AI & SOCIETY
https://doi.org/10.1007/s00146-024-01962-8

MAIN PAPER

Navigating technological shifts: worker perspectives on AI and emerging technologies impacting well-being

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Received: 11 January 2024 / Accepted: 1 May 2024

Abstract
This paper asks whether workers' experience of working with new technologies and workers' perceived threats of new technologies are associated with expected well-being. Using survey data for 25 OECD countries we find that both experiences of new technologies and threats of new technologies are associated with more concern about expected well-being. Controlling for the negative experiences of COVID-19 on workers and their macroeconomic outlook both mitigate these findings, but workers with negative experiences of working alongside and with new technologies still report lower expected well-being.

Keywords New technologies · Well-being · Workers experiences · Perceived threats

JEL Classification I31 · J81 · O32

1 Introduction

The adoption and diffusion of new technologies and innovation are seen as being vitally important in raising productivity and growth levels amongst economists. During the 1980s and 1990s, the introduction and then widespread diffusion of computers in the workplace resulted in a switch in demand towards more educated workers (Autor et al. 1998). This has subsequently been argued to result in a wage premium associated with using computers within jobs based on the "premise that computers increased cognitive skill requirements and complemented skilled and educated workers" (Freeman et al. 2020, p.394 taken from Handel, 2007). The idea that automation impacts on the occupational distribution equally is further considered in the works of Goos and Manning (2007), Autor et al (2003, 2006), Goos et al (2009), Aksoy et al (2021) and Anton et al. (2022) with findings indicating a hollowing-out of middle-occupations, polarization of labour markets, greater pay inequality and greater gender pay inequality.

More recent adoption of new robotic technologies by firms is resulting in further automation of tasks across many occupations. This has resulted in many studies estimating what impact these new technologies will have on the demand for labour, wages and wage inequality. Acemoglu and Restrepo (2020) model robots as displacing labour in the US and find evidence for this displacement effect and a negative effect on wages. de Vries et al. (2020) find that robots displace routine manual task-intensive employment in high income countries. Graetz and Michaels (2018) find usage of robots across 17 industrialised countries to raise growth, wages and total factor productivity while having no impact on polarization. Dauth et al. (2021) find that 23 per cent of overall decline of manufacturing employment in Germany is due to robots but that incumbent robot exposed workers are more likely to remain employed but perform different tasks. They also find that while robots raise labour productivity this does not result in higher wages.

As well as advances in robotics there are other technologies that are resulting in greater automation of tasks. At the forefront of these is artificial intelligence. AI is now used in a variety of industries notably finance, healthcare and transport where algorithms are used to identify patterns and predict outcomes. AI is at the forefront of driverless/autonomous vehicles alongside advancements in sensor technology. More recently publicly available, free to use platforms based on large language models and natural language processing are impacting many tasks that have previously been performed by humans (e.g., Chat GPT and Gemini).

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Focusing on automation more broadly, Frey and Osbourne (2013, 2017) use O*NET data to estimate that 47% of total employment is at a high risk of being automatable in the next decade in the United States. Using similar techniques figures of 59% and 35.7% are estimated for German and Finish employment (Brzeski and Burk 2015; Pajarinen and Rouvinen 2014). These job displacement estimates for broad automatability have been questioned as missing important parts of how demand for labour reacts to automation with Arntz et al (2016) and Felten et al (2019) both estimating negative but significantly lower changes to employment. Acemoglu and Restrepo (2018, 2019) argue that automation can and does have displacement effects but can also result in positive productivity effects that contributes to increased labour demand. There is also the argument that adoption of new technologies can create new tasks, as well as new occupations (Wilson et al. 2017) and possibly new industries and markets. This creates the opportunity for job-reinstatement effects into jobs with a broader and more flexible range of tasks (ibid. p4). McGuinness et al. (2023) find evidence to support such an effect amongst employees who encounter skills displacing technological change and that this may be correlated with higher wages. These beneficial effects are only felt by people already in high-skilled occupations though, implying that labour market polarization will continue.[1]

