Dyal Singh Journal of Humanities and Social Sciences (DSJHSS)
Vol. 4, No. 1, 2026, pp. 117-149
ISSN (P): 3006-6522
ISSN (E): 3006-6530

AI Adoption, Employee Well-being and Job Performance: The Mediating Role of Well-being and the Moderating Role of AI Anxiety

Dr. Mehreen Aslam[1]

Abstract

Received: 19-02-26

Reviewed: 03-05-26

Accepted: 20-05-26

Published: 30-06-26

Drawing on job demands–resources (JD-R) and conservation of resources (COR) theories, this study tested whether employee well-being mediates the association between artificial intelligence (AI) adoption and job performance and whether AI anxiety moderates the first stage. A three-wave, time-lagged study paired employee reports with supervisor-rated job performance (N = 400 complete matched cases). Regression, bootstrapped conditional indirect effects, confirmatory factor analysis and robustness checks were applied. The retained five-factor model fit well (CFI = .992, RMSEA = .017, SRMR = .033); however, the proposed four dimensions of AI anxiety were not empirically separable in this sample. Well-being was positively associated with subsequent job performance ($b = 0.24$, $p < .001$). AI adoption did not show a statistically significant adjusted association with well-being at mean anxiety ($b = 0.03$, $p = .50$), and neither the conditional indirect effect (95% CI [−0.014, 0.027]) nor the AI adoption × AI anxiety interaction ($b = -0.04$, $p = .12$) was statistically significant. AI adoption had a positive direct association with job performance ($b = 0.23$, $p < .001$), while AI anxiety was negatively associated with both well-being and job performance. An exploratory inverted-U pattern varied across specifications. The findings do not support the proposed mediation or moderation, but suggest that technology use, anxiety and well-being warrant separate attention. The observational design does not establish causal effects.

Keywords: artificial intelligence adoption; employee well-being; job performance; AI anxiety; job demands–resources theory; conservation of resources theory; moderated mediation

This is an open access article distributed under the terms of CC-BY-4.0, which permits unrestricted use, distribution, reproduction, and adaptation in any medium and for any purpose with proper attribution to the original author(s), title, journal, and URL.

[1] Institute of Management Science, Baha ud Din Zikria University, Multan

ISSN (P): 3006-6522
ISSN (E): 3006-6530

1. INTRODUCTION

Artificial intelligence (AI) is increasingly used to draft documents, screen applicants, analyze customer information and support professional decisions. Reviews identify both opportunities for efficiency and concerns about workers' experiences (Bankins et al., 2024). For organizations, the important question is not simply whether AI is used but how its use relates to employees' psychological states and job performance.

Empirical studies so far point in different directions. Field and experimental evidence shows that dependence on intelligent machines can be a mixed blessing: it can move employees closer to their work goals and raise task performance, but it can also threaten self-esteem and lower performance (Tang et al., 2023a). Interaction with AI at work has also been linked to both adaptive and maladaptive consequences, some of which reach into employees' time after work (Tang et al., 2023b). In a three-wave study of employees in eight Chinese companies, organizational AI adoption led to challenge appraisals and promotion-focused job crafting among employees with an internal locus of control, but to hindrance appraisals and prevention-focused crafting among employees with an external locus of control (Cheng et al., 2023). Kim and Lee (2024) found that AI adoption increased job stress and, through stress, burnout, and that confidence in learning AI weakened the first link. Together, these results suggest that AI adoption is neither simply good nor simply bad for employees. Its effect depends on how employees experience it.

Three questions motivate this study. First, whether general psychological well-being accounts for part of the relationship between AI adoption and job performance remains insufficiently resolved in the literature reviewed here. Second, findings on job performance do not consistently identify the pathways involved. Third, AI anxiety may represent a relevant boundary condition, but its role as a first-stage moderator warrants direct testing rather than assumption.

We therefore proposed a first-stage moderated mediation model in which AI adoption is positively related to well-being, well-being is related to job performance and AI anxiety weakens the first association. Job demands–resources (JD-R) theory allows AI to be conceptualized as either a resource or a demand (Bakker et al., 2023); conservation of resources (COR) theory directs attention to perceived threats to valued resources (Hobfoll et al., 2018). These arguments motivate the hypotheses rather than establish that the proposed mechanism operates in the observed data.
The study tests a specific psychological pathway while separately estimating the direct adoption–job performance association. It also examines AI anxiety as a possible moderator and uses temporally separated employee assessments and supervisor ratings to reduce, though not eliminate, shared-method concerns. The findings provide a test of the proposed model, including its unsupported paths.

The paper is organized as follows. Section 2 develops the theory and hypotheses. Section 3 describes the method. Section 4 reports the measurement model, hypothesis tests, robustness checks and exploratory analyses. Section 5 discusses the results against prior studies and sets out theoretical and practical implications, limitations and directions for future research. Section 6 concludes.

2. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1 Job demands–resources and conservation of resources

JD-R theory proposes that every job has demands and resources. Demands are physical, psychological, social or organizational aspects of work that require sustained effort and therefore carry costs. Resources are aspects of work that help to reach goals, reduce demands or stimulate growth (Bakker & Demerouti, 2007). Two processes follow. In the health-impairment process,

ISSN (P): 3006-6522
ISSN (E): 3006-6530

high demands without enough resources exhaust employees and harm well-being. In the motivational process, resources support engagement and job performance (Bakker & Demerouti, 2017). The most recent review of the theory adds a person × situation view and proactive responses of employees to their jobs, which makes room for individual differences in how a given job feature is experienced (Bakker et al., 2023).

COR theory starts from the principle that people strive to obtain, retain and protect resources, and that the threat or actual loss of resources produces stress (Hobfoll, 1989). Two propositions matter here. Resource loss has a stronger impact than resource gain of the same size, and people who lack resources are more vulnerable to further loss, while those who hold resources are better placed to gain more (Hobfoll et al., 2018). Halbesleben et al. (2014) added that resources include objects, personal characteristics, conditions and energies, and that investment of resources is the main way people prevent loss and create gain.

The two theories fit together in the study of AI. JD-R gives the structure of demands and resources in the job. COR gives the dynamic logic of gain and loss, including the reason why a perceived threat to one's skills or position can outweigh objective benefits. The challenge–hindrance stressor framework offers a link: demands that employees appraise as challenges tend to motivate, and demands appraised as hindrances tend to drain (LePine, 2022). AI adoption can be appraised in both ways, and the appraisal depends on the employee (Cheng et al., 2023).

2.2 AI adoption and employee well-being

In this study, AI adoption means the extent to which an employee uses AI-based tools in daily tasks and the degree to which these tools are integrated into the employee's core work processes. This follows the logic of use behaviour in technology acceptance research (Venkatesh et al., 2003), and it focuses on actual use, not on organizational announcements or on intention.

Employee well-being is defined as the employee's overall psychological state of positive mood, vitality and interest in daily life. We use this broad, resource-like conception because JD-R and COR both treat energy and positive affect as resources that employees invest in their work. Positive emotions also broaden thought and action and build lasting personal resources (Fredrickson, 2001), so well-being is a plausible carrier of the effect of AI on later performance.

From a JD-R view, AI adoption can work as a job resource. AI tools reduce routine and time-consuming activity, speed up information search, support decisions and help employees reach goals (Bankins et al., 2024; Tang et al., 2023a). These features correspond to the definition of a resource as something that helps to reach goals and reduces the costs of demands. When employees save effort on routine tasks, they gain energy and time that can be used for tasks they value, and this should be reflected in higher well-being.

AI adoption can also add demands, including learning requirements, changed roles, loss of control over work steps and monitoring (Bankins et al., 2024). Evidence that AI adoption raises job stress (Kim & Lee, 2024) shows that the demand side is real. The question for the average effect is therefore which side is larger in the population studied. We expect that in a sample of employees who use AI tools voluntarily or with organizational support, and who therefore have some control over how they use them, the resource side will be dominant on average. The demand side is expected to dominate for employees who are anxious about AI, and we address this separately in Section 2.5.

H1. AI adoption is positively related to employee well-being.

2.3 Employee well-being and job performance

The link between well-being and job performance has a long history in organizational research. A meta-analysis found a moderate positive relationship between job satisfaction and job

ISSN (P): 3006-6522
ISSN (E): 3006-6530

performance (Judge et al., 2001), and broaden-and-build theory gives a mechanism: positive states widen attention and build skills and social ties that improve later functioning (Fredrickson, 2001). In JD-R terms, employees who are energetic and positive have the personal resources to meet task demands, to concentrate and to complete role requirements (Bakker & Demerouti, 2017). From the COR perspective, employees with higher resource levels can invest more in their work without risking depletion, whereas those low in resources enter a defensive mode and protect what remains (Hobfoll et al., 2018).

We focus on in-role job performance, defined as the fulfilment of formal duties and requirements of the job (Williams & Anderson, 1991). This outcome is directly tied to the evaluation of the employee by the organization, and it is the performance criterion most often affected by changes in how work is done, such as the introduction of AI tools.

H2. Employee well-being is positively related to job performance.

2.4 The mediating role of well-being

Combining the two preceding arguments, AI adoption should influence job performance through well-being. The JD-R motivational process describes this type of sequence: a job resource raises a positive psychological state, and that state raises performance (Bakker et al., 2023). COR theory supports the sequence through resource gain spirals, in which an initial gain makes later gains more likely. Evidence that AI use has simultaneous benefits and costs for performance (Tang et al., 2023a) suggests that the net effect of AI on performance passes through psychological states, and that those states are the place to look for the mechanism. We therefore expect that the part of the AI–performance relationship that is explained by AI works through well-being, and we test it as an indirect effect while controlling for the direct path.

H3. Employee well-being mediates the relationship between AI adoption and job performance.

2.5 The moderating role of AI anxiety

AI anxiety is a state of apprehension about AI that arises from beliefs about its consequences for one's learning demands, one's job and one's place in a technological environment. Li and Huang (2020) identified four dimensions on the basis of integrated fear acquisition theory, and Wang and Wang (2022) developed a validated scale with four factors: learning, job replacement, sociotechnical blindness and AI configuration. AI anxiety is related to general technology anxiety, but it differs because AI can act autonomously and may compete with employees for tasks. It is also distinct from perceived job insecurity, which concerns the stability of the job in general. Workers who feel threatened by smart technology and automation report higher job insecurity (Brougham & Haar, 2018; Koo et al., 2021), so we measure job insecurity and control for it, to make sure that AI anxiety has an effect beyond a general fear of job loss.

COR theory predicts that threatened resources are more damaging than gained resources are helpful (Hobfoll et al., 2018). For an employee with high AI anxiety, the same AI adoption that saves effort also signals a possible loss of skills, status or position. This employee will appraise AI as a hindrance (LePine, 2022; Cheng et al., 2023), spend energy on monitoring the threat and on learning anxiously, and so will not convert the efficiency gain into well-being. For an employee with low AI anxiety, the same adoption is appraised as a challenge or as plain support, and the resource gain is realized. The findings of Kim and Lee (2024) point in the same direction: the stress effect of AI adoption weakened when employees had more confidence in learning AI. Kim et al. (2024) report a related result for job insecurity and depression in AI-integrated workplaces, in which self-efficacy in AI use acted as a moderator. We therefore expect AI anxiety to weaken the positive relationship between AI adoption and well-being, and possibly to reverse it at high levels.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

H4. AI anxiety moderates the relationship between AI adoption and employee well-being, such that the relationship is more positive when AI anxiety is low and weaker (or negative) when AI anxiety is high.

