Artificial intelligence technologies and employee pay in the United Kingdom: evidence from matched employer-employee data

Abstract

This paper examines the impact of AI-enabled technologies on employee pay in the United Kingdom. We use matched nationally representative data from the Employers' Digital Practices at Work Survey and an original survey of 6,000 UK workers and apply machine learning techniques to uncover relationships between AI technology and employee pay across qualification and occupation skill groups. We find that lower-skilled workers were the primary beneficiaries of AI, but this effect was contingent on the extent of worker interaction with AI. Further analysis shows that employee involvement in pay determination facilitates a more equitable distribution of AI-related pay benefits by enabling a significant uplift in pay among lower qualified workers. Overall, while the implications of AI for pay outcomes are broadly positive, the study highlights the need to strengthen workplace voice mechanisms to ensure a more equitable distribution of benefits from the growing use of AI.

Keywords: artificial intelligence, pay, machine learning, employee voice

1. Introduction

The paper is framed against contemporary debates on the impact of digital technologies on work and employment. Policy makers, in particular, have been animated by a potential future of large scale job displacement due to automation (Frey and Osborne, 2017), even if available evidence does not support such speculation (Stuart et al., 2023). Academic debate, in contrast, is increasingly focused on the likely impacts of digital technologies on workplace transformation (Boyd and Holton, 2018), the nature and quality of work (Yao, 2020), workforce digital skills (Dhondt et al., 2022; Holm and Lorenz, 2022) and new forms of 'algorithmic' management control (Heiland, 2022). Such debates are, of course, not new; nor is recognition that technological advancement in itself is not determinant but is influenced by prevailing social forces and institutions (Joyce et al., 2023). Nevertheless, robust empirical analyses on how contemporary technologies are impacting work and workplaces remain in their infancy.

Of particular interest is the potential impact of emerging Artificial Intelligence (AI)-powered technologies on employee pay. Economic theories tend to focus on the extent to which technological development impacts certain groups of workers at the expense of others (Acemoglu and Restrepo, 2022; Autor et al., 2003; Goos et al., 2014). Much of the existing empirical evidence concerns the role of established information and communication technologies. The rapid expansion of new AI technologies could therefore have implications for existing pay disparities and inequalities at work more broadly. Emerging research on the effect of AI technology predominantly focuses on Germany or East Asia as leaders in industrial robotics and automation (e.g., Genz et al., 2021, 2019) or relies on aggregated industry or job vacancy data (Acemoglu and Restrepo, 2022; Bone et al., 2024; Stephany and Teutloff, 2024). These macroeconomic or industry-focused studies provide limited insights into AI adoption and labour process within organisations.

Given this, we address two overarching research questions. First, to what extent do AI technologies influence employee pay? Second, how is this relationship shaped by broader dynamics of qualifications, skills and employee voice?

Taking a non-deterministic approach, we situate established economic debates – on skill-biased and routine-biased technological change – within the context of AI adoption (Berg et al., 2023; Spencer, 2017; Thompson and Laaser, 2021) and industrial relations concerns regarding workplace power dynamics and employee voice (Blanchflower and Bryson, 2003; Garnero et al., 2020; Hirsch et al., 2022; Zwysen and Drahokoupil, 2024). We match two original, nationally representative datasets: the Employers' Digital Practices at Work Survey and employee-level data drawn from a representative online survey of 6,000 UK workers. We apply machine learning techniques to uncover the relationship between AI and pay across qualification and occupational skill groups. Our findings reveal that contrary to previous technological advancements that were biased towards highly skilled workers (Autor et al., 2003; Goos et al., 2014), early AI adoption disproportionately benefits lower skilled workers if their jobs involve continuous interaction with AI. These benefits are particularly pronounced where employees are involved in decisions over pay. Consideration thus needs to be given to strengthening employee voice mechanisms as a foundation for more equitable distribution of AI benefits.

The remainder of the paper is structured as follows. Section two reviews relevant literature and sets out our key hypotheses. Section three explains our methods and analytical approach. This is followed in section four by the presentation of our data analysis. The final section discusses the main contributions of our paper and draws out some wider practical conclusions and areas for future research.

2. Literature Review

2.1. Technology and Pay: Skill-Biased and Routine-Biased Technical Change

Two theoretical perspectives are central to the mainstream economic debate on technology: skill-biased technological change (SBTC) and routine-biased technological change (RBTC). Both theories are concerned with the unequal effects of technology in the labour market. SBTC emerged as a response to a sharp decline of less-skilled jobs in the last quarter of the 20th century. As technology favours more educated, skilled labour, they benefit from a substantial pay rise while lower qualified workers are pushed outside the labour market (Autor et al., 1998; Krueger, 1993). A consistent empirical finding within this school of thought is the effect of computers, as computer-intensive industries have seen a dramatic increase in demand for skilled workers and a concomitant uplift in wages (Autor et al., 1998). For Acemoglu (2002, p. 9), this relationship "suggests the occurrence of skill-biased technological change" whereby labour demand and supply determine pay based on the relative speed of technological change while creating demand for investment in human capital (Krueger, 1993; Peng and Eunni, 2011).

Yet, increasingly polarised labour markets, with the growth of low- and high- wage jobs and a decline in middle-level skilled jobs, have challenged the SBTC narrative (Autor et al., 2006; Autor and Dorn, 2013; Goos and Manning, 2007). Against this backdrop, RBTC emerged as an alternative explanation that suggests technological change is biased "toward replacing labor in routine tasks" (Goos et al., 2014, p. 2509). This represents a shift away from a dichotomy of high-skilled (high-educated) and low-skilled (low-educated) jobs towards a greater understanding of tasks: routine, non-routine, manual and cognitive. Computers are thus seen to substitute routine manual and routine cognitive tasks thereby reducing demand for such jobs. In contrast, the inability of technology to competently mimic non-routine tasks leads to an increased demand for such jobs. Because non-routine tasks can be found at the opposite ends of the occupational hierarchy, the effect on pay is uneven, with a rise of both high-paid and low-paid jobs (Goos and Manning, 2007). This U-shaped effect on employment cannot be fully explained by skill-biased technological change alone. The growth of low-skilled, low-paid employment has led to increasingly polarised labour markets, arguably the most significant socio-economic legacy of computerisation.

Whether the adoption of artificial intelligence intensifies existing inequalities or offers a pathway to a more equitable distribution of opportunities remains an open question. This is the lacuna that our research seeks to address. As with previous waves of technological change Goos et al. (2014), artificial intelligence is likely to influence a broad range of skills and tasks. However, we diverge considerably in our theoretical interpretation of the key forces driving this transformation. While the technological-driven demand for skills is undoubtedly important, it must be understood within the broader context of labour processes and workplace power dynamics (Thompson and Laaser, 2021).

2.2. Rethinking the SBTC and RBTC argument: AI adoption and labour process

Demand for skills and tasks are central to the economic argument and have intuitive appeal when trying to theorise how the implementation and use of artificial intelligence (AI) may affect employee pay. Yet, several important caveats must be made. First, research has only just started to engage with the potential impacts of new AI-powered digital technologies. The few RBTC studies that have engaged with new technologies focus primarily on automation from robotics, with mixed results for wage levels (Bessen et al., 2020, 2019; Dauth et al., 2021; Graetz and Michaels, 2015). Acemoglu and Restrepo (2022, p. 1973), for example, find that “between 50% and 70% of changes in the US wage structure over the last four decades are accounted for by relative declines in worker groups specialized in routine tasks in industries experiencing rapid automation”. This would suggest that today’s technologies are characterised by a higher degree of labour substitution than by the creation of demand for specialised skills. Yet, care is needed in extrapolating more widely from such US data. The focus on automation from (industrial) robots misses a wide range of AI technologies underpinned by machine learning that are capable of replicating basic cognitive tasks (Office for AI, 2019).

