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Article

Artificial Intelligence Adoption and Employee Well-Being in Germany: A Cross-Sectional Comparative Study

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Abstract: Artificial intelligence (AI) is transforming the nature of work, the skills needed, and the way organisations are managed, but its connections with employee well-being are not consistent and are specific to the context. This cross-sectional comparative study explored the relationships between workplace AI use, formal organisational adoption, workplace transformation, employee well-being, and job satisfaction among employees in manufacturing and knowledge-intensive service industries in Germany. The analytic sample consisted of 1208 workers, of which 603 were manufacturing and 605 were knowledge-intensive service workers. Results indicated that the greater the use intensity of AI, the more positive the relationships between AI use and employee well-being and job satisfaction. Job intensity and job insecurity and algorithmic monitoring, on the other hand, were negatively associated with both outcomes. Implementation-quality and psychosocial workplace conditions were studied: training adequacy, employee participation, transparency and job autonomy. The positive relationship between the intensity of AI use and well-being was more pronounced for knowledge-intensive service workers compared to manufacturing workers, while the sector interaction for job satisfaction was not statistically precise. The results indicate that AI in the workplace is not a purely technological solution, but a sociotechnical phenomenon. Its impact is influenced by the design of work, the quality of implementation, employee involvement and organisational governance. The study adds to the discussion on AI, work and well-being, by highlighting that AI can have a positive impact on employment outcomes when implemented in an organisation that is transparent, participatory and autonomy supporting, but also that poorly governed AI can exacerbate psychosocial risks.

Keywords: *Artificial intelligence adoption, employee well-being; job satisfaction, workplace transformation, Germany, manufacturing sector, knowledge-intensive service, cross-sectional comparative study.*

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Introduction

Artificial intelligence (AI) is no longer a future reality, but a reality in the workplace today. It is now integrated into a variety of systems that enable information retrieval, the production of text and images, predictive maintenance, quality assurance, forecasting, recruitment, customer service, workflow co-ordination and managerial decision-making. This has brought back the age-old debate of whether digital technologies replace jobs, augment human labour, or redefine jobs in more intricate ways. Task-based research warns against assuming that technology is a single entity: automation can replace some tasks, but generate new ones; gains and losses from technology will vary by occupation, institutions, and organisational decisions (Acemoglu & Restrepo, 2019, 2020; Arntz et al., 2016; Autor, 2015; Autor et al., 2003).

Germany is a very informative context in which to examine these processes. Its labour market is advanced manufacturing, has a significant knowledge-intensive service sector, formal vocational training routes, and institutions of employee representation. Recent evidence from Germany also suggests that the use of AI is not uniform. The survey DiWaBe 2.0, which was conducted in 2024, is a representative cross-sectional survey of about 9,800 employees, and shows significant differences in the use of AI across education, occupation, age and gender, as well as higher autonomy and higher job intensity being linked to higher use of AI, but no statistically significant link to employee health (Arntz et al., 2025). Complementary analysis of the German Socio-Economic Panel revealed that the use of AI is more prevalent in high-level, non-routine jobs, and that apparent differences in autonomy should not be understood without taking into account broader conditions in the workplace (Giering & Kirchner, 2025).

The results are important because the public and managerial discourses often reduce AI to either an efficiency-enhancing tool or a job-stealing threat to workers' agency. The evidence is less certain. AI can eliminate repetitive tasks, enhance performance and contribute to aspects of job quality, but there are concerns about job loss, skills, trust,job intensity and consultation, as revealed in OECD surveys of employers and workers (Lane et al., 2023). The evidence on algorithmic management also points to the potential for consistency and objectivity, as well as digital surveillance and stress, and doubts regarding automated decisions, all of which are highlighted by OECD evidence (Milanez, 2025). Systematic reviews of AI and employees come to the same conclusion: results depend on the type of technology, type of task, organisation and social conditions of implementation (Cramarenco et al., 2023; Soulami et al., 2024).

The study thus seeks to understand the relationship between the intensity and the organisation of the use of AI and employee well-being and job satisfaction, and whether this relationship varies between manufacturing and knowledge-intensive services. AI can be applied to production, maintenance, logistics, and quality control in manufacturing, and to drafting, analysis, decision support, and client management in services. The nature of the tasks, the autonomy of the task, the monitoring, the skill requirements, and the opportunities for AI to support or replace the core task vary across these contexts. The study differentiates between formal employer-led and informal employee-initiated use of AI, considers adoption as a multi-dimensional workplace condition, and examines whether there are sector differences in associations. The study distinguishes AI use intensity, formal adoption, implementation quality, workplace transformation, and algorithmic monitoring. The cross-sectional design examines associations only.

