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Artificial Intelligence, Job Quality and the Trade Union Effect: Evidence from linked Employee-Employer Data in the United Kingdom

Abstract

This paper investigates the relationship between AI-enabled digital technology and two components of intrinsic job quality: work autonomy and emotional well-being at work. Using probabilistic methods, we link a nationally representative employers' digital practices at work survey and Understanding Society, a representative household survey in the United Kingdom. Multilevel regression analysis revealed that AI investment is associated with higher wellbeing and lower work autonomy depending on technology type. Notably, while the adoption of cloud computing can positively influence employees' emotional wellbeing, investments in AI-enabled software and applications are negatively associated with work autonomy. Trade union membership and sectoral union density moderate these relationships, underscoring the importance of worker voice in mitigating the adverse effects of AI and maximizing its benefits for workers.

Keywords:

AI, wellbeing, work autonomy, labor unions, job quality, probabilistic linkage

Introduction

Debates on the rise of Artificial Intelligence (AI) and the future of work are marked by contrasting perspectives. Optimistic accounts of new opportunities for skill development and higher quality jobs (Brynjolfsson and Mitchell 2017) contrast with risks of widespread job displacement, increased managerial control and ethical concerns associated with a growing use of AI at work (Bailey 2022). Earlier waves of digitalization improved job quality while also producing negative outcomes such as work intensification and work-related stress (Bader and Kaiser 2017; Patel et al. 2018). Emerging evidence on the impact of AI is inconclusive and lacks representative data on the effect of employers' actual decisions to invest in AI.

This study examines the relationship between employer investment in AI in the United Kingdom and two dimensions of intrinsic job quality: work autonomy and work-related emotional wellbeing. Drawing on the view of technology as both enabling and constraining (Orlikowski 1992), we ask three inter-related questions. First, can employers' decisions to invest in AI simultaneously enhance and erode employees' job quality? Second, does this relationship vary across different types of AI technology? Third, recognizing the role of power relations at work (O'Brady and Doellgast 2021), do labor unions moderate the relationship between AI investment, work autonomy and employee wellbeing?

Existing empirical evidence relies heavily on worker level data and offers limited insight into patterns of employer investment in AI. To address this gap, we use probabilistic linkage methods to integrate data from a nationally representative employer survey on technology adoption, the Digital Practices at Work Survey, with data from a long running household panel survey in the United Kingdom, Understanding Society. The use of a dedicated employer survey allows us to measure AI investment directly and to distinguish between different forms of technology, including AI powered equipment, software and algorithms, business support tools and cloud computing.

Overall, our contribution to the growing literature on the consequences of AI adoption for job quality (Bryson, Kauhanen, and Rouvinen 2026; Rohenkohl and Clarke 2023; Schulz et al. 2026) is twofold. First, we move beyond worker-reported technology use and examine the effect of employer investment in different types of AI technology. Second, we theorize the role of labor unions at individual (union membership) and sectoral (union density) level and empirically estimate their interplay with different types of AI technology.

Theoretical background

AI, duality of technology and job quality

The implications of technological change for the quality and quantity of jobs have been widely studied. Contemporary economic analysis is grounded in the Skill-Biased Technological Change (SBTC) and Routine-Biased Technological Change (RBTC) narratives, which posit that technology's ability to displace or augment human labor depends primarily on the nature of tasks (Acemoglu 2002). The focus is primarily on job displacement and wages where automation has a polarizing effect with expansion of high- and low-quality jobs and erosion of routine occupations in the middle. Advancements in machine learning and AI have sparked debates about the implication of these novel technologies (Brynjolfsson and Mitchell 2017; Acemoglu and Restrepo 2019). Early studies, citing the impressive capabilities of machine learning and mobile robotics in handling cognitive, non-routine tasks, predicted job displacement on an unprecedented scale (Frey and Osborne 2017).

However, as these technologies integrate into workplaces, such radical expectations appear increasingly misplaced, and recent studies recognize a more complex relationship between technology and work (Berg et al. 2023; Litwin et al. 2022; Schulz et al. 2026). Accordingly, the debate has shifted toward understanding the conditions under which digital transformation can augment human labor, enhance productivity and improve skill utilization (Berg et al. 2023; Holm and Lorenz 2022). Yet, the influence of technological determinism (whereby technology is seen as the primary driver of changes in employment and job quality) on academic and policy debates remains significant.

Our argument is sociologically grounded, recognizing the influence of social forces, organizational norms and managerial decisions in shaping the outcomes of technological change (Wajcman 2006; Howcroft and Taylor 2023; Joyce et al. 2023). Orlikowski's (1992) seminal work proposed the *duality of technology* principle, which characterizes technology as having both enabling and constraining features, thereby leading to non-deterministic implications for job quality. That is, the use of technology in organizations is not a fixed tool with predetermined effects; rather, the consequences of technology investment emerge through the interplay of management agency and organizational and institutional contexts that shape how technology is developed and implemented (Hyman and Streeck 1987; Mazmanian, Orlikowski, and Yates 2013; Orlikowski and Gash 1992; Scott and Orlikowski 2025).

While the duality of technology approach has proved influential in studies of digitalization and employee outcomes, empirical analysis to-date has focused mainly on the use of Information and Communication Technology (ICT) rather than AI (e.g., Day et al. 2012; Derks and Bakker 2014; Castellacci and Tveito 2018; Pfaffinger et al. 2020). Extrapolating the results of these studies to AI is challenging. Powered by machine learning and continuous flows of data, AI can transform digital communication and perform cognitive tasks that were previously inaccessible to conventional ICT (Myers 2024). This is likely to have significant consequences for job quality beyond those observed in more traditional ICT environments.

Emerging literature tends to focus on extrinsic, objective dimensions of job quality such as working time, job displacement and pay (Berg et al. 2023; Schulz et al. 2026). Industrial relations research on the implications of AI for more subjective, intrinsic components of job quality is only beginning to emerge. In line with this nascent research (for example, Bryson, Kauhanen, and Rouvinen 2026), we focus on two dimensions of intrinsic job quality: (i) workers' discretion over when, where and how work is performed (work autonomy); (ii) employee wellbeing proxied by "people's feelings about themselves in relation to their job." (Warr 1990, p. 393).

The dual focus on autonomy and wellbeing is consistent with the literature on the enabling and constraining effects of technology, where technologies are understood to reshape workers' lived experiences of work and their control over tasks, pace, methods of work and working time (Orlikowski 1992; Mazmanian et al. 2013). It is well documented that in digitally advanced industries, technology investment can create demands for constant availability and the ability to communicate from anywhere, leading to the blurring of work-life boundaries (Derks and Bakker 2014; Mazmanian, Orlikowski, and Yates 2013). While digitalization can offer opportunities for flexible working arrangements, greater autonomy and higher overall job satisfaction, it may also result in increased work intensity and a diminished ability to disconnect (Bloom et al. 2014; Felstead and Henseke 2017; Hassard and Morris 2022; Kelliher and Anderson 2010). Thus, the introduction of AI-enabled communication technologies can enhance autonomy regarding work location and schedule while simultaneously facilitating non-hierarchical monitoring and peer-based control (Leclercq-Vandelannoitte, Isaak, and Kalika 2014; Mazmanian, Orlikowski, and Yates 2013), potentially leading to negative consequences for employee well-being (Becker et al. 2019; Siegel, Konig, and Lazar 2022).

