophy, with more significant gains linked to more frequent use of ICTs and practically no difference between those who use ICTs less often. More revealing is the fact that the gain in flexibility by using ICTs extensively is slightly steeper for employees in poor HR environments.

Exposure to newer technologies reveals different patterns. In the case of AI and machine learning, the raw relationship between them and flexibility seemed positive, as shown in Figure 2. However, Figure 8 reveals that this positive relationship is present only in the context of good HR policies: it remains virtually unchanged for those with poor HR policies (blue line), while it increases for those with good HR policies (red line). However, it is important to note that at the highest level of exposure ("always",) the confidence intervals overlap between good and poor HR policies.

The role of HR policies is less notable when it comes to wearables. Regardless of the type of HR policy in place, flexibility first is negatively associated with the use of wearables, then it improves for those who use it "often" and decreases again with persistent exposure. The widening gap as exposure increases may suggest that good HR slightly buffers the potentially negative effect of wearables on flexibility, with the caveat that confidence intervals marginally overlap.

Robotics are monotonically associated with poorer workplace flexibility in contexts of poor HR policies. Interestingly, in contexts of good HR policies, moderate use of robotics brings some gains in flexibility but then plummets again with extensive use, in a way much more exacerbated than in contexts of poor HR.

Figure 9 presents the results of the interaction analysis between different types of workplace technologies and levels of HR philosophy on employees' opportunities to learn new things. A positive association is observed between the frequent use of digital ICTs and learning opportunities across both poor (blue line) and strong (red line) HR environments, though the probability of learning is consistently higher in organisations with more developed HR philosophies. In contrast, the interaction between AI technologies and HR philosophy reveals a sharper divergence: under poor HR philosophy, more intensive exposure to AI is associated with a decline in learning opportunities. However, under good HR philosophy, this negative association is not observed; in fact, slightly higher levels of flexibility are seen.

Regarding wearables, although employees in good HR philosophy environments tend to report higher levels of learning opportunities, the plots do not display a substantial or consistent change as exposure increases, regardless of HR philosophy, indicating a weak or absent association.

For automated tools and robots, the impact on learning opportunities appears minimal or flat at lower levels of use. However, at the highest levels of exposure, a divergence emerges: positive effects are amplified in good HR settings, while poor HR environments show a drop in predicted learning outcomes.

Figure 10 illustrates the interaction between frequency of exposure to different workplace technologies and levels of HR philosophy in predicting the likelihood that employees can use their own ideas at work. For digital ICTs, the predicted probability of using one's own ideas increases noticeably with more frequent exposure, but only in contexts of strong HR philosophy (red line), where the slope is clearly upward. In contrast, under poor HR conditions (blue line), the probability remains flat across all levels of exposure. This indicates that digital ICTs contribute to idea use primarily when supported by high-quality HR practices.

A similar interaction pattern is observed with AI and Machine Learning technologies. As shown in the baseline results in Figure 4, higher use of these technologies was strongly associated with better use of own ideas. However, this plot reveals that that pattern occurs primarily among workers in supportive HR environments. Under good HR, the likelihood of using one's ideas rises steadily with increased exposure. Under poor HR probabilities are consistently lower and largely unchanged across exposure levels, with an increase only between "sometimes" and "often". This suggests that AI and Machine Learning technologies may enhance employee autonomy only when accompanied by strong HR frameworks.

In the case of wearables, the probability of using one's own ideas does not increase significantly with more frequent use under either HR condition. Nonetheless, employees in strong HR environments consistently report a higher level of idea use than those in poor HR settings, suggesting that HR quality, rather than the technology itself, is the primary driver of this outcome.

For automated tools and robots, the pattern is mixed. In strong HR environments, predicted probabilities of idea use are moderately higher but remain flat across exposure levels. However, in poor HR settings, increased exposure to robotics is associated with a steady decline in the likelihood of using one's own ideas. Given that the overall baseline pattern observed in Figure 4 shows a negative relationship between robotics and idea use, these results suggest that supportive HR practices act as a protective factor, mitigating a potentially negative impact of robotics on employee autonomy.

Figure 11 displays the interaction between the frequency of use of various technologies and levels of HR philosophy in predicting the perceived reduction of repetitive work. Across all technologies, there is no strong evidence that any consistently reduce repetitive work, either overall or in interaction with HR philosophy.