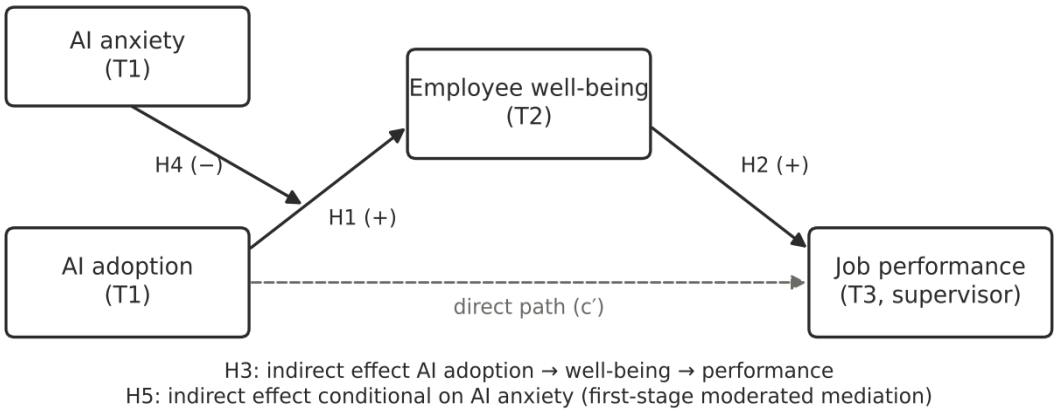
Because AI anxiety conditions the first stage of the mediation chain, the indirect effect of AI adoption on performance through well-being should vary with AI anxiety. This is a first-stage moderated mediation model (Hayes, 2015).

H5. The indirect effect of AI adoption on job performance through employee well-being is conditional on AI anxiety: it is positive when AI anxiety is low and weaker, or not different from zero, when AI anxiety is high.

2.6 Research questions and conceptual model

The hypotheses answer three research questions. RQ1: Under what conditions does AI adoption raise or lower employee well-being? RQ2: Does well-being carry the effect of AI adoption to job performance? RQ3: Does the strength of this indirect effect depend on employees' AI anxiety? Figure 1 shows the model.

Figure 1. *Conceptual model: first-stage moderated mediation.*



Note. T1–T3 = measurement waves about four weeks apart. Control variables predict both well-being and performance.

3. METHOD

3.1 Research design, procedure and data

This study used a three-wave, time-lagged quantitative design to examine associations among employee AI adoption, AI anxiety, well-being and supervisor-rated job performance. Employees were recruited from organizations in Punjab, Pakistan, spanning information technology, education, finance, manufacturing, healthcare, retail and public-sector settings. The manuscript describes recruitment as systematic sampling, but does not identify the underlying sampling frame, selection interval or recruitment protocol; therefore, probability-based representativeness cannot be established from the information reported.

Data collection was conducted over three measurement waves, separated by approximately four weeks. At Time 1 (T1), employees provided information regarding AI adoption, AI anxiety, perceived job insecurity, and demographic and job-related characteristics. At Time 2 (T2), participating employees completed the employee well-being assessment. At Time 3 (T3),

ISSN (P): 3006-6522
ISSN (E): 3006-6530

employees' immediate supervisors evaluated their in-role job performance. This temporal separation of the predictor, mediator, and outcome variables, together with the use of supervisor-rated job performance, was intended to reduce potential common method bias (Podsakoff et al., 2003).

Responses across the three waves were linked using a self-generated identification code comprising the last two digits of the participant's mobile number and the day of birth. Supervisors assessed employees whose responses could be matched through the identification procedure. Before participation, respondents were informed about the purpose of the research, the voluntary nature of participation, confidentiality arrangements, and their right to withdraw. Responses were treated as confidential rather than completely anonymous because the identification procedure permitted matching across measurement waves. The research instrument is reproduced in *Appendix A*.

At T1, 700 employees participated in the initial survey. Of these, 639 completed the second-wave survey, corresponding to a retention rate of 91.29%. At T3, 450 employee responses were successfully matched with supervisor-rated job performance assessments, representing 70.42% of the T2 sample and 64.29% of the initial T1 sample. Following data screening and application of the study's exclusion criteria, 400 complete employee–supervisor matched observations were retained for the final statistical analysis.

The overall analytical retention rate was 57.14%, calculated relative to the 700 participants at T1. A total of 61 participants were not retained between T1 and T2, while a further 189 cases were not successfully matched at T3. An additional 50 observations were excluded during data screening. Thus, 300 of the initially participating employees were not represented in the final analytical sample. The participant flow is summarized in Table 1.

The final dataset was analyzed using R 4.3.3, including lavaan 0.6-17 and semTools 0.5-6, and Python with statsmodels, as documented in the original analysis pipeline. The analytical procedures included confirmatory factor analysis, regression-based moderated mediation analysis, bootstrap estimation, and robustness checks, as described in Section 3.5. All reported statistical findings relate to the final sample of 400 matched observations.

Institutional ethics approval was reported as having been obtained before data collection. The source contains a malformed approval date ("21-02-206"); the correct date and approving committee must be checked against the institutional approval document. Informed consent and confidentiality measures were reported.

Table 1.

Participant recruitment, retention, and final analytical sample

Study stage	Number of cases	Retention from preceding stage
T1: Initial employee survey	700	100.00%
T2: Completed employee well-being survey	639	91.29%
T3: Successfully matched supervisor evaluations	450	70.42%
Final sample after data screening	400	88.89%
Overall analytical retention (T1 to final)	400	57.14% of initial sample

Note. Retention percentages for T2, T3, and the final sample are calculated relative to the immediately preceding stage. The overall analytical retention rate is calculated as 400/700 × 100. The 50 cases excluded after T3 are screening exclusions rather than longitudinal attrition.

3.2 Participants

The final analytical sample consisted of 400 employees with complete responses across the three measurement waves and matched supervisor-rated job performance assessments. The mean

ISSN (P): 3006-6522
ISSN (E): 3006-6530

age of participants was 35.53 years (SD = 9.04; range = 21–61), and their mean organizational tenure was 5.65 years (SD = 3.85). Male participants accounted for 51.2% of the sample, while female participants represented 48.0%, and 0.8% preferred not to disclose their gender.

Regarding educational attainment, 55.2% of respondents held a bachelor's degree, 24.0% held a master's degree, 14.2% held a diploma, and 5.0% held a doctoral qualification. Managerial employees represented 27.0% of the sample, whereas 73.0% occupied non-managerial positions.

Participants represented several employment sectors, including information technology (19.0%), education (17.8%), finance (17.5%), manufacturing (15.0%), healthcare (11.0%), retail (9.2%), the public sector (7.2%), and other sectors (3.2%). All participants included in the final sample reported using AI-based tools in their professional activities. The most frequently reported tools were generative AI assistants (66.2%) and AI features integrated into office software (57.2%). The average duration of AI use was 20.96 months (SD = 12.54). Regarding AI-related training, 48.2% of respondents reported informal self-learning, 31.2% had received formal organizational training, and 20.5% reported no AI training.

The planned minimum sample was 300 matched cases, with reference to the difficulty of detecting small indirect effects (Fritz & MacKinnon, 2007). The final analytical N of 400 exceeded this target. This threshold was not a design-specific power guarantee for the small interaction tested here; the manuscript reports an exploratory Monte Carlo sensitivity assessment in Section 4.7 (Schoemann et al., 2017).

Sample profile (N = 400).

Characteristic	Category	*n*	%
Gender	Male	205	51.2
	Female	192	48.0
	Prefer not to say	3	0.8
Education	Bachelor	221	55.2
	Master	96	24.0
	Diploma	57	14.2
	Doctorate	20	5.0
	Other	6	1.5
Position	Non-managerial	292	73.0
	Managerial	108	27.0
AI training	Informal self-learning only	193	48.2
	Formal training by the organization	125	31.2
	None	82	20.5
Frequency of AI use	Most days	157	39.2
	Several times a day	100	25.0
	Weekly	84	21.0
	A few times a month	59	14.8
Sector	IT	76	19.0
	Education	71	17.8
	Finance	70	17.5
	Manufacturing	60	15.0

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Characteristic	Category	*n*	%
	Healthcare	44	11.0
	Retail	37	9.2
	Public sector	29	7.2
	Other	13	3.2
Tools used (multiple)	Generative AI assistant / office AI / analytics / decision support / other		66.2 / 57.2 / 29.8 / 19.8 / 5
Age (years)	*M* (*SD*); range		35.53 (9.04); 21–61
Tenure (years)	*M* (*SD*)		5.65 (3.85)
AI use (months)	*M* (*SD*)		20.96 (12.54)
AI training hours, last year	*M* (*SD*)		10.74 (9.32)

Note. Percentages may not sum to 100 because of rounding.

3.3 Measures

Unless stated otherwise, items use seven-point scales. Reverse-scored items were recoded before scoring. Scale scores are item means. Reliabilities are reported in Table 3.

AI adoption (T1). Six items written for this study measure the extent of use and integration of AI tools in daily work (e.g., "AI tools are built into the main processes of my job"; 1 = strongly disagree, 7 = strongly agree). The items follow the use-behaviour logic of Venkatesh et al. (2003). Because they are new, their structure was tested in the confirmatory factor analysis (CFA).

AI anxiety (T1). AI anxiety was measured with the 21-item AI Anxiety Scale of Wang and Wang (2022), covering learning (eight items), job replacement (six), sociotechnical blindness (four) and AI configuration (three). On the instrument used here the anchors were 1 = never and 7 = completely. The mean of all 21 items is the AI anxiety score used in the model. Because the four dimensions could not be separated in the CFA (Section 4.2), dimension scores are used only in supplementary analyses.

Employee well-being (T2). The five-item WHO-5 Well-Being Index measures positive mood, vitality and interest in daily life over the previous two weeks (0 = at no time to 5 = all of the time). Its validity is supported in a systematic review (Topp et al., 2015). The item mean (0–5) is used in the models. For comparability with other studies, the conventional percentage score (raw total × 4) is also reported. The printed response grid of the instrument displayed 1–5 while the written anchors specified 0–5; the data follow the written 0–5 anchors.

Job performance (T3). Supervisors rated in-role job performance with the seven-item scale of Williams and Anderson (1991), including two reverse-scored items (e.g., "This employee fails to perform essential duties"; 1 = strongly disagree, 7 = strongly agree).

Control variables. Perceived job insecurity (four items, T1; two reverse-scored) is controlled because AI-related threat and general job insecurity overlap (Brougham & Haar, 2018; Koo et al., 2021). Age, gender (1 = female, 0 = male or not stated), education (1 = master's or doctorate), organizational tenure, position (1 = managerial), AI training (two dummies, informal self-learning and formal organizational training, with no training as the reference) and sector (seven dummies, information technology as the reference) are also included, because each may relate to both AI use and well-being.

