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Measuring the impact of AI on jobs at the organization level: Lessons from a survey of UK business leaders

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ABSTRACT

Advances in artificial intelligence (AI) have reignited debates about the impact of technology on the future of work, raising concerns about massive job losses. However, extant evidence is beset by methodological limitations. The majority of studies are either (1) based on modelling predictions, underpinned by subjective judgements or (2) measure the effect of automation technologies more broadly using proxies for AI effects. Analysis of what actually happens in organisations introducing AI-enabled technologies is lacking. This Research Note proposes a third methodology based on the use of bespoke employer surveys. Drawing on a new and unique survey of UK business leaders, it illustrates the utility of this approach through the presentation of descriptive findings on the association between introduction of AI and job creation and destruction within organisations. Directions for future research using this approach are suggested.

Introduction

Developments in digital technology have raised debates about the future of work and, indeed, whether there will be any work in the future for humans (Dunlop, 2016). Such debates are not new and accompanied earlier waves of workplace automation (e.g. Jenkins and Sherman, 1979). The predicted mass job losses, however, did not occur (Whitley and Wilson, 1982). This time is thought to be different, as AI combined with greater availability of data and enhanced processing power enables computers to perform a far greater range of tasks than previous waves of digitalisation (Brynjolfsson and McAfee, 2014). Seemingly, jobs really could disappear with the coming of these clever robots – a future that has been called 'robo-geddon' by some commentators (see Brown Review, 2019).

For simplicity, we refer to this type of AI-enabled advanced automation as 'AI-enabled' or simply 'AI' to distinguish it from other non-AI-enabled technology. A key issue, and the focus of this Research Note, are the methodological challenges in measuring AI-enabled technology's impact on jobs within organisations. In Europe at least, there is no administrative dataset or statutory survey dedicated to the impact of AI on jobs at the organisational level. Datasets that do include items on job-related new technology and innovation do not allow in-depth examination of the effects of these on jobs (Napolitano and Greenan, 2021). Two main methodological approaches have emerged: (1) studies using econometric modelling and forecasting, (2) studies using proxies within existing datasets. Neither enable analysis of actual developments to jobs within organisations introducing AI specifically. As a consequence, there is an important gap in empirical understanding. This Research Note proposes a third methodological approach – the use of bespoke employer surveys – and illustrates the potential contribution of this approach drawing on a new and unique UK employer survey.

The Research Note first discusses some of the methodological challenges in investigating the impact of AI on jobs. The UK employer survey is then outlined in the following section, which also presents descriptive findings to demonstrate the utility of the third methodological approach. The concluding section offers suggestions for how this approach can be developed in future research.

Challenges in measuring the effect of AI on jobs

This section outlines the limitations of the two main types of existing research that analyses the potential effects of AI on jobs and how a third approach can offer better understanding.

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Studies using econometric modelling

Following influential research by Frey and Osborne (2013, 2017), the econometric modelling in this type of study is based upon a number of subjective assumptions about the capabilities of new technologies, particularly advancements in AI. Experts are asked to judge whether a subsample of occupations are automatable by digital technology taking account of AI 'engineering bottlenecks', that is, tasks or competencies thought not to be automatable by AI. Machine learning is then used to estimate the risk of remaining occupational categories being automated. Subsequent studies either use the insights from the Frey and Osborne study incorporating different modelling assumptions or employ a similar approach using their own expert 'foresight' workshops. Depending upon modelling assumptions, estimates of jobs at risk of automation range from the alarming - 47% for the US and 35% for the UK (Deloitte, 2014; Frey and Osborne, 2017) - to the more circumspect 9% of jobs in OECD countries (Arntz et al., 2016).

