The Pissarides Review into the Future of Work and Wellbeing

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Analysing the distribution of capabilities in the UK workforce amidst technological change

Working Paper prepared by Shuting Xia[1], Xingzuo Zhou[1,2] Rolando Leiva-Granados[2], Magdalena Soffia[1], and Jolene Skordis[1,2]

[1] Institute for the Future of Work [2] University College London

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Executive Summary

Workplaces are rapidly adopting new technologies, raising questions about how our workforce can navigate this transition positively.

Sen's capability framework, adapted by Nussbaum (2000) for use in operational research, highlights the conditions required for human flourishing and the freedom of individuals to choose specific ways of living ("functionings") that contribute to their preferred state of being (Sen, 1985). Sen and Nussbaum's capability approach considers the capability of individuals to achieve "outcomes that they have reason to value" (Sen, 1999, p. 291).

Rather than placing weight solely on how individual choices determine life satisfaction, happiness or earnings, this framework focuses on the freedoms individuals are given to pursue these choices. Thus, in the context of work, capabilities are likely to be a core determinant of resilience to change, including the rapid technological changes we are currently seeing. Towards this, elsewhere in the Pissarides Review, we reviewed the literature on capabilities to ask what it can tell us about work (Soffia et al., 2023). However, little is known about the *distribution* of capabilities in the UK workplace or in any other working environment.

In this paper, we measure this distribution of capabilities in the UK workforce and comment on the unequal distribution of what we consider to be a potentially important measure of freedoms and resilience to transition. To this purpose, the study employs the ICECAP-A questionnaire (Al-Janabi et al., 2012), a preference-based measure of capabilities, rooted in Sen's (1993) capability approach. ICECAP-A comprises five domains including the freedom to feel stable, attached, autonomous, and to have a sense of achievement and enjoyment. Using survey data from over 5000 employees, we look at the distribution of capabilities across workers, considering how that distribution differs when exposed to different types of technology and controlling for factors such as institutional and management practices.

This study reveals significant disparities in capability levels across age, ethnicity, relationship status, occupational level and industrial sector. Older employees, those partnered, in higher occupational roles and in the professional, scientific and technical sector generally report higher capabilities, and employees from Asian backgrounds report significantly lower capabilities than their counterparts from white ethnic backgrounds. Institutional factors, including HR philosophy, employer-provided training, and access to formal representative structures, are positively associated with capabilities.

Our analyses further highlight that the trend in the correlation between socioeconomic factors and capabilities is disrupted by technological exposure, particularly exposure to newer technologies such as wearables, AI and robotics. The findings underscore the importance of supportive institutional frameworks to foster a sense of freedom to live a life employees value. Targeted policies may also be needed to support an equitable distribution of capability across the workforce, as a way of developing resilience to negative consequences of technological transition.

Headline findings

Headline findings from the survey on the distribution of capabilities in the UK workforce include that:

- **Several socioeconomic and demographic characteristics are correlated with higher levels of capability among UK employees.** This indicates significant variability within the workforce that has not been captured before.
- **Consistently higher capabilities scores are reported by those:**
  - with access to independent representative structures such as trades unions and employee forums
  - who have undergone formal or passive training provided by their employer
  - who perceived their organisation to have an employee-centred HR philosophy.
- **Persistent age gradient in capability scores found in our study is novel and has not been reported elsewhere.** However, further work is needed to understand whether older age is potentially associated with more experience and stability, thus enhancing perceived capabilities.
- **The ethnic, occupational and industry variabilities in capability scores are additional novel findings.** These require further attention to guard against the further widening of inequalities.

Digging into more detail:

- **The finding that wellbeing-centred HR policies correlate positively with capabilities becomes even more marked in contexts of new technology adoption.** In sectors or jobs where new technologies are being introduced, it is even more important to have good HR policies that emphasise employee engagement.
- **The observed disparities between ethnic groups persisted across the spectrum of technology exposure, with some evidence that those from Asian backgrounds face extra disadvantages when exposed to newer technologies.** This highlights the need for targeted policies to overcome systemic inequalities.
- **Exposure to wearables is correlated negatively with the 'autonomy' capability dimension, but positively with 'stability' and 'achievement.'** This highlights the divergent impact of these newer technologies, and points to the need for a highly context-sensitive approach to technology adoption.
- **The capability advantage conferred by higher occupational grades is attenuated by exposure to newer technologies.** This reinforces the need for technology-specific policies that account for the particular impacts of newer technologies across occupational grades.
- **Those in the Agriculture, Transport and Energy sectors face a particularly stark impact on perceived capabilities when exposed to newer technologies.** This indicates a need for better resourcing of those in this group as they navigate change.

Key implications for policy and practice

Our research suggests that:

- **Beyond ideas of workplace wellbeing and job quality, policymakers must embrace an approach that accounts for variations in people's capabilities.**
- **The survey confirms earlier findings that workplaces with high-engagement HR practices and that encourage representative structures improve workers' perception of their capabilities.** This supports the introduction of an Employment Bill to update labour law and include specific protections and incentives for these practices.
- **In a similar way, the finding that formal or passive training provided by employers protects workers' capabilities also supports new legislation to mandate higher levels of training provision, especially in the use of newer technologies, which appear to be a particular cause of anxiety.**
- **The divergent impacts of newer technologies on capabilities, and with these varying across demographics and sectors, policymakers should consider the best way to mandate or incentivise higher levels of involvement in the process of automation and design of work, as well as the assessment and monitoring of impacts on perceived capabilities.** This is particularly important in relation to wearables.

1. Introduction: why we need a capabilities approach

The work that we do is an important factor in how we see our lives. Our jobs aren't just the most important factor in determining our living standards, they also play a huge part in our overall wellbeing, in our social relationships and thus – in this network of connections with others – the kinds of communities that we create and are part of our individual and collective flourishing.

Research on how technological transition is impacting work has largely focused on system-level and firm-level impacts, and overlooked how resilient individuals are to the changes in play.

In other work conducted as part of the Pissarides Review, we have described how technological transition will likely lead to workers experiencing more frictions to move within the labour market, including geographic, informational and skills frictions, which may be financially and psychologically costly and unequally distributed across the workforce. We have already documented how growing technology exposure is having significant and varied impacts both on employees' quality of life, and the quality of jobs that people are doing in the UK.

In the literature documenting technological transitions and their consequences for the labour market, the determinants of individual resilience to change have received relatively little attention. And while useful for explaining the practical consequences of technological exposure, measuring outcomes such as quality of life, job quality or earnings tells us little about the freedom of workers to choose those outcomes, which we believe is key to their resilience to change. To illustrate the point, one might use the hypothetical example of a 'smart' new technology for the management of customer invoicing and payments. The 'outcome' of a firm adopting this new technology may be that an employee feels scared or stressed at the prospect of learning to use the new technology (a decline in mental health). The employee may feel the need to work longer hours to learn how to operate that technology (a decline in job quality). They may not be paid more while they are transitioning to the effective use of that technology (earnings stagnate) because the firm is not yet more profitable as a result of the technology adoption. Now, consider whether or not the employee in this example feels that this is an excellent new technology, about which they feel curious and which they believe will add to the effective functioning of the firm, support the more timely and accurate completion of their own tasks and possibly add to the prestige of their own role (they value this transition). Consider also whether that employee felt obligated to adopt the valuable new technology or not, and whether the dips in wellbeing and job quality were expected and freely chosen in order to transition to a more valued state thereafter.

The example above demonstrates how outcomes such as job satisfaction and happiness (while important) do not tell us whether workers have a sense of freedom or the capability to make choices that they value. Whether people have the freedom to make the choices that will lead to better life outcomes is the key question driving the 'capability approach'. Sen's capability framework, adapted by Nussbaum (2000) for use in operational research, focuses on the enabling conditions for human flourishing and the freedom of individuals to choose specific ways of living ("functionings") that contribute to their preferred state of being (Sen, 1985).