3.4 Data screening and common method bias

Of the 450 matched cases available at T3, 50 were removed according to the study's screening and eligibility rules, leaving 400 observations. The source manuscript does not

ISSN (P): 3006-6522
ISSN (E): 3006-6530

enumerate the specific reasons for these 50 exclusions, which should be documented before submission. Screening of the retained cases addressed missingness, out-of-range responses, duplicate codes, response patterns, univariate distributions and multivariate outliers, as reported below.

The final analytical dataset was examined for out-of-range values, missing observations, duplicate identification codes, straight-lining, univariate normality, and multivariate outliers. Response patterns were assessed using within-person standard deviations and the longest sequence of identical responses. Distributional assumptions were examined using skewness and kurtosis statistics, Mahalanobis distance ($p < .001$), and Mardia's multivariate kurtosis. The planned attention-check item (att1) was not included in the analyzed dataset; consequently, potential careless responding was assessed through response-pattern diagnostics. These screening procedures were applied to evaluate the quality and suitability of the final dataset for subsequent statistical analyses.

3.5 Analytic strategy

Analyses were run in *R 4.3.3* with *lavaan 0.6-17* (Rosseel, 2012) and semTools 0.5-6 (Jorgensen et al., 2022), and in *Python* with *statsmodels* (Seabold & Perktold, 2010). The analysis proceeded in four steps.

1. **Measurement model.** Maximum likelihood CFA tested the hypothesized model against alternatives in which factors were merged. Fit was judged by CFI and TLI (≥ .95), RMSEA (≤ .06) and SRMR (≤ .08) (Hu & Bentler, 1999); robust (MLR) indices are also reported. The planned specification treated AI anxiety as a second-order factor over its four dimensions. Reliability was assessed with Cronbach's alpha and McDonald's omega computed from the CFA loadings (equivalent to composite reliability; Hayes & Coutts, 2020). Convergent validity was judged by average variance extracted (AVE ≥ .50). Discriminant validity was judged by the Fornell–Larcker criterion (Fornell & Larcker, 1981), the heterotrait–monotrait ratio (HTMT < .85; Henseler et al., 2015) and chi-square difference tests that fix each latent correlation to 1.
2. **Descriptive statistics.** Means, standard deviations, correlations and reliabilities are reported.
3. **Hypothesis tests.** H1 to H5 were tested with a regression-based first-stage moderated mediation model equivalent to PROCESS Model 7 (Hayes, 2022). The well-being equation contained AI adoption, AI anxiety, their product and the controls. The job performance equation contained AI adoption, well-being and the controls. AI adoption and AI anxiety were mean-centred before the product term was built. Inference on the indirect effects used 5,000 nonparametric bootstrap samples with 95% percentile and bias-corrected intervals. Conditional effects were probed at the mean and ±1 *SD* of AI anxiety. The Johnson–Neyman technique located any region of AI anxiety in which the effect of AI adoption on well-being is significant. The index of moderated mediation (a_3b) was tested directly (Hayes, 2015), and moderated mediation is supported only when its interval excludes zero. Heteroscedasticity-consistent (HC3) standard errors were checked for the regression paths.
4. **Robustness checks.** (a) The model was re-estimated without control variables and without job insecurity. (b) A latent-variable version was estimated in structural equation modelling (SEM), using double-mean-centred matched-pair product indicators for the latent interaction (Lin et al., 2010) and 5,000 bootstrap samples. (c) A quadratic term of AI adoption was added to examine curvilinearity. (d) Supervisor-only re-estimation was not needed because all job performance ratings came from supervisors. (e) Sector heterogeneity was tested with sector-by-path interactions. (f) Each AI anxiety dimension was used as the moderator in turn. (g)

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Cases flagged in screening were excluded. (h) AI anxiety and its interaction with AI adoption were allowed to predict job performance (a Model 8-type specification), because omitting a moderator that predicts the outcome can bias the *b* path.

The hypotheses, measures and analysis plan were fixed in the draft manuscript before the data were analysed. Analyses that were added after the data were seen are labelled exploratory: the specification without job insecurity, the screened-sample model, the Model 8-type specification, the second-stage moderation test, the Ganzach (1997) check and the Lind–Mehlum (2010) test of the quadratic term, and the power simulation.

4. RESULTS

4.1 Data screening

The final analytical dataset comprised 400 complete employee–supervisor matched observations obtained from the three-wave data collection procedure. As described in Section 3.1, the initial sample of 700 participants was reduced to 639 at T2 and 450 successfully matched observations at T3. Following the exclusion of 50 cases during data screening, 400 observations were retained for the main analyses.

Within the final analytical dataset, all 400 cases contained complete data for the variables included in the statistical models. All item values were within the specified response ranges, and no duplicate personal identification codes were detected. No case demonstrated a within-person standard deviation below 0.5 across the 31 T1 items. The longest sequence of identical responses was 14 items (median = 4), indicating that no T1 response pattern was flagged under the specified screening criteria.

For the five-item WHO-5 well-being measure, 32 cases (8.0%) provided identical responses across all items. Because identical responses on a short, positively worded scale may represent legitimate response patterns, these observations were retained in the primary analyses and subsequently excluded in a sensitivity check.

Item skewness ranged from −0.44 to 0.42, while excess kurtosis ranged from −0.77 to −0.01. Mardia's multivariate kurtosis did not indicate a significant departure from normality (b_2 = 1933.6, expected = 1935.0, z = −0.23). No observation exceeded the Mahalanobis critical value across the 43 scale items ($\chi^2(43) = 77.42$ at p = .001). One observation exceeded the corresponding critical value based on the five scale scores; this case was retained in the primary analysis and excluded in a subsequent sensitivity check. The participant-flow records establish the numerical reduction in sample size across the three waves.

4.2 Measurement model

The planned model with AI anxiety as a second-order factor fit the data well ($\chi^2(846)$ = 947.72, CFI = .992, TLI = .991, RMSEA = .017, SRMR = .033), but the solution was improper. The standardized loading of sociotechnical blindness on the second-order factor exceeded 1 (1.007), with a negative residual variance (−0.022, *SE* = 0.019). The four first-order anxiety factors correlated between .987 and 1.008. In a CFA of the 21 anxiety items alone, a single-factor model did not fit worse than the four-factor model ($\Delta\chi^2(6) = 9.95$, $p = .127$), and both AIC (23,397 vs. 23,399) and BIC (23,565 vs. 23,591) favoured the single factor. In these data, therefore, the four dimensions are not empirically distinct. AI anxiety was specified as one first-order factor of 21 items, which is consistent with the use of the overall mean score in the model.

The resulting five-factor model (AI adoption, AI anxiety, job insecurity, well-being and job performance) fit well: $\chi^2(850) = 953.86$, $p = .007$, CFI = .992, TLI = .991, RMSEA = .017, 90% CI [.010, .023], SRMR = .033. The robust estimator gave the same picture (scaled $\chi^2(850)$ =

ISSN (P): 3006-6522
ISSN (E): 3006-6530

948.17, robust CFI = .992, robust RMSEA = .017). All standardized loadings were significant and ranged from .78 to .82 for AI adoption, .78 to .84 for AI anxiety, .74 to .77 for job insecurity, .76 to .82 for well-being and .64 to .73 for job performance (Appendix Table B1). Every alternative model in which constructs were merged fit significantly and substantially worse (Table 2).

Table 3.

Confirmatory factor analysis: comparison of measurement models.

Model	χ^2	*df*	$\Delta\chi^2$ (Δdf)	CFI	TLI	RMSEA [90% CI]	SRMR
M1: Five factors (hypothesized; anxiety first-order)	953.86	850	—	.992	.991	.017 [.010, .023]	.033
M0: Planned, anxiety second-order over four dimensions*	947.72	846	—	.992	.991	.017 [.009, .023]	.033
M2: Four factors, AI anxiety + job insecurity	1489.21	854	535.35 (4)	.948	.945	.043 [.039, .047]	.058
M3: Four factors, AI adoption + AI anxiety	2462.35	854	1508.49 (4)	.869	.861	.069 [.065, .072]	.091
M4: Four factors, well-being + job performance	1774.37	854	820.51 (4)	.925	.921	.052 [.048, .055]	.075
M5: Three factors, all T1 constructs merged	2985.26	857	2031.40 (7)	.826	.817	.079 [.076, .082]	.101
M6: One factor	4709.47	860	3755.61 (10)	.686	.670	.106 [.103, .109]	.125

Note. $N = 400$; maximum likelihood estimation. $\Delta\chi^2$ is relative to M1; all differences $p < .001$. *M0 gives an improper solution: the standardized loading of sociotechnical blindness on the second-order factor is 1.007 and its residual variance is negative.

Reliability was high for every construct (α and ω from .84 to .98; Table 3). AVE exceeded .50 for AI adoption (.66), AI anxiety (.66), job insecurity (.57) and well-being (.64). For job performance it was .48, just below the threshold, so convergent validity of the job performance scale is marginal, although all its loadings were significant and its ω was .86. Discriminant validity was supported. The square root of each AVE exceeded the construct's correlations with every other construct, the largest HTMT ratio was .50 (job insecurity–well-being), and fixing any latent correlation to 1 worsened fit considerably (smallest $\Delta\chi^2(1) = 429.17$).

Table 4.

Reliability, convergent and discriminant validity.

Construct	α	ω	AVE	1	2	3	4	5
1. AI adoption	.92	.92	.66	.81	.25	.28	.19	.44
2. AI anxiety	.98	.98	.66	−.26	.81	.46	.38	.48
3. Job insecurity	.84	.84	.57	−.30	.47	.76	.50	.33
4. Well-being	.90	.90	.64	.19	−.39	−.50	.80	.41
5. Job performance	.86	.86	.48	.44	−.48	−.33	.41	.69

Note. ω = McDonald's omega (composite reliability) from CFA loadings; AVE = average variance extracted. Diagonal (bold) = square root of AVE; below the diagonal = latent correlations from the five-factor CFA; above the diagonal = HTMT ratios.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

4.3 Common method bias

The procedural remedies were supported by the statistical checks. When an unmeasured latent method construct with equal loadings on all 43 items was added to the five-factor model, its loading was estimated at zero and fit did not change ($\Delta\chi^2(1) = 0.00$). Allowing the method loadings to vary improved fit ($\chi^2(807) = 866.56$; $\Delta\chi^2(43) = 87.30$, $p < .001$), but the freely estimated loadings had mixed signs (from −.54 to .62). A factor with loadings of opposite sign does not behave like a common method factor, and is more plausibly absorbing substantive covariance. This is a known weakness of the ULMC technique (Richardson et al., 2009). Even in this model the substantive latent correlations kept their signs and rank order. The same model restricted to the T1 self-report items produced an inadmissible solution. Full collinearity VIFs for the five scale scores ranged from 1.22 to 1.46, well below 3.3 (Kock, 2015). The first unrotated factor explained 39.4% of item variance, and five factors had eigenvalues above 1. Common method variance is therefore unlikely to account for the relationships reported below.

4.4 Descriptive statistics and correlations

Table 5.