Another lens through which to view automation is the impact it has on incumbent workers themselves. Not just through changes in tasks, but in terms of changes in complexity, how they view the different aspects of their job currently and in the future, and the meaningfulness of jobs. Automation can extend the working life of people whose jobs require a degree of physical activity (Di Pasquale et al. 2022; Borges et al. 2021; Hopko et al. 2022). Automation can reduce the risk of dangerous or unhealthy work conditions. Automation reduces repetitive and monotonous tasks of workers, freeing them up to undertake more creative, nonroutine tasks that they have a comparative advantage in and may enjoy more (Makridakis 2017; Eglash et al. 2020; Bettoni et al. 2020; Paschkewitz and Patt 2020; Gihleb et al. 2022). Through these mechanisms it would be reasonable to expect automation to improve the quality of jobs and job satisfaction.

In recent years, though there has been a rise in technological anxiety (Mokyr et al. 2015) as evidenced in the works of Robelski and Wischniewski (2018), Körner et al. (2019), Szalma and Taylor (2011) and Gihleb et al. (2022). Conceptually, it is important to understand that a driver of this anxiety is a fear of technology or technophobia.[2] Such fears are based on perceptions that AI is not safe with respect to complex and dynamic circumstances, something highlighted in Cugurullo and Acheampong (2023) in relation to autonomous vehicles. This fear is though likely to be less of a concern when AI is used in non-life threatening settings, such as when to buy and sell equities in financial markets. Fears with respect to AI are also triggered by the technology failing or breaking somehow. With respect to workers specifically, Khogali and Mekid (2023) find triggers of fearfulness include identity loss, being obsolete and being alienated from other humans in the workplace and this relates to Ivanov et al (2020) who argue the dehumanizing effects of automation and job automatability contribute to a fear of automation.[3]

One prediction of such fears of new technologies like AI is that workers' job satisfaction is reduced. Gornay and Woodard (2020) find evidence that jobs most at risk from automation are associated with lower job satisfaction in both the US and Europe, though mitigated by how workers value their jobs in the first place. Schwabe and Castellacci (2020) find fear of automation reduces job satisfaction. Dekker et al (2017) and Hinks (2021) find that people who are more fearful of robots with respect to future employment report lower levels of current life satisfaction, though this is mitigated slightly by the experience of working alongside robots. Giuntella et al. (2023) find evidence that German workers, particularly those in medium-skilled jobs, who are highly exposed to artificial intelligence suffer a relative decline in both life and job satisfaction. These findings are important, since they are likely to predict how resistant or embracing workers will be to firms adopting new technologies (Bhargava et al. 2021).

This paper contributes to the growing literature about the impact of new technologies on workers' well-being by asking whether workers who fear becoming technologically redundant or unemployed, or workers who already feel technology is having a negative impact on their work report lower expected well-being. This paper contributes to the literature in a number of ways. First, we use survey data for OECD countries for the first time. The number of questions related to working with new technologies also means we can

[1] Studies based on current job markets, rather than forecasts and predictions, indicate little or no impact of automation on employment e.g. Acemoglu et al. 2020; Georgieff and Milanez 2021; Lane and Saint-Martin 2021. For a broader literature review on the relationships between AI and work see Deranty and Corbin (2024).

[2] It is important to remember that previous technological revolutions were met with similar anxieties and fears, such as the "automation hysteria" of the 1950s and 1960s (Terborgh 1965).