Digital ICTs show only minor differences by HR condition, although blue (poor HR) and red (good HR) lines go slightly in opposite directions as exposure intensifies. Wearables appear to have a slight negative impact on repetition, which, paradoxically, is more marked in contexts of good HR philosophies, but the differences with contexts of poor HR are modest and likely not statistically significant.

For AI and robotics, slight benefits may emerge of intensive exposure to robotics but, again, specifically in contexts of poor HR conditions. Contrary to expectations, strong HR philosophy does not consistently enhance the probability that technologies reduce repetitive work and, in some cases, may even coincide with lower predicted benefits.

Figure 12 presents the interaction between exposure to various workplace technologies and levels of HR philosophy in predicting employees' perceived job security. Results for Digital ICTs are notable: under poor HR conditions, predicted job security remains relatively flat across all levels of exposure. In contrast, in strong HR environments, job security increases slightly with more frequent use of ICTs, although the overall gain is modest and does not markedly exceed the levels observed in poor-HR settings.

For newer technologies – wearables, AI and Machine Learning tools, and robotics – the expected pattern of reduced job security with greater exposure is less straightforward when accounting for HR philosophy. In fact, in organisations with strong HR philosophies (red lines), more frequent use of these technologies is associated with a decline in predicted job security. Conversely, in poor HR environments (blue lines), job security levels tend to remain relatively stable or show only minor declines across exposure levels. Notably, for AI/ML technologies, the negative slope is more pronounced in good-HR contexts than in poor-HR ones, while with robotics, a similar though milder pattern emerges.

Overall, strong HR philosophy appears to have a limited and somewhat paradoxical influence: while it offers slight improvements in job security with the use of digital ICTs, it does not mitigate –and may even exacerbate– the negative association between exposure to newer technologies and job security.

Figure 13 presents interaction plots showing the predicted impact of exposure to different workplace technologies on employees' quality of life (QoL), moderated by the type of HR philosophy. Across all technologies, individuals working in organisations with strong HR philosophies (red lines) consistently report higher predicted QoL, underscoring the broadly beneficial role of supportive HR practices.

For digital ICTs, quality of life remains stable or increases modestly with more frequent exposure, especially in strong HR environments. The difference between good- and poor HR contexts becomes more pronounced at higher levels of exposure, suggesting that ICTs may enhance wellbeing when implemented within a supportive HR framework.

In contrast, wearables are associated with a clear and consistent decline in quality of life as exposure increases, most notably in poor HR settings (blue line). Even in good HR contexts, a slight downward trend is observed. This suggests that wearables may negatively affect wellbeing, and that strong HR policies alone may not be sufficient to reverse this trend.

For AI and machine learning software, the overall trends are relatively flat, with only a modest decline in predicted QoL in poor HR settings as exposure increases. A similar pattern is observed with robots: predicted QoL declines very slightly with greater exposure under poor HR conditions. Under strong HR conditions, QoL remains relatively stable across exposure levels. While a downward trend is not clearly evident, neither is there a clear indication that strong HR policies can mitigate or offset the potential negative effects of these technologies on quality of life.

5. Discussion

This study provides new evidence that the effects of workplace technologies on job quality and wellbeing are contingent on organisational context, particularly HR philosophy. Consistent with non-deterministic and capability-based theories, our results show that technologies do not deliver constant work and wellbeing results. Rather, these outcomes depend on the institutional conditions in which technologies are introduced, deployed, and experienced.

The most consistent and positive interactions between HR philosophy and technology are observed in relation to digital ICTs. Workers in organisations with strong employee-centred HR philosophies report improved flexibility, learning, use of ideas, and overall quality of life as ICT exposure increases. This aligns with prior studies showing that digital technologies enhance autonomy and flexibility when embedded in supportive organisational frameworks ((Zapata, Ibarra and Blancher, 2024). Felstead and Henseke, 2017; Parker & Grote, 2019). These findings also resonate with the capability approach: employee-centred HR philosophy appears to act as a conversion factor, specifically enabling the translation of digital ICT resources into valued outcomes (Sen, 1999).

Moreover, the positive effect of ICTs on flexibility may also have spillover benefits for other job aspects like learning and idea use, as well as for overall wellbeing—particularly when employees have the discretion to integrate technologies into their work on their own terms (Hunter, 2019; Zapata et al., 2024). That the same technologies produce neutral or negative outcomes under poor HR conditions further confirms that technologies do not deliver improvements automatically and that institutional context matters.