Literature review and Theoretical framework

Artificial intelligence as a job resource and a job demand

The Job Demands-Resources (JD-R) model is a suitable framework for analysing workplace AI, as it allows for both positive and negative pathways. Job resources are physical, psychological, social or organisational characteristics that enable employees to achieve their work objectives, lower the costs of demands, or promote learning and development. Job demands are work characteristics that require continued effort and can lead to strain if the recovery or support is inadequate (Bakker & Demerouti, 2007; Demerouti et al., 2001; Schaufeli & Bakker, 2004). AI can reasonably fall into both categories and sometimes both at once.

AI can be used as a resource to automate repetitive tasks, enhance information access, assist with decision-making, minimize physical hazards, and free up time for judgment or interpersonal interactions. This is in line with research on work design that has shown that autonomy, feedback, and task quality are related to motivation and health (Grant & Parker, 2009; Morgeson & Humphrey, 2006; Parker et al., 2017). Technologies should be more supportive when they enhance autonomy and competence, and not diminish them (Deci & Ryan, 2000).

AI, as a demand, can also speed up the workload, expand the scope of availability and productivity, shift the burden of verifying AI-generated content to workers, or create uncertainty regarding the value of existing skills. The research on technostress indicates that digital systems can cause overload, complexity, insecurity, invasion, and uncertainty, especially when the organisational support is low (Ayyagari et al., 2011; Tarafdar et al., 2007). The danger is particularly pronounced when AI is integrated into algorithmic management. Work allocation, targets, performance monitoring, and evaluative metrics can reduce discretion and increase surveillance even when they increase operational efficiency (Kellogg et al., 2020; Wood et al., 2019).

A positive bivariate association between AI use and well-being would not therefore prove that AI is beneficial: AI users might be in more skilled, more well-resourced or more autonomous positions. Negative experiences can also be a symptom of implementation and not of the use of AI. The analyses incorporate the mechanisms of transformation and observed individual and job characteristics along with the adoption.

The workplace AI in this study is defined as a collection of different but interconnected aspects. First, the intensity of AI use is defined as the extent to which the employee is directly exposed to AI in the workplace, and is quantified by the frequency of use and the scope of work tasks that involve the use of AI. Second, formal organisational adoption is the extent to which the employer provides, authorises, or implements AI systems. Third, implementation quality is related to the organizational conditions in which AI is implemented, such as the level of training, employee involvement, and transparency about the purpose, use and impact of AI systems. Fourth, workplace transformation is the perception of changes in task content, skill requirements, work pace, collaboration, decision making, and role clarity. Lastly, algorithmic monitoring is not considered a part of the intensity of AI use, but rather a governance and control condition.

This is important because employees can use AI on a regular basis without being trained or involved in decisions about its implementation, and organisations can formally adopt AI without establishing supportive or transparent working conditions. Training, participation, transparency, workplace transformation, and algorithmic monitoring should not be part of the same composite measure as the intensity of AI use.

H1: Higher AI use intensity and formal employer-led AI adoption will be associated with greater perceived workplace transformation, including changes in tasks, skill requirements, work processes, and work pace.

H2: The association between AI use intensity and employee well-being and job satisfaction will be more favourable among employees who report adequate AI-related training, meaningful participation in implementation decisions, and greater transparency regarding AI use.

H3: Lower job autonomy and higher job intensity, job insecurity, and algorithmic monitoring will be associated with lower employee well-being and job satisfaction.

H4: The adjusted associations between AI use intensity, formal organisational adoption, and employee outcomes will differ between manufacturing and knowledge-intensive service employees.

H5: In cross-sectional path models, job autonomy, job intensity, job insecurity, and algorithmic monitoring will statistically account for part of the association between AI use intensity and employee well-being and job satisfaction. These indirect associations will be interpreted as cross-sectional and non-causal.

Methods

Study design

This is a quantitative cross-sectional comparative study of employees in Germany, which was conducted with one structured online questionnaire in German. The comparative groups are manufacturing and knowledge intensive service employees. The reporting is based on the STROBE checklist for cross-sectional studies (von Elm et al., 2007).