[3] It has also been argued that workers may fear a change in their relationship with new technologies perhaps moving from a complementary relationship to being subservient (Scripter 2023) which has implications for the meaningfulness of work and possible 'achievement gaps' (Danaher and Nyholm 2021).

capture people's experiences and expectations with greater accuracy than previous research. Since we are considering expected well-being an important control is to consider the macroeconomic expectations of workers. Those who think their jobs are under threat from an economic downturn would likely report lower expected well-being, but a downturn could also mean firms adopting new technologies if or when they recover, which could be seen as a threat to future employment thus representing a potentially important omitted variable. Since the data were collected during the COVID-19 pandemic, this allows for consideration of the impact the pandemic had on workers' well-being. We capture this impact by controlling for whether workers were adversely affected by the pandemic in terms of employment and/or earnings. It is likely this would both directly impact expected well-being but also impact on experiences of working with new technologies and on fear of becoming technologically unemployed, given the pandemic sped-up the adoption of many new technologies (Soto-Acosta 2020; Amankwah-Amoah et al. 2021). We find evidence that workers who feel new technologies are impacting negatively on their work report lower well-being, but that people who fear becoming technologically redundant do not report any change in well-being when macroeconomic expectations and the impact of COVID-19 are considered.

In the next section we discuss the data and methods used. Section 3 presents the initial results followed by a number of robustness checks. Section 4 discuss the results and we conclude in Sect. 5.

2 Data and methodology

2.1 Data

This paper uses the OECD's Risks that Matter (RTM) survey collected between September and October 2020. The survey draws on a representative sample of over 25 000 people aged 18–64 years in 25 OECD countries: Austria, Belgium, Canada, Chile, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Korea, Lithuania, Mexico, the Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Switzerland, Turkey and the United States. RTM is implemented online using non-probability samples recruited via the internet and over the phone. Sampling is conducted through quotas, with sex, age group, education level, income level, and employment status (in the last quarter of 2019) used as the sampling criteria. Survey weights are used to correct for any under- or over-representation based on these five criteria with the target and weighted sample being 1,000 respondents per country. The 2020 survey questionnaire had additional subsections of questions regarding people's experiences during COVID-19, the future of work, and inequality. For our purposes, the survey contains detailed questions on people's perceptions of workplace automation and digitalisation in general and how they think that it will impact their current work. Since the survey was conducted during the COVID-19 pandemic, the generalizability of our findings is conditional on these circumstances. We do aim to mitigate the impact of the pandemic in our results by considering how people were affected by the pandemic.[4]

2.2 Dependent variable

The RTM asks people "In general, thinking about the next year or two, how concerned are you about your household's finances and overall social and economic well-being?" with the four responses being *Not at all concerned = 1, Not so concerned = 2, Somewhat concerned = 3 and Very concerned = 4.* While this question is framed at the household level, we assume that respondents' responses are centred around themselves rather than the household.

Since we are interested in new technologies in the workplace and well-being, we restrict the sample to those who are currently employed (employee or self-employed).[5]

2.3 Main independent variables of interest

In line with Busemeyer et al (2023), we use responses to three questions:

1. My job will be replaced by a robot, computer software, an algorithm, or artificial intelligence.
2. My job will be replaced by a person providing a similar service on an internet platform.
3. I will lose my job because I am not good enough with new technology or because I will be replaced by someone with better technological skills

to calculate the perceived job threat of new technologies on people currently employed. Responses are *Very unlikely = 1, Unlikely = 2, Likely = 3 and Very Likely = 4.* The questions are each framed over what workers think will happen to their job (or job opportunities) over the next 5 years. We adopt a principal components method that is

[4] For more details of the sample design and method see Box 1.1 in the OECD (2021) "Main Findings from the 2020 Risks that Matter Survey".

[5] Selection into being employed is not random. Traditionally a Heckman selection model is adopted to address this bias that may subsequently arise. However, it is not clear what variable would impact the decision to be employed or not but would not impact well-being. For example, if the household has children living with them then this could mean finding employment harder because of childcare responsibilities but having children residing in a house could also impact directly on well-being.

justified, since the Kaiser–Meyer–Olkin statistic is above 0.5 (0.708) for the three variables.[6] The ordering of the responses of our dependent variable means that we would expect workers who fear new technologies to be more concerned about expected well-being meaning that the estimated coefficient would be positive.