Early research on novel digital technologies suggests that, at the aggregate level, investment in digital technology positively affects pay, irrespective of whether organisations operate in knowledge intensive sectors (Genz et al., 2019). This supports theoretical claims about how the productivity gains from AI investments may be shared among employees (Acemoglu and Restrepo, 2019; Graetz and Michaels, 2015). Lower-skilled and higher-skilled workers may benefit disproportionally in terms of higher pay compared to those with middle-level, routine skills (Genz et al., 2021, 2019). Genz et al. (2019) show that firms adopting new digital technologies create demand for IT-related jobs requiring non-routine analytic skills, particularly in service-oriented industries where digital advancements improve customer experience.

The UK labour market is characterised by significant qualification and occupational pay gaps. Recent analysis of empirical data from millions of job vacancies suggests that current demand for digital and AI skills outpaces the supply of labour (Bone et al., 2024; Stephany and Teutloff, 2024). Demand for AI-related job positions grew by 21 per cent between 2018 and 2023 (Bone et al., 2024). At the same time, evidence suggests that employers are not investing enough in advanced digital skills training to fill the demand they have for these job roles (Joyce et al., 2023). This concurrent increase in demand and lack of supply of AI-related skills may: a) increase the market rate for workers with these skills; and b) improve the bargaining power of workers with AI skills in pay negotiations. Analysis of UK vacancy data suggests workers with AI skills earn a pay premium (Bone et al., 2024). Yet, it remains to be seen whether this extends beyond vacancy data to actual employee pay. In line with previous findings, we expect:

Hypothesis 1: Employer adoption and employee use of AI is positively associated with employee pay levels.

Hypothesis 2: There is a variation in the effect of AI on pay across qualification and occupation skill groups.

The second major caveat regarding SBTC and RBTC is the limited attention paid to the labour process and workplace employment relations that shape the implementation of new digital technologies. General equilibrium models, typically based on "a simple relative supply and demand framework" (Autor et al., 1998, p. 1171), treat technology as an exogenous and orthogonal factor (Acemoglu, 2002). In doing so, they overlook the role of institutional dynamics and processes (Gahan and Turnbull, 2023). In contrast, we argue that the outcomes of new digital technologies, such as AI, for pay should not be viewed deterministically but as shaped by power relations and structures of employee voice and participation (Berg et al., 2023; Boyd and Holton, 2018; Spencer, 2017; Thompson and Laaser, 2021).

A framework for assessing the effect of employee voice on wages is well-established (Card et al., 2003; Machin, 1997; Metcalf, 1982). This typically operates through collective representation and pay bargaining, whereby workers secure some input into management decision-making power (Lloyd and Payne, 2019; Pontusson, 2013; Thompson and Laaser, 2021; Zwysen and Drahokoupil, 2024). Historically, this influence has been understood through Freeman and Medoff's (1984) account of the dual role of unions: raising wages above market levels and improving workplace governance by ensuring equity in pay and decision-making (Metcalf, 1982; Metcalf et al., 2001). A substantial body of empirical evidence supports the link between union representation, collective bargaining, and both a wage premium and more equitable pay distribution (Blanchflower and Bryson, 2003; Hayter and Weinberg, 2011; Hirsch et al., 2022; Parolin and VanHeuvelen, 2023; Zwysen and Drahokoupil, 2024).

However, union influence over pay has been on the decline, particularly in liberal market economies such as the UK (van Wanrooy et al., 2012, p. 22). While collective bargaining retains some influence in the public sector and large firms, most UK workplaces lack formal mechanisms of collective voice (van Wanrooy et al., 2012; O'Brady and Doellgast, 2021). In such contexts, pay is typically determined by management, albeit sometimes with direct employee involvement in decision-making. The evidence on whether direct involvement benefits workers remains mixed. Some studies identify potential mutual gains (Cullinane et al., 2014), whereas other, more critical perspectives, highlight risks of work intensification and limited, if any, material benefits (Boxall and Macky, 2014). Ultimately, the impact of employee involvement in pay decisions depends on the depth of that involvement and the degree of managerial commitment (Marchington and Suter, 2013; Dundon and Gollan, 2007; Wilkinson et al., 2020).

Emerging evidence on voice and digital adoption indicates that where workers are empowered through involvement in decision-making outcomes tend to be positive (Doellgast and Wagner, 2022; Kornelakis et al., 2022; Lloyd and Payne, 2019). Where such involvement extends to formal consultation or negotiation over pay, more equitable pay distributions may be expected. That said, the causal relationship is complex, as external market pressures, sectoral employment practices, and firm size also play a significant role in wage determination (e.g., Böckerman et al., 2013). This informs our third hypothesis:

Hypothesis 3: Employee involvement in decision-making moderates the relationship between AI-powered digital technology and employee pay.

3. Methodology

3.1. Data

To investigate the relationship between AI technologies and pay, we draw from matched, representative employer-employee data in the United Kingdom. Employer level data were collected between January 2021 and September 2023 using Computer Assisted Telephone Interviews (CATI), based on a stratified (by industry and firm size) sample drawn from the Dun and Bradstreet database. The data were collected by professional interviewers through structured (questionnaire-based) interviews with either a general manager, human resource manager or any person at the establishment level responsible for overseeing human resources and, where applicable, the adoption of digital technology. The survey included questions on employer investments in different types of ICT and AI-enabled technologies, and human resource practices including pay. An average interview lasted 27 minutes. The response rate was 35 per cent, with a final derived sample of 2001 employers.

Employee level data were collected from an original online survey of 6000 workers in the UK. The survey was designed to be representative of the workforce population (including those in employment and self-employed) at the regional level with sampling quotas set at the International Territorial Units Level 1 (ITL1). The online survey was conducted between May and June 2023 and included questions on the use of different types of digital technologies, ranging from ICT and wearable devices to AI software and AI hardware. We used a subset of employed workers, excluding the self-employed. The final employee sample included 5460 respondents.

Both surveys were motivated by the lack of representative data on employer adoption and employee use of contemporary and emerging digital technologies, including AI. Existing evidence relies on a somewhat crude, dichotomous measurement of technology adoption often combining AI with more traditional forms of ICT. In contrast, both our surveys purposefully singled out AI to enable a more refined quantitative analysis.

The employee and employer data were matched by intersection of industry (using SIC industry codes), region (TFL level 1) and establishment size (split into three categories: those with less than 24 employees; 25-499 employees; and 500 or more employees). The intersection of these three variables returned 576 unique industry-region-firm size clusters. Employer data were then aggregated to represent average levels of technology adoption within each cluster, resulting in a 2-level hierarchical dataset with employees at level 1 and the industry-region-size clusters at level 2. In a small proportion of cases, there were no matches for equivalent three-way clusters in one of the two surveys. These data were imputed by the nearest available two-way interaction: Industry X Regions or Industry X Size. The imputation did not have material implications for the aggregated statistics (see online supplementary materials).

3.2. Measurements

Measurements at level one (employee data)

Pay. Participants were asked about their "usual pay including overtime, bonuses or tips, but **before tax and other deductions** are taken out?". The measure refers therefore to gross pay levels. Pay was measured on a 6-point ordinal scale ranging from 1= £10.41 an hour or less (£20,300 per year or less for a full-time job) to 6= £38.01 an hour and above (£74,101 per year or over for a full-time job). The ordinal measurement of employee pay is consistent with the employee survey from the 2011 Workplace Employment Relations Survey (WERS2011).