Means, standard deviations, reliabilities and correlations.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
Age	35.53	9.04	—									
Female	0.48	0.50	.02	—								
Postgraduate	0.29	0.45	.03	.11*	—							
Tenure	5.65	3.85	.19**	−.01	−.04	—						
Managerial	0.27	0.44	−.01	.00	−.10*	.03	—					
Formal AI training	0.31	0.46	−.04	.00	−.04	.03	−.03	—				
Job insecurity	3.38	1.14	−.07	.04	−.04	−.06	−.04	−.16**	(.84)			
AI adoption	4.62	1.25	.02	−.04	.00	.03	.03	.12*	−.26**	(.92)		
AI anxiety	3.72	1.24	−.10	−.07	.01	−.07	.03	−.01	.42**	−.25**	(.98)	
Well-being	3.20	0.99	.00	−.05	.04	.04	−.01	.05	−.44**	.18**	−.36**	(.90)
Job performance	5.26	0.88	.06	−.03	−.02	.02	−.03	.04	−.28**	.39**	−.44**	.36**

Note. $N = 400$. Cronbach's α in parentheses on the diagonal. Female, postgraduate, managerial and formal AI training are dummy-coded (1 = yes). Well-being is the WHO-5 item mean (0–5); the corresponding percentage score was $M = 63.9$ ($SD = 19.9$), and 24.0% of cases scored 50 or below. * $p < .05$. ** $p < .01$.

The correlations are in the expected directions (Table 5). AI adoption was positively related to well-being ($r = .18$) and job performance ($r = .39$), and negatively related to AI anxiety ($r = −.25$) and job insecurity ($r = −.26$). AI anxiety was negatively related to well-being ($r = −.36$) and job performance ($r = −.44$), and positively related to job insecurity ($r = .42$). Well-being correlated with job performance ($r = .36$). Demographic variables were essentially unrelated to the focal constructs. Formal AI training was weakly associated with higher adoption ($r = .12$) and lower job insecurity ($r = −.16$).

4.5 Hypothesis tests

Table 6 presents regression coefficients for the two equations in the moderated mediation model; the subsequent conditional-effects table presents conditional slopes, indirect effects and the index of moderated mediation.

Table 6.

Regression results of the first-stage moderated mediation model (PROCESS Model 7 logic).

ISSN (P): 3006-6522
ISSN (E): 3006-6530

	Outcome: Well-being (T2)					Outcome: Job performance (T3)				
Predictor	*B*	*SE*	*t*	*p*	95% CI	*b*	*SE*	*t*	*p*	95% CI
Constant	4.286	0.280	15.33	< .001	[3.736, 4.835]	4.600	0.311	14.81	< .001	[3.989, 5.211]
AI adoption (*X*)	0.026	0.038	0.68	.499	[−0.049, 0.100]	0.227	0.033	6.95	< .001	[0.163, 0.292]
AI anxiety (*W*)	−0.178	0.041	−4.37	< .001	[−0.258, −0.098]					
X × *W*	−0.044	0.028	−1.57	.118	[−0.098, 0.011]					
Well-being (*M*)						0.240	0.044	5.51	< .001	[0.154, 0.326]
Job insecurity	−0.298	0.045	−6.67	< .001	[−0.386, −0.210]	−0.069	0.039	−1.76	.080	[−0.146, 0.008]
Age	−0.004	0.005	−0.72	.469	[−0.014, 0.006]	0.005	0.004	1.13	.261	[−0.004, 0.014]
Female	−0.110	0.090	−1.22	.223	[−0.288, 0.068]	0.017	0.079	0.22	.825	[−0.137, 0.172]
Postgraduate	0.060	0.101	0.60	.551	[−0.138, 0.258]	−0.083	0.088	−0.94	.346	[−0.256, 0.090]
Tenure	0.001	0.012	0.10	.918	[−0.022, 0.025]	−0.005	0.010	−0.46	.649	[−0.025, 0.016]
Managerial	−0.048	0.101	−0.47	.635	[−0.247, 0.151]	−0.095	0.088	−1.08	.282	[−0.269, 0.079]
Informal AI training	−0.008	0.118	−0.07	.947	[−0.240, 0.225]	−0.016	0.103	−0.15	.879	[−0.219, 0.187]
Formal AI training	−0.019	0.129	−0.15	.882	[−0.273, 0.235]	−0.054	0.113	−0.48	.630	[−0.275, 0.167]
Sector dummies (7)	all $p > .18$					all $p > .21$				
R^2	.247					.261				
F (*df*)	6.95 (18, 381), $p < .001$					7.94 (17, 382), $p < .001$				
ΔR^2 for *X* × *W*	.005; $F(1, 381) = 2.46$, $p = .118$									

Note. $N = 400$. Unstandardized coefficients with OLS standard errors. AI adoption and AI anxiety are mean-centred. Reference categories: male or not stated, below postgraduate, non-managerial, no AI training, information technology sector. HC3 standard errors led to identical conclusions (e.g., *X* × *W*: $SE = 0.027$, $p = .103$).

H1 predicted that AI adoption is positively related to well-being. With AI anxiety, the interaction and the controls in the model, the conditional effect of AI adoption at mean AI anxiety was small and not significant ($b = 0.026$, $SE = 0.038$, $p = .499$, 95% CI [−0.049, 0.100]). The zero-order correlation ($r = .18$, $p < .01$) shows that the two variables do covary. However, the association was reduced when AI anxiety and job insecurity were held constant: without controls $b = 0.074$ ($p = .053$), and in a simple mediation model without the moderator $b = 0.141$ ($p < .001$) without controls

ISSN (P): 3006-6522
ISSN (E): 3006-6530

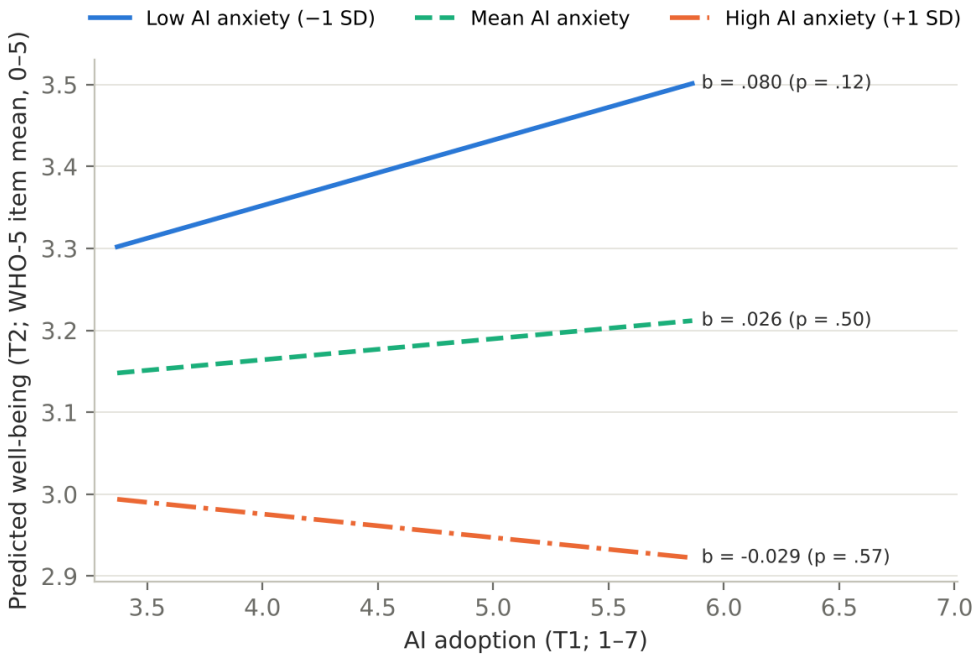
and 0.052 ($p = .172$) with controls. Well-being was instead predicted by job insecurity ($b = -0.298$, $p < .001$) and AI anxiety ($b = -0.178$, $p < .001$). H1 is not supported.

H2 predicted that well-being is positively related to job performance. Controlling for AI adoption and the covariates, well-being at T2 predicted supervisor-rated job performance at T3 ($b = 0.240$, $SE = 0.044$, $p < .001$, 95% CI [0.154, 0.326]; bootstrap 95% CI [0.147, 0.338]). H2 is supported.

H3 predicted an indirect effect of AI adoption on performance through well-being. The total effect of AI adoption on job performance was significant ($c = 0.240$, $SE = 0.034$, $p < .001$), and almost all of it remained as a direct effect ($c' = 0.227$, $p < .001$). The indirect effect at mean AI anxiety was 0.006 (bootstrap $SE = 0.010$, 95% CI [−0.014, 0.027]). In the simple mediation model without the moderator it was 0.013, 95% CI [−0.006, 0.035]. The indirect effect was significant only without control variables (0.038, 95% CI [0.016, 0.064]), and it disappeared once AI anxiety and job insecurity entered the model. H3 is not supported.

H4 predicted that AI anxiety weakens the AI adoption–well-being relationship. The interaction was negative, as predicted, but not significant ($b = -0.044$, $SE = 0.028$, $p = .118$), and it added 0.5% of explained variance. The simple slope of AI adoption was 0.080 at low AI anxiety (−1 *SD*; $p = .124$), 0.026 at the mean ($p = .499$) and −0.029 at high AI anxiety (+1 *SD*; $p = .573$) (Figure 2). The Johnson–Neyman analysis found no value of AI anxiety within the observed range (1.14–6.71) at which the effect of AI adoption on well-being was significant. The effect was largest at the lowest observed anxiety (0.138, $p = .092$) and crossed zero at about 4.3 (Figure 3a; Appendix Table B5). H4 is not supported.

Figure 2. *Simple slopes of AI adoption on well-being at three levels of AI anxiety.*



Note. Lines span ±1 *SD* of AI adoption. Controls are held at their means. *b* = conditional effect of AI adoption on well-being; none differs significantly from zero.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

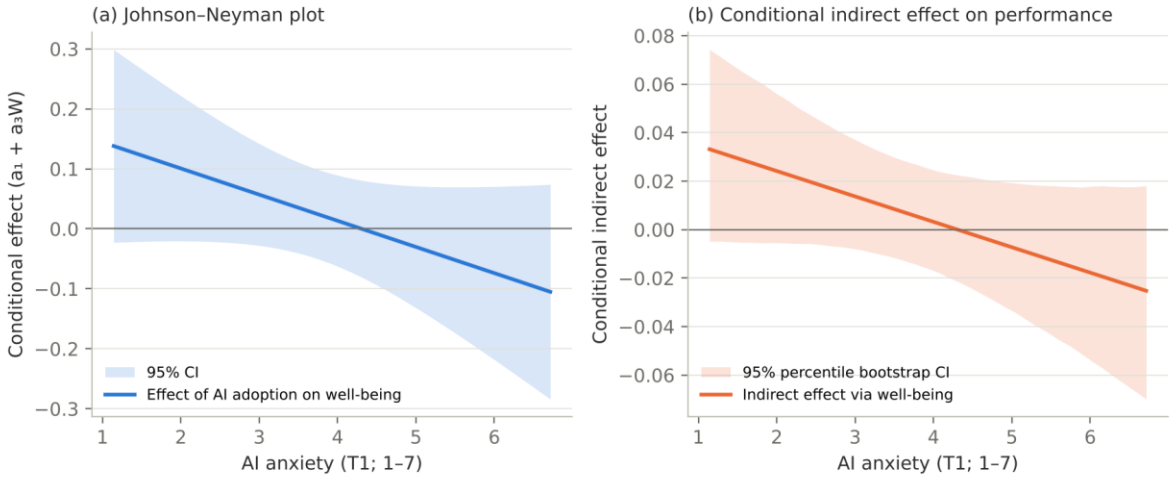
H5 predicted that the indirect effect depends on AI anxiety. The conditional indirect effects decreased from 0.019 at low AI anxiety to 0.006 at the mean and −0.007 at high AI anxiety, but every 95% interval included zero (Table 6; Figure 3b). The index of moderated mediation was −0.0105 (bootstrap *SE* = 0.0066; percentile 95% CI [−0.0237, 0.0021]; bias-corrected 95% CI [−0.0249, 0.0013]). H5 is not supported.