The data also allow us to capture workers' experiences of working with new digital technologies in the workplace, through the following statements:

1. I feel that technology forces me to do more work than I can handle.
2. I feel that technology is leading to work invading my personal life.
3. I often find it difficult to understand how to use new technologies.
4. I feel that new technologies are a constant threat to my job security.
5. I feel that the pace at which new technologies are introduced in my workplace is overwhelming.

where people respond that they *Strongly disagree = 1, Disagree = 2, Neither agree nor disagree = 3, Agree = 4 or Strongly agree = 5.* The first statement represents whether workers think their workload has increased in some way. The remaining statements we argue could proxy for anxiety and stress both in the workplace and in relation to statement 2, on life outside of work. We again use a principal components approach using responses to all five questions with this being justified, since the KMO statistic is 0.839. As with the perceived job threat variable, we expect workers who agree that new digital technologies are having a negative impact on their workplace to be more concerned about their expected well-being.

Using subjective measures of workers' views on risks and experiences of new technologies may be subject to biases in workers' responses to anything new in or outside the workplace, not just responses to new technologies. Previous work has calculated the degree to which tasks in jobs are more or less likely to be automated (e.g., Autor et al. 2003; Frey and Osbourne 2017) but are not without short-comings, not least the speed with which new technologies are advancing and replacing tasks. In this respect, the measures used in this paper are more likely to reflect what is actually happening in workplaces with respect to new technologies.[7]

[6] When we adopted a factor analysis method instead, the loadings of the three terms were similar and the results did not change qualitatively. These results are available on request from the authors.

[7] That said, the negative framing of the technology experience questions used in this paper may create a bias in responses that may not occur if the questions were positively framed.

2.4 Other variables of interest and control variables

Workers' responses to the questions above may be mitigated by workers' frequency in using digital technologies at work. We create a dummy that takes a value of 1 when someone constantly uses digital technologies at work and 0 when it is used less frequently. 58% of our sample constantly use digital technologies. This highlights the issue of what people mean by digital technologies, and in the RCT questionnaire, this is never defined. Using the internet, and using various apps are digital technologies as are using any computer software and the Cloud. Such technologies have been disruptive in the workplace over the last 20 years. New technologies such as machine learning, artificial intelligence, Big Data and predictive software have the potential to be even more disruptive, but people and indeed firms are not necessarily aware they are using them, because they are not easily defined and not easily observed unlike, for examples, co-bots.

We control for age and age-squared to test the general empirical finding that life satisfaction is U-shaped as age increases. Gender is captured by a group of dummies for female, male and other. Education is captured by a dummy for whether someone has a level of tertiary education or not. We also control for the population size of the town the respondent resides in with previous research finding that living in more populous areas is associated with lower well-being. Household income is an important control in any empirical well-being study and is measured here as the log of disposable annual income equivalized for household size. To standardize income across the countries, we use purchasing power parities from the OECD.

Since the dependent variable is framed in the household's expected well-being, we control for the composition of the household by including whether people have children living at home with them, marital status and whether the partner of the respondent is employed or not. The latter term is expected to mean less concern about expected well-being perhaps acting as an insurance mechanism if the respondent loses their job.

We control for occupational group of the employed by 1-digit ISOC codes. The data do not allow us to delve into more detail for occupations which is a limitation when considering who is being impacted most by new technologies and how this then impacts on well-being. Ideally information is required into the risk new technologies pose for the tasks undertaken and to specific occupations themselves being completely automated but this is not available in the data.