By contrast, HR philosophy appears to play a weaker or more ambiguous moderating role when it comes to newer technologies such as AI tools, robotics, and wearables. In some cases, good HR practices enhance outcomes like idea use or learning opportunities brought about AI technologies. Good HR policies can also help offset the constraints to flexibility associated with robotics, although such effect is not sustained when exposure to robotics is intensive perhaps due to the in-person, physically embedded nature of robotic systems, which constrain spatial autonomy. In other cases —such as unrepetitive work or job security—HR philosophy does little to buffer negative effects of emerging technologies and may even coincide with worse outcomes.

We can offer some interpretations to the latter and seemingly counterintuitive set of findings. In particular, the slight suggestion that the repetition associated with wearable technologies is exacerbated in supportive HR environments may reflect the growing integration of “wellbeing technologies” such as biometric smart watches and hand-scanners, which, though presented as supportive of workers physical and mental health, often introduce rigid structures, increased need to digitally input information and diminish task variety. Furthermore, such tools can blur the line between self-care —as experienced by those who self-expose to wearable technologies— and monitoring —as experienced by those who are obliged to work with these tools (Moore and Robinson, 2016).

We also found that employee-centred HR environments do not reliably offset the insecurity associated with emerging technologies. In fact, job insecurity often persists or even increases when exposure is at its highest, regardless of HR context. This may reflect broader macroeconomic uncertainty or sector-specific disruption. It also suggests that subjective job security—unlike flexibility or learning—may be structurally determined and less sensitive to the influence of HR philosophy alone. Naturally, the pervasiveness of job insecurity is fed into the consistently flat or negative association between emerging technologies and quality of life, regardless of the HR scenario.

These findings challenge assumptions that simply embedding new technologies in supportive HR environments is sufficient to generate positive results. They rather suggest a possible misalignment between traditional HR practices and the transformative potential of some emerging tools. This underscores the point made in the theoretical literature that institutional conversion factors must evolve alongside the technologies themselves (Lamers et al., 2022).

Possible mechanisms

To understand why HR philosophy moderates some outcomes but not others, it is useful to examine potential mechanisms. One such mechanism and concrete expression of employee-centred HR is employer-provided training. In theory, training should help employees adapt to technological change and reduce anxieties around skill obsolescence or displacement (Greenhalgh & Mavrotas, 1996; Kumar et al., 2019). In practice, however, our data show that training is not evenly distributed across technologies.

Spearman correlation analysis (Table 3) reveals that employees exposed to newer technologies (e.g., wearables, AI, robotics) are significantly less likely to have undergone employer-provided training than those exposed to digital ICTs. This training gap may explain why supportive HR philosophies have limited moderating power in the context of emerging technologies. Although training is positively associated with supportive HR philosophies ($r = 0.1376$, $p < 0.01$), the strength of this association is relatively weak, suggesting that many firms with positive HR orientations may still lack the capability or resources to deliver training to keep pace with technological change. This lag undermines the conversion potential of HR practices and limits their ability to counterbalance the risks associated with new technologies.