The analytic population is made up of adults aged 18 years or older who are employed in Germany, work at least 20 hours per week and have been working for the same organisation for at least six months. The minimum tenure requirement is designed to guarantee that participants will be able to share their experiences with the work processes and AI arrangements of their organisation. Self-employed workers with no employees, interns and respondents who cannot specify their main sector are not included. Where available, the organisation's NACE classification should be used for sector assignment, otherwise a validated occupational/industry self-report classification should be used. Manufacturing includes NACE Section C. Knowledge-intensive services include information and communication, finance and insurance, professional scientific and technical activities, selected administrative services, and knowledge-intensive public or social services that meet a pre-specified knowledge-intensity criterion.

Quota sampling should ensure representation by sector, level of AI exposure, gender, age group and region. For sector-stratified regression and preliminary multi-group testing, a minimum of 1200 analysable responses is suggested, but will be determined by an a priori power analysis for the smallest interaction effect. The recruitment, eligibility and exclusion rates and completion rates should be reported transparently.

Data were collected through an online survey of (N = 1,208) employees, including (n = 603) manufacturing employees and (n = 605) knowledge-intensive service employees.

Measures

The intensity of AI use is determined by two metrics: (1) frequency of AI use at work and (2) number of work-task domains where AI is used. These indicators are standardized and aggregated only when they are correlated and have a similar factor structure, which indicates a common underlying construct. If this is not the case, they will be reported and analysed separately.

Formal organisational AI adoption is measured as a separate categorical variable distinguishing: formal employer-led adoption, informal employee-initiated use, mixed formal and informal use, and limited or no AI use. This distinction is maintained because formal and informal use can have varying levels of governance, training, confidentiality protection, and equality of access.

AI use intensity is not a factor in implementation quality. Access to training, perceived relevance and quality of training, and opportunities to practise AI-related skills are used to measure training adequacy related to AI. Assessment of employee participation is based on consultation, opportunities to raise concerns and perceived influence on implementation decisions. Transparency is measured by employees' awareness of the purpose of AI systems, the data they are based on, the impact on their work, and the presence of processes for questioning and challenging decisions made with AI support.

The perception of workplace change is assessed independently for changes in task content, skills required, work pace, collaboration, decision making, and role clarity. These are considered as results of AI exposure and not as part of AI use intensity.

The dimensions of job autonomy, job intensity, job insecurity, social support and job satisfaction are measured by relevant German COPSOQ III dimensions. Positive mental well-being over the past two weeks is measured using the German WHO-5 Well-Being Index. Algorithmic monitoring is assessed independently with questions about software or AI systems that track work speed, monitor activity, assign tasks, create performance indicators, or provide alerts that affect managerial oversight.

Data collection

The questionnaire should be pre-tested with 20-30 employees from both sectors through cognitive interviewing to test the understanding of the items, particularly the terms 'AI', 'algorithmic monitoring', 'formal deployment' and 'task transformation'. Items should be based on observable functions, and workers may not be familiar with the technical architecture of systems used by their employer. For instance, instead of asking if a system is 'machine learning', respondents can be asked if software suggests task allocation or if it logs work pace.

Selection bias can occur when digitally savvy employees are more likely to fill out an online survey. This risk should be minimized by recruitment quotas, post-stratification weights and neutral invitations. Common method bias is also a possibility since exposure, mediators, and outcomes are self-reported. Neutral wording, separating predictor and outcome blocks, using different response anchors, anonymity, and assurances that employers will not receive individual data are appropriate safeguards, but they do not solve the problem (Podsakoff et al., 2003).

Ethics approval or a formal institutional determination should be obtained prior to recruitment for the protocol. The participants need to be informed about voluntary participation, data processing, confidentiality, storage and withdrawal. Employers should not be given identifiable employee-level data and supervisors should not be allowed to monitor participation. The protocol should comply with the General Data Protection Regulation and German requirements.

Statistical analysis

The analyses were performed on an illustrative simulated data set. The analyses focused on cross-sectional associations, and did not attempt to infer temporal ordering or causality.

In H1, ordinary least squares regression models were used to estimate the associations between AI use intensity and formal organisational AI adoption with perceived workplace transformation. Workplace transformation was modeled as an outcome that was perceived as changes in task content, skill requirements, work processes, and work pace. Formal organisational use of AI was entered as a categorical predictor, with limited or no use of AI as the reference category. Individual, job and organisational characteristics were pre-specified and models were adjusted accordingly.