Employee use of AI. To measure the use of AI-powered digital technologies, participants had to indicate how often they interacted with two types of AI powered technology "software technologies using artificial intelligence (AI) and machine learning (ML)" and AI powered hardware such as automated tools, equipment, machines and robotic technology. The variable took the form of a 5-point Likert-type scale ranging from 1 = "never" to 5 = "always". The variable is a composite (average) index of employee use of AI hardware and software.

Qualifications. Qualifications were measured as a 4-point ordinal variable, where: 1= no qualifications; 2= qualifications below A levels or vocational level 3 or equivalent; 3= A levels or vocational level 3 or equivalent, and above; 4= Degree or equivalent, and above.

Occupational skill groups were measured in line with the Standard Occupational Classification (SOC) 2020 and grouped by skill levels according to the Office for National Statistics (ONS) classification scheme:

- *Level 4* includes corporate managers and directors; science, research, engineering and technology professionals; health professionals; teaching and other educational professionals; business, media and public service professionals.
- *Level 3* comprises other managers and proprietors; science, engineering and technology associate professionals; health and social care associate professionals; protective service occupations; culture, media and sports occupations; business and public service associate professionals; skilled agricultural and related trades; skilled metal, electrical and electronic trades; skilled construction and building trades; textiles, printing and other skilled trades.
- *Level 2* includes administrative occupations; secretarial and related occupations; caring and personal service occupations; leisure, travel and related personal service occupations; community and civil enforcement occupations; sales occupations; customer service occupations; process, plant and machine operatives; transport and mobile machine drivers and operatives.
- *Level 1* includes elementary trades and related occupations and elementary administration and service occupations.

Measurements at level two (employer data)

Consistent with the measurement of AI use at employee level, we measured employer adoption of **AI-enabled digital technologies** based on whether employers had invested (in the past 5 years) in the following types of AI-powered technology:

- AI-enabled equipment (e.g., robotics, drones, robot process automation, digital identification); and
- AI applications (using AI to generate streaming content, natural language processing, recognition software virtual reality etc.).

Binary (0;1) variables were created for each type and combined into an aggregate index of AI use. Since employer data were aggregated, the measurement in question represents the extent of AI adoption within industry-region-firm size clusters.

Employee involvement in decision-making. We employed a specific measure of employee involvement in decisions on pay and pay rises. Each item was coded as “1” if not involved, “2” if informed, and “3” if consulted or engaged in negotiation. Although consultation and negotiation represent qualitatively distinct forms of involvement in decision-making, we merged these categories owing to the high risk of measurement error. During cognitive piloting, respondents tended to interpret the distinction between consultation and negotiation subjectively. Similar challenges were reported in WERS2011, where managers and employee representatives held divergent perceptions of employee involvement. This suggests that multisource data would be necessary to distinguish reliably between workplaces with consultation and negotiation practices in pay determination. In the absence of such data, we opted to reduce measurement error at the cost of a more fine-grained analysis of employee voice. We acknowledge this limitation, which prevents us from estimating differences between more substantive forms of employee involvement in decision-making and may also obscure the specific effects of collective bargaining and union representation. Nevertheless, our approach allows us to assess the difference between workplaces with and without mechanisms of employee involvement in pay determination, thereby enabling us to test Hypothesis 3.

Contextual variables. Several contextual (control) variables were included, such as standard socio-demographic measurements at employee level including gender, age (and age squared) and ethnicity in addition to tenure, company size, weekly working hours and trade union representation. We further controlled for employee use of more traditional forms of ICT (e.g., the use of desktops, laptops, tablets etc.). We treat trade union representation as a contextual rather than a moderating variable because the survey item is not sufficiently precise to establish its relationship to pay. Instead of capturing the extent of trade union influence in decision-making, the item asks whether employees have access to a trade union "to express their views about what is happening in your work or industry." This wording does not allow us to draw inferences about the union's role in wage-setting or bargaining outcomes.

3.3. Analytical approach

Owing to the nested structure of the matched employer-employee data, we first deployed multilevel regression modelling to partition variance estimates into level one (employees) and level two (employer) clusters. Regression analysis enabled us to account for variation within and between employer clusters and establish a basic association between the variables of interest. However, this approach is limited in assessing how well AI technology predicts employee pay and whether this relationship is non-linear and/or non-monotonic.

Instead, our primary analytical approach utilises machine learning algorithms. Machine learning (ML), as a model-agnostic and algorithmic approach, can harness the explanatory power of observational data (Breiman, 2001a). By emphasising out-of-sample predictions alongside cross-validation and regularisation, ML enhances the generalisability and replicability of findings beyond traditional in-sample fit metrics (Leavitt et al., 2021). Its non-parametric "black-box" algorithms, combined with interpretable ML, allow researchers to detect complex, non-linear, and non-monotonous effects often overlooked in traditional regression models, thereby strengthening theory testing and development (Leavitt et al., 2021). Moreover, ML provides higher predictive accuracy in cases where patterns do not follow strict functional forms and can reveal important inflection points (Valizade et al., 2024). In short, ML complements multilevel regression modelling by potentially revealing hidden patterns, while also strengthening the robustness of our findings.

We employed Random Forest (RF), an ensemble algorithm comprising simple predictive models (decision trees) built by resampling a random selection of features. This is similar to bootstrapping in canonical regression analysis: RF uses a bootstrapped sample to algorithmically select cut-off points to grow decision trees, estimating the effect of a predictor on an outcome at each split (Breiman, 2001). This splitting procedure is repeated multiple times, generating an ensemble ('forest') of decision trees. The random forest's prediction is derived from the average of fitted decision trees, based on a random division of the dataset into training and test subsets. These models have been shown to produce results with greater accuracy than traditional regression models and to detect potential non-linear, non-monotonic effects (Valizade et al., 2024).

We applied several techniques to estimate the direction and magnitude of the relationship between AI technology and pay. First, we computed variable importance scores using the increased node purity method. These scores measure how much a given predictor enhances the homogeneity (purity) of the target variable in the random forest algorithm: the higher the importance score, the more relevant the variable is to the overall predictive accuracy of the model. This is conceptually similar to the mean decrease in the residual sum of squares in traditional regression analysis. Second, we used Accumulated Local Effect (ALE) plots and Individual Conditional Expectation (ICE) plots (Goldstein et al., 2015). ALE plots resemble marginal effects in regression models, approximating the relationship between independent and dependent variables while accounting for correlations between other variables in the model. ICE plots visualise ALE prediction lines for each respondent in the sample alongside the average prediction, thereby illustrating the extent to which average predictions align with individual patterns in the data.

An essential step in machine learning analysis is cross-validation and parameter tuning. We ran in-sample goodness of fit and out-of-sample predictive accuracy procedures to generalise our findings. This is important to avoid overfitting where predictive accuracy in the training set significantly exceeds that in the validation set. In the first step of cross-validation and parameter tuning we split the data into training (70%) and validation (30%) samples and ran random forest algorithms on both. We then applied 10-fold cross-validation by splitting the training data into ten equally sized subsamples and used nine groups to train the algorithm, while keeping the remaining group as a validation sample (James et al., 2017). This was repeated until each sample had been used as a validation sample. The overall performance in terms of mean squared residuals and variance explained is the average of the ten models. The random forest parameters (e.g., number of trees, number variables tried at each split) were adjusted to improve predictive accuracy and ensure consistency between training and validation sets.