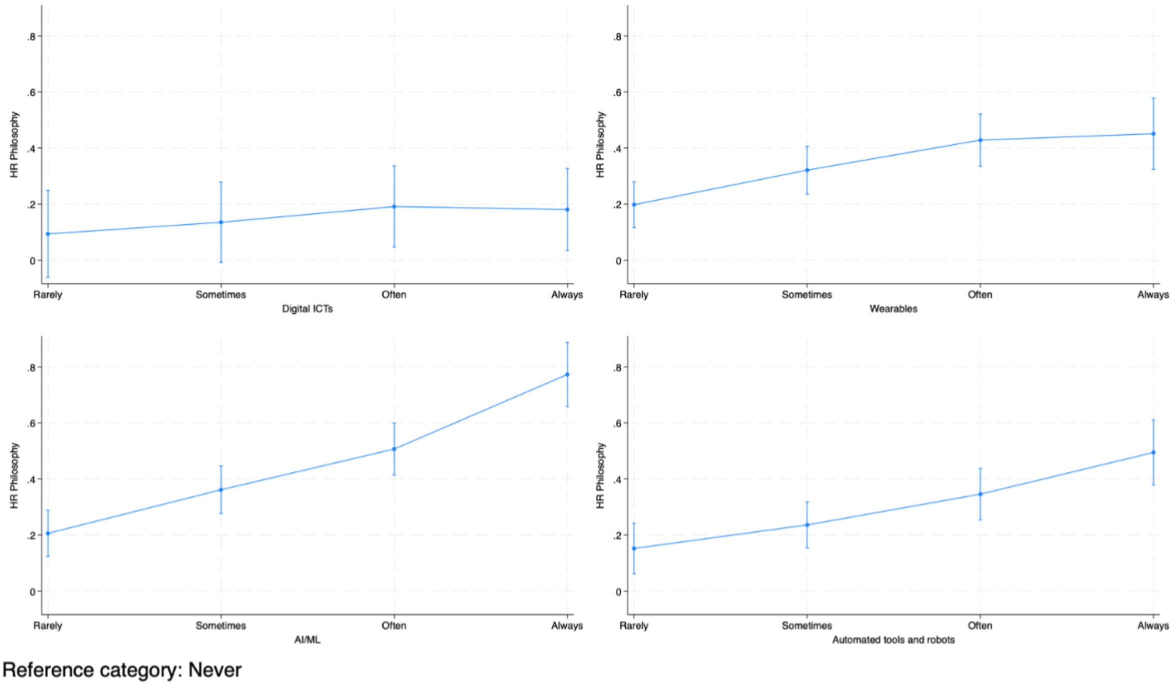
Table 3 - Spearman's correlations with training provided by employers

Technology	Spearman's correlation	Difference (compared to Digital ICTs)
Digital ICTs	0.14	n/a
Wearables	0.04	0.10 *** (0.02)
AI and ML	0.06	0.08*** (0.02)
Robotics	0.06	0.08*** (0.02)

Notes: * p<0.1 ** p<0.05 *** p<0.01; bootstrap standard error calculated using seed 39 with 500 replications presented in parentheses.

Another possible explanation lies in the bidirectional relationship between HR philosophy and technology exposure. Figure 14 shows that employees with higher exposure to technology are also more likely to perceive their organisation as employee-centred. This supports previous findings that the integration of digital tools into HR functions - such as algorithmic management - can both enable and constrain supportive HR practices (Sidhu et al., 2024; Sapta et al., 2021). In some cases, algorithmic tools may improve feedback, transparency, and customisation of HR support. In others, they may be used to standardise or control workers in ways that conflict with developmental HR philosophies. This suggests that technologies do not merely operate within HR environments: they also reshape them, creating feedback loops that require careful monitoring and governance (Shukla, Mishra and Agnihotri, 2023) (Shukla et al., 2023; Lamers et al., 2022).

Figure 14 - Association between technology exposure and HR philosophy



Implications for theory and practice

Theoretically, our findings support a capability-informed, anti-deterministic approach to workplace technology. Technologies themselves are not good or bad for workers—what matters is how they are deployed and embedded within organisations. HR philosophy, as a proxy for institutional values and practice, can enable more beneficial work outcomes but is not a silver bullet. Its effects may be conditioned by complementary practices such as training, participation in decision-making and by the characteristics of the technologies themselves.

Practically, these findings suggest that employee-centred HR approaches remain a critical tool for managing technological transitions—but only if they are accompanied by timely investment in training and participatory mechanisms. Employers should not assume that a supportive culture alone can offset the risks of automation for the workforce. Instead, they must adapt HR strategies to the specific advantages and disadvantages of each type of technology.

This study also opens further research questions. First, future research should explore how different elements of HR philosophy—such as employee involvement, training policy, and organisational culture—individually and collectively influence the experience of technologies. Second, more longitudinal data are needed to assess how the moderating role of HR evolves over time, particularly as technologies become more embedded in the workplace. Third, multilevel studies that distinguish between employee perceptions and organisational characteristics would help clarify how firm-level HR strategies interact with individual-level outcomes.

6. Conclusions

This study contributes to our understanding of how institutional factors –particularly the type of HR practices– can shape the associations between workplace technologies and job quality and employee wellbeing. When embedded in supportive HR environments, digital ICTs are generally associated with improved outcomes or reduced harms.

The effects of newer technologies such as AI and machine learning also can be contingent to the type of HR practices, with employee-centred HR contexts being more likely to foster positive gains on flexibility, learning opportunities and idea use. However, employee-centred HR practices are not always sufficient to counteract potentially negative impacts on job quality or quality of life, particularly in cases of high exposure to wearables and robotics.