It is also possible that well-being is correlated with country-level macroeconomic factors and we include a number of country-level macro-economic variables. First, the log GDP per capita PPP for 2019 and the unemployment rate for 2020. We expect workers in higher income countries to be less concerned about expected well-being, while those in countries with higher unemployment levels to be more concerned. We also capture country-level differences in labour markets by controlling for trade union density and the extent to which workers have employment protection. We would expect both to be positively related to expected well-being. While hard to capture country differences in workers being exposed to new technologies we attempt this by controlling for the percentage of businesses who use artificial intelligence and the percentage of businesses which provide any type of training to develop ICT-related skills of the persons employed.[8]

2.5 Methodology

We adopt a multi-level approach as our data have a hierarchical structure, where individuals represent level one and countries represent level two. The well-being variable can be explained by both individual and group-level variables. Following previous work by Raudenbush and Bryk (2002), we standardise all continuous variables to the same scale so all variables can be compared. Beginning with an intercept-only model, we found that the country group effects were statistically significant with the intraclass correlations for this model being 0.142 which exceeds the 0.05 critical value suggested by Hayes (2006) meaning that we accept the multilevel approach. Our model is specified in the following equation:

$$\text{ExpectedWellBeing}_{i,c} = \beta_1 \text{TechThreat}_{i,c} + \beta_2 \text{TechExperiences}_{i,c} + \sum_{k=1}^{n} \beta_k X_{k,i,c} + u_c + \varepsilon_{i,c} \quad (1)$$

where the subscripts represent individuals 'i', country 'c' and different controls 'k'. u_c represents the random intercept and $\varepsilon_{i,c}$ is the individual-level residuals. Since expected well-being is ordered so that large numbers represent lower expected well-being and that for our variables of interest higher values represent being more concerned about technological threats and having had worse experiences with digital technologies then we expect that our estimated coefficients will be positive, so that someone who agrees that digital technologies are a threat to their job report being more concerned about expected well-being.

3 Results

3.1 Initial results

The main results in Table 1, for each of the four models, indicate that workers who have higher perceptions of technological threats towards their job are significantly more concerned about expected well-being. For model 4, this represents a 0.097 point increase in being concerned about expected well-being. The same is also true of those who agree technology is negatively contributing to their job experience with there being a 0.152 point increase in being concerned about expected well-being. The inclusion of frequency of using digital technologies has no mitigating impact on these results (models 2, 3 and 4).

Other controls are consistent with previous empirical well-being work. Those with higher household income are less concerned about expected well-being, while the U-shaped relationship between well-being and age is confirmed. This is re-assuring, since we are using a measure of expected well-being framed at the household level but answered by one person in the household. Traditionally in the well-being empirical literature questions are framed at the individual level. This would suggest that respondents' responses are centred around themselves. Male workers are significantly less concerned about well-being than female or other-gendered workers. Workers with a tertiary education are less likely to be concerned about well-being, but this becomes insignificant in models 3 and 4. Children living in a household are associated with greater concern about well-being, while marital status is not associated with well-being. As expected, having a partner who is employed reduces concern about expected well-being. Those workers residing in smaller towns report less concern about expected well-being. Occupational group does play a role in expected well-being with clerical, sales and elementary workers reporting lower expected well-being compared to professionals.

When country-level controls are included in model 4, we find that workers living in countries with higher unemployment report more concern expected with well-being and those living in countries where firms are more likely to train incumbent workers in ICT are less concerned about expected well-being. For each model the inclusion of additional variables results in the goodness of fit (where a smaller value of the Akaike information criterion indicates a better fit) increasing, including when country-level controls were included in Model 4.

[8] The country-level technology measures can be found at https://data.oecd.org/

Table 1 Well-Being Regression Estimates (Multi-Level)