Table 7.
Conditional effects, conditional indirect effects and the index of moderated mediation.

Effect	AI anxiety (raw score)	Estimate	*SE*	95% CI (percentile)	95% CI (bias-corrected)
Conditional effect of AI adoption on well-being	Low (2.47)	0.080	0.052	[−0.022, 0.182][a]	—
	Mean (3.72)	0.026	0.038	[−0.049, 0.100][a]	—
	High (4.96)	−0.029	0.051	[−0.129, 0.071][a]	—
Conditional indirect effect on job performance	Low (2.47)	0.019	0.013	[−0.006, 0.046]	[−0.005, 0.048]
	Mean (3.72)	0.006	0.010	[−0.014, 0.027]	[−0.013, 0.028]
	High (4.96)	−0.007	0.013	[−0.033, 0.019]	[−0.033, 0.019]
Index of moderated mediation	—	−0.0105	0.0066	[−0.0237, 0.0021]	[−0.0249, 0.0013]
Direct effect of AI adoption on job performance	—	0.227	0.034	[0.159, 0.292]	[0.160, 0.293]

Note. 5,000 bootstrap samples; *SE*s for indirect effects, the index and the direct effect are bootstrap *SE*s. [a] OLS-based 95% confidence intervals of the simple slopes. Low and high = 1 *SD* below and above the mean of AI anxiety.

Figure 3. *Effect of AI adoption on well-being (a) and conditional indirect effect on job performance (b) across the observed range of AI anxiety.*



Note. Shaded bands are 95% confidence intervals (OLS-based in panel a; percentile bootstrap with 5,000 samples in panel b). Neither band excludes zero at any observed value of AI anxiety.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

4.6 Robustness checks

Table 7 summarizes the robustness checks. In every specification except the quadratic model (c), discussed in Section 4.7, the first-stage interaction stayed negative (−0.036 to −0.045) and non-significant, and the index of moderated mediation stayed negative with an interval that included zero. In all specifications the well-being–job performance path stayed positive and significant (0.19 to 0.27), and the direct effect of AI adoption on job performance stayed substantial.

Table 7.

Summary of robustness checks.

Specification	*n*	a_1 (*X*→*M*)	a_3 (*X*×*W*)	*b* (*M*→*Y*)	Index of moderated mediation [95% CI]
Main model (all controls)	400	0.026	−0.044	0.240***	−0.0105 [−0.0237, 0.0021]
(a) No controls	400	0.074†	−0.038	0.269***	−0.0102 [−0.0239, 0.0044]
(a′) Controls without job insecurity	400	0.061	−0.036	0.272***	−0.0098 [−0.0245, 0.0054]
(b) Latent SEM, product indicators	400	0.016	−0.044	0.243***	−0.011 [−0.025, 0.003]
(c) Adding AI adoption² (planned)	400	0.012	−0.063*	0.240***	−0.0150 [−0.0292, −0.0015]
(e) Sector × path interactions	400	$F(7, 374) = 0.44$, $p = .876$	$F(7, 360) = 1.40$, $p = .203$	$F(7, 375) = 1.13$, $p = .341$	—
(g) Excluding flagged cases	367	0.048	−0.045	0.260***	−0.0116 [−0.0266, 0.0028]
(h) *W* and *X*×*W* also predict *Y*	400	0.026	−0.044	0.186***	−0.0081 [−0.0195, 0.0015]

Note. Unstandardized estimates; percentile bootstrap intervals with 5,000 samples. In (e), the three cells report joint tests of sector × AI adoption (well-being equation), sector × AI adoption × AI anxiety (well-being equation) and sector × well-being (performance equation). In (g), one multivariate outlier and 32 cases with identical WHO-5 answers were removed. In (h), AI anxiety predicted performance ($b = −0.214$, $p < .001$) but the $X \times W$ term did not ($b = 0.014$, $p = .550$). † $p < .10$. * $p < .05$. *** $p < .001$.

Latent-variable model. The latent model fit well ($\chi^2(262) = 395.05$, CFI = .980, TLI = .977, RMSEA = .036, SRMR = .051) and reproduced the regression results after correction for measurement error: $a_1 = 0.016$ ($p = .710$), AI anxiety → well-being = −0.160 (β = −.21, $p < .001$), $a_3 = −0.044$ (β = −.07, $p = .132$), $b = 0.243$ (β = .30, $p < .001$) and $c' = 0.232$ (β = .35, $p < .001$). The bootstrap interval of the index of moderated mediation included zero (−0.011, 95% CI [−0.025, 0.003]), as did those of the conditional indirect effects (Appendix Table B2). The model explained 28.9% of the variance in well-being and 31.7% in job performance.

AI anxiety dimensions. When each dimension was used as the moderator, the interaction was not significant for learning ($b = −0.032$, $p = .240$), job replacement ($b = −0.043$, $p = .112$) or sociotechnical blindness ($b = −0.043$, $p = .119$). It reached nominal significance for AI configuration ($b = −0.056$, $p = .041$; index = −0.0135, 95% CI [−0.0274, −0.0014]), but not after Bonferroni correction for four tests (α = .0125). Because the dimensions were not empirically distinct, this result should not be interpreted substantively (Appendix Table B4).

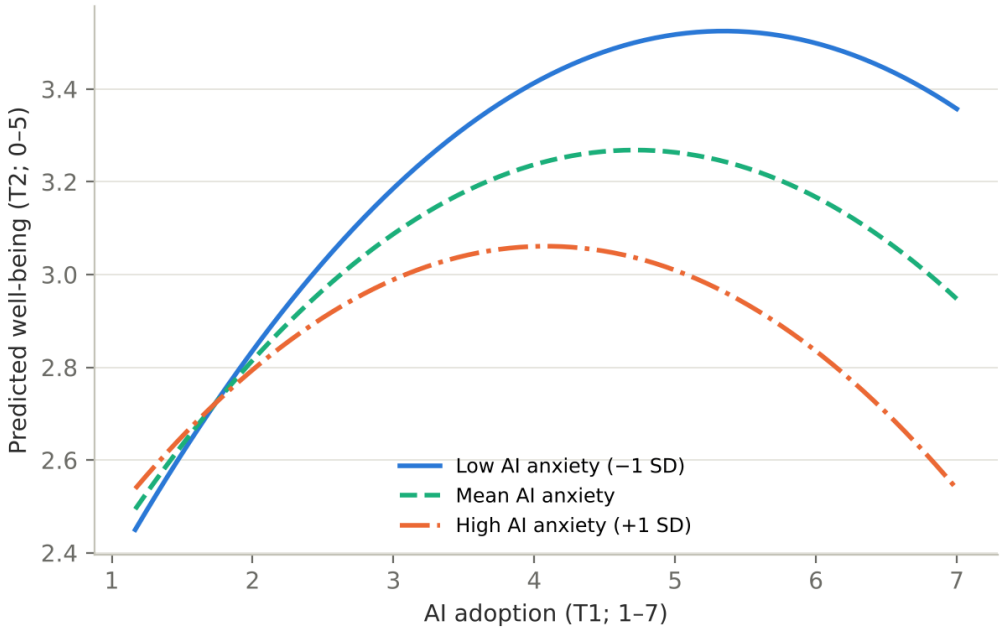
ISSN (P): 3006-6522
ISSN (E): 3006-6530

Sector. Sector moderated neither the first-stage path, nor the interaction, nor the second-stage path (Table 7). The per-sector estimates in Appendix Table B3 are based on small subsamples (13 to 76 cases) and are descriptive only.

4.7 Exploratory analyses

Curvilinearity. The planned quadratic check (robustness check c) suggested an inverted-U relationship between AI adoption and well-being, but the evidence depends on the specification. Alone, the quadratic term was marginal ($b = -0.046$, $p = .061$). With the interaction in the model it was significant ($b = -0.062$, $SE = 0.026$, $p = .017$), and the interaction then also reached significance ($b = -0.063$, $p = .030$; index of moderated mediation −0.0150, 95% CI [−0.0292, −0.0015]). Following Ganzach (1997), we also added the quadratic term of AI anxiety. All three terms were then significant: AI adoption² $b = -0.059$ ($p = .020$), AI anxiety² $b = -0.054$ ($p = .046$) and $X \times W$ $b = -0.082$ ($p = .007$). Without control variables the quadratic term was not significant ($b = -0.036$, $p = .156$). The Lind and Mehlum (2010) test was satisfied in the full model: the slope was positive at the lowest observed adoption score (1.17; slope = 0.437, $p = .013$) and negative at the highest (7.00; slope = −0.281, $p = .035$). The turning point was at 4.72 on the 1–7 scale, close to the sample mean, but its bootstrap 95% interval was wide ([3.93, 6.63]). Only seven cases scored below 2 on AI adoption, so the rising part of the curve rests on few observations (Figure 4). Together, these results are suggestive, not conclusive. They indicate that the linear first-stage specification may hide a non-linear pattern, which future studies should test as an a priori hypothesis.

Figure 4. *Exploratory: predicted well-being from a model with linear and quadratic AI adoption terms and the AI adoption × AI anxiety interaction.*



Note. Controls are held at their means. Curves are drawn over the full observed range of AI adoption; only 18 cases scored below 2.5, so the left tail is estimated imprecisely.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

AI anxiety and performance. AI anxiety predicted supervisor-rated performance even with AI adoption, well-being and the controls in the model (b = −0.214, SE = 0.035, p < .001). Its interaction with well-being on performance (a second-stage moderation) was not significant (b = 0.029, p = .352).

Sensitivity of the moderation test. Observed (post hoc) power is not evidence for or against an effect (Hoenig & Heisey, 2001), so we treat the following simulation only as information for planning a replication. We generated 500 datasets from the estimated model, with the interaction fixed at its observed size (a_3 = −0.044, ΔR^2 = .005), and tested the index of moderated mediation with Monte Carlo confidence intervals. The probability of detecting the effect was .34 at N = 400, .58 at N = 800, .76 at N = 1,200, .87 at N = 1,600 and .94 at N = 2,000. A sample of roughly 1,400 would be needed for 80% power. This agrees with the long-standing observation that interactions in field data are small and hard to detect (McClelland & Judd, 1993).

Table 9.
Summary of hypothesis tests.