Moreover, technologies framed as supportive within an employee-centred approach – such as wearables used for health monitoring– may unintentionally increase routine and repetitive tasks. These findings underscore the need for a more nuanced and proactive approach to technology adoption, in which investment in training, organisational voice and –more broadly– approaches to HR management keeps pace with the technologies themselves.

References

Baker, M. A., and Kim, K. (2020). Dealing with customer incivility: The effects of managerial support on employee psychological well-being and quality-of-life. International Journal of Hospitality Management, 87, 102503.

Bloom, N., Liang, J., Roberts, J., and Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. The Quarterly journal of economics, 130(1), 165-218.

Bradley, L., Brown, K., Lingard, H., Townsend, K., and Bailey, C. (2010). Talking the talk and walking the walk: How managers can influence the quality of work-life balance in a construction project. International Journal of Managing Projects in Business, 3(4), 589-603.

Greenhalgh, C., and Mavrotas, G. (1996). Job training, new technology and labour turnover. British Journal of Industrial Relations, 34(1), 131-150.

Hashmi, M. A., Al Ghaithi, A., and Sartawi, K. (2023). Impact of flexible work arrangements on employees' perceived productivity, organisational commitment and perceived work quality: A United Arab Emirates case-study. Competitiveness Review: An International Business Journal, 33(2), 332-363.

Kara, D., Kim, H., and Uysal, M. (2018). The effect of manager mobbing behaviour on female employees' quality of life. Current Issues in Tourism, 21(13), 1453-1467.

Karneli, O., Nimran, U., Al Musadiq, and Nayati, U. H. (2015). The influence of organisational culture and entrepreneurial orientation on job satisfaction, organisational commitment, and employee's performance. European Journal of Business and Management, 7(2), 55-68.

Kelliher, C., and Anderson, D. (2008). For better or for worse? An analysis of how flexible working practices influence employees' perceptions of job quality. The International Journal of Human Resource Management, 19(3), 419-431.

Koca, M., Deniz, S., İnceoğlu, F., and Kılıç, A. (2024, March). The Effects of Workload Excess on Quality of Work Life in Third-Level Healthcare Workers: A Structural Equation Modeling Perspective. In Healthcare (Vol. 12, No. 6, p. 651). MDPI.

Kumar, A., Singh, S. K., and Kumar, G. (2019). Impact of on-job trainings on technical employee performance in biotech industry. International Journal of Innovative Science, Engineering & Technology, 6(8), 225-232.

Lepak, D. P., Taylor, M. S., Tekleab, A., Marrone, J. A., & Cohen, D. J. (2007). An examination of the use of high-investment human resource systems for core and support employees. Human Resource Management, 46(2), 223–246. https://doi.org/10.1002/HRM.20158

Maghsoud, F., Rezaei, M., Asgarian, F. S., and Rassouli, M. (2022). Workload and quality of nursing care: the mediating role of implicit rationing of nursing care, job satisfaction and emotional exhaustion by using structural equations modeling approach. BMC nursing, 21(1), 273.

Mathew, J. (2007). The relationship of organisational culture with productivity and quality: A study of Indian software organisations. Employee relations, 29(6), 677-695.

Meng, J., and Berger, B. K. (2019). The impact of organisational culture and leadership performance on PR professionals' job satisfaction: Testing the joint mediating effects of engagement and trust. Public Relations Review, 45(1), 64-75.

Nazareno, L., and Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. Technology in Society, 67, 101679.

SAPTA, I., Muafi, M., and SETINI, N. M. (2021). The role of technology, organizational culture, and job satisfaction in improving employee performance during the Covid-19 pandemic. The Journal of Asian Finance, Economics and Business, 8(1), 495-505.

Sidhu, N. K., Gupta, S., and Kalra, D. (2024). The Impact of Technological Advancements on Corporate Culture and Employee Well-Being: A Comprehensive Analysis. In Embracing Transhumanism and Genomics in Human Resources Management (pp. 233-246). IGI Global.