VARIABLES	(1)	(2)	(3)	(4)
Dependent Variable—Level of concern regarding expected Well-Being (1 = not at all concerned, 4 = very concerned)				
Technological Threat	0.100***	0.098***	0.097***	0.096***
Technological Experiences	0.152***	0.151***	0.152***	0.152***
Constant ICT		0.001	0.008	0.008
HH income equivalent PPP 2019		−0.105***	−0.101***	−0.099***
Age		0.226***	0.226***	0.227***
Age-squared		−0.209***	−0.208***	−0.209***
Male		−0.137***	−0.128***	−0.128***
Identify as neither male nor female		0.171	0.181	0.178
Tertiary education		−0.025*	−0.008	−0.008
Household has at least 1 child living at home		0.055***	0.058***	0.058***
Married		−0.021	−0.019	−0.020
Partner employed		−0.051***	−0.049***	−0.048***
Under 10,000		−0.036	−0.037*	−0.031
Btw 10–50,000		−0.055**	−0.056**	−0.050**
Btw 50–100,000		−0.019	−0.020	−0.015
Btw 100–500,000		−0.017	−0.019	−0.015
Over 500,000		Ref	Ref	Ref
Manager			−0.012	−0.012
Professional	Ref	Ref	Ref	Ref
Associate professional			−0.003	−0.002
Clerical			0.041*	0.042*
Sales			0.098***	0.099***
Skill agricultural			0.054	0.055
Craft			−0.012	−0.012
Plant			−0.004	−0.003
Elementary			0.132***	0.132***
Other occupation			0.006	0.007
Country-Level				
Ln GDP per capita (2019)				−0.035
Unemployment Rate (2020)				0.129***
Union Density (2020)				−0.056
Employment Protection (2020)				0.010
Percentage of firms who train current workforce in ICT				−0.118**
Percentage of firms who use artificial intelligence				0.025
Constant	2.838***	2.967***	2.924***	2.919***
Observations	14,146	14,146	14,146	14,146
Number of groups	25	25	25	25
Akaike information criterion	34,854.31	34,542.46	34,529.92	34,516.71

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.2 Additional controls for omitted variable bias

Workers views on how technology will impact their jobs in the next 5 years may capture a general underlying economic view of the near future. If workers think their jobs are under threat from an economic downturn then this could directly impact on expected well-being but also contribute to workers' views on threats from new technologies as these threats would increase during a downturn. When we include people's views on if they think their "…job could be lost due to a general downturn of the economy" in Table 2 we see this is associated with a 0.228 point rise in being concerned

Table 2 Well-Being Regression Estimates (Multi-Level) including impact of COVID-19 and Economic Outlook

VARIABLES	(1)	(2)	(3)	(4)
Dependent Variable—Level of concern regarding expected Well-Being (1 = not at all concerned, 4 = very concerned)				
Technological Threat Index	0.098***	0.004	0.006	0.001
Technological Experiences	0.152***	0.123***	0.116***	0.100***
Job could be lost due to economic downturn		0.228***	0.204***	0.193***
C19 impact			0.270***	0.138***
C19 impact on household finances				0.372***
Constant	2.911***	2.359***	2.285***	2.237***
Observations	13,834	13,834	13,834	13,834
Akaike information criterion	33,775.91	33,159.85	32,805.13	32,357.36

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

about expected well-being and that the technological threat index remains positive but is now insignificant. At this point it is important to remember that these questions were asked during the COVID-19 pandemic, when there was huge uncertainty regarding whether people would keep or retain their jobs now and in the near future. The pandemic also represented an unprecedently quick and permanent shift in many working practices to being online. The exposure and frequency in using new technologies by many workers during this period meant that an economic downturn could be reasonably expected by workers to trigger businesses to move towards replacing many tasks with these new technologies, thus threatening jobs and increasing worker concerns about expected well-being. Unfortunately, there is no information in the RCT data that allows us to consider the speed with which new technologies were being implemented in workplaces at this time.

The technological experience index by comparison falls in size but remains significant at 0.123 points. This confirms previous work in the literature in that workers who have negative experiences of working with new technologies that impact how they feel about their work report lower levels of expected well-being (Hinks 2021).

To test whether our findings are robust to the impact COVID-19 had on workers, we consider whether current workers have been impaired negatively by COVID-19 (e.g., reduced hours, placed on job retention, fall in pay, had to take leave from work) and whether the household they live in has been impaired financially because of COVID-19. Models 3 and 4 in Table 2 indicate that both of these terms are associated with workers being more concerned about expected well-being. With respect to our variables of interest, controlling for a negative impact of COVID-19 reduces the magnitude of technological experiences on expected well-being but this remains at around 0.100 points and is significant.