These studies have several limitations. First, while the methodology used allows for systematic modelling of occupations and tasks at risk, the modelling is still based on subjective judgements about the capabilities of technology, judgements which often prove to be overly optimistic (Arntz et al., 2016). Second, modelling tends to consider only the technical capabilities of technology and ignores firm adoption rates and uses, which depend on economic, social and cultural factors (Brynjolfsson et al., 2018; Manyika et al., 2017). Third, such approaches fail to consider that many automatable parts of jobs have already been automated by previous technology (Arntz et al., 2019) or that cost reduction through technology may lead to the reshoring of jobs previously offshored to low-wage countries (Krenz et al., 2020). Finally, these studies often fail to take into account job creation effects of technology. Technology can complement as well as substitute labour, increasing productivity, lowering prices, stimulating demand and creating jobs (Autor, 2015; Levy, 2018). Only two studies using this approach have attempted to predict creation effects alongside substitution effects (Bakhshi et al., 2017; Manyika et al., 2017) but are arguably more prone to subjectivities as it is difficult to predict what new occupations may emerge in future. At best, this type of study offers insights into what *might happen* to jobs as a consequence of AI.

Studies using administrative and panel data

There have been relatively few studies of this second type. Given the lack of measures of AI specifically in existing datasets (Napolitano and Greenan, 2021), it is unsurprising that studies that do attempt to analyse organisation-level effects on jobs use proxy measures, such as spending on 'machine-based digital technologies' (Balsmeier and Woerter, 2019), 'automation services' (Bessen et al., 2019) or imports of 'automation intensive goods' (Domini et al., 2020). As a consequence, a wide range of technologies are enveloped, including robots, autonomous vehicles, CNC/DNC machines, 3-D printers and computerised automated control systems.

While administrative data incorporates broadly objective measures – and time series data that can aid in the attribution of causality – they do not measure the impact of AI specifically. Clearly 'automation services' and 'advanced computer-controlled machines' could include a wide range of technologies, not all of which involve AI. Moreover, a number of applications that do use AI would not be included in these designations (e.g. chatbots, the use of machine learning in HR process, etc.) meaning the effects observed may have more to do with existing technologies such as industrial robots than technologies driven by advances in AI. Thus, while this second type of research can reveal what is happening in organisations that introduce technology, they are unable to say anything about the specific impact of AI.

Potential contribution of bespoke employer surveys

Thus, extant research only indicates either what might happen in organisations introducing AI or what happens in organisations introducing technology more broadly. There is a significant gap in empirical understanding of what is currently happening to jobs in organisations that introduce AI specifically. A third methodological approach may go some way to address this problem – the use of bespoke employer surveys. Employer surveys are a common and valued form of firm-level data generation internationally (e.g. Kerr and Kerr, 2020; McGuirck et al., 2015), and are used extensively to examine developments to jobs (e.g. Holm et al., 2020).

We have already noted the lack of existing organisation-level data adequately capturing the impact of AI on jobs. A bespoke employer survey that undertakes this task offers a number of advantages. First, it enables research to drill down to focus on adoption of AI-enabled technologies specifically. Second, given that it is employers who provide jobs and who make decisions about introducing new technology, they can be a valuable source of detailed information about the why, what and how of that introduction. While these advantages are significant, it is also important to note the corresponding limitations. First, while careful development and piloting of questions can capture the intended measures of interest, questionnaire items may not always be understood as intended. Second, while employer surveys can explore potential effects in detail, self-reports are to some extent subjective. Respondents may provide answers that are socially desirable or simply incorrect. Third, bespoke surveys can be time-consuming and expensive, and so not always feasible, particularly where longitudinal data is required. Longitudinal data, capturing key measures over time, allows research to control for firm-level variation in factors related to the outcome of interest and enabling identification of effects that take longer to accrue. Attribution of causality in its absence is therefore difficult.