Soffia, M., Leiva-Granados, R., Zhou, X., & Skordis, J. (2024). Does technology use impact UK workers' quality of life? A report on worker wellbeing. Institute for the Future of Work. https://zenodo.org/doi/10.5281/

zenodo.10470301

Soffia, M., Leiva-Granados, R., Zhou, X., & Skordis, J. (2024). From technology exposure to job quality: evidence from a comprehensive UK survey. Institute for the Future of Work. https://zenodo.org/doi/10.5281/zenodo.10908895

Spieler, I., Scheibe, S., Stamov-Roßnagel, C., and Kappas, A. (2017). Help or hindrance? Day-level relationships between flextime use, work–nonwork boundaries, and affective well-being. Journal of applied psychology, 102(1), 67.

Wood, A. J. (2016). Flexible scheduling, degradation of job quality and barriers to collective voice. Human Relations, 69(10), 1989-2010.

Zapata, L., Ibarra, G., & Blancher, P. H. (2024). Engaging new ways of work: The relevance of flexibility and digital tools in a post-COVID-19 era. Journal of Organizational Effectiveness: People and Performance, 11(1), 1-17.

Appendix

Table 1 - Descriptive statistics

Variable	Obs	Mean	Median	SD	Min	Max
Quality of Life (UK_VAS)	4,870	0.77	0.78	0.22	-0.073	1
HR Philosophy (hr_ave)	4,870	2.45	2.67	1.01	0	4
Age	4,870	43.54	43.00	14.03	18	85

Unrepetitive work (TECHEFFECTAE_5_3)		
	Count	%
Worse	1,499	30.8
Unchanged	2,599	53.4
Better	772	15.9
Total	4870	100.0
Workplace flexibility (TECHEFFECTKO_11_3)		
	Count	%
Worse	247	5.1
Unchanged	2336	48.0
Better	2287	47.0
Total	4,870	100.0
Job security (TECHEFFECTPS_17_3)		
	Count	%
Worse	1,169	24.0
Unchanged	3,072	63.1
Better	629	12.9
Total	4,870	100.0
Learning opportunities (TECHEFFECTAE_3_3)		
	Count	%
Worse	347	7.1
Unchanged	1,754	36.0
Better	2,769	56.9
Total	4,870	100.0
Use of own ideas (TECHEFFECTAE_4_3)		
	Count	%
Worse	527	10.8
Unchanged	2,481	50.9
Better	1,862	38.2
Total	4,870	100.0

Gender		
	Count	**%**
Female	2398	49.4
Male	2455	50.6
Total	4853	100.0

Ethnic group		
	Count	**%**
White	4263	87.5
Asian or Asian British	278	5.7
Black, Black British, Caribbean or African	183	3.8
Mixed, multiple or other ethnic group	146	3.0
Total	4870	100.0

Relationship status		
	Count	**%**
Single	1155	23.7
Separated/ divorced/ widowed	433	8.9
Living with a partner	911	18.7
Married/ in a civil partnership	2371	48.7
Total	4870	100.0

Dependent children		
	Count	**%**
No child	3003	61.7
1 child	956	19.6
1+ child	911	18.7
Total	4870	100.0

Highest qualification		
	Count	**%**
No qualification/ below A levels or vocational level 3	1003	20.6
A levels or vocational level 3	1238	25.4
Degree or equivalent	2328	47.8
Other qualification	301	6.2
Total	4870	100.0

Skill level based on SOC2020 sub-major group		
	Count	**%**
Level 1	292	6.0
Level 2	1870	38.4
Level 3	1112	22.8
Level 4	1596	32.8
Total	4870	100.0

Pay		
	Count	%
¬£20,300/year or less	488	10.0
¬£20,301 - ¬£27,300/year	1649	33.9
¬£27,301 - ¬£35,100/year	1000	20.5
¬£35,101 - ¬£54,600/year	1025	21.1
¬£54,601/year or over	708	14.5
Total	4870	100.0
Job tenure		
	Count	%
Less than 1 year	515	10.6
1-3 years	957	19.7
3+ years	3398	69.8
Total	4870	100.0
Standard Industrial Classification 2007		
	Count	%
Agriculture, energy and transport (A,B,D,E,H)	280	5.8
Manufacturing (C)	416	8.5
Construction (F)	236	4.9
Commerce and hospitality (G,I)	704	14.5
Information and communication (J)	350	7.2
Finance and real estate (K,L)	153	3.1
Professional, scientific and technical (M)	436	9.0
Administrative and support services (N)	661	13.6
Public administration (O)	147	3.0
Education (P)	579	11.9
Health (Q)	653	13.4
Other services (R,S,T)	255	5.2
Total	4870	100.0
Urban rural classification		
	Count	%
London	401	8.2
Predominantly urban (without London)	2254	46.3
Urban with significant rural	379	7.8
Predominantly rural	615	12.6
Wales	420	8.6
Scotland	398	8.2
Northern Ireland	403	8.3
Total	4870	100.0
Formal or passive training provided by employer		
	Count	%
No	1232	25.3
Yes	3638	74.7
Total	4870	100.0