In the following section, we draw primarily on the machine learning analysis. Full regression outputs can be found in the online supplementary materials. Descriptive statistics are based on weighted survey data, accounting for sampling imbalances along sector, region and firm size.

4. Findings

4.1. Descriptive analysis

Table 1 presents descriptive statistics for the key study variables. Mean and median pay was equal to 3, equivalent to hourly pay of £14.01 - £18.00 or £27,301 - £35,100 per year for a full-time job. This is close to the £34,963 median gross annual earnings for full time employees in 2023 (ONS, 2024). At level two, the average proportion of AI equipment adoption across the 576 industry-region-size clusters was eight per cent. Unsurprisingly, at the employee level (level one) the use of ICT was high (median score 3.69). With the mean qualification score 3.30 and median equal to 4, more than half of employees in the sample had a qualification level at or above A-levels. The mean value of occupational skill levels (2.74) was close to that of the national population (2.83) (ONS Annual Population Survey, 2023). The median employee had been in their current job for three years or more, typically in a company with 24 to 499 employees.

The sample was almost evenly split between men (51%) and women (49%). The share of women is thus one percentage point higher in the employee survey compared to the UK workforce (Francis-Devine et al., 2025). Nearly nine in ten (87%) respondents were white, 6 per cent identified themselves as Asian or Asian British, 3.7 per cent as Black, Black British, Carabeen or African and another 3 per cent as mixed, multiple or other ethnic group. Around a third of employees (31%) were members of a recognised trade union, a higher share compared to the 22 per cent in the UK working population (Department for Business & Trade, 2024).

Table 1: Descriptive statistics

	Mean	Std. Dev	Median	Min	Max
Employee level data					
Pay	3.01	1.35	3	1	6
Employee use of AI	2.24	1.20	2	1	5
Employee use of ICT	3.69	1.22	4	1	5
Qualification groups	3.30	0.85	4	1	4
Weekly working hours	2.77	0.67	3	1	4
Tenure	2.59	0.67	3	1	3
Trade union member	0.31	0.46	0	0	1
Age	43.21	13.59	42	18	70
Gender	0.49	0.50	0	0	1
SOC skill levels	2.74	0.95	3	1	4
Employer level data					
Employer adoption of AI	0.08	0.13	0	0	0.7
Voice: employee involvement in pay negotiations	2.10	0.43	2.00	1	3
Establishment size	3.05	0.86	3	1	4

Source: employee survey (upper portion); employers' digital practices at work survey (lower portion)

Table 1 shows employer level statistics aggregated at the intersection of industry, region and firm size. Only one-in-five employers had invested in AI in the previous five years, a finding that is supported by the employee level data where around 20 per cent of workers reported that they had used AI equipment or software often or always. A significant minority of employees, four-in-ten, reported no interaction with AI technology at work at all.

Another important variable for our study is employee involvement in decisions on pay and pay increases. Only a third of employers involved employees in consultations and negotiations about pay, which is consistent with the findings from the 2011 Workplace Employment Relations Survey (van Wanrooy et al., 2012).

Prior to our regression and machine learning analysis, we estimated the correlation between employer adoption and employee use of AI (see Table 2 below). The AI technology variables derived from aggregated (at the sector-region-size level) employer survey and employee data were highly correlated, with ß=0.61 (the lowest 95% confidence estimate was

0.22 and the highest 1.01). We are therefore unlikely to critically distort the distribution of technology adoption at level two by aggregating employer data at the intersection of industry, region and firm size bands.

Table 2: Relationship AI technologies Level 1 and Level 2

	Employee adoption of AI	
Predictors	*Estimates*	*p*
(Intercept)	2.18 (2.12 – 2.24)	**<0.001**
Employer adoption of AI	0.61 (0.22 – 1.01)	**0.002**
Random Effects		
σ^2	1.26	
$\tau_{00\ \mathrm{SectorRegionSize}}$	0.19	
ICC	0.13	
$N_{\mathrm{SectorRegionSize}}$	580	
Source:	Matched employer-employee data	
Observations	5294	
Marginal R^2 / Conditional R^2	0.004 / 0.133	

4.2. Direct effect of AI technologies on employee pay

We now turn to our main analysis, focusing first on the direct effect of AI on employee pay. Both machine learning and multilevel regression modelling found a meaningful association between AI and pay. Table 3 presents regression coefficients from a random intercept regression model (Part A) alongside variable importance scores from the random forest algorithm (Part B). The regression coefficients for the effect of employer adoption and employee use of AI on pay were both positive and statistically significant (at $p<0.05$ and $p<0.01$ respectively).

Variable importance scores produced by the machine learning algorithms are particularly informative as they indicate the relative contribution of each explanatory variable to the algorithm's predictions. Employee use of AI was among the most important predictors of pay, though was ranked below occupational skill groups, employee voice and employer clusters as a predictor of pay. AI, therefore, is an important predictor of employee pay, alongside other variables central to our theoretical assumptions. While employee voice emerged as an important predictor, trade union presence ranked among the least important.

This reinforces our earlier argument that the survey item on union presence is not well suited to capturing unions' potential role in wage bargaining.

Table 3: Multilevel regression estimates

Part A: Regression estimates: AI technology – employee pay		
Predictors	*Estimates*	Estimates
Employer adoption of AI	0.66** (0.18 – 1.15)	-
Employee use of AI		0.17*** (0.14 – 0.20)
*** p<0.001; ** p<0.01; * p<0.05		
Random Effects		
σ^2	1.05	1.50
τ_{00}	0.09 SectorRegionSize	0.34 SectorRegionSize
ICC	0.08	0.18
N	568 SectorRegionSize	576 SectorRegionSize
Observations	4676	5184
Marginal R^2	0.359	0.004
Covariates in the model		

Part B: Variable importance scores based on increase in node purity	
Predictor	*Importance score*
Occupations Skill Groups	1285.9964
Industry X Region X Size	923.3913
Employee voice	598.4270
Employee use of AI	587.2513
Weekly working hours	563.9576
Age	553.2120
Qualification groups	360.5459
Employer adoption of AI	305.6034
Firm size	280.6016
Gender	273.3133
Tenure	260.5347
Trade union representation	131.4020
Ethnicity	117.8039
Model fit: training set	Number of trees: 1500 No. of variables tried at each split: 4 Mean of squared residuals: 1.127037 % Var explained: 38.08
Model fit: validation set	Number of trees: 1500 No. of variables tried at each split: 4

	Mean of squared residuals: 1.111857 % Var explained: 39.8
Source	Matched employer-employee data

While the regression coefficients and confidence intervals reported in Table 3 provide readily interpretable measures of the magnitude of the relationship between AI and pay, machine learning analysis allows for more accurate predictions and is generally superior in uncovering nuanced patterns within the data (Valizade et al., 2024). We present Accumulated Local Effect (ALE) plots (the machine learning equivalent of marginal effects) in Figures 1 and 2.

Figure 1 visualises the relationship between AI technology at level two (region × sector × size clusters of employers) and employee pay. The data reveal a generally moderate positive association between AI technology and pay, up to a key inflection point when more than 40 per cent of employers within a given industry and regional cluster adopt AI. At this point, there is a step change in the probability of moving towards a higher pay band. This suggests a critical level of AI adoption at the industry level that begins to spill over into individual workplaces.

Overall, this analysis supports Hypothesis 1, demonstrating a consistent and positive association between employer adoption and employee use of AI and employee pay levels.