Despite these limitations, self-report data from cross-sectional employer surveys have a long history of providing valuable insights into a range of issues related to technology use and innovation in firms, including: the effect of ICT, process and office automation, and new plant and machinery on jobs (Newton, 1989; Blanchflower and Burgess, 1998; Tambe et al., 2012; Dinlersoz and Wolf, 2018), and the impact of innovation on flexible work practices (Wachsen and Blind, 2016). These examples reveal how this methodology can provide insights in relation to phenomena that are not routinely captured in administrative data or existing statutory surveys and provide the empirics absent from forecasts and predictions.

The remainder of this Research Note illustrates this third approach by investigating the association between AI investment and the self-reported effects at the organisational level, drawing on data from a new and original bespoke survey of UK business leaders.

The research

This section outlines the data and measures used in the study and presents some descriptive findings.

Data

The *Investment in Work Technology Survey* was designed by the authors in collaboration with the Chartered Institute for Personnel and Development and administered by YouGov in 2018, achieving 759 eligible responses. At that time, there was no other survey in the UK dedicated to capturing the introduction of AI and other new technologies in organisations and focused on jobs.

The sample was drawn from a YouGov panel of more than 850,000 British adults in the UK.[1] The survey sample was selected from the contact database using a random selection method based on the following eligibility criteria: business leaders (i.e. board-level management) in organisations with ten or more employees across the private, public and third sectors. The sample (Appendix, Table A.1) was weighted to be representative of the eligible population in terms of size (i.e. number of employees) and sector (i.e. private, public, third) using a poststratification weight based on 2017 ONS figures.[2]

Survey questions focused on organisations' recent investments in technology (AI and other new technologies), its implementation and perceived impacts. The development of the survey instrument drew on a review of existing related surveys and inputs from a steering group consisting of industry experts. The survey instrument was piloted with 48 business leaders in order to test operation of the questionnaire and comprehension of key measures, including those related to the adoption of AI and the other technologies covered.

Measures and definitions

The first key measure is whether organisations had invested in AI or other new technologies. A multi-response question asked respondents to indicate from a list all the new technologies in which they had invested during the last five years (including options for other and none) (Fig. 1). Response categories were designed to capture new technological changes and not maintenance upgrades. Two response categories were designed to capture AI-enabled advanced automation:

- *'Introduced AI, robotic or automated equipment to undertake a physical task'*
- *'Introduced AI, robotic or automated software to undertake a cognitive/non-physical task'*

AI was defined in a previous question as technology 'which is able to learn from data, reasoning or self-correction' and relates to Manyika et al.'s (2017: 2) definition of robotics ('machines that perform physical acts') and AI ('software algorithms that perform calculations and cognitive activities'). Overall, a quarter of respondents (25%) had introduced some form of AI technology during the last five years, either equipment to do physical tasks (15%) or software to do cognitive tasks (21%). Eleven per cent had introduced both. Our measure finds a degree of external validity in the European Enterprise Survey (European Commission, 2020), conducted two years later and covering private sector organisations only, which found an AI adoption rate in the UK of 34%.

The second key measure aimed to identify whether the organisation's introduction of AI-enabled technologies had led to any job creation or destruction in the organisation. Respondents who had introduced any new technology were asked:

- *'Has the introduction of […] created any jobs in your organisation?'* (job creation)
- *'Has the introduction of […] eliminated or replaced any jobs in your organisation?'* (job destruction).

In cases where both job creation and job destruction had occurred, respondents were asked:

- *'Overall, has the introduction of […] led to more or fewer jobs in your organisation?'* (overall effect)

Note that these questions are worded in such a way as to indicate that the business leaders felt that the job creation/destruction was a consequence of the named technology. In organisations introducing AI these questions asked about AI; in organisations not introducing AI these questions asked about the technology that involved the greatest change in the tasks staff undertake or how work is organised. For the multinomial logistic regression described in the following section, if the technology had led to job destruction only or the overall effect was fewer jobs, this outcome was defined as 'Net destruction'. If the technology led to job creation only or the overall effect was more jobs, it was defined as 'Net creation'. If there had been no job creation or destruction, or if there had been both but the overall effect was 'about the same', this outcome was defined as 'No change'. Descriptive statistics for the key outcome measures can be seen in Table 1. Full descriptive statistics, including control variables are included in the supplementary appendix (Appendix, Table A.2).