The material features of technology also play a crucial role, albeit again in conjunction with how employees and managers engage with them (Scott and Orlikowski 2025). For instance, while email software enables monitoring of electronic correspondence and enforces constant availability, wearable devices provide employers with additional means to track workers' exact locations, movement patterns, frequency of engagement, and even health-related data such as heart rate and fitness levels (Mau 2017). The increasing use of advanced computing services, such as cloud computing, removes technological barriers inherent in traditional ICT and expands the potential for blurring work-life boundaries (Myers 2024). Enhanced data processing capabilities, pattern and image recognition, real-time analysis and granular monitoring enabled by AI-powered technologies (Charlwood and Guenole 2022; Zuboff 2019) may contribute to greater tension and anxiety among employees (Wright and Lund 2008). However, cloud computing can also reduce stress by ensuring secure data storage, eliminating the need to transfer and transport information via hardware devices that can be lost or damaged.

In more traditional manufacturing settings, automation through robotics can relieve employees of routine tasks, allowing them to focus on more meaningful, autonomous work (Gekara and Nguyen 2018; Green 2012), thereby enhancing work-related well-being (Smids, Nyholm, and Berkers 2020). However, robotics can also have adverse effects. First, concerns about job displacement have been linked to negative mental health outcomes among workers (Nikolova, Cnossen, and Nikolaev 2022). Second, as demonstrated in logistics warehouses, robots can drive work intensification by dictating employees' work pace and direction, ultimately increasing job strain (Muldoon, Graham, and Cant 2024).

Beyond platform work, mechanisms of algorithmic control are increasingly evident in more traditional organizational settings (Krzywdzinski, Evers, and Gerber 2024; Zhang et al. 2025). In already mentioned logistics warehouses and retail, algorithmic systems can be used to allocate, standardize tasks and evaluate performance. This can result in increased work intensity and diminished well-being (Gregory 2021). At the same time, AI software also creates new work opportunities, particularly for knowledge workers. Interacting with generative AI (e.g., ChatGPT, Microsoft Co-Pilot) enables workers to generate or refine content, streamline tasks and foster creativity (Brynjolfsson and Mitchell 2017). These interactions may have a positive impact on skill utilization, working time and, consequently, worker well-being.

Against this backdrop, we hypothesize that the association between employer investment in AI technology and the two dimensions of intrinsic job quality (employee wellbeing and work autonomy) is contingent on the type of AI technology. In line with the duality of technology argument, we do not hypothesize the specific direction of these effects expecting both positive and negative consequences of AI for job quality to manifest in the empirical analysis.

Hypothesis 1: Employer investment in AI technology is associated with work autonomy, with the direction and magnitude of this association varying by technology type.

Hypothesis 2: Employer investment in AI technology is associated with employee wellbeing, with the direction and magnitude of this association varying by technology type.

The trade union effect

Underlying the duality of technology thesis is the principle that "codes and algorithms are neither objective nor neutral" (Pettersen 2019, p. 1059). Rather, they reflect the values and intentions of those who design and implement them, thereby emphasizing the role of both agency and structure. Hypotheses 1 and 2 examine AI technology in relation to employer agency and the decisions employers make when investing in AI. As the effects of technology use on employee well-being are "highly context-dependent" (Rohenkohl and Clarke 2023), we extend this argument by theorizing the union effect as a moderator in the relationship between AI investment and employees' intrinsic job quality.

Orlikowski (1992) insists that the organizational outcomes of technology adoption are "a function of the institutional context in which the technology is developed and used, and the power, knowledge, and interests of human actors" (p. 409). The balance of power in the employment relationship is particularly relevant, as trade unions can help mitigate the demands imposed by digital technologies, increase employees' sense of control (Wood 2008) and reduce stress (Bakker et al. 2003; Conway et al. 2016). Industrial relations researchers have long emphasized benefits of union membership. Freeman and Medoff (1984), for example, argue that unions and their representatives can "encourage procedural justice" (p. 308) by serving as a "countervailing labor power in the firm and workplace" (p. 308).

In this capacity, unions can rebalance the power relationship between workers and employers through distinct mechanisms operating at the individual and sectoral levels (Benassi and Vlandas 2022; Berg et al. 2023; Kornelakis, Kirov, and Thill 2022). At the individual level, union membership can support worker-centered, high-road human resource practices which can improve employee wellbeing and enhance worker discretion (Appelbaum et al. 2000; Budd, Gollan, and Wilkinson 2010). Through representation, formal recognition and collective bargaining rights, union members may be better protected from dismissal than non-union workers (Doellgast and Benassi 2020), which can reduce fears of job displacement associated with automation and AI. Such employment security may mitigate anxiety and uncertainty, which are key channels through which technological change can undermine wellbeing (Nikolova, Cnossen, and Nikolaev 2022).

In unionized workplaces, employees are also more likely to receive adequate digital and data literacy training, enhancing their digital skills and reducing anxiety associated with technological change (Haepp 2022; Green 2012; Litwin 2011, 2015). As Wood (2008) argues, unions can act, and be perceived by their members, as supportive organizations. This support may alleviate stress and help workers cope with increased job demands associated with technological change. O'Brady and Doellgast (2021) reach a similar conclusion in their study of electronic performance monitoring and employee wellbeing in U.S. call centers, showing that voice can mitigate the negative consequences of monitoring for workers.

We hypothesize that union membership supports worker-centered human resource practices, information flows and governance structures that are protective of workers. Union membership is therefore expected to ameliorate the negative effects of technology and amplify its positive effects.

Hypothesis 3: Union membership moderates the relationship between AI technology and intrinsic job quality, such that higher levels of union membership weaken the negative effects of AI on work autonomy and employee wellbeing and strengthen its positive effects.

At the industry level, union density captures a broader institutional mechanism through which collective labor power and negotiated regulation can improve job quality. As Benassi and Vlandas (2022) show, union effects may operate not only through individual membership but also through sectoral institutions and bargaining coverage that shape employment conditions beyond the individual workplace. In the United States, Kochan et al. (2024, p. 8) note that the AFL-CIO, America's largest union confederation, has established a Technology Institute with the explicit purpose of "advancing worker and union voice across the full spectrum of issues related to new technologies in the workplace." In the United Kingdom, recent decades have been characterized by declining union density and fragmented collective bargaining, where the liberalization of employment standards has weakened the power of collective voice (Dundon 2019; Valizade, Ali, and Stuart 2023). Yet, while the United Kingdom lacks a long-standing corporatist tradition, institutions of collective bargaining continue to operate in some industries (McLachlan, Stuart, and MacKenzie 2025; Valizade, Ingold, and Stuart 2023).

In sectors where union density is high and collective bargaining remains significant unions may influence the implementation of AI technologies by negotiating safeguards and standards that protect workers from algorithmic harm. Labor unions have actively campaigned for a worker-centered approach to AI adoption, emphasizing the need for regulatory "guardrails" to protect workers from AI-related risks at work (TUC 2025). These collective interventions can help offset potential declines in job quality associated with AI investment. Stronger unions, particularly where membership density is relatively high, may also influence how technologies are deployed, securing gains in work autonomy and limiting work intensification (Bryson, Barth, and Dale-Olsen 2013).

We therefore expect higher levels of union density to strengthen unions' capacity to influence the governance and regulation of technological change. Thus, sectoral union density may mitigate the negative consequences of AI and help ensure that its benefits are shared more equitably between workers and employers.