The scarce literature across different countries – including studies in the UK, Hungary, China and Iran – has suggested that education, employment, income, relationships, and marital status are consistently associated with an individual's capability. However, in an early review, we highlighted that little research had been done on the role of capabilities in the UK workplace, on how those capabilities are distributed or on how they might enable workers to navigate rapid technological transition. Without an understanding of this distribution, we cannot begin to understand how exposure to technology in rapid transition, might disrupt the known determinants of higher capabilities.

In this paper, we aim to fill that evidence gap by measuring the distribution of capabilities in the national workforce and exploring how frequent exposure to different technology types might disrupt average patterns. We measure capabilities using the widely applied ICECAP-A measure, which is described in more detail in the next section. After presenting our findings, we briefly reflect on the value of the insights while considering what might be gained from future work to create (or revisit attempts of) capability measures for work, that appraise particularly the freedoms that employees value in the workplace.

2. Measuring capabilities

ICECAP-A, the Investigating Choice Experiments Capability Measure for Adults, comprises five conceptual attributes or freedoms that adults in the UK are believed to value: stability, attachment, achievement, autonomy and enjoyment. The literature validating the ICECAP-A measure claims that it's better than alternative measures at reflecting individuals' perceived freedom and it is widely used in the UK for economic evaluation policies and strategies (Al-Janabi et al., 2013). However, studies describing how ICECAP scores vary across various socioeconomic factors are limited and the measure has not been used to understand the expected impact of technology adoption at work – or the role of institutional frameworks and HR practices in promoting capabilities in the workforce.

Gender differences in capability scores have been observed, although the findings are not consistent across all studies. A study of a UK-based convenience sample of 943 people using the ICECAP-A capability questionnaire found that males tend to report higher levels of capabilities than females (Al-Janabi, 2018). Similarly, a study of 1,000 adults in China found that the total average score for the ICECAP-A was significantly lower for females than for males, with females reporting feeling less stable, autonomous, and fulfilled than males (Tang et al., 2018). However, in Iran, a study of 2,000 adults, found no differences between the ICECAP-A scores of males versus females (Shahtaheri et al., 2020).

Some studies have found socioeconomic and health characteristics to be associated with an individual's capability, as measured by ICECAP, in the UK and other countries. Relationships, home ownership, education, income and employment, were significantly associated with ICECAP-A capability levels in a sample of 418 UK adults (Al-Janabi et al., 2013).

Marital status has been found to correlate significantly with ICECAP-A scores (Tang et al., 2018). Compared to those who are single, married persons tend to have higher ICECAP-A scores. Being divorced or widowed is negatively correlated with ICECAP-A, especially on the attributes of stability, attachment and enjoyment.

Education and employment status have been consistently associated with capability scores across different studies. People with a university degree tend to report higher capabilities in the UK (Al-Janabi, 2018). Similarly, in Iran, Shahtaheri et al. (2020) found differences in capability scores among people with different education levels and job status. In that study, adults with a primary/high school education had lower capability scores compared to those with a diploma or university degree, and unemployed individuals had lower scores compared to those in employment.

Using a cross-sectional survey of 2,023 Hungarian adults aged 50 to 70, Baji et al. (2021) found that pensioners, 'disability pensioners', and the unemployed had significantly lower ICECAP-A scores. Additionally, they found that location had a significant association with capability scores, with respondents living in the capital city reporting significantly lower scores compared to those living in other towns or villages. Furthermore, people in the lowest income third had significantly lower ICECAP-A scores than those in the highest income third.

Interestingly, many studies have found no significant differences in terms of capability between age groups (Al-Janabi et al., 2013; Shahtaheri et al., 2020; Tang et al., 2018). This was also the case in Al-Janabi's (2018) research, which found no difference in capability scores between age groups below and above 50 years old.

The available evidence therefore suggests that education, employment, income, relationships, and marital status are consistently associated with an individual's capability, as measured by ICECAP, across different settings. However, no known studies to date have described the distribution of capabilities within the UK workforce. Without an understanding of this distribution, we cannot begin to understand how institutional frameworks (including HR policies) and exposure to technology in rapid transition, might disrupt the known determinants of higher capabilities.

Institutional support, participation infrastructures, and the role of governance bodies may significantly influence the opportunities and prospects available to workers transitioning into the use of workplace technologies (Soffia et al., 2023). In short, freedoms can be fostered, and they can be removed. The institutionalist perspective in the capability framework is noted (Farvaque, 2005, p. 47; Nambiar, 2013) and formally integrated into this study.

3. Data and Methodology

Survey data

We conducted an online survey of adults in paid work and resident in the UK, between 22 May and 30 June 2023.[1] The survey aimed to assess the distribution of general capabilities relative to various worker and organisational characteristics, and whether these patterns varied in contexts of frequent exposure to specific technologies.

The sample was designed to represent the working adult population across the UK in terms of age, gender, education, and employment type, as well as geographic region of residence. Weighting based on the Labour Force Survey was used post-fieldwork to ensure the final sample accurately reflected these demographics.

This working paper is based on a sample of n=5368 employees with complete information for all the relevant variables being analysed.

Measures

The Investigating Choice Experiments Capability Measure for Adults (ICECAP-A) is a preference-based measure of capabilities, rooted in Sen's capability approach (Sen, 1993), designed for economic evaluations. Developed in the UK through qualitative methods (Al-Janabi et al., 2012), this framework assesses individuals' ability to achieve significant 'functionings' in life.

The ICECAP-A comprises five distinct domains of wellbeing:

Stability: the ability to feel settled and secure.
Attachment: the ability to experience love, friendship, and support.
Autonomy: the ability to maintain independence.
Achievement: the ability to progress and achieve in life.
Enjoyment: the ability to derive pleasure and enjoyment.

These domains – described more fully in Table 1 over the page - aim to capture valued capabilities distinct from outcomes such as income and health status. Respondents rate each attribute using a 4-level response scale, selecting the option that best describes each aspect of their capability at that moment. For each attribute, an index score ranging from 0 (indicating 'no capability') to 1 (indicating 'full capability') can be calculated based on tariff sets developed using best-worst scaling methods. Index scores derive from these tariffs, which have been validated for the general adult population in the UK (Al-Janabi et al., 2013). An overall ICECAP index score (ranging from –0.001 to 1), signalling the overall capability of an individual, can then be calculated by summing the values across the five individual attributes.

[1] The survey was administered to a non-probability panel hosted by Dynata, a first-party data provider platform for market research.

The ICECAP-A has been successfully applied in various international contexts, including the USA, Australia, New Zealand, the Netherlands, and Hungary (Baji et al., 2020; Flynn et al., 2015; Rohrbach et al., 2022).

Table 1 - The ICECAP-A capability questionnaire

Domain label	Heading	*Thinking about your life in general, please indicate which of the following statements best apply to you.*
Stability	A – Feeling settled and secure	1 I am able to feel settled and secure in **all** areas of my life 2 I am able to feel settled and secure in **many** areas of my life 3 I am able to feel settled and secure in **a few** areas of my life 4 I am **unable** to feel settled and secure in **any** areas of my life
Attachment	B – Love, friendship, and support	1 I can have **a lot** of love, friendship and support 2 I can have **quite a lot** of love, friendship and support 3 I can have **a little** love, friendship and support 4 I **cannot have any** love, friendship and support
Autonomy	C – Being independent	1 I am able to be **completely** independent 2 I am able to be independent in **many** things 3 I am able to be independent in **a few** things 4 I am **unable** to be at all independent
Achievement	D – Achievement and progress	1 I can achieve and progress in **all** aspects of my life 2 I can achieve and progress in **many** aspects of my life 3 I can achieve and progress in **a few** aspects of my life 4 I **cannot** achieve and progress in **any** aspects of my life
Enjoyment	E – Enjoyment and pleasure	1 I can have **a lot** of enjoyment and pleasure 2 I can have **quite a lot** of enjoyment and pleasure 3 I can have **a little** enjoyment and pleasure 4 I **cannot have any** enjoyment and pleasure

Source: Al-Janabi, Flynn, and Coast (2012)

As independent variables, we analysed the distribution of capabilities relative to the following socioeconomic and demographic characteristics of employees: gender, age, ethnicity, relationship status, education, occupation, industry, and geographic region.