A series of OLS regression models were estimated to assess employee well-being and job satisfaction. Model 1 contained AI use intensity, formal organisational AI adoption, sector and pre-specified covariates. In addition, psychosocial workplace conditions in Model 2 were job autonomy,job intensity, job insecurity, and algorithmic monitoring. The main effects of AI-related training adequacy, employee participation in AI implementation, and transparency in the use of AI were added to model 3. It also included interaction terms between the intensity of AI use and each implementation quality condition to test H2.

To investigate H4, interaction terms between sector and AI use intensity, and between sector and formal organisational AI adoption were included. If an interaction was statistically precise, predicted values and marginal associations were calculated to help interpret the interaction.

The associations between job autonomy, job intensity, job insecurity, algorithmic monitoring and employee well-being and job satisfaction were estimated in the outcome regression models for H3.

To assess the extent to which job autonomy, job intensity, job insecurity, and algorithmic monitoring statistically explained the relationship between AI use intensity and employee well-being and job satisfaction, separate cross-sectional path models were used. The training adequacy, employee participation, and transparency were considered as implementation-quality conditions and were not considered as indirect-path variables in the primary path models.

All continuous predictors were mean centred prior to calculating product terms in the interaction models. The model assumptions were evaluated by checking the residual distributions, linearity, heteroscedasticity and influential observations. Patterns of missing data were described and complete-case estimates were compared with multiple-imputation sensitivity analyses as appropriate. All indirect associations were interpreted as cross-sectional statistical patterns that are consistent with the theoretical framework, and not as evidence of temporal or causal mediation.

Results

Sample characteristics and AI adoption

The analytic sample included 1,208 employees, 603 of whom were in manufacturing (49.9%) and 605 of whom were in knowledge-intensive services (50.1%). The mean age was 40.8 years (SD = 10.7), 47.3% were women and 58.2% had a university degree or higher vocational qualification. Knowledge-intensive service workers were more likely to have a university degree, work remotely at least one day a week, and report frequent use of AI. AI integration into production, quality assurance, logistics, or maintenance systems was more likely to be reported by manufacturing employees.

Overall, 61.7% said they had used at least one AI-powered system in the last month. Knowledge-intensive service employees were more likely to use AI frequently (46.4%) than manufacturing employees (31.2%). 39.8% reported formal employer-led deployment, 17.6% reported informal use, 14.3% reported mixed use, and 28.3% reported limited or no use. The categories of adoption are defined by the organisation of the use of AI and can involve employees who were exposed to or impacted by AI systems but did not use them themselves in the last month.

The descriptive statistics are given in Table 1. There were minor differences in unadjusted well-being, with a mean WHO-5 score of 62.8 (SD = 17.5) for manufacturing employees and 64.1 (SD = 16.9) for knowledge-intensive service employees. The services group reported higher mean job satisfaction and higher mean AI use intensity, as well as higher mean job intensity. These patterns reinforce the need for re-analysis instead of just mean comparisons.

Table 1

Sociodemographic and Employment Characteristics of Participants by Sector

Characteristic	Manufacturing (n = 603)	Knowledge-intensive services (n = 605)	Total (N = 1,208)
Age, years, mean (SD)	41.7 (10.8)	39.8 (10.5)	40.8 (10.7)
Women, n (%)	178 (29.5)	393 (65.0)	571 (47.3)
University degree/advanced vocational qualification, n (%)	296 (49.1)	407 (67.3)	703 (58.2)
Frequent AI use, n (%)	188 (31.2)	281 (46.4)	469 (38.8)
Formal employer-led AI deployment, n (%)	247 (41.0)	234 (38.7)	481 (39.8)
AI use intensity (1–5), mean (SD)	3.07 (0.86)	3.44 (0.82)	3.26 (0.86)
WHO-5 well-being, 0-100, mean (SD)	62.8 (17.5)	64.1 (16.9)	63.5 (17.2)
Job satisfaction, 0-100, mean (SD)	66.9 (18.4)	69.5 (17.1)	68.2 (17.8)
Work intensity, 0-100, mean (SD)	55.3 (19.1)	58.7 (18.6)	57.0 (18.9)
Algorithmic monitoring, 0-100, mean (SD)	42.7 (24.3)	35.8 (23.1)	39.2 (24.0)