Hypothesis	Key evidence	Decision
H1: AI adoption → well-being (+)	b = 0.026, p = .499 (zero-order r = .18)	Not supported
H2: Well-being → job performance (+)	b = 0.240, p < .001	Supported
H3: Indirect effect via well-being	0.006, 95% CI [−0.014, 0.027]	Not supported
H4: AI anxiety weakens AI adoption → well-being	b = −0.044, p = .118 (predicted sign)	Not supported
H5: Conditional indirect effect	Index = −0.0105, 95% CI [−0.0237, 0.0021]	Not supported

5. DISCUSSION

The central finding is a differentiated pattern rather than support for the proposed moderated mediation model. Well-being at T2 was positively associated with supervisor-rated performance at T3. AI adoption was not uniquely associated with well-being in the adjusted first-stage equation, and neither the indirect effect nor its proposed moderation by anxiety was statistically supported. AI adoption nevertheless retained a positive direct association with performance. These results call for separating observed direct associations from unconfirmed psychological mechanisms.

5.1 Well-being and job performance

The supported second-stage path is consistent with the long-standing evidence that positive states at work go with better performance. In their meta-analysis, Judge et al. (2001) concluded that "The mean true correlation between overall job satisfaction and job performance was estimated to be .30." (Judge et al., 2001, p. 376)

Our observed correlation between context-free well-being and supervisor-rated in-role performance (r = .36; latent r = .41) is of a similar size, and the path held after controlling for AI adoption, job insecurity and demographic variables, with a four-week lag and a different source for the outcome. The same authors warned against dismissing the relationship: "It does not appear to be a correlation that should be generally dismissed" (Judge et al., 2001, p. 389). Our result adds that the relationship also holds for the WHO-5, a short and widely used index whose "applicability across study fields is very high" (Topp et al., 2015, p. 167). In JD-R terms, this supports the second

ISSN (P): 3006-6522
ISSN (E): 3006-6530

half of the motivational process: energy and positive affect are personal resources that employees invest in meeting role requirements (Bakker & Demerouti, 2017).

5.2 AI adoption and well-being: a resource that did not register

H1 rested on the JD-R definition of a job resource. Bakker et al. (2023) define job resources as "the physical, psychological, social, or organizational aspects of the job that have motivating potential" (Bakker et al., 2023, p. 32). and state that "Job resources satisfy basic psychological needs and foster employee work engagement" (Bakker et al., 2023, p. 33). In our data, AI adoption did not behave like such a resource for well-being. Its bivariate association with well-being (r = .18) was largely shared with lower AI anxiety and lower job insecurity: employees who used AI more were also less anxious about it and less worried about their jobs, and these two variables, not adoption itself, predicted well-being. This pattern matters for interpreting earlier studies that did not measure AI anxiety or job insecurity. Part of what appears to be a well-being benefit of AI use may reflect differences in how threatened employees feel.

The null first-stage result also fits the view that AI has offsetting effects. Tang et al. (2023b) argued that integrating AI into work "may be a double-edged sword" (p. 1767) and reported that "the more employees interact with AI in the pursuit of work goals, the more they experience a need for social affiliation" (p. 1766), a need with both adaptive and maladaptive consequences. A recent scoping review reaches a similar conclusion for well-being: "Studies examining the impact of RAISA on well-being have produced mixed findings" (Saraswati et al., 2025, p. 2), and "employee well-being in RAISA-integrated work environment is an impact of both personal and organisational factors" (p. 9). If AI adoption saves effort and at the same time adds learning demands, social isolation or role ambiguity (Tang et al., 2022, reported that "Employees felt more role ambiguity on days when they more frequently worked with artificial intelligence", p. 1030), a net effect close to zero on a broad well-being index is what one would expect.

Our result also differs from that of Kim and Lee (2024), who studied the demand side directly:

> "The results also show that AI adoption significantly increases job stress, thus increasing burnout." (Kim & Lee, 2024, p. 1)

We found no negative unique effect of adoption on well-being. One explanation is the outcome: a stress or burnout measure captures the strain of demands, whereas the WHO-5 captures positive mood and vitality, and the two need not move together. Another is the reference period: WHO-5 refers to the last two weeks of life in general, not to work only, which may dilute work-specific effects. The exploratory quadratic analysis suggests a third explanation. Low-to-moderate adoption may add to well-being while heavy dependence subtracts from it, so a linear test averages the two. Pierce and Aguinis (2013) describe this general pattern as the too-much-of-a-good-thing effect, in which "positive monotonic relations reach context-specific inflection points after which relations turn asymptotic" (p. 325). Our evidence for such an inflection was fragile, so this remains a hypothesis to test.

5.3 Why the mediation chain was not supported

The hypothesized indirect path was not supported because its bootstrap interval included zero. Although the adjusted first-stage coefficient was also small and non-significant, that fact alone is not a formal test of mediation. The adjusted direct association between AI adoption and performance ($c' = 0.23$; latent $\beta = .35$) was appreciably larger than the conditional indirect estimate at mean anxiety (0.006). Possible alternative mechanisms include task speed, accuracy or the allocation of routine work, but the present study did not measure these pathways. This pattern can be considered alongside research on AI and self-relevant work outcomes (Tang et al., 2023a) without treating those mechanisms as demonstrated here.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

The pattern of the indirect effects also illustrates a methodological point. Without controls, the conditional indirect effect was significant at low AI anxiety (0.033, 95% CI [0.006, 0.061]) but not at high anxiety, which might tempt a conclusion of moderated mediation. Yet the formal test, which Hayes (2015) calls "a parameter that I call the index of moderated mediation" (p. 1), had an interval that included zero in that model too. A difference between a significant and a non-significant conditional effect is not itself a significant difference, and we draw no moderated-mediation conclusion.

5.4 AI anxiety: a direct risk rather than a switch

H4 and H5 built on studies showing that individual differences decide whether AI is appraised as a challenge or a hindrance. Cheng et al. (2023) reported that

> "Organizational AI adoption induces challenge appraisals for employees with an internal locus of control" (Cheng et al., 2023, p. 1)

whereas "When employees possess an external locus of control, organizational AI adoption induces their hindrance appraisal" (p. 1). Kim and Lee (2024) similarly found that "self-efficacy in AI learning was found to moderate the relationship between AI adoption and job stress" (p. 1). Our interaction had the same sign: the slope of AI adoption on well-being fell from positive at low anxiety to slightly negative at high anxiety. But the effect was small ($\Delta R^2 = .005$) and not significant in any of the main or latent specifications. The simulation in Section 4.7 shows that an effect of this size would need about 1,400 respondents to be detected reliably. The present null result is therefore better described as inconclusive than as evidence against moderation.

AI anxiety did, however, matter directly. It was the second strongest predictor of well-being after job insecurity, and a strong negative predictor of supervisor-rated performance beyond AI adoption and well-being. This fits the first principle of COR theory:

> "The first principle of COR theory is that resource loss is disproportionately more salient than resource gain." (Hobfoll et al., 2018, p. 105)

In our data, the perceived threat (AI anxiety) was related to well-being about seven times as strongly as the potential gain (AI adoption). The pattern also matches earlier evidence on perceived technological threat. Brougham and Haar (2018) found that "Greater STARA awareness was negatively related to organisational commitment and career satisfaction," and "positively related to turnover intentions, cynicism, and depression" (p. 239) (Abbas et al., 2021). Our addition is that AI anxiety predicted lower well-being and performance even when general job insecurity was controlled, which supports treating AI anxiety as distinct from a general fear of job loss (cf. Koo et al., 2021).

The measurement results qualify the dimensional view of AI anxiety. Li and Huang (2020) report that "We identified four dimensions of AI anxiety" (p. 1), and Wang and Wang (2022) validated a four-factor scale. In the present data the four dimensions correlated at about .99 and a single factor fit equally well, so only the overall score could be used. Field studies with the scale should test this structure before interpreting dimension scores. This applies especially to the job-replacement and AI-configuration dimensions, which relate to job insecurity and humanoid robots respectively and may behave differently in office settings.

5.5 Theoretical implications

First, the results caution against assuming that more AI use functions as a net well-being resource in every context. JD-R theory distinguishes resources from demands by their functioning, and emphasizes interactions between individuals and situations (Bakker et al., 2023). In the present adjusted model, anxiety and job insecurity were more closely associated with well-being than AI

ISSN (P): 3006-6522
ISSN (E): 3006-6530

adoption itself. Future JD-R tests could directly measure threat appraisals and organizational support rather than infer these mechanisms from adoption frequency.

Second, the negative associations of AI anxiety with well-being and performance are consistent with COR theory's attention to perceived resource threat (Hobfoll et al., 2018). They do not confirm that resource-loss processes caused poorer outcomes. Research incorporating repeated measures of anxiety, security and actual job conditions could test this proposed explanation.

Third, the mechanism connecting AI use and performance remains open. General well-being did not account for the association in the tested model. Future studies could examine more proximal work processes, including goal progress, self-esteem concerns (Tang et al., 2023a), job stress (Kim & Lee, 2024), challenge and hindrance appraisals (Cheng et al., 2023) or role ambiguity (Tang et al., 2022). Well-being nevertheless remains a relevant outcome and was positively associated with subsequent performance.

5.6 Practical implications

If replicated, the findings point managers less to the amount of AI use than to how threatening employees find it. First, reducing AI anxiety may protect both well-being and performance. Transparent communication about how AI will and will not change jobs, involvement of employees in decisions about AI deployment, and clear statements about job security address the threat appraisal directly. Formal AI training was associated with lower job insecurity in these data ($r = -.16$). Second, organizations should not expect higher AI use, on its own, to improve employee well-being. Well-being needs separate attention through workload, recovery and social contact; Tang et al. (2023b) suggest, for example, that "managers can arrange other opportunities for socializing" (p. 1782) for employees who work closely with AI. Third, because well-being predicted later performance, monitoring well-being with brief tools such as the WHO-5 during AI roll-outs can give early warning. Fourth, the exploratory curvilinear pattern suggests caution about pushing AI use to the maximum. Moderate, well-supported use may be better for well-being than near-total reliance.

5.7 Limitations and future research

Despite its theoretical and methodological contributions, this study has several limitations that should be considered when interpreting the findings. First, although the research employed a three-wave time-lagged design with supervisor-rated job performance, participant loss and incomplete matching across the data collection waves may have introduced selection bias. Of the 700 employees who participated at T1, 400 matched observations were retained for the final analysis, representing an overall analytical retention rate of 57.14%. Consequently, the extent to which the final analytical sample represents the initial participants warrants consideration. Future research should incorporate systematic attrition-bias assessments and more comprehensive participant-follow-up procedures.

Second, the time-lagged research design established temporal ordering among AI adoption, employee well-being, and job performance but did not establish causality. AI adoption, AI anxiety, and job insecurity were all measured at T1, limiting the ability to determine the direction of their mutual relationships. Future studies could employ longitudinal panel designs with repeated assessments of all principal constructs, cross-lagged models, or organizational field experiments to strengthen causal inference. The approximately four-week interval between measurement waves may also have been insufficient to capture longer-term psychological adaptation to AI adoption.

Third, the measurement approach presents several limitations. The AI adoption instrument was developed for the present study and demonstrated satisfactory reliability and validity in the analyzed sample; however, independent validation remains necessary. The average variance

ISSN (P): 3006-6522
ISSN (E): 3006-6530

extracted for the job performance construct was slightly below the conventional threshold of .50, indicating marginal convergent validity. Furthermore, the four theoretical dimensions of AI anxiety were not empirically distinguishable in the confirmatory factor analysis, suggesting that the construct operated as a unidimensional factor in the present sample. The WHO-5 captured general psychological well-being rather than work-specific well-being, and subsequent studies may benefit from incorporating occupational well-being measures, including work engagement and work-related psychological strain (Azim et al., 2021).