To explore the possible role of institutional factors in shaping the distribution of capabilities, we added five key institutional characteristics as independent variables:

- *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 about their level of agreement with three statements:
  1) 'we take care of our workforce, no matter what business challenges we face';
  2) 'we invest heavily in our employees because we know that they determine the success of our business'; and,
  3) 'we maintain a long-term commitment to the growth and well-being of our employees). The average scale is reversed score and ranges from 1 (representing maximum efficiency-centrality) to 5 (representing maximum employee-centrality).
- *FRIS* is a dichotomous variable which stands for access to Formally Recognised and Independent Structures such as trade unions, staff associations, or employee forums.
- *ICPS* is a dichotomous variable which stands for access to Internal Consultative and Participative Structures such as work councils or joint consultative committees.
- *Employer training* is a dichotomous variable indicating whether employees have undergone formal or passive training provided by the employer.
- *Self-training* is a dichotomous variable indicating whether employees have undergone informal or actively self-pursued training.

To measure technology exposure, survey participants were asked their degree of interaction with four types of technologies in their main job, during a typical working week. The four technology types are described in Table 2. Frequency of interaction with these technologies were scored on a 5-point scale ranging from 'never' (1) to 'always' (5). To ease interpretation of results, employees were considered to be exposed to technology if they reported interacting with it 'sometimes', 'always' or 'often'.

Table 2 - Survey measures of technology exposure

Short label	*In the course of your job on a typical work week, how often do you interact with the following technologies?*
Digital ICTs	1. **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).*
Wearables	2. **Wearable and remote sensing technologies** *(for example: CCTV cameras, proximity cards, fitness trackers, smartwatches, smart glasses, GPS devices, and other sensors that gather data).*
AI Software	3. **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, and self-checkouts).*
Robotics	4. **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).*

Data analyses

Descriptive statistics (means and standard deviations) were first used to explore the distribution of ICECAP scores across various employee and organisational characteristics in a univariate analysis. These descriptive statistics provide a baseline understanding of the unadjusted correlations between various personal or contextual conditions and capabilities, to inform the variable selection process for the following multiple regression model, and to identify any anomalies or outliers in the relationship between each independent variable and the ICECAP index. Analyses of variance (ANOVA) were conducted to assess the difference in capability means between groups.

Given that our dependent variable can be considered a continuous scale, a standard OLS regression was then conducted to determine the relative contribution of the different employee characteristics and organisational conditions to the variability in capabilities, accounting for all covariates simultaneously. We have denoted this exercise as **Model 1**. The linear regression for Model 1 has the form:

$$ICECAP_i = \beta_0 + \beta_k X_{ik} + \varepsilon_i$$

Where:

- *$ICECAP_i$ is the estimated capability score of the i^{th} individual.*
- *β_0 is the intercept of the model*
- *β_k is a vector of coefficients for the independent variables*
- *X_{ik} represents a vector of independent variables (socioeconomic and demographic characteristics of employees, as well as institutional factors) for individual i*
- *And ε_i is the error term*

Next, to understand how the distribution of capabilities might differ in contexts of high automation, we conducted four additional OLS regressions using the same list of independent variables as in Model 1, with the sample stratified into the following cohorts: employees sometimes/ often/ always interacting with Digital ICTs (Model 2), employees sometimes/ often/ always interacting with Wearables (Model 3), employees sometimes/ often/ always interacting with AI Software (Model 4) and employees sometimes/ often/ always interacting with Robotics (Model 5). Of note, these technology exposure indicators were not included as independent variables in Model 1, hence this further sample stratification by technology exposure does not imply perfect multicollinearity.

While results from subgroup analyses are easy to interpret and useful for understanding how relationships differ across technological contexts, they can be less efficient at identifying effects when the size of the subgroup is small, as is the case of those frequently interacting with newer technologies. As a sensitivity check, we further assessed if the distribution of capabilities observed for the general sample (Model 1) was conditional to the level of exposure to different technologies, via moderation analyses. Adding interaction terms between each technology dummy and key independent variables we are more efficiently modelling for the entire sample size and directly testing whether the relationship between the respondent characteristics and capabilities changes depending on the level of exposure to different technologies.

Thus, four additional OLS regressions were conducted. Model 6 includes interaction terms between exposure to Digital ICTs and gender, age, ethnicity, qualification and HR philosophy, in addition to the full list of independent variables included in Model 1. Models 7 to 9 replicate Model 6 but using exposure to Wearables, AI Software and Robotics as technology dummies respectively. The linear regression for Models 6 to 9 with interaction terms has the following generic form:

$$ICECAP_i = \beta_0 + \beta_k X_{ik} + \gamma_m (Tech_i \times X_{im}) + \varepsilon_i$$

Where:

- $Tech_i$ represents the technology exposure dummy (e.g., Digital ICTs, Wearables, AI Software, Robotics)
- γ_m represents the coefficients for the interaction terms between the technology exposure and specific variables (gender, age, ethnicity, qualification, HR philosophy).

In a final step, to explore more closely the associations between exposure to different technologies and specific capability domains, we ran five logistic regression models (Models 10 to 15) using the five dimensions of ICECAP as dependent variables (stability, attachment, autonomy, achievement and enjoyment). Each capability domain was dichotomised into 0 = 'no capability or some capability' and 1 = 'many or full capability'. These dichotomised variables were then regressed on the same set of independent variables used in Model 1, with additional four technology exposure dummies entered simultaneously. The logistic regressions for Models 10 to 15 have the generic form:

$$P(Y_i = 1) = \frac{e^{(\beta_0 + \beta_k X_{ik} + \delta_j Tech_{ij})}}{1 + e^{(\beta_0 + \beta_k X_{ik} + \delta_j Tech_{ij})}}$$

Where:

- $P(Y_i = 1)$ *is the probability of having 'many or full capability' for the* i^{th} *individual*.
- β_0 *is the intercept of the model*
- β_k *is a vector of coefficients for the independent variables*
- X_{ik} *represents a vector of independent variables (socioeconomic and demographic characteristics of employees, as well as institutional factors) for individual i*
- *And* δ_i *represents the coefficients for the technology exposure dummies (Digital ICTs, Wearables, AI Software, Robotics).*

Prior to conducting the OLS and binary logistic regressions, we assessed multicollinearity using variance inflation factors (VIF) and partial correlations and found that it was not a significant concern. All multiple regression analyses (Models 1 to 15) included sampling weights and robust standard errors.

This study received ethical approval from the Humanities and Social Science Research Ethics Committee (HSSREC) of the University of Warwick, UK.

4. Results

1: The distribution of capabilities among UK employees

Table 3 - available here as a spreadsheet - presents the distribution of people who scored highly in all levels of the various ICECAP domains (those who selected the highest two response options), across sample groups, showing their direct correlation without accounting for the influence of any other variables. Means for the ICECAP index are reported alongside standard deviations, as well as the results of ANOVA tests, which give an indication of whether the categorial variable, as a whole, is significant. These means (and error bars) are further visualised in **Figure 1**. The overall sample exhibits a mean capability score of M=0.772 (SD=0.174).