3.3 Additional robustness check

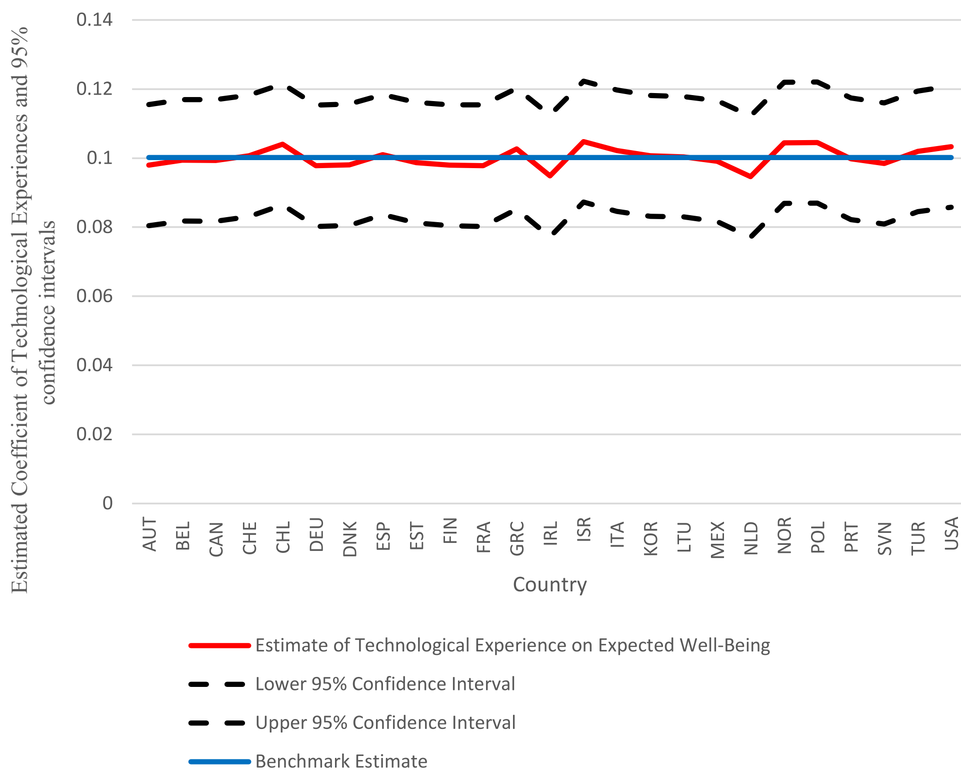
Given the heterogeneity of countries included in the data, we checked if our results could be driven by a specific country. We re-estimated our final model in Table 2 by removing one country at a time. The estimate of the technological experience index remains positive and significant at the 95 per cent level meaning no country is driving the effect on expected well-being (Fig. 1).[9]

4 Discussion and limitations

The results confirm previous findings in that workers who have negative experiences of working with new technologies like AI report lower levels of expected well-being. This remains the case when taking account of people's economic outlook over the next 5 years and when considering different negative impacts of COVID-19 and when we consider the heterogeneity of the sample of countries. The results also indicate that the threat of new technologies including AI increase workers' concerns about expected well-being, but this relationship disappears when people's views on the macroeconomic outlook are considered. This suggests that those who think it more likely they will lose their job in a downturn in the next 5 years also think it likely they will be replaced by AI and other new technologies during this downturn.

[9] We also ran a Bayesian multi-level model based on 105,000 Markov chain Monte Carlo iterations for the reasons outlined in Busemeyer et al (2023). The estimated coefficient on the technology experience index and its significance are similar to what is produced using the likelihood based, multi-level models in Tables 1, 2 and 3 and are available upon request from the author.

Fig. 1 Estimated Coefficient for the Technological Experience Index in relation to Well-Being



These findings signal that experiences of working with AI and other new technologies and, to some extent, the fear workers have of new technologies are negatively correlated with expected well-being of workforces across OECD countries.