The analysis

This section presents analysis of whether the introduction of AI-enabled technology is more likely to be associated with job destruction or creation than other types of new technology.

Bi-variate analysis indicates that organisations introducing AI-enabled technology (sometimes alongside other technologies) were more likely to report job destruction (44%) and creation (46%) compared to organisations that invested in other technology (but no AI) (6% and 11% respectively) (Table 1). When considering net change, 22% of organisations introducing AI reported net creation and 22% reported net destruction, compared to 9% net creation and 4% destruction amongst organisations introducing technology but no AI.

However, the AI adoption and other (non-AI) technology groups vary by organisational characteristics (Appendix, Table A.2). Relative to those investing in other technologies but not AI, organisations investing in AI tend to be: private sector, larger, newer, have higher (or very low) financial turnover; are relatively technology intensive (computers and handheld devices) and in the manufacturing/construction or the legal/financial/media/marketing/sales industries. These organisational differences may have a role to play in the job destruction and creation.

Therefore, binary and multinomial logistic regression was used to investigate whether the propensity to report job creation/destruction was higher in organisations introducing AI compared to those introducing other technologies but no AI, while controlling for organisation-level characteristics. Concerns have been raised about interpretation of odds ratios in logistic regression when comparing estimates between groups due to unobserved heterogeneity (Mood, 2010). However, this concern is lessened when reporting marginal effects and when the focus is on the significance and direction of associations rather than size and causality (Kuha and Mills, 2018). While our analysis cannot prove causation due to potential endogeneity and simultaneity, it can reveal whether business leaders introducing AI were more likely to report that its introduction had led to more or fewer jobs in the organisation. Given the lack of availability of any other survey data that specifically captures AI introduction and the reported effects, this data provides otherwise lacking insights into what happens within these organisations in the short term.

First, logistic regression analysis was conducted with a binary dependant variable that takes value 1 where the organisations experienced job destruction and 0 otherwise, as explained in Eq. (1). The job destruction dummy is regressed on the dummy indicating whether an organisation invested on AI-enabled technology or any other technology (but not AI), denoted by AI_dummy_i in the equation. The analysis was repeated with a dummy for job creation in which the dependant variable took the value of 1 where jobs were created and 0 if jobs were not created. This analysis allows estimation of the association between AI_dummy and the outcome occurring while holding other factors in the model constant. Two regression equations were modelled separately for

[1] Details about the panel and how it is compiled can be found on the YouGov website: https://yougov.co.uk/about/panel-methodology/.

[2] https://www.gov.uk/government/statistics/business-population-estimates-2017.