The data reveals a clear trend in the relationship between capabilities and demographic characteristics. Men in our sample (M=0.780, SD=0.175) report higher mean capability scores than women (M=0.764, SD=0.173)[2].

ICECAP scores gradually increase alongside age, with the 65+ groups reporting the highest capability scores (M=0.823, SD=0.162).

Respondents who identified themselves as Asian (M=0.733, SD=0.183), reported lower capability scores than White respondents (M=0.775, SD=0.174) and other minority ethnic groups such as Black and Caribbean (M=0.763, SD=0.170), and mixed or other ethnicities (M=0.769, SD=0.161).

Average capability scores also vary depending on the employee's relationship status, with those 'single' recording the lowest score (M=0.713, SD=0.190) and those married or in a civil partnership registering the highest capability scores (M=0.805, SD=0.159).

To a lesser extent, having one or more dependent children also appears to be positively correlated with higher employees' capability levels.

The distribution of capability scores by level of respondent education also follows a distinct pattern, with employees holding a university degree (or equivalent) and above reporting the highest average capability score (M=0.788, SD=0.167), higher than those with educational attainment below A levels/Vocational level 3 or equivalent (M=0.742, SD=0.190), and those with no qualification at all (M=0.746, SD=0.209).

There are also clear occupational differences in capability scores, with Managers, Directors and Senior Officials recording the highest scores (M=0.818, SD=0.160), followed closely by respondents in Skilled Trades roles (M=0.805, SD=0.161). Respondents in Elementary occupations reported the lowest capability scores (M=0.714, SD=0.185).

Industry-wise, the highest capability scores were found in the Construction sector (M=0.810, SD=0.157), followed by the Professional, Scientific and Technical sector (M=0.808, SD=0.151). Employees in Information and Communication, Education, and Manufacturing

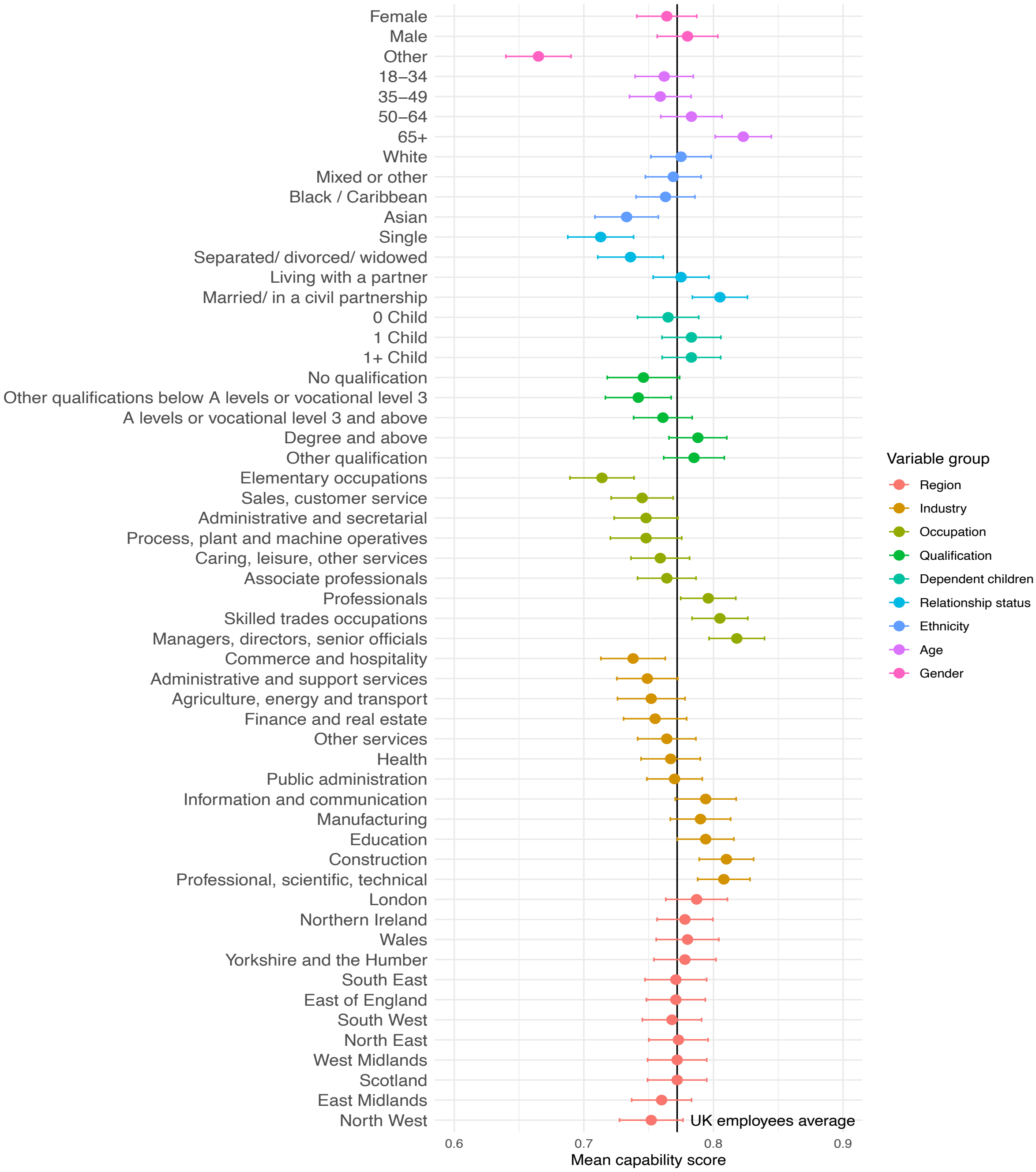
[2] Respondents self-identifying as non-binary reported the lowest capability score (M=0.665, SD=0.188), although this group sample was too small as to consider this a stable pattern.

sectors also reported capability scores higher than the average. The lowest capability scores, in turn, were reported by respondents working in Commerce and Hospitality (M=0.738, SD=0.186).

In this study, we found no significant differences in capability scores by region.

It is important to note that these results only show the direct correlation between respondent characteristics and capability scores. In what follows, we describe the results of multiple linear regression and examine whether these associations hold after accounting for other factors.

Figure 1 - Capability (ICECAP) mean scores and error bars across socioeconomic groups



Note: means scores are depicted by dots, and standard errors are depicted by horizontal whiskers. Error bars indicate variability or precision of the estimate, and are typically narrower than 95% confidence intervals.

Table 4 - available here as a spreadsheet - presents the results of a linear regression model examining the associations between capability scores and respondent characteristics as outlined above, controlling for five additional factors representing institutional resources (see Model 1 specification in the methods section).

All differences previously mentioned were observed in this multivariate model, with a few exceptions. First, the differences between the capability scores of male and female employees become statistically insignificant. The number of dependent children also loses significance as a predictor of capability scores. In terms of education, the higher capability score reported by employees with higher levels of qualification, equivalent to a degree or above, is still higher than those with no qualification, though the difference is only statistically significant at the 90% confidence level.

Various factors indicative of more supportive working environments also showed positive associations with employees' capability scores. For instance, respondents reporting stronger human resource philosophies, report higher capabilities scores. Undergoing formal employer-provided training, and accessing formally recognised representative structures like trade unions, also correlate positively with employees' capabilities when holding other variables constant.

2: Does the capability distribution change in contexts of technological exposure?

In order to examine whether the socioeconomic distribution of capabilities varied in contexts of high technological exposure, we split the total sample into subgroups representing employees who 'sometimes' / 'often' / or 'always' interact with Digital ICTs, wearables, AI software and robotics, and we ran separate regression models for each subgroup.