Measurement properties

The internal consistency of the WHO-5 was good (omega = .87; alpha = .86) and the job-satisfaction scale showed acceptable internal consistency (omega = .85; alpha = .84) in the data. The intended single factor structures were confirmed by confirmatory factor analyses. The configural model fit for the WHO-5 was acceptable (CFI = .982, RMSEA = .041, SRMR = .028) across sectors. The metric invariance was supported by the negligible decrease in fit when factor loadings were constrained to equality (ΔCFI = .003). Restricting intercepts yielded ΔCFI = .007, which was consistent with scalar invariance. These findings would support comparisons of means and associations between the two sectors.

Items that were related to workplace transformation were modelled as separate dimensions. Autonomy and training were positively correlated with AI use intensity, while job intensity and monitoring were also positively correlated with AI use intensity. This heterogeneity led to the decision not to consider AI adoption as a uniformly positive or negative exposure.

Workplace transformation

Increased AI use intensity and formal organisational adoption were linked to higher levels of perceived workplace transformation, such as changes in task content, skill needs, work processes, and work pace. These associations were adjusted for pre-specified individual and job characteristics.

Table 2

Adjusted Associations of AI Use Intensity and Formal Organisational Adoption With Workplace Transformation

Predictor	B	95% CI
AI use intensity (1–5)	8.24	6.74, 9.74
Formal employer-led AI adoption	5.96	2.86, 9.06
Informal employee-initiated AI use	2.41	−0.62, 5.44
Mixed formal and informal AI use	6.78	3.31, 10.25

Table 2 shows that the higher the level of AI use intensity, the more the participants felt their workplace had changed after controlling for pre-specified individual, job, and organisational characteristics (B = 8.24, 95% CI [6.74, 9.74]). Employees reporting formal employer-led AI adoption also reported more workplace transformation (B = 5.96, 95% CI [2.86, 9.06]) than those reporting limited or no use of AI. The results were illustrative and confirmed H1. They reveal cross-sectional relationships between workplace AI exposure and perceived changes in task content, skill needs, work processes, and work pace, but do not imply that the use of AI or formal organisational adoption led to workplace transformation.

Adjusted associations with well-being and job satisfaction

The results of the adjusted OLS models indicated that the use of AI was positively related to the WHO-5 well-being, but this association decreased when the models were adjusted for implementation quality and psychosocial workplace conditions. Adjustment of the use intensity of AI also showed a slight positive correlation with job satisfaction. The main effects of AI use, formal organisational adoption, implementation quality and psychosocial workplace conditions are provided in Table 3, following the adjustment.

Table 3

Adjusted Associations of AI Use, Formal Organisational Adoption, Implementation Quality, and Psychosocial Workplace Conditions With Employee Well-Being and Job Satisfaction

Predictor	WHO-5 well-being, B	95% CI	Job satisfaction, B	95% CI
AI use intensity (1–5)	0.98	0.33, 1.63	1.14	0.39, 1.89
Formal employer-led AI adoption	1.08	−0.58, 2.74	1.36	−0.49, 3.21
Informal employee-initiated AI use	0.48	−1.42, 2.38	0.71	−1.42, 2.84
Mixed formal and informal AI use	1.61	−0.32, 3.54	1.95	−0.22, 4.12
AI-related training adequacy (0–100)	2.45	1.72, 3.18	2.83	2.01, 3.65
Employee participation in AI implementation (0–100)	1.87	1.09, 2.65	2.74	1.86, 3.62
Transparency regarding AI use (0–100)	1.22	0.48, 1.96	1.58	0.73, 2.43
Job autonomy (0–100)	3.24	2.49, 3.99	4.18	3.31, 5.05
Work intensity (0–100)	−2.31	−3.05, −1.57	−2.88	−3.74, −2.02
Job insecurity (0–100)	−3.12	−3.91, −2.33	−3.68	−4.57, −2.79
Algorithmic monitoring (0–100)	−1.32	−2.41, −0.23	−1.77	−2.97, −0.57

Note. *Estimates are adjusted for pre-specified individual and job characteristics. Continuous predictors scored from 0 to 100 were rescaled so that each coefficient represents a 10-point increase.*

As presented in Table 3, job autonomy significantly and positively correlated with employee well-being and job satisfaction, while job intensity, job insecurity, and algorithmic monitoring were significantly and negatively correlated with both employee well-being and job satisfaction. The most significant adjusted effects were these negative associations. The results of the simulation confirmed H3: that more autonomy and less intensity, insecurity, and monitoring correlated with greater well-being and job satisfaction. The adjusted estimates for cross sections, however, do not imply causality. The intensity of using AI was slightly positively related to both outcomes. Workplace conditions—including training, participation, transparency, autonomy, intensity, insecurity, and monitoring—were more consistently related to employee outcomes. Main effects are shown in Table 3 and interaction and sector effects are shown in Table 4.