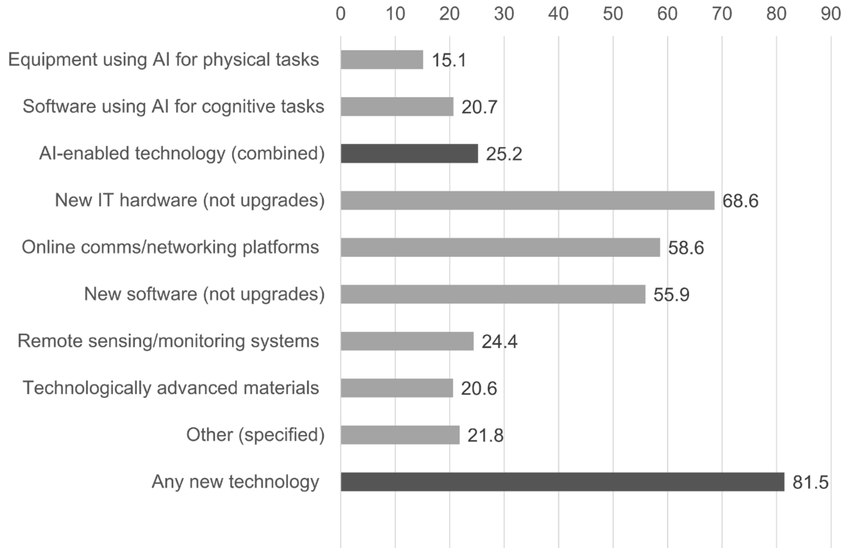

Fig. 1. Investments in AI and other technologies during the last five years (%)*.
Base: All respondents (n = 759): Bases exclude item non-response (Dont know).
Note: *respondents could tick multiple technologies in this question.

Table 1
Job creation and destruction.

	AI	Other new technology*
Job creation/destruction (self-reported)		
Creation only	10.1	7.8
Destruction only	7.6	3.1
Creation and destruction	36.3	3.1
No creation or destruction	44.9	86.0
Net job creation/destruction		
Net creation	21.5	8.8
Net destruction	22.2	4.4
No change	56.3	86.6
Base, N	183	425

Base: Organisations introducing technology during the previous five years.
Note: *'AI' includes those who introduced other technologies alongside AI; 'other technologies' includes those who introduced any other technology but no AI.

job destruction and job creation.

$$E\left(JobDestrucion_{dummy_i}\right) = Prob\left(JobDrestruction_{dummy_i} = 1\right) = F\left(Org_i,\ AI_{dummy_i},\ Error_i\right) \quad (1)$$

Control variables in Org_i include: organisation size, age and gross revenue, industry and sector, and the gender and age composition of employees, skill composition, and use of computers and handheld devices (a proxy for technology use). Skill composition within the organisation was self-reported by respondents as either: 'Mostly high skilled (university level or higher)', 'Mostly intermediate skilled (A-Level, NVQ 3 level, apprenticeships)', 'Mostly lower skilled (GCSEs, NVQ level 2, basic skills or lower)' or 'A range of skills levels'.

Marginal effects from the binary logistic regressions are presented in Table 2 (models 1 & 2). The results show that the association between AI introduction and job destruction and creation was statistically significant. Compared to the introduction of other technology, the introduction of AI is 28.4 percentage points more likely to be associated with job creation. Similarly, introduction of AI is 26.6 percentage points more likely to be associated with job destruction compared to introduction of other technology.

However, job creation and destruction in an organisation are not different processes, they are simultaneously determined.[3] Furthermore, the above model does not differentiate between those organisations that experienced only creation or destruction and those that experienced both. Therefore, in the second analysis a multinomial logit model was estimated to consider the two processes together using the three net job change categories (c) outlined in the previous section: 1) Destruction but no creation, 2) Creation but no destruction, and 3) No net change (the reference category).

The probability of the occurrence of job change category c by organisation i is given by:

$$E(JobChange_i) = Prob(JobChange_i = c) = F(Org_i,\ AI\_dummy_i,\ Error_i) \quad (2)$$

Where $c \in \{1, 2, 3\}$.

The Multinomial logit model (Table 2, models 3 & 4) found similar results to the binary model – net job destruction and net job creation were more likely to be associated with the introduction of AI than other technology (but no AI). Although the marginal effects of AI_dummy suggest slightly higher association between AI introduction and job creation than job destruction, the difference, when tested by changing the reference category to net creation, was not statistically significant ($p = 0.583$). This finding implies that AI is equally likely to be associated with job creation as job destruction compared to other non-AI technology.

Concluding remarks

Developments in workplace-based AI-enabled technology have prompted concerns that a growing number of jobs are at risk of technological substitution resulting in mass unemployment. However, the methodologies used to analyse this possibility do not present data on what is happening to jobs in organisations that introduce this technology. Instead, studies either are based on modelling predictions infused with subjective judgements of what might happen or draw conclusions

[3] A bivariate probit model that considers job creation and destruction as a simultaneous process found similar results to the bivariate logistic regression (Appendix, Table A.3).