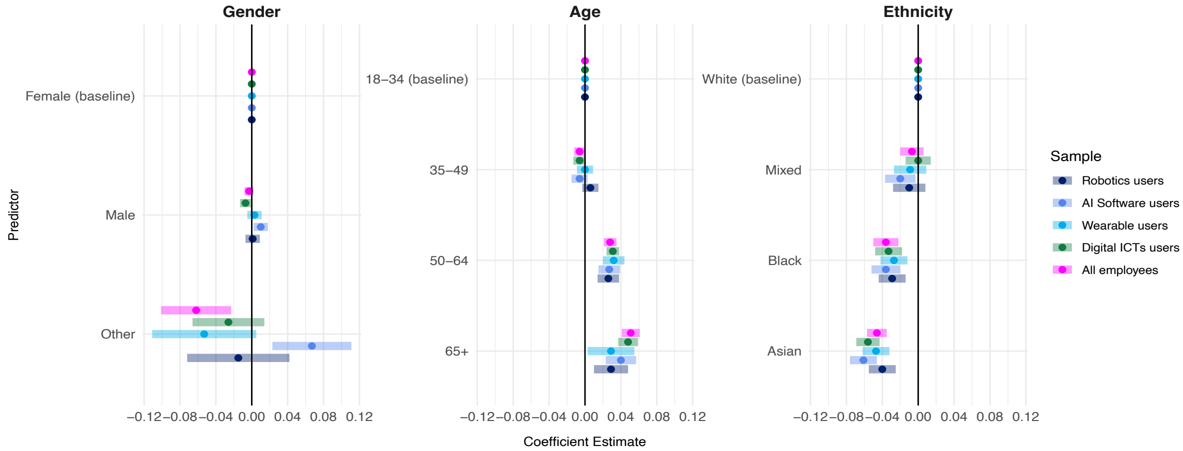
Table A1 - available here as a spreadsheet - presents the results of the same generic linear regression examining associations between various respondent characteristics and capability scores, for subgroups of employees who "sometimes", "often" or "always" interact with Digital ICTs (Model 2), wearables (Model 3), AI software (Model 4) and robotics (Model 5). Several notable differences emerge compared to the overall workforce (Model 1). Figures 2 to 6 illustrate the resulting regression coefficients and associated error (represented by bars accompanying each coefficient, which depict robust standard errors) for various groups of independent variables (demographics, institutional factors, etc.) and across technology exposure samples, including the pooled sample of employees as a baseline for comparison (points coloured pink).

Demographics

The gender distribution of capability scores remains consistent in contexts of exposure to different technologies, with no statistical differences between men and women.
The positive association between age and capability observed for the overall population remains broadly constant among employees who interact with Digital ICTs, it weakens considerably in contexts of exposure to newer technologies. When exposed to AI software, older workers continue to record higher capabilities than their younger counterparts but the magnitude of the differences decreases. Moreover, with exposure to Wearables and Robotics, the capabilities premium observed for the eldest group (65+) loses statistical significance.

The disadvantage observed for the Black ethnic group compared to White employees persists in contexts of exposure to technologies, but the ethnic gap weakens among users of wearables and robotic technologies to be statistically significant only at the 90% confidence level. In contrast, the apparently lower capability scores of Asian individuals are exacerbated in contexts of frequent technology exposure, especially among AI software users.

Figure 2 - OLS regression coefficients (with robust standard errors) for ICECAP on gender, age and ethnicity factors, across sub-samples of technology exposure

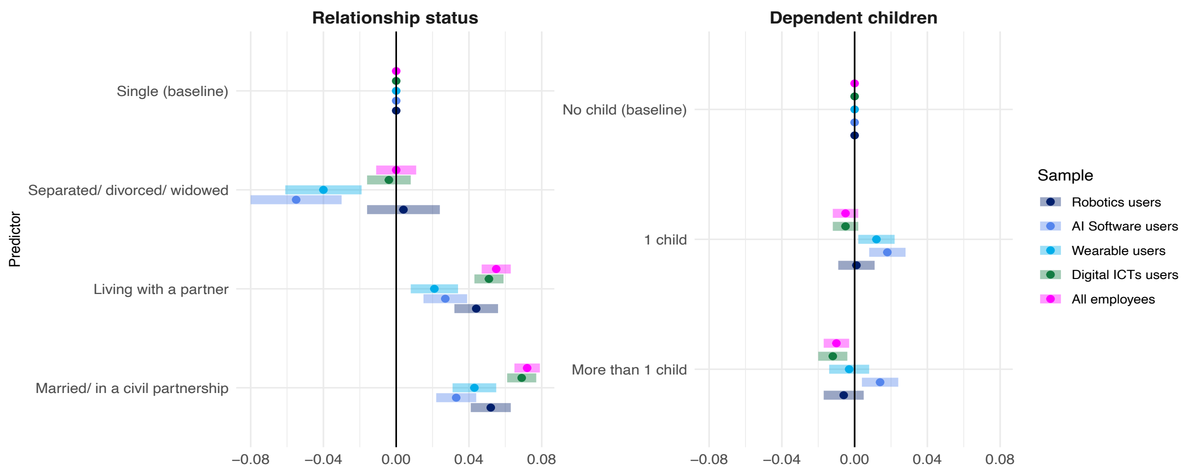


Life stage factors

The positive association between capabilities and being partnered or in a relationship continues to manifest within groups of employees that are exposed to technologies, albeit the strength of such effect reduces slightly in contexts of exposure to newer technologies. In the cases of wearables and AI software exposure, being separated/ divorced/ or widowed becomes more of a disadvantage for capabilities, as these individuals record significantly lower ICECAP scores than those who are single.

The number of dependent children continues to show little effect on capability scores, although having 1 dependent child represents some capability advantage among employees interacting with AI software, a difference only significant at the 90% confidence level.

Figure 3 - OLS regression coefficients (with robust standard errors) for ICECAP on life stage factors, across sub-samples of technology exposure

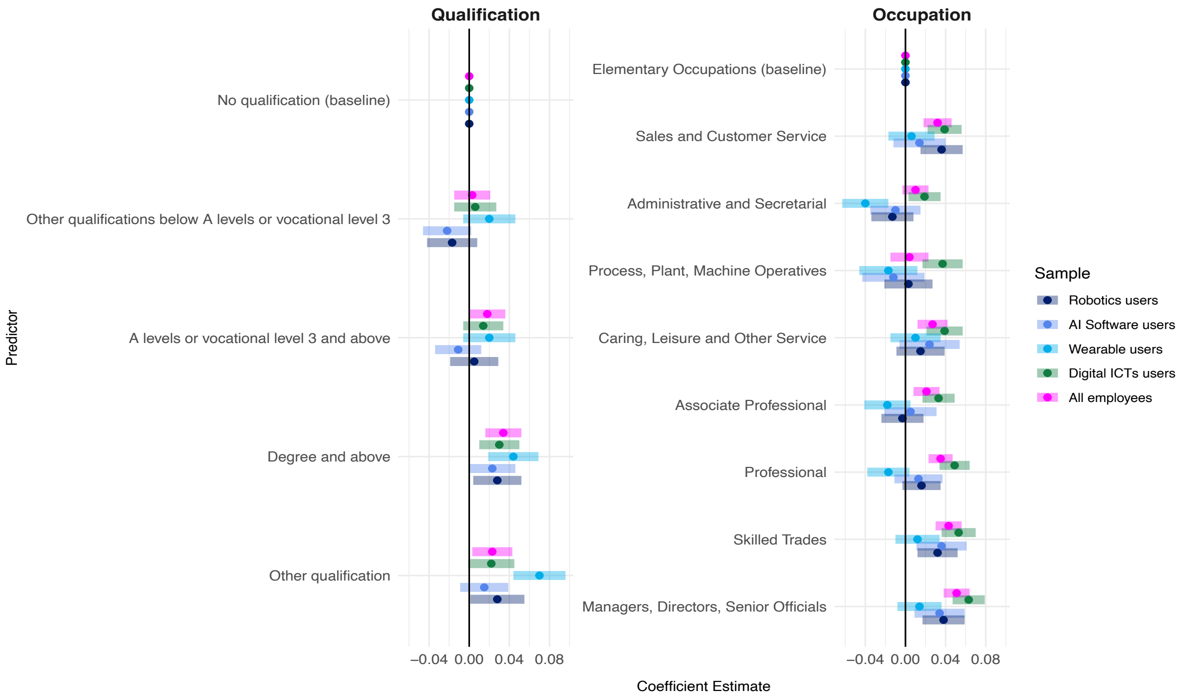


Qualification and occupation

The distribution of capabilities across levels of education observed for the general sample continues to be uniform when looking into sub-groups of employees exposed to different technologies. A single exception is observed among those interacting with wearable technologies, where employees with “other qualification” show significantly higher capability scores than those with “no qualification”.

