

Human–AI Collaboration and Workplace Well-Being: Examining the Mediating Role of Employee Engagement in Employee Productivity

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Abstract:

The integration of artificial intelligence (AI) into organisations is transforming how people work effectively, collaborate and create value. AI-enabled work environments might help to drive efficiency and access to intelligent support, but employee engagement, engagement, and productivity will be impacted significantly by how workers interact with AI-enabled tools. In this context, we have studied the connection between human-AI collaboration (HAC), workplace well-being (WB), employee engagement (ENG), and employee productivity (PROD) with the mediation of employee engagement as a central focus in this study. The study is based on the Job Demands-Resources (JD-R) theory that provides an idea on how technology-enabled work conditions and employee resources can influence motivation and performance. The data were derived from 356 knowledge workers who regularly use AI-based tools. The relationships we proposed were modelled using structural equation and confirmatory factor analysis and bootstrap-based mediation analysis. The study finds that human-AI collaboration and work well-being are positively related to employee engagement with HAC ($\beta = .30, p < .001$) and WB ($\beta = .29, p < .001$) having strong correlations with Engagement. Employee engagement also positively affects productivity ($\beta = .41, p < .001$). The mediation analysis shows that employee engagement is a big player in the relationship between HAC and WB in terms of employee productivity, with a moderate indirect effect of 12 for each. The model accounts for 33% of the variance in employee productivity. These findings indicate that the contribution of AI to productivity is not just about technological adoption but is very much about employee engagement and well-being. This paper adds to the expanding literature on AI-enabled work by portraying employee engagement as an important means by which human-technology collaboration and good workplace experiences can lead to productive outcomes in the workplace.

Keywords: Human–AI collaboration, Workplace Well-being, Employee Engagement, Employee Productivity, Job Demands–Resources Theory

1. Introduction

The rapid application of generative and analytic artificial intelligence into everyday knowledge work has turned AI from a passive tool to a partner in the enterprise that shares task execution, judgment, and decision-making with humans [1]. Businesses are investing heavily in AI-based workflows on the basis that more human–AI collaboration leads to more output. But the reality is more nuanced: AI can be an energizer or an enabler for employees by relieving routine labor and increasing the scope and value of meaningful work, or it can be a hindrance to employee engagement through technostress, role uncertainty, and a feeling of lack of control. HAC is not a direct function of productivity, it is more psychologically based on the state of the employee, as JD-R theory shows [2]. A well-designed HAC setup is a job resource that can motivate employees. A supportive workplace environment, based on workplace well-being, a combination of psychological well-being, satisfaction, and manageable stress, is also a source of support. These resources are then estimated to be translated into employee engagement a simultaneous experience of vigor, dedication, and absorption which drives employee productivity [3]. While many studies have identified HAC as a novel job resource, few have considered engagement as a source of cooperation that brings AI and overall workplace well-being to productivity outcomes in a single structural model [4]. Here we aim to fill that gap by testing an integrated model where HAC and WB are exogenous predictors of ENG, and ENG predicts PROD directly from HAC and WB, and we keep direct paths from HAC and WB to PROD for full mediation. As usual in this literature [5] the study estimate the model using

a two-step covariance-based structural equation modeling (SEM) approach similar to IBM SPSS AMOS, by measurement CFA model, then the structural model and bootstrap-based tests of indirect effects.

2. Theoretical Background and Hypothesis Development

2.1. Job Demands–Resources Theory as an Integrating Framework

JD-R theory posits that all jobs are described by job demands that part that requires constant effort and job resources that are needed to achieve goals, reduce demands or promote growth [6]. Resources activate a motivational process that leads to engagement and productivity as well as demands that affect health. Recent work in the field specifically mentions human–AI collaboration as a new technology-based job resource that can be leveraged to enter the motivational pathway, but also acknowledges that it may have dual effects, if not used properly as a demand [7]. We use JD-R as the organizing framework and treat HAC and WB as resource inputs that are linked to a single engagement-based motivational pathway to productivity.