Figure 1: ALE plot for the relationship between employer adoption of AI technology (level two) and employee pay (source: employers' survey)

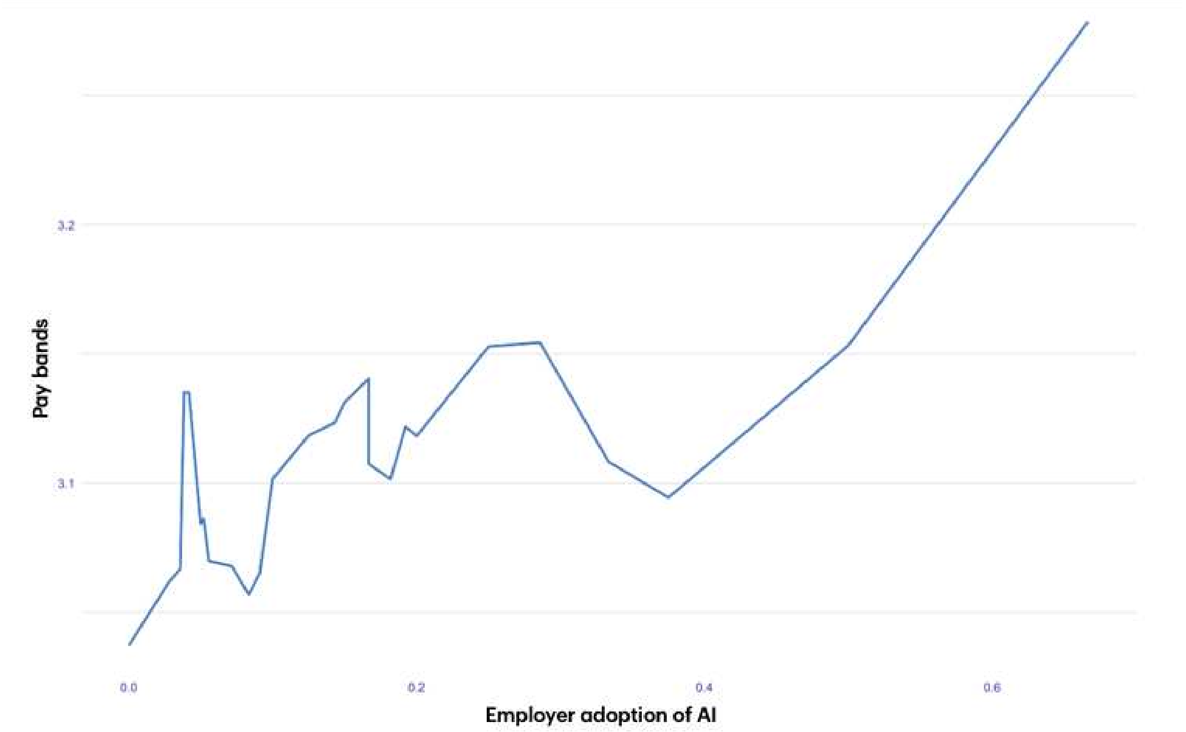
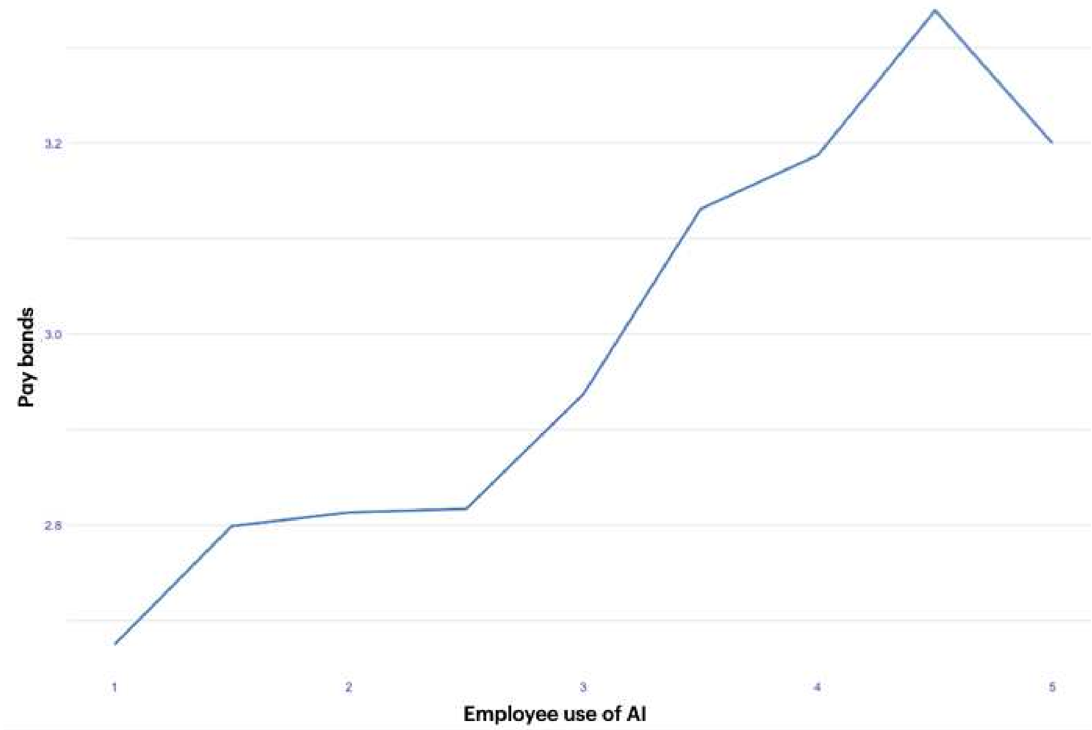


Figure 2 presents the ALE plot for the effect of employee use of AI (level one) on pay. This shows a positive, predominantly linear association between employee AI usage and pay. The data reveal an upward shift from pay band two (£10.42-£14.00 per hour or £20,301-£27,300 per annum) towards pay band three (£14.01-£18.00 per hour or £27,301-£35,100 per annum). For a worker in the middle of pay band two, a shift towards the middle of pay band three represents a pay increase of 14.7 per cent, potentially triggered by the adoption and use of AI.

Figure 2: ALE plot for the relationship between employee use of AI technology (level one) and employee pay (source: employee survey)



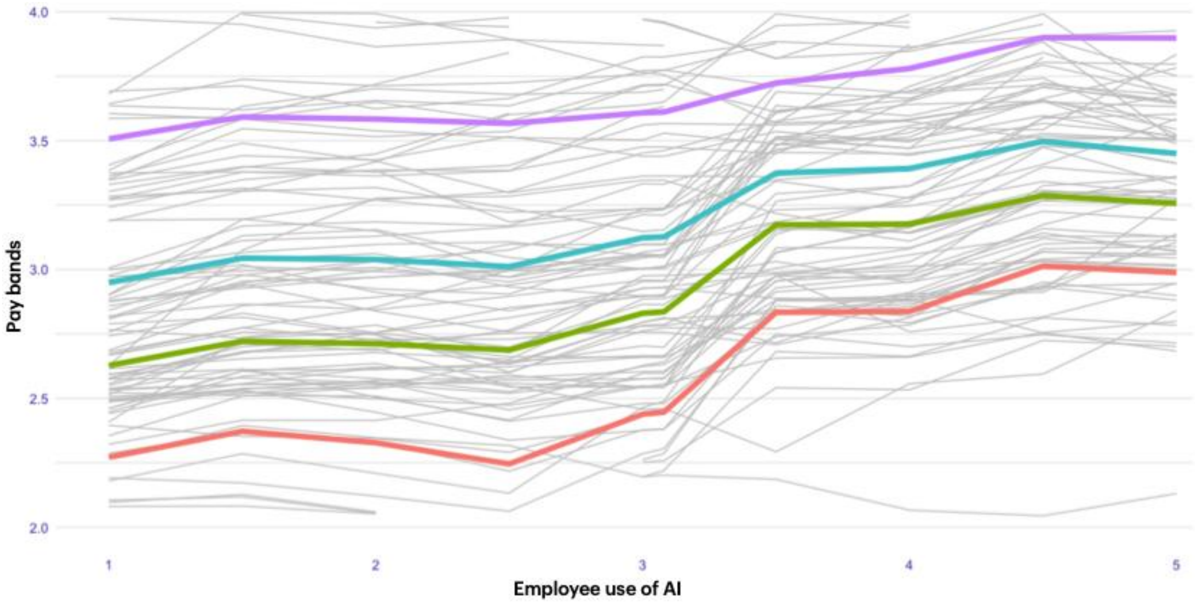
Variables in the model: age, weekly working hours, tenure, gender ethnicity, occupational skill group, educational qualification, firm size, employee voice