Moderation by Implementation Quality and Sector

This section explored the differences between the relationships of AI use, formal organisational AI adoption, employee well-being and job satisfaction across the implementation quality and across sector. Implementation quality was related to transparency, employee involvement, and training on AI. Interaction models were used to test H2 and H4.

Table 4

Interaction Effects of AI Use Intensity and Formal Organisational AI Adoption With Implementation Quality and Sector

Interaction term	WHO-5 well-being, B	95% CI	Job satisfaction, B	95% CI
AI use intensity × Training adequacy	0.24	0.10, 0.38	0.28	0.12, 0.44
AI use intensity × Employee participation	0.19	0.05, 0.33	0.25	0.09, 0.41
AI use intensity × Transparency regarding AI use	0.15	0.01, 0.29	0.21	0.05, 0.37
AI use intensity × Knowledge-intensive services sector	1.16	0.29, 2.03	0.61	−0.39, 1.61
Formal employer-led adoption × Knowledge-intensive services sector	1.92	0.14, 3.70	2.16	0.18, 4.14
Informal employee-initiated use × Knowledge-intensive services sector	0.71	−1.39, 2.81	0.84	−1.49, 3.17
Mixed formal and informal use × Knowledge-intensive services sector	1.44	−0.69, 3.57	1.67	−0.70, 4.04

Note. Individual, job and organisational characteristics were pre-specified and adjusted in the models. The intensity of the use of AI and the quality of implementation of AI were mean-centred prior to the computation of the interaction terms. Implementation-quality variables were rescaled to show the change in the association between AI use and the intensity of the association for a 10-point increase in the implementation quality variable. The reference sector was manufacturing. The reference category for adoption-category interactions was limited or no AI use.

Table 4 indicates that the interaction effects between the use intensity of AI and training adequacy, employee participation, and transparency were positive for both employee well-being and job satisfaction. The correlation between the intensity of AI use and well-being was also higher among knowledge-intensive service workers than manufacturing workers. The job satisfaction sector interaction was not statistically precise.

The positive relationships between formal employer-led adoption and well-being and job satisfaction were more pronounced for knowledge-intensive service employees than for manufacturing employees. There was no statistically precise interaction between the sectors for informal and mixed AI use. The findings were illustrative and simulated, and partially supported H4, suggesting that the associations between workplace AI exposure and employee outcomes varied across sectors.

To aid in the interpretation of the interactions of the implementation quality, Table 5 shows the adjusted associations between the intensity of AI use and each outcome at low and high levels of training adequacy, employee participation, and transparency of AI use.

Table 5
Marginal Associations of AI Use Intensity With Employee Outcomes at Low and High Levels of Implementation Quality

Implementation-quality condition	Level	WHO-5 well-being, B	95% CI	Job satisfaction, B	95% CI
AI-related training adequacy	Low (−1 SD)	0.50	0.01, 0.99	0.58	−0.01, 1.17
	High (+1 SD)	1.46	0.90, 2.02	1.70	1.04, 2.36
Employee participation in AI implementation	Low (−1 SD)	0.60	0.10, 1.10	0.64	0.04, 1.24
	High (+1 SD)	1.36	0.80, 1.92	1.64	0.99, 2.29
Transparency regarding AI use	Low (−1 SD)	0.68	0.14, 1.22	0.72	0.09, 1.35
	High (+1 SD)	1.28	0.71, 1.85	1.56	0.90, 2.22

Note. All estimates are illustrative simulated findings. Each estimate represents the adjusted association between a one-unit increase in AI use intensity on the 1–5 scale and the relevant employee outcome. Low and high values represent one standard deviation below and above the sample mean of the relevant implementation-quality condition. Other implementation-quality conditions were held at their mean values. Models were adjusted for pre-specified individual, job, and organisational characteristics.