Table 2
Self-reported job destruction/creation as a consequence of the introduction of technology, Logistic and multinomial logistic regression (marginal effects).

	Logit		Multinomial logit	
VARIABLES	(1) Job creation	(2) Job elimination	(3) Net elimination	(4) Net creation
Technology introduction (Ref: Other technology)				
AI	0.284***	0.266***	0.117***	0.158***
	(0.039)	(0.036)	(0.028)	(0.036)
Sector (Ref: Private)				
Public sector (e.g. civil service, local government)	−0.108	−0.057	−0.068	−0.057
	(0.089)	(0.074)	(0.056)	(0.077)
Third sector- non-profit, non-governmental (e.g. charity, social enterprise)	0.211*	−0.012	−0.093	0.019
	(0.110)	(0.117)	(0.110)	(0.120)
Organisation age (Ref: 10 years and less)				
Over 10 to 20 years	−0.072	−0.076	−0.035	−0.060
	(0.061)	(0.055)	(0.041)	(0.056)
Over 20 to 35 years	−0.060	−0.067	−0.080*	−0.074
	(0.063)	(0.058)	(0.047)	(0.059)
Over 35 to 100 years	−0.150**	−0.162***	−0.063	−0.077
	(0.066)	(0.062)	(0.045)	(0.058)
Over 100 years	−0.113	−0.058	−0.001	−0.047
	(0.072)	(0.064)	(0.046)	(0.064)
Organisation size (Ref: 10 to 49)				
50 to 249	0.028	−0.010	0.070	0.003
	(0.065)	(0.061)	(0.052)	(0.060)
250 to 999	0.081	0.021	0.052	0.072
	(0.068)	(0.063)	(0.054)	(0.062)
1000 or more	0.121	0.052	0.088	0.088
	(0.075)	(0.071)	(0.057)	(0.069)
Turnover (£) (Ref: Below 250,000)				
250,000 to 1.9 million	−0.144	−0.166*	−0.013	−0.090
	(0.098)	(0.088)	(0.071)	(0.092)
2 to 9.9 million	0.006	−0.053	0.032	0.056
	(0.084)	(0.075)	(0.060)	(0.079)
10 to 99.9 million	−0.050	0.002	0.045	0.028
	(0.084)	(0.074)	(0.059)	(0.078)
100 to 999.9 million	−0.051	0.078	0.114*	0.037
	(0.090)	(0.080)	(0.062)	(0.084)
1 billion or more	0.016	0.123	0.087	0.073
	(0.098)	(0.088)	(0.068)	(0.091)
Industry (Ref: Education and health)				
Legal/finance/media/ professional services	−0.023	0.047	0.037	−0.051
	(0.077)	(0.072)	(0.060)	(0.067)
Transport/retail/ hospitality/leisure	0.036	0.168**	0.115*	0.031
	(0.084)	(0.074)	(0.060)	(0.073)
Manufacturing/ construction	0.142*	0.105	0.101	0.089
	(0.081)	(0.075)	(0.062)	(0.072)
IT/telecom/other	−0.000	0.123*	0.122**	−0.015
	(0.080)	(0.074)	(0.060)	(0.071)
Workforce gender composition (Ref: Mostly Male)				
Mostly female	−0.054	0.044	0.070	−0.019
	(0.067)	(0.059)	(0.045)	(0.060)
Fairly balanced	−0.028	0.059	0.037	−0.042
	(0.043)	(0.039)	(0.031)	(0.038)
Workforce age composition (Ref: Mostly younger (30 or under))				
Mostly mid-career (31–49)	−0.072	−0.012	0.000	−0.010
	(0.059)	(0.052)	(0.040)	(0.055)
Mostly older (50 and above)	−0.068	−0.027	0.022	−0.005
	(0.085)	(0.076)	(0.055)	(0.079)
A range of ages	0.018	−0.035	−0.041	0.065
	(0.063)	(0.055)	(0.043)	(0.058)
Workforce skills composition (Ref: Mostly high skilled)				
Mostly intermediate skilled (A-Level, NVQ 3 level, apprenticeships)	−0.016	0.095*	0.043	−0.044
	(0.055)	(0.050)	(0.039)	(0.049)
Mostly lower skilled (GCSEs, NVQ level 2, basic skills or lower)	−0.136*	0.071	0.081*	−0.168**
	(0.071)	(0.059)	(0.043)	(0.071)
A range of skills levels	−0.045	0.042	0.047	−0.083*
	(0.049)	(0.045)	(0.035)	(0.044)
Proportion of staff that regularly work with computers (Ref: 50% or more)				
25% to 50%	−0.018	0.046	0.036	−0.024
	(0.053)	(0.045)	(0.033)	(0.049)
25% or less	−0.162*	−0.069	−0.056	−0.123
	(0.089)	(0.078)	(0.059)	(0.083)
Proportion of staff that regularly work with handheld devices (Ref: 50% or more)				
25% to 50%	−0.082*	−0.078*	−0.056*	−0.026
	(0.048)	(0.044)	(0.033)	(0.044)
25% or less	−0.056	−0.006	0.004	−0.001
	(0.052)	(0.047)	(0.034)	(0.046)
Pseudo R^2	0.186	0.249	0.183	
Observations	547	549	528	528