Hypothesis 4: Union density moderates the relationship between AI technology and intrinsic job quality, such that higher levels of union density weaken the negative effects of AI on work autonomy and employee wellbeing and strengthen its positive effects.

Across Hypotheses 1-4 our conceptual contribution lies in disaggregating relationships that are often considered jointly in debates on technology and job quality. First, we distinguish between different forms of AI-enabled technology, recognizing that equipment, software and AI-powered forms of information storage and communication (e.g., cloud computing) may have different effects on autonomy and wellbeing. Second, we distinguish between two mechanisms by which labor unions can affect these relationships. Union membership captures the impact of representation and support located primarily in the workplace while industry-level union density captures the institutional power resources through which unions negotiate conditions and boundaries of AI investment and use.

Methodology

Data

Our analysis draws on linked, representative employer and employee level datasets. Employer data comes from an original, nationally representative survey of employers in the United Kingdom collected between November 2021 and September 2022: the Digital Practices at Work Survey (DPAW). The survey employed Computer Assisted Telephone Interviews (CATI) based on a stratified (by industry, region and firm size) sample drawn from the Dun and Bradstreet global database, with over 500 million records that contains population level data on registered private enterprises and non-private organisations. Interviews were conducted using a structured questionnaire with a general manager, human resource manager or any person at the establishment level overseeing human resources and, where applicable, investment in digital technology. The response rate was 35 per cent and an average interview lasted 27 minutes, resulting in an achieved sample of 2001 employers. The most common managerial roles interviewed were general managers (34% of respondents), HR managers (14.6%) and partners or directors (13%). Given the response rate and diversity of roles among interviewees, we conducted several checks to ensure that the respondent's job role does not materially affect the outcome of our analysis. We controlled all regression models for the job role. Furthermore, sampling design of the employer survey assumed paired interviews for a subset of interview organizations (n=180). In this sub-sample, we checked whether responses to the AI investment questions are consistent between the two independent interviewees and found no significant patterns.

Employee data were derived from Understanding Society: The UK Household Longitudinal Study (UKHLS), which is a large, nationally representative longitudinal survey of households in the United Kingdom. UKHLS provides a rich source of information on working lives, job quality and wellbeing. We extracted the data from Waves 12 to 14 and selected respondents by the time of the interview to match the data collection timeframe with that of DPAW. The sample was further restricted to those in formal employment (excluding self-employed, retired, respondents in full-time education, unemployed or out of work due to long-term illness or disability). To ensure consistency with DPAW, we excluded respondents working in organizations with less than 10 employees.

Sample: data linkage procedure

UKHLS and DPAW do not permit deterministic data linkage through unique employer identifiers. However, both datasets contain extensive contextual information on the type of organization, industry within which it operates, its geographical location and the number of people employed. Both Understanding Society and DPAW contain the following observed employer characteristics:

- detailed 5-digit Standard Industry Classification of Economic Activity (SIC2007);
- sector identifier separating private firms and limited companies from other types of organizations with the latter further divided into public limited companies, nationalized industry/state corporations, central and local government or civil service, charities and public services including healthcare, schools and universities;

- firm size along the following bands: 10-24 employees; 25-49; 50-99; 100-199; 200-499; 500-999; over 1000 employees;
- regional identifiers across 12 regions: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland, Norther Ireland.

Using these characteristics, we implemented stochastic (probabilistic) linkage algorithms to link employees to their most likely employer. The stochastic linkage strategy follows established practice in the administrative data literature, where linkage is treated as a probabilistic exercise with inherent uncertainty addressed through repeated or multiple linkages rather than deterministic assignment (Chambers et al. 2023; Abowd et al. 2019). We followed these established methods by creating, in the first step, candidate employer–employee pairs using blocking on employment identifiers. We then estimated pair-specific posterior match probabilities capturing interactions in agreement patterns across the employer characteristics.

Mismatch in the linkage of probability based representative samples is inevitable. As of 2024, there were over 2.7 million registered businesses in the United Kingdom (registered for Value Added Tax and Pay as You Earn tax collection system). Of those, circa 220,000 are estimated to employ 10-49 employees, 38,000 are thought to be medium sized firms and 8,000 are large enterprises employing over 250 workers (Department for Business and Trade, 2025). While the likelihood of a match based on characteristics provided is higher for larger firms, the precise linking of small firms without a firm ID variable is practically impossible.

We treat this problem as that of multiple imputation (Abowd et al. 2019). For each worker, we restricted candidate employers to those classified as likely employers (by the core characteristics) and then created K-linked datasets (K=50 with further variations in the value of K having no material consequences for the outcomes of our analysis) with repeated stochastic assignments of workers to employers within the same cell, drawing employers with probabilities proportional to posterior match probabilities (weighted by firm size, with greater match weights assigned to larger firms). Taken together, this approach allowed us to probabilistically link 17,237 workers to 1743 employers with characteristics as similar to their actual employers as we can achieve with the available data.

Our regression models incorporate outlier robust solutions by explicitly allowing for the presence of linkage errors (Chambers et al. 2023). We report pooled regression estimates in the main regression tables and provide extensive robustness checks in the Appendix (Table A3 and Figures A1 and A2), where we report the distribution of regression coefficients by repeated data linkage exercises to demonstrate that across the specifications they main findings are robust to linkage uncertainty, with coefficient distributions tightly clustered around their median estimates.

We accept that employer-employee mismatch is consequential in many employment relations applications. For example, achieving a precise match is essential for estimating the effect of employment policies, human resource practices and objective firm level characteristics such as turnover, financial performance and so forth. However, in our study, the rationale for data linkage is to understand the effect of employer investment in digital technology. Such investment is driven largely by the intersection of industry, firm size and economic activity (Stuart et al. 2023). Specific digital solutions and how they are utilized can vary from firm to firm, but the type of technology adopted is much more likely to be consistent (than, for example, performance management practices) across firms within the same industrial code, of similar size located in the same region (e.g., two mid-sized private client-oriented law firms located in the same town) are likely to invest in similar types of applications and algorithms (pertinent here is the notion of organizational isomorphism in relation to technology adoption, see Lai, Wong, and Cheng 2006). These considerations further mitigate concerns related to a linkage error. To the best of our knowledge, this is the first study of its kind (at least in the United Kingdom) using linked nationally representative employer-employee data capturing the extent of employer investment in AI technology and associated employee outcomes.

Variables

The key study variables and the respective measurement scales are outlined below focusing first on level one (employee level measurements) and then level two (employer clusters).

Employee level measurements

Work autonomy: represents a composite index measuring the degree of control respondents have over their work tasks, pace, work manner, task order and working hours. It is derived from five survey questions that ask about the extent to which respondents can decide how to do their work, what tasks they do, and when they do them. Original responses were recoded into a four-point Likert scale from '4' (a lot of autonomy) to '1' (none) such that higher scores indicate more autonomy.

Employee wellbeing: This is assessed using a composite measure based on the Likert scale indicators of subjective work-related well-being capturing the extent to which employees feel tense, uneasy, worried, depressed, gloomy and miserable about their job. The responses ranged from '1' (never) to 5 ('all the time'). These scores were reverse coded and averaged into an index with higher scores indicating better wellbeing.

Both work autonomy and employee wellbeing are established measurement scales that were combined in a composite index. We report their detailed descriptives and reliability scores in the Appendix (Table A1 and A2).