Informal active self-pursued training		
	Count	%
No	1232	25.3
Yes	3638	74.7
Total	4870	100.0

Informal active self-pursued training		
	Count	%
No	1852	38.0
Yes	3018	62.0
Total	4870	100.0

Access to formally recognised and independent structures		
	Count	%
No	4086	83.9
Yes	784	16.1
Total	4870	100.0

Use of digital ICTs		
	Count	%
Never	327	6.7
Rarely	537	11.0
Sometimes	1044	21.4
Often	1378	28.3
Always	1584	32.5
Total	4870	100.0

Use of wearables		
Never	2352	48.3
Rarely	879	18.1
Sometimes	694	14.3
Often	629	12.9
Always	316	6.5
Total	4870	100.0

Use of AI and Machine Learning		
Never	2170	44.6
Rarely	905	18.6
Sometimes	835	17.2
Often	637	13.1
Always	323	6.6
Total	4870	100.0

Use of automated tools and robots		
Never	2076	42.6
Rarely	778	16.0
Sometimes	888	18.2
Often	751	15.4
Always	377	7.7
Total	4870	100.0

Table 2 - Marginal effects from an ordered logistic regression model for job quality indicators, and coefficients from a Tobit regression model for quality of life

		(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Flexibility	Learning	Idea use	Unrepetitive work	Job security	QoL
Digital ICTS (ref: never)	Rarely	0.00707	0.00469	0.00515	0.0190	0.00296	0.00631
		(-0.0547 - 0.0688)	(-0.0612 - 0.0706)	(-0.0573 - 0.0676)	(-0.0125 - 0.0504)	(-0.0222 - 0.0281)	(-0.0418 - 0.0544)
	Sometimes	-0.0221	0.0405	-0.00788	0.0119	0.0214*	0.0127
		(-0.0796 - 0.0354)	(-0.0187 - 0.0996)	(-0.0657 - 0.0499)	(-0.0151 - 0.0389)	(-0.00285 - 0.0456)	(-0.0327 - 0.0580)
	Often	0.0827***	0.137***	0.0602**	0.000505	0.0160	0.0698***
		(0.0234 - 0.142)	(0.0769 - 0.197)	(0.00244 - 0.118)	(-0.0256 - 0.0267)	(-0.00749 - 0.0394)	(0.0243 - 0.115)
	Always	0.168***	0.189***	0.0727**	-0.00537	0.0325**	0.0661***
		(0.109 - 0.228)	(0.129 - 0.249)	(0.0133 - 0.132)	(-0.0316 - 0.0209)	(0.00768 - 0.0573)	(0.0207 - 0.112)
Wearables (ref: never)	Rarely	-0.0238	0.0355	0.0381*	-0.00719	0.0269**	-0.0114
		(-0.0711 - 0.0236)	(-0.0117 - 0.0827)	(-0.00699 - 0.0833)	(-0.0343 - 0.0199)	(0.00384 - 0.0499)	(-0.0409 - 0.0181)
	Sometimes	-0.0960***	-0.0228	-0.0121	-0.0489***	0.0127	-0.0233
		(-0.153 - -0.0386)	(-0.0816 - 0.0360)	(-0.0677 - 0.0436)	(-0.0776 - -0.0201)	(-0.0168 - 0.0422)	(-0.0581 - 0.0115)
	Often	-0.00706	-0.000701	0.0294	-0.0756***	-0.0406***	-0.0556***
		(-0.0732 - 0.0590)	(-0.0664 - 0.0650)	(-0.0346 - 0.0933)	(-0.103 - -0.0479)	(-0.0634 - -0.0178)	(-0.0950 - -0.0161)
	Always	-0.0602	-0.0134	-0.00521	-0.0927***	-0.0276	-0.0751***
		(-0.150 - 0.0299)	(-0.100 - 0.0732)	(-0.0883 - 0.0779)	(-0.123 - -0.0625)	(-0.0607 - 0.00562)	(-0.125 - -0.0254)
AI/ML Software (ref: never)	Rarely	-0.00837	0.00740	0.00625	0.00467	-0.00530	-0.0233
		(-0.0574 - 0.0406)	(-0.0422 - 0.0570)	(-0.0384 - 0.0509)	(-0.0195 - 0.0289)	(-0.0263 - 0.0157)	(-0.0539 - 0.00739)