4.3. AI and pay levels across qualification skill groups and the role of employee voice

Having established the direct association between AI-enabled technologies and employee pay levels, we now turn to Hypothesis 2 and examine the effect of AI across qualification and occupational skill groups. We present findings for the effect of employee use of AI only (level one), as the sample size of employer clusters within each qualification group does not allow for a robust and reliable analysis at level two.

Figure 3 presents ICE plots illustrating the effect of AI on pay levels across four qualification groups: no formal qualifications (red); qualifications below A levels or vocational Level 3 or equivalent (green); A levels or vocational Level 3 or equivalent (blue); and degree or equivalent, and above (purple). The ICE plot indicates a positive effect of AI on pay across all qualification groups while revealing several distinctive patterns. Among the most educated employees in the sample (the purple line), the association between AI use and pay is broadly stable, with incremental gains linked to more extensive use of technology. However, there is little to no effect among other groups where technology is used less frequently. Employees with lower qualification levels begin to experience an uplift in pay when they use AI-powered technology most or all the time (scores 4 and 5 on the X-axis). Workers without formal qualifications (the red line) stand to gain the most from AI, though this is contingent on the frequency of their interaction with AI.

Figure 3: ICE plot for the effect of employee use of AI on pay levels by qualification groups (Source: Matched employer-employee data)

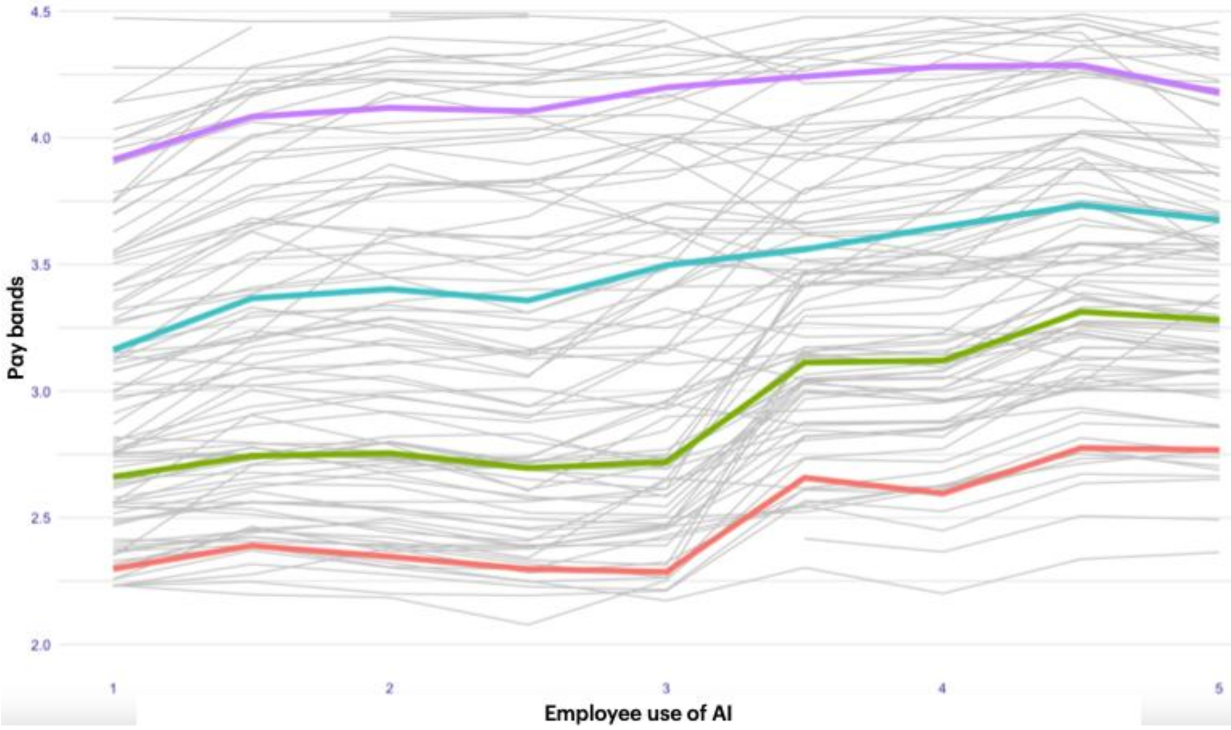


Note: red=no qualifications; green= other qualifications below A levels or vocational level 3 or equivalent; blue= A levels of vocational level 3 or equivalent; purple= Degree or equivalent, and above.

Qualification groups may not always accurately reflect the nature of jobs and tasks. To address this, we analysed the relationship between employee use of AI across four occupational skill groups: SOC Level 4 (purple), SOC Level 3 (blue), SOC Level 2 (green), and SOC Level 1 (red). Figure 4 presents the respective ICE plot, which reveals patterns consistent with those observed in Figure 3. As with qualification groups, employees at the lower end of the occupational hierarchy appear to benefit disproportionately from the use of AI technology at work. However, this effect is most pronounced in environments where AI is fully integrated into job tasks (i.e., where workers interact with AI always or most of the time). The positive effect among higher-skilled occupational groups is less pronounced, with only marginal gains accrued by these workers.

Overall, our machine learning analysis supports Hypothesis 2.

Figure 4: ICE plot for the effect of employee use of AI on pay levels by occupation skill groups (Source: Matched employer-employee data)