Union membership: This binary variable indicates whether the respondent is a member of a recognised trade union at the workplace. It is coded as 1 for members and 0 for non-members.

Union density: Calculated as the average union membership (i.e., membership density) aggregated at the industry (three digit SIC 2007) level. We take it as a proxy for union strength.

Employer level measurements

AI-enabled digital technologies. Managers were asked to indicate if they had invested in the following AI-enabled technologies in the past five years noting that such investment does not include routine upgrades of existing equipment and software: AI-enabled equipment, software and applications (e.g., robotics, drones robot process automation, digital identification; AI applications to generate streaming content; natural language processing; recognition software; chat bots; virtual reality); business support tools and peer-to-peer networks; and, cloud computing. We created binary variables taking the value “1” if employers had adopted the specific technology and “0” otherwise.

The questionnaire was explicit in distinguishing cloud computing as an AI solution relative to more basic data storage and sharing applications. These questions were separated in the survey and respondents prompted accordingly thereby minimizing potential response bias (i.e., assuming data storage facilities as AI driven cloud computing)

Control variables

Regression models controlled for a number of contextual factors measured at the employee level: employee demographic characteristics; typical weekly working hours; monthly income; overtime; remote working (working from home); type of employment contract; highest qualification level; occupational status; managerial duties in day-to-day job; presence of recognized trade unions in the workplace; employees' use of traditional ICT including desktops, laptops, smartphones and tablets. We also controlled for several metrics from DPAW, including the use of data analytics and customised software applications to monitor working hours and absenteeism, and respondents' job differentiating between HR managers, managing directors and technical directors.

Analytical strategy

We estimated a series of multilevel regression models based on the restricted maximum likelihood estimator. The functional form of our baseline regression models (without interaction effects) is as follows:

Equation 1 (work autonomy)

$$Autonomy_{ij} = \beta_{0j} + \beta_{1j}(AI_{1ij}) + \cdots + \beta_{nj}(AI_{nij}) + \gamma X_{ij} + u_{0j} + \lambda_{ij} + r_{ij}$$

Equation 2 (employee wellbeing)

$$Wellbeing_{ij} = \beta_{0j} + \beta_{1j}(AI_{1ij}) + \cdots + \beta_{nj}(AI_{nij}) + \gamma X_{ij} + u_{0j} + \lambda_{ij} + r_{ij}$$

$$\lambda_{ij} \sim N(0, \sigma_{\lambda}^{2})$$

where i denotes employees and j denotes the linked employer. X_{ij} is the vector of control variables, u_{oj} is the employer-level random effect (random slope), r_{ij} is the individual-level residual, and λ_{ij} captures the Exchangeable Linkage Error (ELE) arising from uncertainty in probabilistic employer–employee matching (Chambers et al. 2023; Chambers and da Silva 2020). This reflects the fact that, given the available identifiers, no single employer can be deterministically identified as the true match.

Descriptive results

Prior to examining the outcomes of regression modelling, we provide a general overview of the proliferation of digital technology in the UK labor market. We contrast employer investment in AI enabled digital technology with employees' use of ICT (including desktops, laptops, tablets, or smartphones) measured in *Understanding Society*. The employer survey was designed to capture variations in employers' investment in different types of AI-enabled technology, ranging from AI equipment and software to cloud computing. Table 1 below reports descriptive statistics for the key study variables derived from both surveys.

Table 1: Descriptive statistics

Variable	Measurement	Mean/SD	Frequencies (%)	Internal consistency reliability (Cronbach's Alpha)
Employee data (Understanding Society): 17,237 observations				
Work autonomy (1-4 Likert scale)	Tasks	3.022/0.984	-	0.870
	Pace of work	3.106/0.969		
	Working hours	2.556/1.192		
	Order of tasks	3.315/0.877		
	Manner in which tasks are conducted	3.299/0.870		
Employee wellbeing (1-4 Likert scale)	Feeling tense	3.710/0.987	-	0.917
	Feeling uneasy	4.073/0.981		
	Feeling worried	4.017/0.985		
	Feeling depressed	4.366/0.943		
	Feeling gloomy	4.248/0.947		
	Feeling miserable	4.337/0.934		
Use of ICT (%; Yes/No)	Desktop or laptop	-	71.1%	-
	Smartphone or tablet		44.8%	
Industry of the current job	SIC 07	-	96 unique four-digit industry codes	
Current occupation	SOC 10	-	62 unique three-digit occupational codes	
Employer data: 1743 observations				
Investment in AI technology (%, Yes)	AI equipment and software	-	12.9%	-
	Business support tools		7.1%	
	Cloud computing		26.7%	
	Investment in at least one type of AI technology		36.4%	
	Not investing in any type of AI technology		63.6%	

According to *Understanding Society*, only 16.5 percent of employees had not used ICT at work. Desktop computers or laptops were used by 71 percent of respondents while just over four in ten (45%) used smartphones or tablets. While ICT was clearly well established in UK workplaces, the same could not be said for AI-enabled technology. Just over a third of employers (36.4%) had invested in any type of AI technology, with cloud computing being the most widely adopted (26.7 per cent of workers were covered by this type of technology). Investment in AI powered equipment and applications stood at 12.9 per cent and 7.1 per cent invested in peer-to-peer networks and business support tools. AI investment was uneven. Large firms in specific sectors (e.g., public administration, ICT) were significantly more likely to invest. The leading industries for AI investment were Information and Communication, Public Administration, and Professional, Scientific and Technical Activities (with the level of investment varying between 44% and 65%). The lowest levels of investment in AI were observed in Accommodation and Food Services (22%), Construction (30%), and Transportation and Storage (34%). These descriptives indicate lower levels of adoption among some industries that are thought to be at the forefront of technological innovation (e.g., Transportation). We note that unlike consultancy based reports that tend to dominate the public discourse, the present survey is nationally representative and spans a significant number of small and medium enterprises where investment in AI lags behind larger firms. This is one plausible explanation for the modest levels of employer investment in AI.

Turning to other core variables, the composite work autonomy index averaged 3.06 (where 4 indicates complete autonomy). Among individual components of work autonomy, autonomy over working hours returned the lowest average score (=2.56), while the highest autonomy scores were for discretion over the order (=3.31) and manner (=3.30) in which the tasks are conducted. The average employee wellbeing score was 4.13 on a scale from 1 to 5. Feeling depressed and miserable were the least likely wellbeing implications while the lowest wellbeing scores were recorded for feeling tense and worried at work. Around 28.1 per cent of respondents were union members.

Regression estimates: Association between AI investment, autonomy and wellbeing

In this section, we report multilevel regression estimates of the direct association between employer investment in AI enabled technology, work autonomy and employee wellbeing. Table 2 presents estimates for the key variables, together with 95 percent confidence intervals and model fit statistics. Model 1 in Table 2 estimates the association with work autonomy; Model 2 examines employee wellbeing as the outcome. For brevity, we focus on the coefficients of interest. All models include control variables, and complete regression results are reported in the Appendix (Tables A4-A6).