Employees interacting with Digital ICTs show a similar occupational distribution of capabilities to the general sample, although slightly exacerbated for higher occupational grades. Specifically, managers, directors, senior officials; skilled trades; and professionals exhibit wider gaps compared to elementary occupations when Digital ICTs are considered. Interestingly, when exposed to newer technologies, including wearables, AI software and robotics, disparities between higher occupational categories and elementary occupations (baseline) appear to diminish.

Figure 4 - OLS regression coefficients (with robust standard errors) for ICECAP on qualification and occupation, across sub-samples of technology exposure

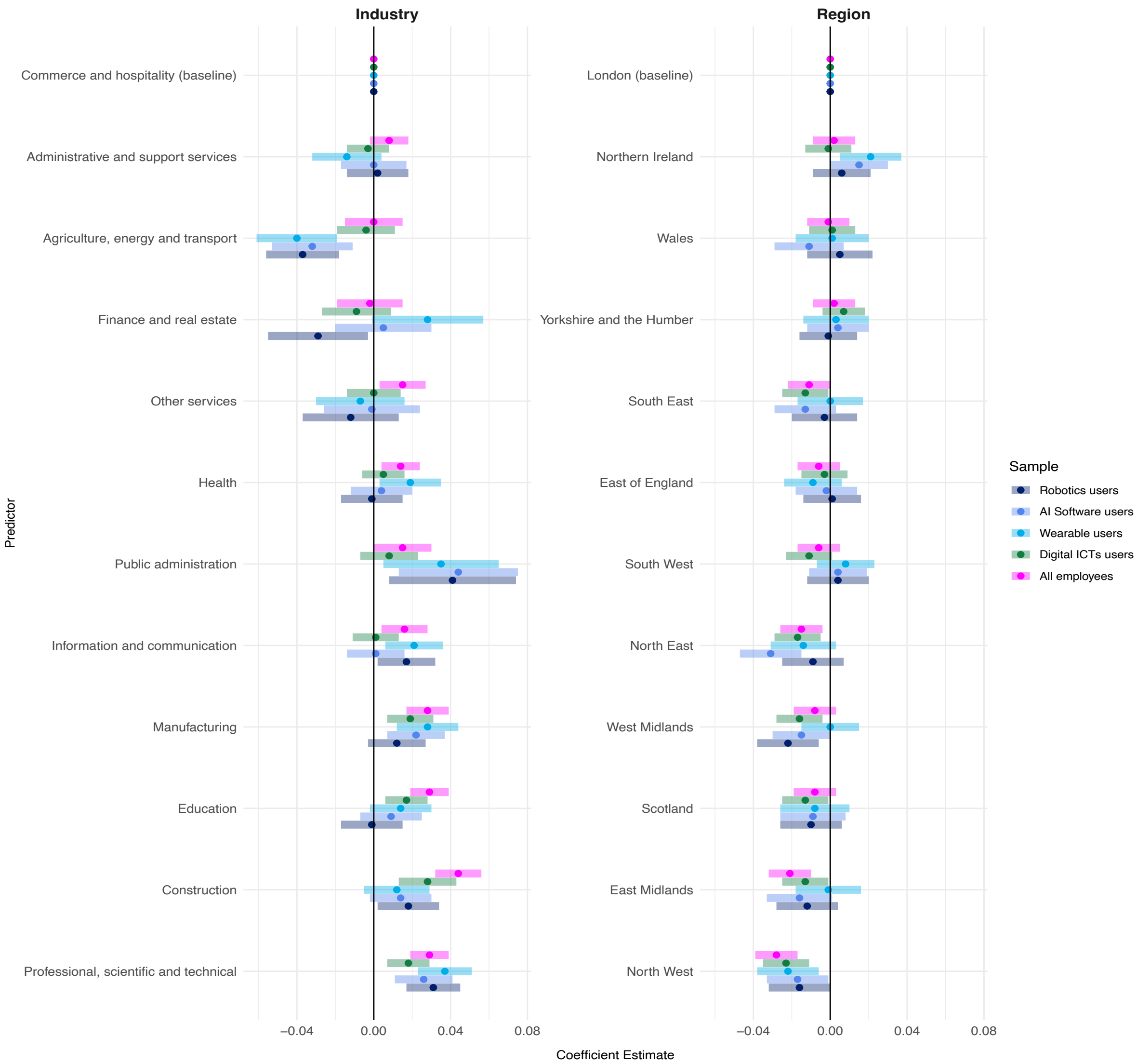


Sector and region

Most differences in capability levels observed across industries are attenuated in conditions of frequent exposure to workplace technologies. Only the capability premium recorded by employees in the Professional, Scientific and Technical sector, compared to the baseline sector (Commerce and Hospitality), remains statistically significant – and even increases in magnitude – in contexts of interaction with wearable and robotic technologies. On the contrary, the capability scores of employees in the Agriculture, Transport and Energy sectors become considerably lower than those of the reference group (Commerce and Hospitality) in contexts of exposure to newer technologies.

Geographically, no further disparities are observed in capability scores when individuals are exposed to newer workplace technologies. Only North West England appears to score significantly below employees from London when interacting with Digital ICTs.

Figure 5 - OLS regression coefficients (with robust standard errors) for ICECAP on industry sector and geographic region, across sub-samples of technology exposure