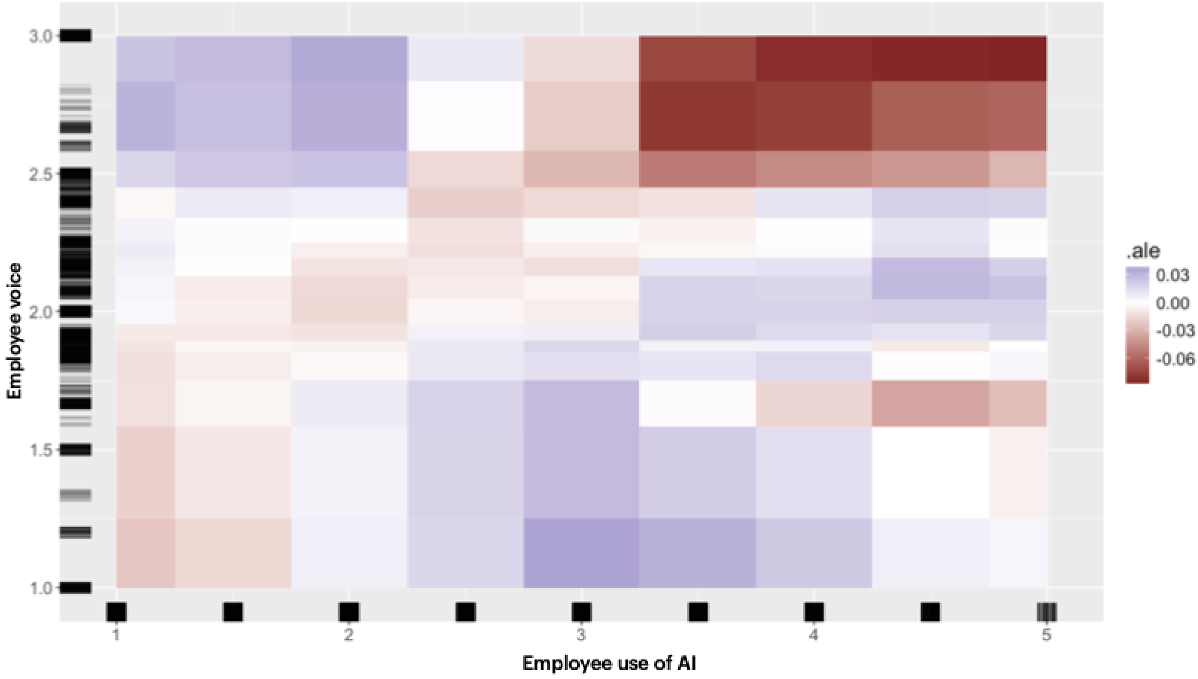


Note: purple=SOC level 4, blue/turquoise=SOC level 3; green=SOC level 2; red=SOC level 1

Thus far, the analysis has presented an optimistic outlook regarding AI's potential to increase pay. In what follows, we examine employee involvement in pay determination as a moderating factor in this relationship. To do so, we employ an interpretive machine learning technique known as two-way ALE plots. Two-way ALE plots are a visualisation tool used to examine interaction effects between two variables in a predictive machine learning model. They extend the one-way ALE plots reported earlier by illustrating how the joint effect of two variables influences the model's predictions while accounting for correlations in the data.

Figure 5 presents a two-way ALE plot depicting the interaction between employee use of AI and employee involvement in pay increases. A colour scale indicates the direction of the interaction effect: blue corresponds to a positive effect on pay while brown indicates a negative association. Two key conclusions emerge from the graph: first, the two variables interactively influence employee pay rather than acting independently (as indicated by the colour contrast); second, the combination of extensive AI use and higher employee involvement in pay decision-making has an overall negative effect on pay (as suggested by the deeper brown colour in the top-right corner and the deep blue at the bottom of the graph).

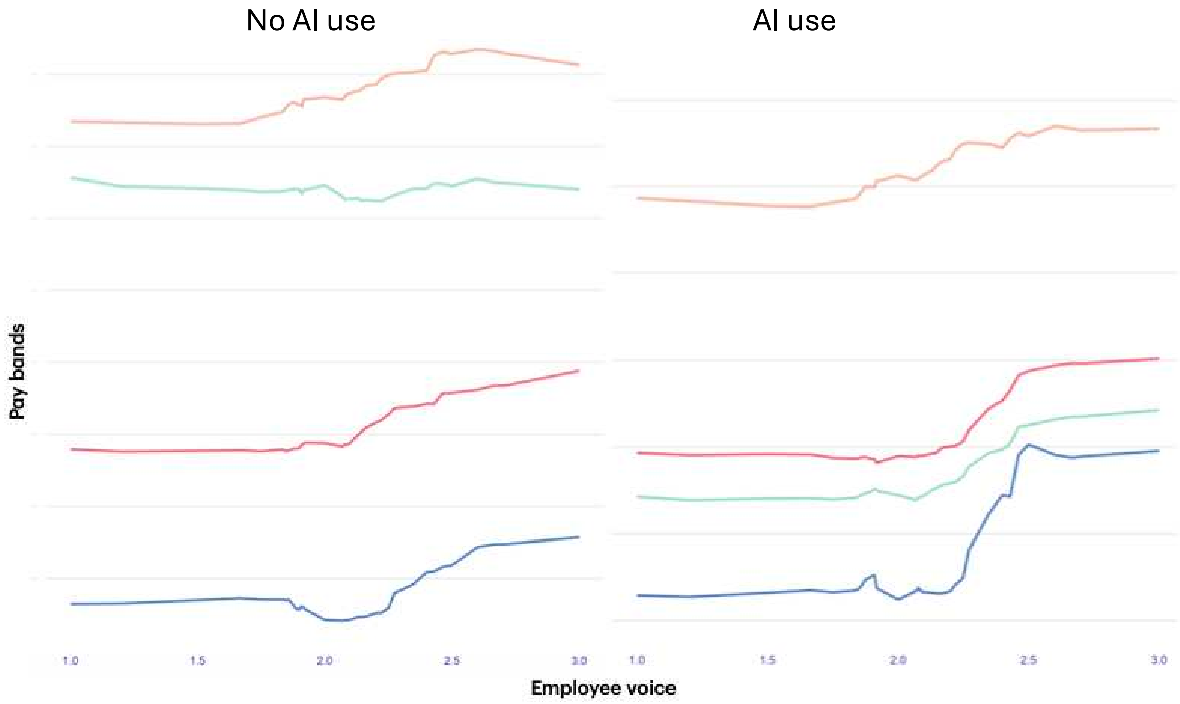
Figure 5: Two-way ALE plots between employee voice and use of AI (Source: Matched employer-employee data)



The two-way ALE analysis supports Hypothesis 3. One possible explanation for the observed interaction effect is that employee involvement amplifies the impact of AI on pay among some skills groups but not the others (Böckerman et al., 2013). To examine this possibility, we extended the two-way ALE analysis to visualise the joint effects of AI use and employee voice across our four occupational groups.

Figure 6 presents the results (the graph on the right-hand side corresponds to higher levels of AI use) and shows how, contingent on AI use, employee involvement in pay determination influences pay across qualification levels (note, the effects across qualification groups were virtually identical). While there is an overall positive association between employee involvement and pay, there is a clear trend toward a more equal pay distribution among AI adopters. This convergence occurs through a substantial pay uplift among the lowest qualification group where employees are involved in consultations and negotiations over pay. Thus, the observed AI pay benefits accrued to lower qualified employees appear to be in part enabled by employee involvement in decision-making.

Figure 6: Two-way ALE plots of the effect of AI and employee voice by qualification skill groups (Source: Matched employer-employee data)



Note: orange=Qualification level 4, red = Qualification level 3; green= Qualification level 2; blue= Qualification level 1

5. Sensitivity and robustness checks

Machine learning offers greater predictive accuracy than more canonical forms of statistical analysis. Yet, sensitivity and robustness checks are essential to ensure that results are not driven by arbitrary modelling choices or unstable features of the data. Most of the common procedures are already embedded in cross-validation and have been performed by default. That includes varying the number of trees grown in the forest to stabilise predictions and adjusting the number of variables randomly sampled at each split to assess whether variable importance measures are consistent across different levels of randomness.

Imbalanced, oversampled data poses problems for regression analysis that can be dealt with by using sampling weights. Machine learning does not function in the same way, but comparable solutions are available and were deployed (Si et al., 2025). First, we utilized over-sampling and under-sampling methods to address imbalances in outcome variables and ensure our predictions remain reliable under different data partitions. Second, we compared variable importance score derived from different importance metrics, such as mean decrease in accuracy versus mean decrease in Gini impurity, to detect whether findings depend on the chosen criterion. Out-of-bag (OOB) error rates were also monitored to ensure that models generalise well without overfitting. Together, these procedures provide reassurance that the random forest's results are unlikely to be the outcome of a complex survey design and specific parameter choices.