Fourth, the nested structure of supervisor-rated job performance may introduce non-independence where individual supervisors evaluate multiple employees. Future investigations should consider multilevel modeling or cluster-robust standard errors when the organizational and supervisory structure of the sample permits such analyses.

Fifth, the sample size of 400 was sufficient for examining several principal relationships but provided limited sensitivity for identifying small interaction effects. The Monte Carlo sensitivity analysis indicated that substantially larger samples may be necessary to detect an interaction of the observed magnitude with adequate statistical power. Future research should therefore use larger samples, include settings with varying levels of AI adoption, and investigate additional psychological and organizational boundary conditions.

Finally, the exploratory evidence of a potentially curvilinear relationship between AI adoption and employee well-being should be interpreted cautiously because its statistical significance depended on model specification. Future studies should formulate and preregister curvilinear hypotheses before data collection and apply appropriate procedures to determine whether an inverted-U relationship can be replicated. Although the analytical strategy was specified in the manuscript before the data were analyzed, the study was not publicly preregistered. Future research could improve transparency by preregistering hypotheses, measurement plans, exclusion criteria, and statistical procedures.

6. CONCLUSION

This three-wave study of 400 matched employee–supervisor observations tested a JD-R- and COR-informed model linking AI adoption, employee well-being, AI anxiety and job performance. Well-being was positively associated with subsequent supervisor-rated performance. However, the adjusted association between AI adoption and well-being was not statistically significant, and the proposed indirect and anxiety-moderated indirect effects were not supported. These null findings are central to the interpretation, rather than evidence that the proposed mechanism was established.

AI adoption remained positively associated with job performance after adjustment, whereas AI anxiety was negatively associated with well-being and job performance. These relationships indicate that use of AI and its psychological correlates may warrant distinct organizational responses. They do not show that encouraging adoption or reducing anxiety would cause improvements. Future studies should address attrition, supervisor clustering, measurement of AI anxiety and work-specific well-being, and the specification-sensitive curvilinear finding.

DECLARATIONS

Data availability. The study was conducted using original employee survey responses collected across three measurement waves and matched with supervisor-rated job performance assessments. The final analytical dataset comprised 400 matched observations. The statistical analyses were conducted using R and Python, and the analysis scripts used to generate the reported tables and

ISSN (P): 3006-6522
ISSN (E): 3006-6530

figures are available from the corresponding author upon reasonable request, subject to applicable data confidentiality and institutional requirements.

Ethics and informed consent. Participants were informed of the purpose of the study, the voluntary nature of participation, confidentiality arrangements, and their right to withdraw.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

REFERENCES

Abbas, F., Rana, A. M. K., Bashir, I., & Bhatti, A. M. (2021). The English language proficiency as a global employment skill: The viewpoint of Pakistani academia. Humanities & Social Sciences Reviews, 9(3), 1071–1077. https://doi.org/10.18510/hssr.2021.93106

Azim, M. U., Hussain, Z., Bhatti, A. M., & Iqbal, M. (2021). 'Observable signals' of motivation in teaching-learning process. Journal of Communication and Cultural Trends, 2(1), 42–59. https://doi.org/10.32350/jcct/2020/21/849

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology, 22*(3), 309–328. https://doi.org/10.1108/02683940710733115

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285. https://doi.org/10.1037/ocp0000056

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands–resources theory: Ten years later. *Annual Review of Organizational Psychology and Organizational Behavior, 10*, 25–53. https://doi.org/10.1146/annurev-orgpsych-120920-053933

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior, 45*(2), 159–182. https://doi.org/10.1002/job.2735

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55

Cheng, B., Lin, H., & Kong, Y. (2023). Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. *Journal of Business Research, 164*, Article 113987. https://doi.org/10.1016/j.jbusres.2023.113987

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. *American Psychologist, 56*(3), 218–226. https://doi.org/10.1037/0003-066X.56.3.218

Fritz, M. S., & MacKinnon, D. P. (2007). Required sample size to detect the mediated effect. *Psychological Science, 18*(3), 233–239. https://doi.org/10.1111/j.1467-9280.2007.01882.x

Ganzach, Y. (1997). Misleading interaction and curvilinear terms. *Psychological Methods, 2*(3), 235–247. https://doi.org/10.1037/1082-989X.2.3.235

Halbesleben, J. R. B., Neveu, J.-P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR": Understanding the role of resources in conservation of resources theory. *Journal of Management, 40*(5), 1334–1364. https://doi.org/10.1177/0149206314527130

Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research, 50*(1), 1–22. https://doi.org/10.1080/00273171.2014.962683

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Hayes, A. F., & Coutts, J. J. (2020). Use omega rather than Cronbach's alpha for estimating reliability. But…. *Communication Methods and Measures, 14*(1), 1–24. https://doi.org/10.1080/19312458.2020.1718629

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist, 44*(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513

Hobfoll, S. E., Halbesleben, J., Neveu, J.-P., & Westman, M. (2018). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual Review of Organizational Psychology and Organizational Behavior, 5*, 103–128. https://doi.org/10.1146/annurev-orgpsych-032117-104640

Hoenig, J. M., & Heisey, D. M. (2001). The abuse of power: The pervasive fallacy of power calculations for data analysis. *The American Statistician, 55*(1), 19–24. https://doi.org/10.1198/000313001300339897

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., & Rosseel, Y. (2022). *semTools: Useful tools for structural equation modeling* (R package version 0.5-6) [Computer software]. https://CRAN.R-project.org/package=semTools

Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The job satisfaction–job performance relationship: A qualitative and quantitative review. *Psychological Bulletin, 127*(3), 376–407. https://doi.org/10.1037/0033-2909.127.3.376

Kim, B.-J., Kim, M.-J., & Lee, J. (2024). The impact of an unstable job on mental health: The critical role of self-efficacy in artificial intelligence use. *Current Psychology, 43*(18), 16445–16462. https://doi.org/10.1007/s12144-023-05595-w

Kim, B.-J., & Lee, J. (2024). The mental health implications of artificial intelligence adoption: The crucial role of self-efficacy. *Humanities and Social Sciences Communications, 11*, 1–15. https://doi.org/10.1057/s41599-024-04018-w

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Koo, B., Curtis, C., & Ryan, B. (2021). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management, 95*, Article 102763.

LePine, M. A. (2022). The challenge-hindrance stressor framework: An integrative conceptual review and path forward. *Group & Organization Management, 47*(2), 223–254.

Li, J., & Huang, J.-S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society, 63*, Article 101410. https://doi.org/10.1016/j.techsoc.2020.101410

Lin, G.-C., Wen, Z., Marsh, H. W., & Lin, H.-S. (2010). Structural equation models of latent interactions: Clarification of orthogonalizing and double-mean-centering strategies. *Structural Equation Modeling, 17*(3), 374–391. https://doi.org/10.1080/10705511.2010.488999

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Lind, J. T., & Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics, 72*(1), 109–118. https://doi.org/1 0.1111/j.1468-0084.2009.00569.x

McClelland, G. H., & Judd, C. M. (1993). Statistical difficulties of detecting interactions and moderator effects. *Psychological Bulletin, 114*(2), 376–390. https://doi.org/10.1037/0033-2909.114.2.376

Pierce, J. R., & Aguinis, H. (2013). The too-much-of-a-good-thing effect in management. *Journal of Management, 39*(2), 313–338. https://doi.org/10.1177/0149206311410060

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Richardson, H. A., Simmering, M. J., & Sturman, M. C. (2009). A tale of three perspectives: Examining post hoc statistical techniques for detection and correction of common method variance. *Organizational Research Methods, 12*(4), 762–800. https://doi.org/10.1177/1094428109332834

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Saraswati, K. D. H., Fajrianthi, F., & Sami'an, S. (2025). Employee well-being in robot, artificial intelligence and service automation-integrated workplace: A scoping review. *SA Journal of Industrial Psychology, 51*, Article a2323. https://doi.org/10.4102/sajip.v51i0.2323

Schoemann, A. M., Boulton, A. J., & Short, S. D. (2017). Determining power and sample size for simple and complex mediation models. *Social Psychological and Personality Science, 8*(4), 379–386. https://doi.org/10.1177/1948550617715068

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with Python. In S. van der Walt & J. Millman (Eds.), *Proceedings of the 9th Python in Science Conference* (pp. 92–96). https://doi.org/10.25080/Majora-92bf1922-011

Tang, P. M., Koopman, J., McClean, S. T., Zhang, J. H., Li, C. H., De Cremer, D., Lu, Y., & Ng, C. T. S. (2022). When conscientious employees meet intelligent machines: An integrative approach inspired by complementarity theory and role theory. *Academy of Management Journal, 65*(3), 1019–1054. https://doi.org/10.5465/amj.2020.1516

Tang, P. M., Koopman, J., Yam, K. C., De Cremer, D., Zhang, J. H., & Reynders, P. (2023a). The self-regulatory consequences of dependence on intelligent machines at work: Evidence from field and experimental studies. *Human Resource Management, 62*(5), 721–744. https://doi.org/10.1002/hrm.22154

Tang, P. M., Koopman, J., Mai, K. M., De Cremer, D., Zhang, J. H., Reynders, P., Ng, C. T. S., & Chen, I.-H. (2023b). No person is an island: Unpacking the work and after-work consequences of interacting with artificial intelligence. *Journal of Applied Psychology, 108*(11), 1766–1789. https://doi.org/10.1037/apl0001103

Topp, C. W., Østergaard, S. D., Søndergaard, S., & Bech, P. (2015). The WHO-5 Well-Being Index: A systematic review of the literature. *Psychotherapy and Psychosomatics, 84*(3), 167–176. https://doi.org/10.1159/000376585

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Wang, Y.-Y., & Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments, 30*(4), 619–634. https://doi.org/10.1080/10494820.2019.1674887

Williams, L. J., & Anderson, S. E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of Management, 17*(3), 601–617. https://doi.org/10.1177/014920639101700305

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Appendix A.

QUESTIONNAIRE

The instrument has three waves about four weeks apart. Each wave opens with the consent page: purpose, voluntariness, the right to stop at any time, use of answers for research only, and the statement that responses are linked by a personal code and treated confidentially but are not fully anonymous. Respondents enter a personal code (last two digits of the mobile number + day of birth, e.g., 47-15) and select "I agree" or "I do not agree." Item order within sections may be randomized; sections keep the order below.

A.1 Wave 1 (T1)

Screening. Do you use any AI-based tool in your work (for example generative AI assistants, AI features in office or analytics software, AI-based recommendation, or decision systems)? Yes / No (No ends the survey).