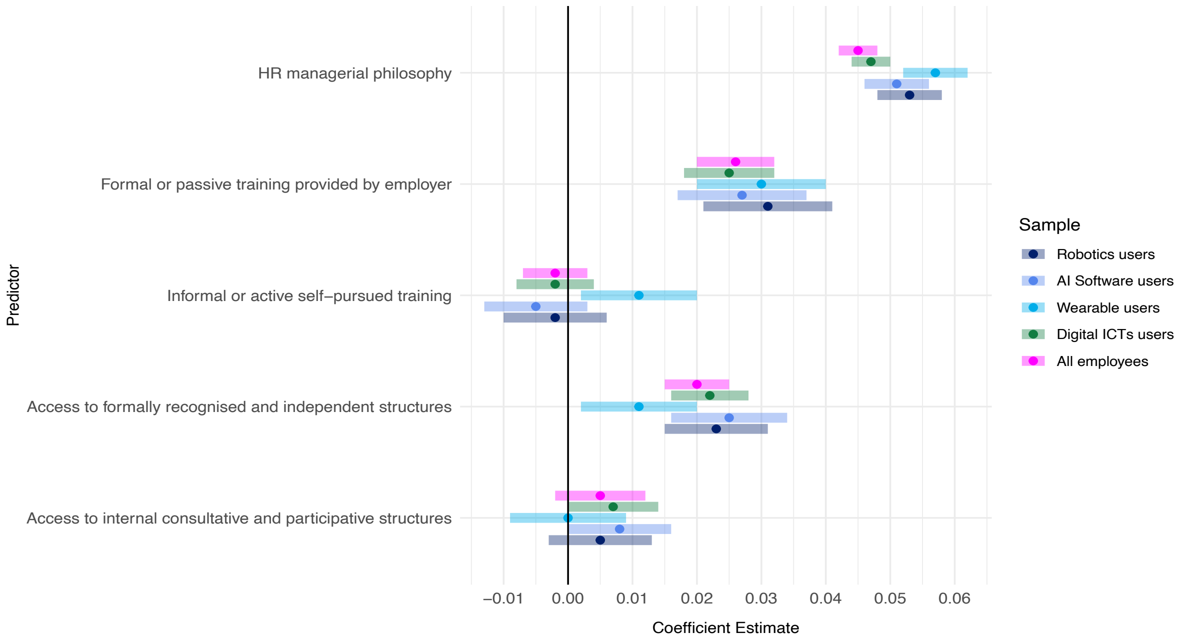
Institutional factors

The positive correlation between capabilities and human resource policies persists in contexts of frequent interaction with workplace technologies and becomes significantly larger in magnitude in the case of newer technologies, especially among those interacting with wearables.

Undergoing formal and employer-provided training also continues to be positively associated with employees' capability levels, and its contribution is even larger within subgroups of employees interacting with wearables and robotics.

Lastly, access to formal representational structures such as Trade Unions remains a significant predictor of higher capabilities, except in the case of employees who interact with wearables. In the case of workers exposed to AI software, the positive effect of this institutional resource is even larger than for the general population.

Figure 6 - OLS regression coefficients (with robust standard errors) for ICECAP on institutional factors, across sub-samples of technology exposure



In summary, while there are significant associations between demographic, socioeconomic, and institutional factors and capability for the overall workforce, these associations differ for workers frequently exposed to various technologies, thereby highlighting the moderating effect that some technologies can have on the distribution of capabilities. Institutional factors, particularly HR philosophy, and access to independent voice structures, are consistently linked to higher capability across all subgroups.

As a sensitivity check, we further assess the potentially moderating role of different technologies on reported levels of capabilities through interaction analyses. The results, presented in Appendix 2, confirm that exposure to different technologies can attenuate or exacerbate the associations between various factors and capability scores, with some factors having stronger or weaker associations depending on the specific technology.

For instance, although it was not evidenced in the sub-group analysis, AI software is the only type of technology interacting with gender. The interaction terms between this technology and the male and non-binary groups were significant and positive, suggesting that in conditions of exposure to AI software, male and non-binary employees enjoy significantly higher capabilities than female employees.

Significant and negative interaction terms were found between exposure to wearables and the eldest group (65+), and between exposure to AI software and the two eldest groups (50-64, and 65+), indicating that the capabilities premium often presented by older workers is conditional to their level of exposure to these technologies.

More notably, this analysis showed significant positive coefficients for the interactions between HR Philosophy and wearables, AI software and robotics respectively, confirming that the contribution of this institutional factor to employees' capabilities, is intensified in contexts of exposure to newer technologies.

3: Is technology exposure correlated with changes across all capability domains?

In this section we explore changes in the sub-domains of the ICECAP capability score, to assess if exposure to different technologies is correlated more strongly with one or other aspect of capability. The results presented in **Table 5** - available here as a spreadsheet - show that the associations between technology exposure and the five capability domains vary in significance and direction.

In summary, reported scores for both the attachment and enjoyment domains do not appear to vary significantly by type of technology exposure. However, for both the stability and achievement domains, being exposed to wearable technologies shows a significant positive association with the capability sub-scores (OR=1.28 and OR=1.37 respectively). Lastly, for the autonomy domain, exposure to Digital ICTs shows a significant positive association with the domain (OR=1.42), whereas exposure to wearables shows a significant negative association with the autonomy domain (OR=0.77).

5. Discussion

This study investigates the distribution of capabilities within the UK workforce, employing the ICECAP-A questionnaire as a measure of capabilities and exploring how capability scores vary in the contexts of technology exposure.

Our initial descriptive analysis of average capability scores across the population suggested that several socioeconomic and demographic characteristics are correlated with higher levels of capability among UK employees. We observed that capability scores were, on average, higher for male employees (compared to female), older workers aged 50 and above (compared to the youngest 18-34 age group), those who identified their ethnicity as white (especially compared to Asian and Black minorities), employees that are married or in a civil partnership (compared to single employees), those with one or more dependent children (compared to those with no children), with a Degree or equivalent qualifications (compared to those with no qualification), in higher occupational grades such as managerial and skilled trades (compared to elementary occupations), and those working in Construction, and the Professional, Scientific and Technical sectors (when compared to employees Commerce and Hospitality who reported some of the lowest capability scores).

Multivariate analysis further confirmed that most of the differences observed initially held when accounting for the effect of all confounders simultaneously, while also controlling for the possible effect of institutional and managerial approaches.

The persistent age gradient in capability scores found in our study is novel and has not been reported elsewhere. Further qualitative research would help to confirm whether older age is potentially associated with more work experience and stability, thus enhancing perceived capabilities. The ethnic, occupational and industry variabilities in capability scores are additional novel findings that we have not observed before and require further attention.

On the other hand, the associations found between employees' capabilities and relationship status and educational attainment closely mirror the findings of other general population studies in the UK and other countries (Al-Janabi et al., 2013; Al-Janabi, 2018; Tang et al., 2018; Shahtaheri et al., 2020), even though in our study the positive correlation with educational attainment weakens when controlling for other factors.

The few differences in capabilities that dissipated in our multivariate analyses were those relative to the number of dependent children and gender. Although we initially observed that gender was a significant predictor of capability scores, we found non-significant difference between the capability levels of men and women after accounting for other factors, mirroring the results reported by Shahtaheri et al. (2020) for Iran, who found no significant differences between the capability scores of male and female adults.

In contrast to the findings of Baji et al. (2021) for Hungary, we found no correlation between capabilities and geographic location. While positive at first sight, this finding must be interpreted with caution as the geographic units used in the analysis may be too coarse to detect within-region inequalities in the distribution of average capabilities. We suspect that at a more granular geographic level, the capability disparities between adults living in capitals and those living in towns or villages, as reported by Baji et al., may emerge.

In exploring the role of institutional or organisational factors we found that respondents who perceived their organisation's HR philosophy is employee-centred, those who have undergone formal or passive training provided by the employer, and those with access to formally recognised and independent representative structures such as trade unions and employee forums, consistently reported higher capability scores. While novel evidence, this result speaks to the importance attributed to institutional conversion factors in the capability approach literature (see Soffia et al., 2023).

We then investigated whether the distribution of capabilities among UK employees looked different in contexts where employees interact more often with workplace technologies. For this, we looked into specific sample groups of employees exposed to digital ICTs, wearables, AI software, and robotic technologies. This sub-group analysis revealed notable cases where the distribution of capabilities can be conditional to the level of exposure to technologies.

First, we found that, although there were no gender disparities evident for the average of the UK workforce, in conditions of exposure to AI software, male employees enjoy significantly higher capabilities than female employees, which aligns with the findings of Al-Janabi (2018) and Tang et al. (2018).

We also noted that ethnic disparities persisted in conditions of technological exposure, highlighting systemic inequalities faced by Asian and Black ethnic employees that need targeted policies. Furthermore, there was emerging evidence that the disadvantage of Asian minorities relative to White employees was exacerbated slightly in conditions of exposure to newer technologies.