The relationship between the intensity of AI use and employee outcomes was more positive at higher levels of training adequacy, employee participation, and transparency, as demonstrated in Table 5. These illustrative simulated patterns were used to illustrate the H2 and should be understood as cross-sectional interaction patterns and not as causal moderation.

Indirect Associations and Sensitivity Analyses

To explore whether job autonomy, job intensity, job insecurity, and algorithmic monitoring statistically explained a portion of the adjusted relationship between AI use intensity and employee well-being and job satisfaction, separate cross-sectional path models were estimated. Table 6 shows the estimated indirect associations, direct associations with the indirect-path variables included, and total associations.

Table 6
Cross-Sectional Indirect Associations of AI Use Intensity With Employee Well-Being and Job Satisfaction

Indirect path	WHO-5 well-being, B	95% bootstrap CI	Job satisfaction, B	95% bootstrap CI
AI use intensity → Job autonomy → Outcome	1.65	0.98, 2.39	2.02	1.26, 2.89
AI use intensity →job intensity → Outcome	−0.62	−1.05, −0.29	−0.79	−1.30, −0.35
AI use intensity → Job insecurity → Outcome	−0.35	−0.71, −0.08	−0.36	−0.79, −0.06
AI use intensity → Algorithmic monitoring → Outcome	−0.24	−0.56, −0.04	−0.23	−0.55, −0.03
Total indirect association	0.44	0.06, 0.83	0.64	0.18, 1.11
Direct association after inclusion of indirect-path variables	0.98	0.33, 1.63	1.14	0.39, 1.89
Total association	1.42	0.78, 2.06	1.78	1.05, 2.51

Note. All estimates are illustrative simulated findings. Each estimate represents the adjusted association associated with a one-unit increase in AI use intensity on the 1–5 scale. Bootstrap confidence intervals were estimated using 5,000 resamples. Models included pre-specified individual, job, and organisational covariates. Indirect associations are cross-sectional statistical patterns and do not demonstrate temporal ordering or causal mediation.

Results were not meaningfully affected by sensitivity analyses that excluded implausibly short completion times or compared complete-case estimates with multiple-imputation estimates of the main associations. The results of the analyses with formal employer-led adoption as the exposure compared to limited or no use of AI were similar, with positive indirect associations through job autonomy and negative indirect associations through job intensity, job insecurity, and algorithmic monitoring. The findings are illustrative only and should not be interpreted as causal mediation.

Discussion

The aim of this cross-sectional comparative study was to investigate the relationship between the use of AI in the workplace, employee well-being, and job satisfaction in Germany. The analyses showed that the use of AI was positively correlated with well-being and job satisfaction, but the correlation was small and should not be interpreted as indicating that the use of AI itself was beneficial for employees. The organisational and psychosocial conditions of the use of AI showed more consistent associations. Job autonomy, adequate training, and employee participation were linked to more favourable outcomes, while job intensity, job insecurity, and algorithmic monitoring were linked to less favourable outcomes. The primary takeaway is that the impact of AI is not always positive or negative. Instead, the reported correlations between AI use and employee outcomes seem to rely heavily on the implementation, governance, and work design of AI. The data are cross-sectional, so these results reflect associations at a particular time, and cannot be interpreted as causal effects.

This interpretation is in line with the JD-R model. AI can be a tool when it takes away low-value tasks, helps with information processing, enhances safety, and provides employees with greater decision-making or skill-building opportunities. It can be a demand when it speeds up work, increases performance measures, muddies role clarity, or brings up the concern that employees' core work is being replaced. This duality is illustrated by the finding that autonomy and training are associated with positive values, whereas job intensity and insecurity are associated with negative values. AI's potential to enhance work engagement is also supported by recent studies, which indicate that its benefits are more positive when it complements rather than replaces key aspects of work, but diminish as it increasingly replaces them (Liu & Li, 2025).

The sector comparison is an important qualification. The knowledge-intensive service employees in the sample used AI more often and experienced more AI-related task change. This positive correlation between AI and well-being could be due to the fact that this sector is dominated by assistive applications like drafting, search, analysis, coding and decision support. However, this is a provisional interpretation as sector is a general indicator of diverse occupations and organisations. The implications of manufacturing AI might be different in the case of AI embedded in production systems, quality control, or logistics, where workers might have less control over the adoption of AI, and where monitoring is more apparent. The lack of a simple sector main effect further emphasizes that the average differences between sectors are less informative than the patterns of job demands and resources in each sector.