Employer investment in AI technology was associated with both work autonomy and employee wellbeing. However, the direction and magnitude of these associations varied by technology type. Investment in AI equipment and applications was negatively associated with work autonomy ($\beta = -0.064$, $p < 0.05$). Figure 1 presents the corresponding marginal effects and shows an average decline of approximately 4 percent in perceived work autonomy associated with the investment in AI. In contrast, employer investment in cloud computing was positively associated with employee wellbeing ($\beta = 0.044$, $p < 0.05$). Marginal effects shown in Figure 2 indicate that cloud computing is associated with an average increase in subjective wellbeing of about 1.2 percent.

We conducted Wald tests of coefficient equality to test whether regression coefficients corresponding to the AI variables are statistically different from one another. The results reported in Table 3 demonstrate statistically significant differences between the coefficients corresponding to AI-powered equipment and applications, and cloud computing. Taken together, our findings suggest that employer investment in AI is associated with enhancement and erosion of job quality contingent on the type of technology. This supports Hypotheses 1 and 2. It is important to note though that the data do not allow us to establish temporal ordering and causal effects. The estimated coefficients therefore capture conditional associations between employer-reported AI investment and employee-reported outcomes, holding observed characteristics constant.

Table 2: Regression estimates for the relationship between technology, work autonomy and employee wellbeing.

	Model 1: Work autonomy	Model 2: Employee wellbeing
Employer investment in AI equipment and applications	-0.064*	-0.031
	[-0.116, -0.011]	[-0.084, 0.023]
Employer investment in AI powered business support tools	-0.037	-0.014
	[-0.099, 0.025]	[-0.077, 0.050]
Employer investment in Cloud Computing	0.015	0.044*
	[-0.024, 0.054]	[0.004, 0.083]
Employer use of data analytics	-0.009	-0.020
	[-0.037, 0.019]	[-0.048, 0.008]
Employer use of monitoring applications	-0.044**	-0.030*
	[-0.072, -0.016]	[-0.059, -0.002]
Employee use of ICT	0.235***	-0.036***
	[0.226, 0.244]	[-0.046, -0.026]
Union membership	-0.119***	-0.120***
	[-0.128, -0.111]	[-0.129, -0.110]
Union density (industry)	-0.294***	-0.062***
	[-0.320, -0.268]	[-0.092, -0.032]
Employee socio-demographic controls	v	v
Employer job role	v	v
Occupational fixed effects (SOC 2000)	v	v
Employer level observations	1736	1736
Individual level (employee) observations	17237	17237
ICC1	0.120	0.100
Marginal R^2 / Conditional R^2	0.128 / 0.229	0.037 / 0.117
* p < 0.05, ** p < 0.01, *** p < 0.001		

Table 3: Wald test of differences between regression coefficients

Comparison	Outcome	χ^2	p-value
AI equipment and applications vs Cloud computing	Work autonomy	4.755	0.029
AI equipment and applications vs Business support tools	Work autonomy	0.221	0.638
Cloud computing vs Business support tools	Work autonomy	2.12	0.145
AI equipment and applications vs Cloud computing	Employee wellbeing	4.063	0.043
AI equipment and applications vs Business support tools	Employee wellbeing	0.125	0.724
Cloud computing vs Business support tools	Employee wellbeing	2.101	0.147

Figure 1: Marginal effects of association between employer investment in AI applications and equipment and work autonomy

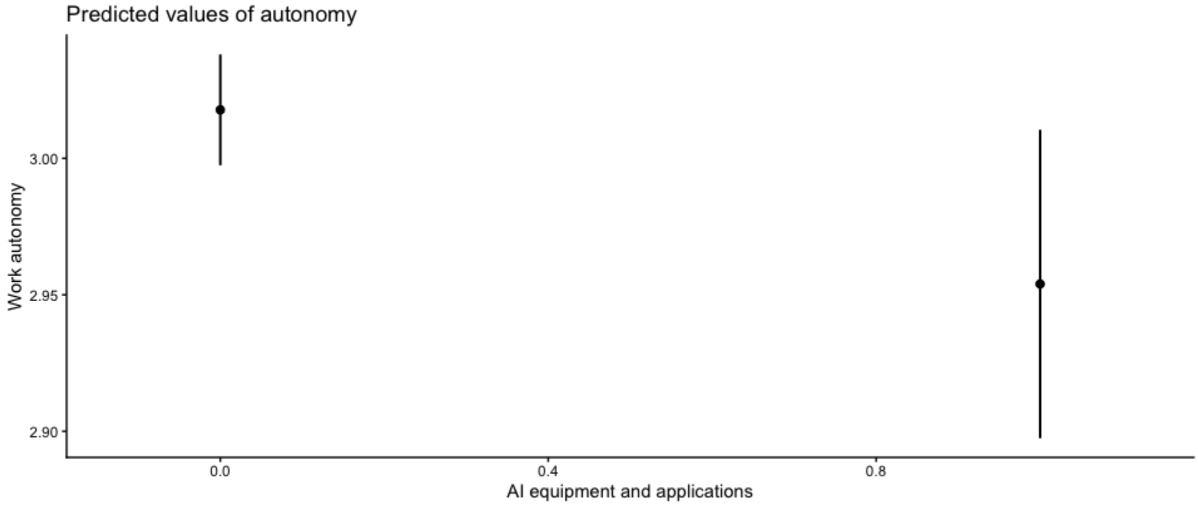
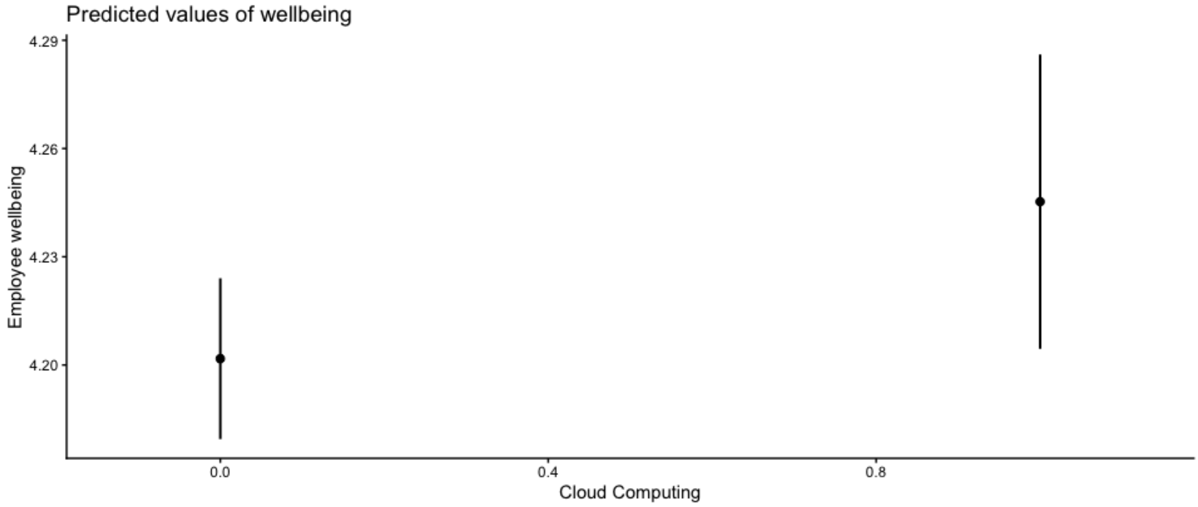


Figure 2: Marginal effects of association between employer investment in cloud computing and employee wellbeing



Moderating effect of labor unions

Next, we examine whether labor unions moderate the relationship between AI investment, work autonomy, and employee wellbeing. We estimated interaction effects for all AI investment variables, irrespective of whether their baseline associations with autonomy or wellbeing were statistically significant. We report the hypothesized interaction effects below; the full set of interactions is reported in the Appendix (Table A7).