Combinations of greater stress, anxiety, work-overload and mental exhaustion that workers experience when working with new digital technologies are contributing factors to these findings and require further exploration. A potential way to analyse these elements is through organisational contexts of work that focus on the power relationships between digital technologies and workers and how these power relationships have changed. Previous research indicates that a loss of autonomy, a loss of power, or a loss of meaning of work by employees who are subservient to AI results in lower well-being (Scripter 2024; Bisht et al. 2021; Danaher and Nyholm 2021).

At a more fundamental level this means changing the narrative of the relationship between AI and other technologies away from what sociologists term technological determinism and towards what Sartori and Bocca (2023) call a socio-technical perspective which overlaps with a social-shaping of technology (Joyce et al. 2023). If workers and society in general can shape technologies like AI then this would potentially yield a number of positive payoffs by questioning peoples' attitudes and perceptions towards AI and possibly changing these attitudes from being negative to positive (Baldry 2011). Certainly, there is evidence that people with greater familiarity and expertise in AI are more likely to support autonomous technologies in different settings compared to people with limited understanding of how the technology works (Mays et al. 2022; Horowitz et al. 2023). This would arguably result in workers and society becoming more trusting towards AI and other digital technologies something which is currently an issue.[10]

Simultaneously, there is also a requirement for more understanding into the psychology of attitudes towards AI (ATAI) and towards other digital technologies. While addressing the primary emotional system (Panksepp 1998, 2011) of fear is one aspect of this, another primary emotional system of importance in relation to AI is the sadness people feel (Montag et al. 2024) which is argued to be triggered by separation distress from not interacting or interacting less with other humans that people feel when using AI.

The main limitation of this paper is that we cannot consider whether expected well-being of workers will itself cause them to express negative views about working with new technologies and about threats of new technologies. This could reflect deeper traits of a person towards being more negative or positive towards things. This relates to another limitation in that we cannot control for the underlying views workers have towards anything

[10] See Yeomans et al. 2019 cited in Araujo et al. 2020 and Dietvorst et al. 2015 for more details.

new, whether this be related to technologies at work or elsewhere. As alluded to previously we also do not have the detailed occupational groupings that we crave to consider heterogeneity within groups. This would allow us to capture the characteristics of jobs such as how repetitive they are and the degree to which they are perceived to have low meaning. This ensures that we interpret the correlations in this paper with a degree of caution.

5 Conclusion

This paper finds evidence that workers who have negative experiences of working with and alongside new technologies like AI have lower expected well-being and that this finding holds when we consider any negative impacts on employment and earnings because of COVID-19. This finding confirms previous research (Dekker et al. 2017; Guintella et al. 2023). Further research is needed into understanding what is driving these findings since this will likely impact on the effectiveness of implementing and adapting to new technologies in firms and industries, which will in turn have implications for the survival and growth of enterprises. While the threat to jobs of new technologies are not found to be associated directly with expected well-being, the more concrete experiences of working with new technologies and the impact this has on workload, stress and anxiety both in and outside of work do correlate with more concern about expected well-being.

While this paper does not explicitly analyse any fears workers might have towards AI and other digital technologies it could be that negative experiences of such technologies contribute to negative attitudes towards these same technologies. These negative experiences may well be weighted more in peoples' memories especially if they are framed as losses and can re-enforce attitudes or can change attitudes from perceiving AI, for example, as positive to negative. Through this psychological lens these experiences can also contribute to peoples' fears towards AI and to other primary emotional systems, which can in turn result in frictions in the workplace that can impact negatively on the diffusion of technologies, productivity and firms' growth. One way to tackle these fears is to see AI and the like as not being exogenous events that we must simply accept. Rather we see AI (as with previous technologies throughout modern history) as something that society can shape and that we have some control over and, in this respect, is not completely autonomous. It will be largely the responsibility of firms' to adopt this kind of framework and to observe what works and what does not and to understand these successes and failures.

Data Availability All data and econometric coding is available upon request from the author.

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