Section 1. AI adoption (think about your work during the last month; 1 = strongly disagree, 7 = strongly agree)

Code	Item	Response
AD1	I use AI-based tools in my daily work tasks.	1–7
AD2	AI tools are built into the main processes of my job.	1–7
AD3	I rely on AI tools to complete a substantial part of my work.	1–7
AD4	A large part of my tasks now includes steps that are supported by AI.	1–7
AD5	During the last month, I used AI tools on most of my working days.	1–7
AD6	AI tools have changed the way I carry out my core tasks.	1–7

Descriptive items (not part of the scale): How often do you use AI tools at work? (Never / A few times a month / Weekly / Most days / Several times a day). For how many months have you used AI tools at work? Which AI tools do you use? (Generative AI assistant / AI in office software / Analytics or prediction tools / AI-based decision-support systems / Other).

Section 2. AI anxiety (Wang & Wang, 2022; 1 = never, 7 = completely)

Code	Item	Dimension
LAX1	Learning to understand all of the special functions associated with an AI technique/product makes me anxious	Learning
LAX2	Learning to use AI techniques/products makes me anxious	Learning
LAX3	Learning to use specific functions of an AI technique/product makes me anxious	Learning
LAX4	Learning how an AI technique/product works makes me anxious	Learning
LAX5	Learning to interact with an AI technique/product makes me anxious	Learning
LAX6	Taking a class about the development of AI techniques/products makes me anxious	Learning
LAX7	Reading an AI technique/product manual makes me anxious	Learning
LAX8	Being unable to keep up with the advances associated with AI techniques/products makes me anxious	Learning
JRX1	I am afraid that an AI technique/product may make us dependent	Job replacement
JRX2	I am afraid that an AI technique/product may make us even lazier	Job replacement
JRX3	I am afraid that an AI technique/product may replace humans	Job replacement

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Code	Item	Dimension
JRX4	I am afraid that widespread use of humanoid robots will take jobs away from people	Job replacement
JRX5	I am afraid that if I begin to use AI techniques/products I will become dependent upon them and lose some of my reasoning skills	Job replacement
JRX6	I am afraid that AI techniques/products will replace someone's job	Job replacement
STB1	I am afraid that an AI technique/product may be misused	Sociotechnical blindness
STB2	I am afraid of various problems potentially associated with an AI technique/product	Sociotechnical blindness
STB3	I am afraid that an AI technique/product may get out of control and malfunction	Sociotechnical blindness
STB4	I am afraid that an AI technique/product may lead to robot autonomy	Sociotechnical blindness
CFG1	I find humanoid AI techniques/products (e.g. humanoid robots) scary.	AI configuration
CFG2	I find humanoid AI techniques/products (e.g. humanoid robots) intimidating	AI configuration
CFG3	I don't know why, but humanoid AI techniques/products (e.g. humanoid robots) scare me	AI configuration

Attention check (placed between Sections 2 and 3): "To show that you are reading carefully, please select 'Strongly agree' for this statement."

Section 3. Perceived job insecurity (1 = strongly disagree, 7 = strongly agree; R = reverse-scored)

Code	Item	Response
JI1	I worry about the future of my job.	1–7
JI2	I think I might lose my job in the near future.	1–7
JI3	I feel secure about my job. (R)	1–7
JI4	I am confident that I can keep my job for as long as I want it. (R)	1–7

Section 4. Background. Age (years); gender; highest education (Diploma / Bachelor / Master / Doctorate / Other); years in current organization; sector; position (Non-managerial / Managerial); AI training (None / Informal self-learning only / Formal training by the organization); approximate AI training hours in the last year (optional).

A.2 Wave 2 (T2): WHO-5 Well-Being Index

Over the last two weeks: 0 = at no time; 1 = some of the time; 2 = less than half of the time; 3 = more than half of the time; 4 = most of the time; 5 = all of the time. (The response grid must show 0 1 2 3 4 5; the earlier version printed 1–5.)

Code	Item	Response
WB1	I have felt cheerful and in good spirits.	0–5
WB2	I have felt calm and relaxed.	0–5
WB3	I have felt active and vigorous.	0–5
WB4	I woke up feeling fresh and rested.	0–5
WB5	My daily life has been filled with things that interest me.	0–5

ISSN (P): 3006-6522
ISSN (E): 3006-6530

A.3 Wave 3 (T3): Supervisor form, job performance

Complete only for an employee who has consented; use the matching code, not the employee's name. 1 = strongly disagree, 7 = strongly agree; R = reverse-scored.

Code	Item	Response
PERF1	This employee adequately completes assigned duties.	1–7
PERF2	This employee fulfills responsibilities specified in the job description.	1–7
PERF3	This employee performs tasks that are expected of him or her.	1–7
PERF4	This employee meets the formal performance requirements of the job.	1–7
PERF5	This employee engages in activities that directly affect his or her performance evaluation.	1–7
PERF6	This employee neglects aspects of the job he or she is obligated to perform. (R)	1–7
PERF7	This employee fails to perform essential duties. (R)	1–7

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Appendix B.

SUPPLEMENTARY RESULTS

Table B1.
Standardized factor loadings, five-factor CFA.

Construct	Item	λ	*SE*	Construct	Item	λ	*SE*
AI adoption	AD1	.823	.019		STB3	.806	.018
	AD2	.780	.022		STB4	.801	.019
	AD3	.809	.020		CFG1	.788	.020
	AD4	.808	.020		CFG2	.805	.018
	AD5	.816	.019		CFG3	.810	.018
	AD6	.822	.019	Job insecurity	JI1	.763	.027
AI anxiety	LAX1	.842	.015		JI2	.768	.026
	LAX2	.800	.019		JI3R	.757	.027
	LAX3	.829	.016		JI4R	.739	.028
	LAX4	.831	.016	Well-being	WB1	.818	.020
	LAX5	.781	.020		WB2	.805	.021
	LAX6	.813	.018		WB3	.760	.024
	LAX7	.822	.017		WB4	.804	.021
	LAX8	.792	.019		WB5	.815	.020
	JRX1	.800	.019	Job performance	PERF1	.663	.032
	JRX2	.794	.019		PERF2	.701	.030
	JRX3	.822	.017		PERF3	.685	.031
	JRX4	.818	.017		PERF4	.643	.033
	JRX5	.826	.017		PERF5	.695	.030
	JRX6	.817	.017		PERF6R	.716	.029
	STB1	.812	.018		PERF7R	.727	.028
	STB2	.803	.018				

Note. All loadings $p < .001$. JI3, JI4, PERF6 and PERF7 were reverse-coded.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Table B2.

Latent moderated mediation model (robustness check b).

Parameter	Estimate	*SE* (boot)	95% CI (percentile)	β
AI adoption → well-being (a_1)	0.016	0.044	[−0.072, 0.098]	.02
AI anxiety → well-being	−0.160	0.045	[−0.249, −0.069]	−.21
AI adoption × AI anxiety → well-being (a_3)	−0.044	0.027	[−0.097, 0.011]	−.07
Well-being → performance (b)	0.243	0.058	[0.135, 0.357]	.30
AI adoption → performance (c')	0.232	0.039	[0.156, 0.309]	.35
Index of moderated mediation	−0.011	0.007	[−0.025, 0.003]	—
Indirect effect, low AI anxiety (−1 *SD*)	0.017	0.014	[−0.009, 0.046]	—
Indirect effect, mean AI anxiety	0.004	0.011	[−0.018, 0.026]	—
Indirect effect, high AI anxiety (+1 *SD*)	−0.010	0.014	[−0.039, 0.019]	—

Note. $\chi^2(262) = 395.05$, CFI = .980, TLI = .977, RMSEA = .036, SRMR = .051. Indicators: three AI adoption parcels (AD1–2, AD3–4, AD5–6), three AI anxiety parcels (learning; job replacement; sociotechnical blindness and configuration), three double-mean-centred matched-pair products, and the items of job insecurity (latent covariate), well-being and performance. 5,000 bootstrap samples.

Table B3.

Path estimates by sector (descriptive).

Sector	*n*	a_1	*p*	a_3	*p*	*b*	*p*	*c′*	*p*
IT	76	0.032	.726	−0.106	.101	0.243	.021	0.130	.088
Education	71	0.060	.460	−0.013	.821	0.347	.001	0.233	.001
Finance	70	−0.079	.480	0.020	.817	0.323	.000	0.400	.000
Manufacturing	60	−0.049	.593	−0.025	.706	0.441	.003	0.073	.445
Healthcare	44	0.057	.606	0.081	.316	0.077	.579	0.388	.000
Retail	37	0.177	.136	−0.127	.129	0.186	.284	0.124	.313
Public sector	29	−0.089	.659	−0.293	.067	0.006	.966	0.282	.037
Other	13	0.170	.613	−0.165	.474	−0.019	.929	0.486	.026

Note. Separate OLS models per sector with job insecurity as the only covariate. Small subsamples; formal tests of heterogeneity are reported in Table 7.

Table B4.

AI anxiety dimensions as moderators (robustness check f).

Moderator	a_3	*p*	Index of moderated mediation	95% CI (percentile)
Learning	−0.032	.240	−0.0076	[−0.0201, 0.0043]
Job replacement	−0.043	.112	−0.0102	[−0.0230, 0.0020]
Sociotechnical blindness	−0.043	.119	−0.0103	[−0.0232, 0.0027]
AI configuration	−0.056	.041	−0.0135	[−0.0274, −0.0014]

Note. All controls included; 5,000 bootstrap samples. Bonferroni-adjusted α for four tests = .0125. The dimensions correlated at about .99 in the CFA and should not be interpreted separately.

Table B5.

ISSN (P): 3006-6522
ISSN (E): 3006-6530

Conditional effect of AI adoption on well-being across the observed range of AI anxiety (Johnson–Neyman).

AI anxiety	Effect	*SE*	*T*	*p*	95% CI
1.14	0.138	0.082	1.69	.092	[−0.023, 0.299]
1.42	0.126	0.075	1.68	.094	[−0.021, 0.273]
1.70	0.114	0.068	1.66	.097	[−0.021, 0.248]
1.98	0.102	0.062	1.64	.102	[−0.020, 0.223]
2.26	0.089	0.056	1.59	.112	[−0.021, 0.200]
2.54	0.077	0.051	1.53	.128	[−0.022, 0.177]
2.81	0.065	0.046	1.42	.156	[−0.025, 0.155]
3.09	0.053	0.042	1.26	.208	[−0.030, 0.135]
3.37	0.041	0.039	1.04	.299	[−0.036, 0.118]
3.65	0.029	0.038	0.76	.451	[−0.046, 0.103]
3.93	0.016	0.038	0.43	.666	[−0.059, 0.092]
4.21	0.004	0.040	0.11	.914	[−0.074, 0.083]
4.49	−0.008	0.043	−0.18	.856	[−0.093, 0.077]
4.76	−0.020	0.047	−0.42	.673	[−0.113, 0.073]
5.04	−0.032	0.052	−0.61	.540	[−0.135, 0.071]
5.32	−0.044	0.058	−0.76	.446	[−0.158, 0.070]
5.60	−0.056	0.064	−0.88	.379	[−0.182, 0.070]
5.88	−0.069	0.070	−0.97	.331	[−0.207, 0.070]
6.16	−0.081	0.077	−1.05	.296	[−0.232, 0.071]
6.44	−0.093	0.084	−1.11	.269	[−0.258, 0.072]
6.71	−0.105	0.091	−1.16	.249	[−0.284, 0.074]

Note. No value of AI anxiety in the observed range (1.14–6.71) yields a significant effect at α = .05.