Table 4 reports Models 3 and 4, which extend Models 1 and 2 by including interactions between AI investment and union membership. Model 3 corresponds to work autonomy and shows a positive and statistically significant interaction effect between employer investment in AI equipment and applications and union membership ($\beta = 0.118$, $p < 0.001$). Figure 2 illustrates this result. Consistent with the main effects reported in Table 2, AI investment was associated with reduced work autonomy among nonunion members. However, union members experienced higher levels of work autonomy where investment in AI equipment and applications took place.

Model 4 estimates the union effect in the association between employer investment in cloud computing and employee wellbeing. The interaction term is positive and statistically significant ($\beta = 0.021$, $p < 0.05$), although the effect size is modest. As shown in Figure 3, the difference in slopes between union members and non-members is small. Thus, while union members appear to have experienced a slightly greater increase, this effect is substantially weaker than the moderating role of unions in the relationship between AI investment and work autonomy.

Table 4: Regression estimates of the interaction effect between AI investment and union membership

	Model 3: Work autonomy	Model 4: Employee wellbeing
Employer investment in AI equipment and applications	-0.074**	
	[-0.118, -0.030]	
Employer investment in Cloud Computing		0.035*
		[0.004, 0.066]
Employer investment in AI equipment and applications × Union membership	0.118***	
	[0.098, 0.137]	
Employer investment in Cloud Computing × Union membership		0.021*
		[0.003, 0.039]
Union membership	-0.148***	-0.127***
	[-0.157, -0.139]	[-0.138, -0.117]
Employee socio-demographic controls	v	v
Employer job role	v	v
Occupational fixed effects (SOC 2000)	v	v
Employer level observations	1736	1736
Individual level (employee) observations	17237	17237
ICC1	0.140	0.110
Marginal R^2 / Conditional R^2	0.210 / 0.320	0.063 / 0.163
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$		

Figure 3: Interaction effect between AI equipment and applications and union membership (outcome variable: work autonomy)

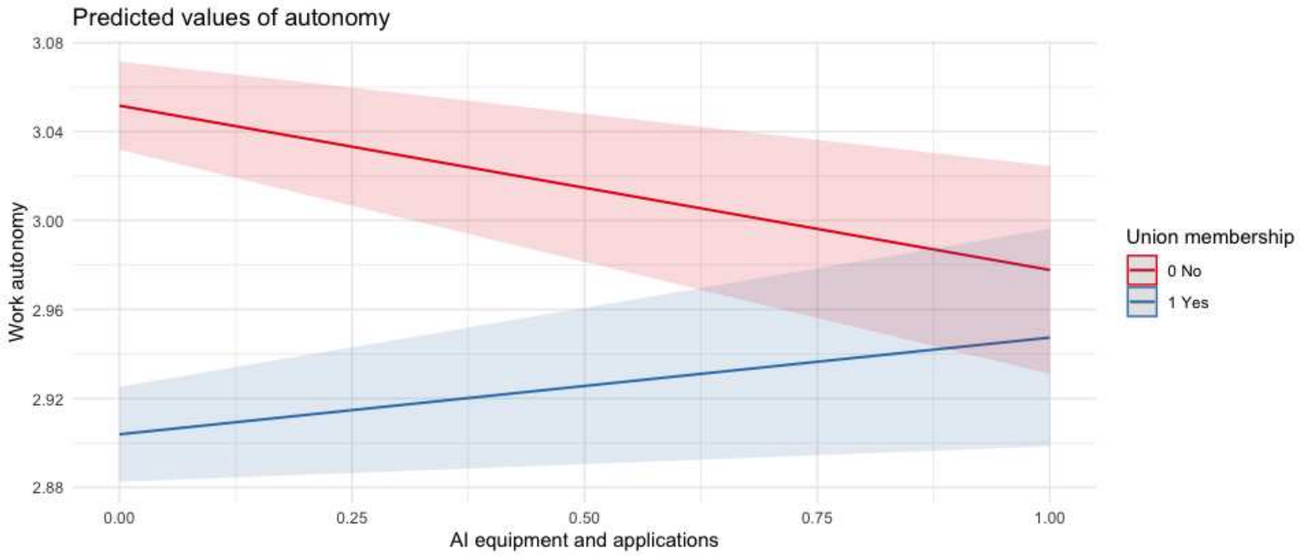


Figure 4: Interaction effect between cloud computing and union membership (outcome variable: employee wellbeing)

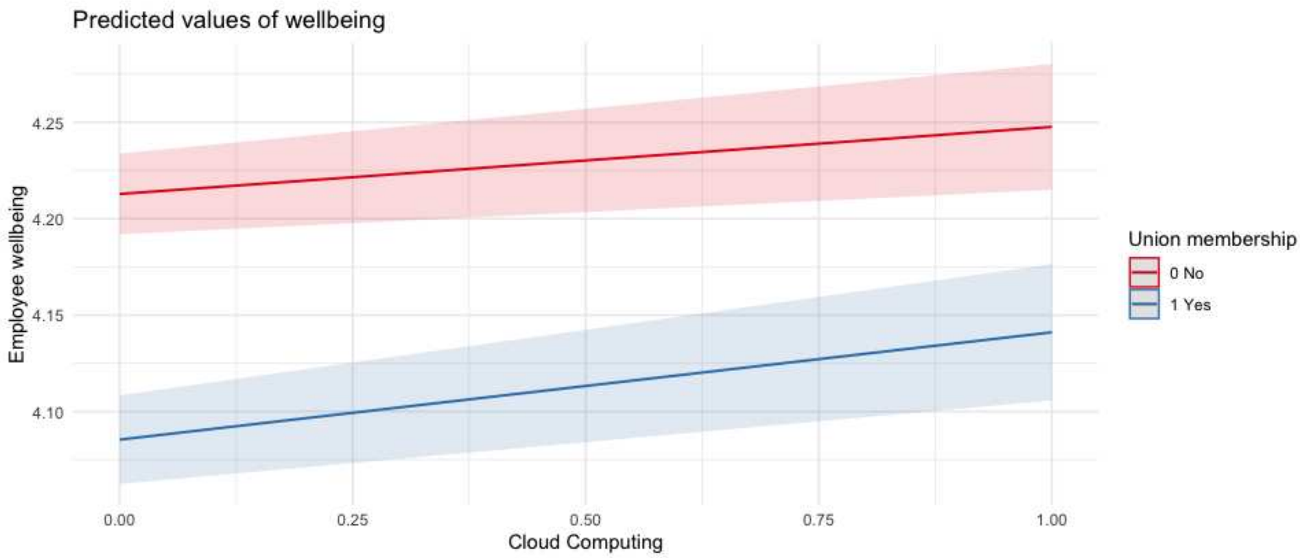


Table 5 reports regression coefficients for the interaction effect between union density and AI investment. Both interaction terms were positive and statistically significant. In Model 5, which examines work autonomy, the interaction between union density and AI investment was estimated at $\beta = 0.143$ with $p < 0.001$. Model 6 focuses on employee wellbeing and showed a strong positive interaction between union density and employer investment in cloud computing

($\beta = 0.379$, $p < 0.001$). It is worth noting that the direct effect of cloud computing in Model 6 turned negative. The coefficient for cloud computing represents the conditional association with employee wellbeing when union density is equal to zero. In this context, the positive interaction term indicates that the association becomes increasingly positive as union density rises. That is, the positive association between cloud computing and wellbeing is concentrated in industries with stronger collective representation (as illustrated in Figure 5).