	Sometimes	0.0328	-0.0453	0.0658**	0.0304*	0.00309	-0.0173
		(-0.0264 - 0.0919)	(-0.105 - 0.0148)	(0.00847 - 0.123)	(-0.00416 - 0.0649)	(-0.0253 - 0.0315)	(-0.0518 - 0.0172)
	Often	0.0680*	-0.0245	0.150***	-0.0188	-0.0471***	-0.0430**
		(-0.00448 - 0.141)	(-0.0964 - 0.0474)	(0.0774 - 0.222)	(-0.0530 - 0.0154)	(-0.0727 - -0.0214)	(-0.0838 - -0.00213)
	Always	0.118**	0.00960	0.201***	-0.0354*	-0.0462***	-0.0362
		(0.0216 - 0.214)	(-0.0850 - 0.104)	(0.108 - 0.294)	(-0.0750 - 0.00422)	(-0.0788 - -0.0137)	(-0.0880 - 0.0155)
Robotics (ref: never)	Rarely	0.0284	0.00603	0.0208	0.0200	0.00104	0.000177
		(-0.0229 - 0.0798)	(-0.0463 - 0.0583)	(-0.0277 - 0.0693)	(-0.00646 - 0.0465)	(-0.0210 - 0.0231)	(-0.0322 - 0.0326)
	Sometimes	0.0151	0.0203	0.00661	0.00698	-0.0162	-0.0293*
		(-0.0390 - 0.0693)	(-0.0330 - 0.0736)	(-0.0457 - 0.0589)	(-0.0203 - 0.0343)	(-0.0376 - 0.00516)	(-0.0619 - 0.00335)
	Often	-0.0206	-0.0129	-0.00418	0.00212	-0.0227*	-0.0363*
		(-0.0855 - 0.0444)	(-0.0752 - 0.0495)	(-0.0635 - 0.0552)	(-0.0301 - 0.0344)	(-0.0491 - 0.00370)	(-0.0740 - 0.00148)
	Always	-0.0642	0.00921	-0.0142	0.0112	-0.0188	-0.0353
		(-0.146 - 0.0177)	(-0.0728 - 0.0912)	(-0.0884 - 0.0600)	(-0.0331 - 0.0555)	(-0.0536 - 0.0160)	(-0.0807 - 0.0100)
HR philosophy		0.0763***	0.102***	0.118***	-0.00108	0.00832**	0.0444***
		(0.0595 - 0.0930)	(0.0854 - 0.119)	(0.103 - 0.133)	(-0.00875 - 0.00659)	(0.00185 - 0.0148)	(0.0342 - 0.0546)
Employer-provided training		0.0253	0.123***	0.0427**	-0.00413	0.0118	-0.00474
			(-0.0131 - 0.0636)	(0.0877 - 0.158)	(0.00970 - 0.0756)	(-0.0210 - 0.0128)	(-0.00293 - 0.0266)
Self-pursued training		0.0188	0.115***	0.0593***	0.0114	-0.00758	-0.0336***
		(-0.0150 - 0.0527)	(0.0811 - 0.148)	(0.0291 - 0.0896)	(-0.00383 - 0.0266)	(-0.0216 - 0.00648)	(-0.0547 - -0.0125)
Constant							0.650***
							(0.585 - 0.714)
Observations		4,853	4,853	4,853	4,853	4,853	4,853
Pseudo R-squared ([a] R-squared)		0.1249	0.0880	0.0867	0.0357	0.0417	0.114[a]

All models adjusted by gender, age, ethnicity, marriage status, children dependency, educational attainment, occupational skills, pay band, job tenure, industry, rural/urban classification, and access to representative structures. Robust Confidence Intervals in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 accelerated through the COVID-19 pandemic, and the ongoing impact of automation is unevenly distributed, with a disproportionate impact on demographic groups in lower pay jobs.

IFOW's Pissarides Review into the Future of Work and Wellbeing - led by Nobel Laureate Professor Sir Christopher Pissarides, is researching 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, Co-Director 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 us on team@ifow.org