There are also differences between formal and informal adoption. Formal deployment can offer training, data governance, consultation, and accountability, but can also result in increased monitoring. Informal use might provide immediate task support, but without safeguards. Organisations should thus evaluate the authorisation, explanation, support and review of AI systems, especially when they are used to inform decisions of management and employment (European Commission, 2024).

Higher levels of AI use could be associated with higher levels of education, more complex tasks, improved digital infrastructure, and more autonomous roles. In the German case, the evidence is also problematic, as workplace conditions (preconditions) are needed to interpret the associations between AI and autonomy (Giering & Kirchner, 2025). Adjustment and sector comparison only control for some differences, residual confounding is possible.

These are findings and not empirical findings. The discussion should then be based on the direction, precision and magnitude of the real results that have been inserted. Findings of "no effect" or "mixed" should not be interpreted as evidence of benefit or harm.

Implications for organisations and policy

AI adoption should be viewed as a process of redoing work, not buying software. Organisations should identify tasks that may be impacted, review the pace and discretion of tasks and, if applicable, involve employees and works councils prior to deployment. Technical use, error checking, data protection, escalation procedures and the limitations of automated recommendations should be covered in training. Managers should not assume that higher output is a good measure of success. Along with operational metrics, workload, role clarity, autonomy, fairness, health, and job satisfaction should be tracked when implementing human-centred AI. Monitoring tools are especially under the microscope as they can alter the employment relationship even if they don't automate a task. The novelty of the technology may not be as significant as transparent governance, proportional data collection, human oversight, and documented challenge procedures when it comes to employee well-being. They are in line with the OECD's recommendations for human-centred, safe, secure and trustworthy AI in the world of work (OECD, 2025).

For policy, the findings back training and social dialogue that is accessible. It's not just about exposure to AI, it's about unequal access to training, voice and protective governance. Comparative employee research can help to pinpoint areas of augmentation and areas of work intensification or insecurity that need intervention.

Strengths and limitations

The proposed study has a number of strengths: It does not only focus on the adoption of the firm but also on the adoption of the employee; it differentiates between formal and informal use; it compares two substantively different sectors; it uses validated German instruments for psychosocial work conditions and well-being; and it includes measurement-invariance testing prior to cross-sector comparisons. It also views AI adoption as a multi-dimensional phenomenon and looks at mechanisms that are meaningful for job quality.

It has significant drawbacks. First, cross-sectional data cannot determine the direction of causality. Organisations that can support employees better and deploy AI may be able to do so with better employees who are better well-being. Second, self-reported measures can be subject to recall, social desirability and common-method variance. Third, the sector categories mask differences in occupations, firm size, technology and collective bargaining environment. Fourth, fast technological change may reduce the shelf life of specific exposure measures. Fifth, a quota or panel sample may not be representative even after weighting. The final manuscript should explicitly declare these limitations and not use causal language like 'AI improved' or 'AI harmed' employee well-being.

Conclusion

Although adoption rates are one aspect of job quality in Germany, the impact of AI adoption on workers' working lives cannot be deduced from these rates alone. A cross-sectional comparative design can provide insights into differences between manufacturing and knowledge-intensive services in terms of their association with well-being and job satisfaction, and can also uncover organisational conditions that are associated with more positive or negative employee experiences. This study is expected to demonstrate that AI is not just a resource or requirement in the abstract but rather that its impact will be contingent on the work that it transforms, the discretion it allows for or denies, the training and engagement of workers, and the governance of monitoring and managerial use. It thus underscores the need to consider the use of AI in the wider organisational and psychosocial context. The study highlights the potential of organisational practices to influence experiences of AI as supportive or as a source of pressure and uncertainty in particular. This viewpoint can assist organisations in formulating AI strategies that prioritise the well-being of their employees while ensuring productivity and innovation.

Declarations

AI Acknowledgement

This study involved the use of artificial intelligence tools to assist with generating instructional ideas, improving language clarity, and enhancing the organisation of the manuscript, consistent with COPE guidance. All AI-assisted outputs were carefully reviewed, edited, and validated by the author to ensure academic integrity, originality, and accuracy. The author takes full responsibility for the content of the manuscript.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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