Figure 4 illustrates that higher levels of union density mitigated the negative association between AI investment and work autonomy. As union density increases, the decline in work autonomy associated with AI investment becomes substantially weaker (however, the effect size is marginal). Figure 5 shows a more pronounced interaction for employee wellbeing. Higher union density amplified the positive association between investment in cloud computing and employees' subjective wellbeing, resulting in steeper gains at higher levels of collective representation.

Taken together, these results corroborate Hypotheses 3 and 4.

Table 5: Regression estimates of the interaction effect between AI investment and union density

	Model 5: Work autonomy	Model 6: Employee wellbeing
Employer investment in AI equipment and applications	-0.078**	
	[-0.124, -0.031]	
Employer investment in Cloud Computing		-0.044*
		[-0.078, -0.009]
Employer investment in AI equipment and applications × Union density	0.143***	
	[0.072, 0.213]	
Employer investment in Cloud Computing × Union density		0.379***
		[0.314, 0.444]
Union density	-0.347***	-0.202***
	[-0.375, -0.319]	[-0.236, -0.168]
Employee socio-demographic controls	v	v
Employer job role	v	v
Occupational fixed effects (SOC 2000)	v	v
Employer level observations	1736	1736
Individual level (employee) observations	17237	17237
ICC1	0.130	0.110
Marginal R^2 / Conditional R^2	0.210 / 0.316	0.063 / 0.163
* p < 0.05, ** p < 0.01, *** p < 0.001		

Figure 5: Interaction effect between AI equipment and applications and union density (outcome variable: work autonomy)

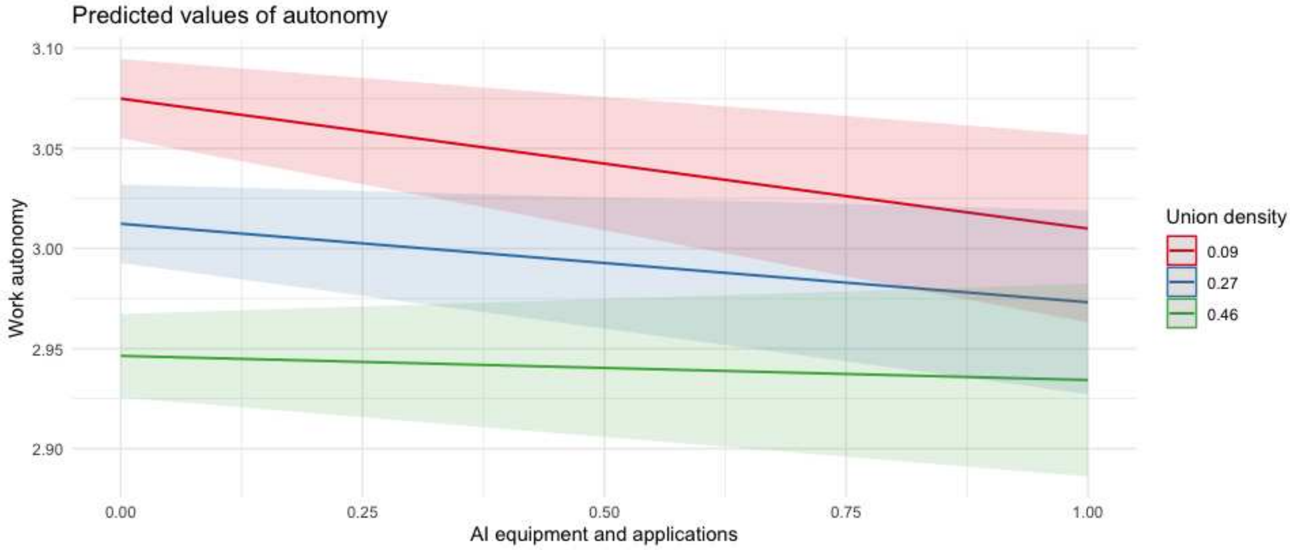
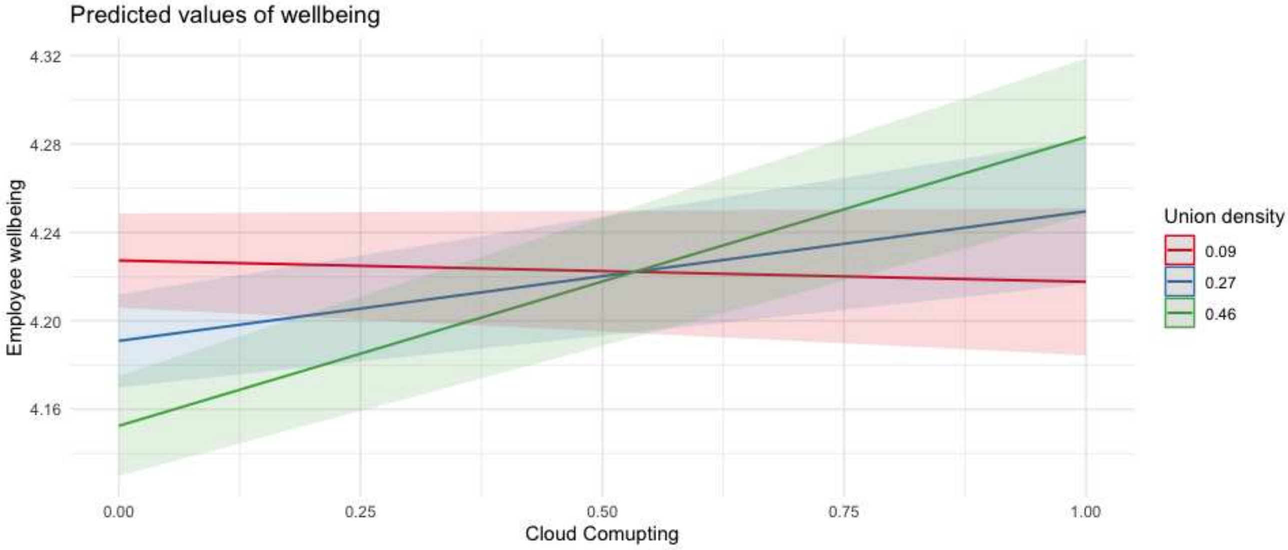


Figure 6: Interaction effect between cloud computing and union density (outcome variable: employee wellbeing)



Heterogeneity analysis: the role of teleworking

One of the main limitations of this study, as stated throughout the article, is its cross-sectional design and inability to establish causal links between employer investment in AI and job quality. While we cannot definitively rule out selection bias and reverse causality, the data enables us to estimate heterogeneity of the main effects conditional on observed characteristics of work organization which are jointly determined with technology and job quality.