Base: Organisations introducing technology during the previous five years; Bases exclude item non-response (‘Don’t know ’)
Note: Significance levels for marginal effects: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$. Standard errors in parentheses.

from organisation-level data using proxy measures that do not fully distinguish between AI and non-AI technology. Whilst these studies undoubtedly offer insights and usefully prompt further analyses, understanding needs to move beyond predictions and proxies.

This Research Note argues that a third approach using bespoke employer surveys can help address the gap in empirical understanding and provide data on what is happening in organisations. Whilst having their own limitations, such surveys are recognised to be useful generally and, in the absence of any data specifically measuring AI adoption in organisations and its effects on jobs (Napolitano and Greenan, 2021), are vital not just to advance scientific understanding but to inform policy thinking. Their value has been illustrated here drawing on a new UK employer survey which reveals that organisations introducing AI have higher rates of both job creation and destruction compared to organisations introducing non-AI technology. It also shows that this job creation is just as likely as job destruction. These findings might allay fears about workplace AI. Importantly, not only do these findings offer proof of methodology in being able to provide such data, the approach extends the long tradition of using employer surveys to capture technological innovation to now encompass AI.

We make no claim of causality from our findings. Investment in AI is not randomly determined by organisations, it is an endogenous process. In the absence of a natural experiment and longitudinal data it is impossible to attempt to estimate the causal effect of AI adoption on employment creation/reduction. Instead, this research demonstrates how such a methodology helps understand the extent of AI use within organisations at a given point in time and is a step towards understanding how the introduction of AI-enabled technology can have different implications for organisations compared to other technologies. The findings also suggest areas for future research. Future research employing this methodology could be useful to understand more about why some firms adopt AI, the issues they face in the adoption process, how these factors effect jobs and the mechanisms by which effects on jobs occur. The addition of a longitudinal element would allow researchers to observe of the same organisations over time and to investigate if AI technologies really do raise new and different questions about work and the adoption process compared to previous general-purpose technologies, such as ICTs.

CRediT author statement

Wil Hunt: Conceptualization, Methodology, Data Curation, Validation, Writing - Original Draft **Sudipa Sarkar**: Conceptualization, Methodology, Formal analysis, Writing - Original Draft **Chris Warhurst**:

Supervision, Funding acquisition, Writing - Review & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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