6. Discussion and conclusions

Against a backdrop of growing academic and political interest in the implications of AI-enabled technologies for the future of work, the relationship between AI adoption and employee pay is of growing concern. Our study is among the first to use matched, nationally representative employer and employee data to examine the use and implications of AI for pay in the UK. Employing machine learning techniques, we identified a generally positive relationship between AI-enabled technologies and employee pay, while also uncovering theoretically and practically significant conditions that shape this effect. These include the extent of worker interaction with AI and the role of employee participation in pay determination.

6.1. Theoretical implications

The finding of a positive relationship between employees' use of AI and pay broadly aligns with previous research in the UK using vacancy data (Bone et al., 2024). This suggests that workers proficient in AI technologies can secure a wage premium that may stem from the current imbalance between the high demand for AI skills (Bone et al., 2024; Stephany and Teutloff, 2024) and the relatively low investment in AI-related training by UK employers (Stuart et al., 2023). Likewise, our findings support research from Germany (Genz et al., 2021) that identifies a positive effect of AI implementation at the employer level on employee pay. However, caution is warranted when interpreting the causal effect of AI on pay. Rather than AI investment directly driving wage increases, it is also plausible that higher-paying firms are more likely to invest in AI-enabled technologies (Berg et al., 2023).

More detailed analyses of formal qualifications and occupational skill groups revealed several key insights. While employers' adoption of AI generally leads to higher levels of pay, lower-qualified and lower-skilled occupational groups appear to benefit to a greater extent. This is an intriguing finding and suggests that workers in lower skilled groups that are using AI may be able to leverage a wage premium, as was the case with computer skills in previous decades (Krueger, 1993; Peng and Eunni, 2011). Nonetheless, in contrast to earlier digital technologies (Acemoglu, 2002; Autor et al., 1998), the adoption and use of AI may have the potential to reduce pay inequalities. It is important to note, however, that our analysis also revealed that for the lowest-qualified workers pay increases were contingent on frequent interaction with AI. In other words, AI must be deeply embedded in daily work routines and tasks to create opportunities for wage growth. Given that employees in higher-skill groups use AI significantly more than those in lower-skill groups (see ANOVA and Tukey test results in the supplementary materials), the anticipated equalising effect may not be realised, unless structural features of the UK labour market are addressed.

Two important caveats should be noted. First, data from the representative Employers' Digital Practices at Work Survey indicate that only a minority of UK employers had invested in AI-powered equipment or software in the previous five years. As a result, only a fraction of lower-paid and lower-qualified employees are currently able to materially benefit from AI. Broader pay increases across the labour market will depend on the pace of AI adoption among UK employers. Second, given that any pay benefits are contingent on regular AI use, potential trade-offs ought to be considered. Increased AI usage may lead to reduced work autonomy and heightened work-related stress (Berg et al., 2023), potentially culminating in burnout. We also cannot rule out that AI adoption at the lower end of the occupational hierarchy may contribute to job displacement. However, the evidence to-date does not support this: indeed, data suggest that AI adopters tend to have a generally positive employment outlook (Stuart et al., 2023).

Finally, our empirical results reinforce the argument that the impact of new digital technologies on workers is shaped by wider workplace employment relations (Joyce et al., 2024; Thompson and Laaser, 2021). Our findings suggest that employee involvement in consultation and negotiation over pay moderates the relationship between AI use and pay. In organisations adopting AI where employees or their representatives have a say in how pay is determined, pay distribution across occupational skill groups appears to be more equitable. This is achieved through a higher likelihood of wage increases among the lowest-skilled employees consistent with the literature on 'what unions do' (Turnbull, 2003; Bennett and Kaufman, 2017).

These findings have important implications for our understanding of employee voice. Rather than directly influencing technology adoption, employee involvement in decision-making appears to serve as a counterbalance to management power, ensuring a fairer distribution of AI-related pay benefits. This contributes to existing conceptual work on the role of participatory work practices and employee voice in shaping the relationship between technology and work outcomes (Berg et al., 2023).

6.2. Practical Implications

In the context of a political and media focus on job displacement through automation, our findings provide robust empirical evidence for the likely impacts of AI for workers, with specific reference to pay. The practical implications are threefold. Firstly, in the context of a lack of employer investment in advanced digital skills (Stuart et al., 2023) and growing demand for AI skills (Bone et al., 2024), employees that are able to use AI technologies currently benefit from higher pay compared to their counterparts. For workers, investment in learning AI-related skills is likely to pay off, irrespective of the formal level of qualifications.

Secondly, while the use of AI in some instances narrowed or even closed the qualification wage gap between workers, we must be cautious. The share of highly skilled occupational groups using AI technologies was significantly higher compared to lower skilled occupations. With more highly skilled workers experiencing pay increases, they are likely to widen existing qualification pay gaps (Office for National Statistics, 2025), as long as structural barriers impede the uptake of AI for lower-skilled workers. Again, widespread training and education initiatives may help to increase the supply of AI skills thereby reducing the competitive advantage of particular groups of workers. Moreover, employee involvement in management decisions around technology implementation, currently absent in many workplaces must be strengthened. This may give employees more collective power, spreading the uptake of AI more equally among different groups of workers.

Thirdly, our findings nonetheless suggest that employee voice could make a significant difference for pay equality associated with the adoption of AI technology. Employee voice can play an important role in achieving sustained positive effects of AI on pay while avoiding further labour market polarisation. How voice arrangements can be extended across UK employers remains an open question, yet within a context of declining union representation and formalised collective bargaining arrangements this is a potential area of concern. It is also notable that where employers have invested in advanced AI technologies, they have typically done so without informing, consulting or negotiating with employees.

6.3. Limitations and Future Research

Our research drew from new representative employer and employee survey data related to emerging digital technologies in the UK. Creating a multilevel data set by matching employer and employee data along the intersection of industry, region and firm size allows for novel insights into the relationship between AI-enabled technologies at different levels and employee pay. The use of random forest in combination with interpretive machine learning techniques increased the nuance and robustness of our findings. Against these strengths we must acknowledge some limitations.

First, data used in the analyses were cross-sectional, limiting our ability to draw more robust conclusions about how changes in AI investments (level 2) and use (level 1) are associated with changes in pay. More longitudinal and linked data are needed to better grasp the relationships between AI, productivity and pay as well as between AI, skills and pay. This will improve our theoretical and practical understanding of these relationships and processes. Second, while the matching process created a unique multilevel dataset, we cannot pinpoint the precise firms that employees are nested in. Matching through clusters based on the intersection of region, sector and firm size is the best approximation with the currently available data. Third, we had to compromise on some of our key measurements to minimise response bias and non-response, given the nature of our original survey. The pay measurement was recorded along restricted pay bands thereby limiting our ability to estimate the exact changes in employees' pay. We decided to bundle consultation and negotiation practices to minimise response bias in employee involvement in pay determination. The limitations of the union representation measurement in terms of capturing unions' role in wage-setting and bargaining may be the reason for its low variable importance score.

Lastly, we emphasised the importance of institutional context when examining the AI-pay relationship. Even though there is a general decline in the power of labour institutions and collective bargaining across Europe, findings from the UK may not be easily transferrable to other country contexts. Future research is needed to investigate the relationship in countries with significantly different pay setting institutions and where there may be a more influential role for collective bargaining.

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