Teleworking is one such characteristic (Qian and Fan 2025). We re-estimated Models 1 and 2 for employees who work remotely at least two days per week and found that the effects of AI investment were concentrated among those who work primarily on employer premises. Among frequent remote workers, the estimated effects were smaller in magnitude and statistically insignificant: for work autonomy β among frequent remote workers = -0.043 (n.s) and -0.077 ($p< 0.05$); for employee wellbeing β among frequent remote workers = -0.040 (n.s) and equal 0.075 ($p< 0.05$). These patterns suggest that the established associations of AI investment can be shaped by the spatial organization of work. That the direction of these effects varies between AI applications and cloud computing indicates the importance of intention with which management deploys these tools. One possible interpretation is that AI powered applications and equipment may be associated with greater managerial coordination and monitoring at work premises. Conversely, cloud computing can provide flexibility and greater reliability than previous generations of IT systems which may explain a positive link with employee wellbeing.

We further estimated the union effect for both remote workers and those working primarily on employer premises. The regression coefficients were significant in both subgroups of workers indicating that the union effect is less sensitive to the spatial organization of work than the main effect of AI investment.

Robustness and Sensitivity checks

We conducted a series of sensitivity and robustness checks to assess the stability of our findings. First, as noted in the methodology section, given the use of probabilistic employer–employee linkage, all regression models were estimated across independently linked datasets. Reported coefficients represent pooled estimates, and the distribution of estimates across linkages showed limited dispersion, indicating that the results are not driven by a small number of stochastic matches. Further details on these tests are reported in the Appendix (Table A3).

Second, we re-estimated all models using alternative specifications of key variables. Work autonomy and employee well-being were modeled separately using their individual scale components rather than composite indices. The direction and statistical significance of the main effects and interaction terms remained unchanged. We also tested alternative operationalizations of union strength, including models excluding industry-level union density and models including workplace union recognition only. The moderating role of unions was robust across specifications.

Third, we re-estimated regression models by gender and among different age groups. While there was variation in the magnitude of regression coefficients the direction of these effects and their statistical significance were consistent. Finally, we tested alternative random-effects structures (e.g., random slope models) and standard error estimates (e.g., clustered standard errors). These adjustments did not materially alter the findings (Table A8).

Discussion

This study advances research on artificial intelligence and job quality by providing the first nationally representative employer–employee analysis of how employer investment in AI relates to intrinsic job quality in the United Kingdom. Using probabilistic linkage methods to integrate a representative employer survey with household panel data, we show that AI investment can have differentiated effects on work autonomy and employee well-being. These effects vary by technology type and are moderated by trade unions. The paper makes three distinctive contributions. First, it moves beyond worker-reported technology use to examine employer investment in AI directly. This is important as decisions around the implementation and use of AI at work are typically taken by employers. Second, it demonstrates that AI investment is associated with improvements in, as well as erosion of, intrinsic job quality. Third, it shows that trade unions play an important moderating role, shaping whether AI investment translates into improved or diminished worker outcomes.

Consistent with previous research (Orlikowski, 1992; Mazmanian, Orlikowski, and Yates 2013; Scott and Orlikowski 2025), our analysis highlights the dual nature of AI investment. On the one hand, employer investment in AI was associated with lower levels of work autonomy. This supports research on algorithmic management and digital monitoring that emphasizes the capacity of AI systems to standardize tasks, intensify performance evaluation and constrain discretion at work (Krzywdzinski, Evers, and Gerber 2024). On the other hand, employer investment in cloud computing was associated with modest but positive improvements in employee well-being. These results highlight that the consequences of AI investment depend on how technologies are designed, implemented and embedded within specific organisational contexts (Wajcman 2006; Howcroft and Taylor 2023; Joyce et al. 2023; Kochan 2021; Kochan et al 2024). AI applications designed to automate decision-making or monitor work processes appear more likely to reduce autonomy, while infrastructural technologies such as cloud computing may improve reliability and flexibility in ways that support employee wellbeing. This is further underscored by the fact that the direct effects of AI investment were concentrated primarily among non-teleworkers, suggesting that physical presence in the workplace increases exposure to algorithmic coordination and monitoring

The finding that labor unions significantly moderate the relationship between employer investment in AI and job quality challenges the current deterministic narratives that frame AI as a key driver of either inevitable job displacement or enhanced productivity and quality of working lives. We showed that the union effect operates at two distinct levels: at workplace level where union membership was associated with higher levels of autonomy relative to non-members and at the industry level where higher union density enabled the positive well-being effects of cloud computing. These findings support the argument that unions can shape the conditions under which AI is deployed (Haepp 2022; Litwin 2011 and 2015). These effects are likely to complement each other. Through sectoral collective bargaining unions can influence implementation processes, negotiate safeguards and limit autonomy-reducing uses of AI. At workplace level, unions can foster a more balanced implementation of technology and provide employees with access to training and support thereby reducing worker anxiety linked to AI investment.

The union effect provides strong evidence for a sociologically grounded account of technological change. The same broad forms of AI investment are associated with different outcomes depending on whether workers have access to union representation and whether they are in industries with stronger collective labor power. The union effect was also more robust than the direct effects of AI investment with respect to teleworking, suggesting it extends beyond the spatial constraints and immediate exposure to technology. This suggests that unions function both as a workplace and an institutional actor (Benassi and Vlandas 2022) limiting negative and amplifying potential positive effects of AI. Thus, we showed empirically that the consequences of AI investment are not technologically predetermined but are shaped by the institutional and employment relations contexts in which technologies are embedded.

Our study has several implications for future research and policy debates. First, our findings underscore the importance of distinguishing between types of AI technologies and incorporating employer-level measures into analyses of the implications of AI. It is important to move beyond binary indicators of adoption to examine diverse effects of AI investment, its functional purpose and governance mechanisms surrounding AI adoption and use. Longitudinal designs would be particularly valuable in identifying causal pathways and in assessing how worker outcomes evolve as AI technologies mature. There is also scope to explore complementarities between unions and other forms of employee voice, including works councils and consultative committees, especially in institutional contexts outside the United Kingdom.

Second, the findings show that the effects of AI are not technologically predetermined. Employer investment choices matter, but so do institutional arrangements that shape how these technologies are introduced and regulated. Strengthening collective representation and embedding worker voice into AI governance frameworks, as advocated by commentators such as Kochan (2021), may prove beneficial for worker autonomy and wellbeing. These insights are relevant considering ongoing debates about AI regulation and the need for worker-centered approaches to digital transformation.

A methodological strength of our analysis is the linking of nationally representative employer and employee data. However, several empirical limitations should be acknowledged. First, employer misclassification is unavoidable given the absence of deterministic employer identifiers. This limitation was partly mitigated by our focus on employer investment in AI technology, which is driven by the industry, firm size and organisational characteristics used in the linkage process. Nevertheless, we cannot observe the actual use of AI or the implementation practices through which technologies are introduced.

Second, while our analysis identified robust associations and moderating effects, it cannot establish causal mechanisms. We cannot exclude reverse causality or self-selection. For example, employers with lower-discretion work organization may be more likely to invest in AI, while workers with higher autonomy and wellbeing may self-select into workplaces that do not use AI. Addressing these issues would require longitudinal data and quasi-experimental analysis.

Finally, our analysis focused on subjective wellbeing and work autonomy as two intrinsic dimensions of job quality. Other dimensions, including work intensity, employment security, quality of working time, are not examined and may have different relationships with AI investment.

Despite these limitations, our study offers a novel approach to estimating the relationship between employer decisions on AI investment and employee outcomes. It is important to treat our findings as emerging patterns of how AI investment reshapes intrinsic job quality in uneven and institutionally contingent contexts. Future studies are necessary to examine whether these patterns hold in other institutional contexts and can be sustained over time.

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