An interesting finding was that the positive association between age and capability observed for the overall population remains broadly constant among employees who interact with Digital ICTs, but it weakens considerably in contexts of exposure to newer technologies. In other words, the age premium initially observed for older workers reduces in conditions of exposure to wearables, AI software or robotics, potentially due to lower technological literacy or adaptability.

Qualification continues to be mildly associated with higher capabilities in contexts of high technological exposure, suggesting that enhancing access to education and continuous professional development can be an effective vehicle for employees to act with freedom amidst technological transformations. Interestingly, employees with "other qualification" show significantly higher capability scores than those with no qualification when exposed to wearable technologies, which could reflect the higher adaptability of employees with specialised skills.

The capability advantages initially associated with higher occupational grades attenuate in conditions of exposure to newer technologies. A similar result was found in terms of industry disparities, whereby the apparent adaptability premium of employees in the manufacturing, construction or education sectors weakens in conditions of exposure to newer technologies. However, a new capability disadvantage emerged for employees in the Agriculture, Transport and Energy sectors, who show significantly lower capability levels in contexts of exposure to newer technologies, indicating that those working in these sectors may be less well equipped to navigate technological change[3].

[3] With the caveat that sample sizes representing employees in the Public Administration sector were rather small, it is worth noting that an opposite trend was observed for this group: in conditions of exposure to newer technologies, public administration employees reported significantly higher capabilities than the baseline group (Commerce and Hospitality).

Possibly the most novel finding revealed in our analyses pertains to the consistently positive association between institutional support mechanisms and employees' capabilities. The contribution of wellbeing-centred HR philosophies, employer-provided training and access to formal representative structures, remains highly significant in conditions of exposure to newer technologies. Moreover, the interaction analyses further indicated that the effect of wellbeing-centred HR policies in increasing capabilities is even more marked in contexts of new technology adoption. This result underscores the importance of fostering supportive and inclusive workplace cultures that prioritise employee wellbeing and empowerment amid technological change.

Overall, the observation that the associations between employees' capabilities and various socioeconomic and institutional factors can change in conditions where employees interact more often with newer technologies, suggests that those facing the technological transition are not uniformly equipped with the right capabilities and freedom of opportunities to navigate such changes, and that may entail new risks in generating social inequalities.

In Section 3, we explored the relationship between exposure to different types of technology and the five ICECAP capability domains: stability, attachment, autonomy, achievement, and enjoyment. Our analysis revealed that Digital ICTs correlated positively with a sense of independence in many areas of life, which resonates with previous findings that relate these technologies to high-discretion augmentation, improvement in decision-making and learning (Soffia et al., 2024). Conversely, exposure to wearables correlated negatively with autonomy, which further supports the hypothesis that these technologies are often deployed in ways that intensify routine tasks and the sense of being controlled and monitored. Notably, exposure to wearables was also positively associated with stability and achievement. A higher sense of stability might be linked to the perception of improved wage premium and career prospects that cutting-edge technologies like this can bring (as seen in Soffia et al., 2024). In addition, qualitative analyses conducted as part of the Pissarides Review (Xia et al., forthcoming) suggest that some wearable technologies like smartwatches and smart glasses are often seen as "fancy" or indicative of technological advancement, which might contribute to that sense of progress among employees and that the company is keeping competitive by investing in modern technology. Interestingly, attachment and enjoyment did not show significant correlations with any type of technology exposure, suggesting that these capabilities might represent more personal factors rather than workplace dynamics.

Having demonstrated the effectiveness and sensitivity of a multidimensional capability measure like ICECAP-A to the socioeconomic and institutional conditions of the UK workforce, and to the varying scenarios of technological transformation, these findings call for the need to create and make use of available workplace-specific capabilities measures. While several approaches have made progress in this direction (see, for instance, Van Der Klink's and Green's sustainable employment and job quality operationalisations in Soffia et al. 2023), these frameworks are still predominantly focused on outcomes and functionings. In contexts where the UK workforce is facing rapid technological change, it becomes all the more critical to identify the kind of workplace freedoms that employees have reason to value and that may not be captured in the ICECAP-A measure. Identifying such freedoms and integrating them into a revised index of workplace capabilities should be the focus of future work.

6. Conclusion

This study underscores the complex interplay between socioeconomic, institutional, and technological factors in shaping the distribution of capabilities within the UK workforce. Our analysis highlights significant disparities in capability levels based on age, ethnicity, and educational attainment, with institutional support playing a crucial role in enhancing capabilities.

The moderating effects of technological exposure on these relationships point to the need for tailored policies that address the specific needs of different workforce segments. As technological advancements continue to reshape workplaces, it is vital to ensure that all employees are equipped with the necessary capabilities to thrive, supported by robust organisational and institutional frameworks. This approach will be critical in fostering a more equitable distribution of capability across the workforce, as a way of developing resilience to negative consequences of technological transition.

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Appendix A: sub-group analysis of capabilities distribution

Table A1 - available here as a spreadsheet - shows the full OLS results of ICECAP relative to socio-demographic and institutional factors for four cohorts of UK employees expose to different technologies.

Appendix B: moderation analysis of technological exposure

Section 2 of Results examined whether the distribution of capabilities varied depending on specific employees' characteristics and institutional factors, in both the general sample and across specific groups of employees exposed to different technologies. To further assess the potentially moderating role of different technologies on reported levels of capabilities, in this section we present the results of interaction analyses that explore whether the relationship between respondent characteristics and capabilities varies significantly depending on the level of exposure to different technologies (exposed vs. not exposed).

Table A2 - available here as a spreadsheet - presents the OLS models examining the associations between various demographic, socio-economic, and institutional factors and capability scores (ICECAP), including interaction terms with the 'Digital ICTs' dummy variable (Model 6), 'Wearables' dummy variable (Model 7), 'AI Software' dummy variable (Model 8) and a 'Robotics' dummy variable (Model 9). These dummy variables respectively indicate whether an individual is often or always exposed to that technology (Tech dummy = 1) or not (Tech dummy = 0). Only interaction terms significant at the 95% confidence level are examined.

Moderating effect of Digital ICTs

A single significant (at the 90% confidence level) and negative interaction was found between employees self-identified as Asian and exposure to Digital ICTs, which indicates that this group reports significantly lower capabilities than their white counterparts when exposed to ICTs.

Moderating effects of Wearables

A negative interaction, significant at the 90% confidence level, was found between the eldest group (65+) and exposure to wearables, denoting that the positive contribution of age to capabilities is weaker in conditions of exposure to wearables.

In addition, a significant and positive interaction is shown between 'other qualification' and exposure to Wearables, suggesting that the positive association between this educational level and capability scores is stronger in contexts of exposure to wearable technologies.

The interaction between HR Philosophy and wearables was significant and positive, suggesting that the capability enabling effect of wellbeing-centred HR policies is larger in contexts where employees are exposed to wearables.

Moderating effects of AI software

AI software is the only type of technology interacting with gender. The interaction terms between this technology and the male and non-binary groups were significant and positive, suggesting that in conditions of exposure to AI software, male and non-binary employees enjoy significantly higher capabilities than female employees.

In a similar case to wearable users, the interactions between AI software and the eldest groups (50-64, and 65+) are significant and negative, indicating that the capabilities premium often presented by older workers is conditional to their level of exposure to this technology.

As with wearables, the interaction between HR Philosophy and AI software was significant and positive, suggesting that the positive effect of wellbeing-centred HR policies is significantly larger in contexts of AI automation.

Moderating effects of Robotics

The only exacerbating effect found for robotic technologies was that between capabilities and HR philosophies. The significant positive interaction term found confirms that the contribution of this institutional factor to employees' capabilities, is intensified in contexts of exposure to robotic technologies.

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.

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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 Kester Brewin, Head of Communications at the Institute for the Future of Work at kester@ifow.org