2.2. Human–AI Collaboration and Employee Engagement

Human-AI collaboration is the cooperation between employees and AI systems in task division, information exchange, mutual adaptation and interpretation of co-operative results [8]. When AI systems can perform well as partners, in data intensive or repetitive sub-tasks and to find well-informed recommendations) employees can spend their energy on higher-value and more autonomous work [9]. This resource gain is expected to lead to more energy (more energy available for other tasks), dedication, a greater sense of task significance, and absorption (the ability to be more focused at a time when people can do more with less cognitive effort). Evidence from the knowledge work and hospitality areas is also in line with the positive HAC-engagement relationship [10].

H1: Human–AI collaboration is positively associated with employee engagement.

2.3. Workplace Well-Being and Employee Engagement

Workplace well-being psychological well-being, satisfaction with one's work, manageable stress levels and work–life balance, is a standard personal/contextual resource in the JD-R tradition [11]. Employees who feel psychologically well and have a manageable workload have more energy and attentional capacity to engage in their work, which engagement literature considers as a fundamental precursor of vigor, dedication, and absorption [12]. We hypothesize:

H2: Workplace well-being is positively associated with employee engagement.

2.4. Employee Engagement and Employee Productivity

Engaged employees, by definition, bring more energy, identification, and focused attention to their work, which the performance literature consistently links to task performance, efficiency, output quality, and goal attainment [13]. We hypothesize:

H3: Employee engagement is positively associated with employee productivity.

2.5. The Mediating Role of Employee Engagement

Like the JD-R motivational pathway, we expect that HAC and WB do not lead to productivity gains automatically, but primarily through the engagement they generate. This is consistent with the recent AMOS-based mediation evidence which indicates that psychological mechanisms tend to play a significant and not exclusively causal role in the effect of AI collaboration on downstream work outcomes [14]. Hence, we test engagement as a partial mediator of resource–productivity relations while allowing for residual direct effects:

H4: Employee engagement mediates the relationship between human–AI collaboration and employee productivity.

2.6. Workplace Well-being, Engagement and Productivity

Workplace well-being creates positive psychological and work conditions that encourage employees to become more engaged with their jobs. From the Job Demands–Resources perspective, positive workplace resources

enhance employee motivation and engagement [15]. Employee engagement, characterized by employees' energy, dedication, and involvement, is subsequently associated with higher productivity and performance. Recent evidence also shows that work engagement mediates the relationship between workplace well-being and task performance [16]. Thus, employees experiencing greater well-being are likely to become more engaged, which in turn can enhance their productivity. Therefore, employee engagement can be viewed as a psychological mechanism linking workplace well-being with employee productivity.

H5: Employee engagement mediates the relationship between workplace well-being and employee productivity.

3. Method

3.1. Research Design, Sample and Data Collection

The study used a cross-sectional quantitative research approach to explore the relationship between HAC, workplace well-being, employee engagement and employee productivity. Our target population comprises knowledge workers who use AI-based tools in their daily work. The data were gathered using a structured questionnaire using a five-point Likert scale of 1 = strongly disagree and 5 = strongly agree. A total of 356 usable responses were considered for the analysis. Since the four-factor model was used and the sample size was sufficient for structural equation modeling, the number of observed indicators was expected to be sufficient to provide a good generalization of the data. Respondents were approached based on their experience with AI work practices, to ensure that the participants had exposure to AI tools so as to assess their collaboration with such technologies, workplace well-being, engagement, and productivity.

3.2. Measures

The study employed multi-item measures to operationalize the four constructs. Human-AI collaboration was measured by four measures that indicate the degree to which employees are interacting and relying on AI in decision making, forecasting, problem-solving, and task execution. Workplace well-being in terms of psychological well-being, satisfaction, work-life balance, and productivity were evaluated through four measures. Employee engagement was measured with three dimensions that were based on Utrecht Work Engagement Scale (UWES), that includes vigor, dedication, and absorption. Productivity was assessed with four items that were based on task performance, work efficiency, quality of output, and achievement of performance targets. All items were measured on a five-point Likert-type scale, with higher scores indicating perceptions of the respective construct. The measurement items were adapted from previous scales and contextualized for the workplace with AI enabled tools.

3.3. Common Method Bias

Since the study used self-reported responses collected through a common questionnaire, common method bias was considered. Procedural measures were integrated into the research design so that the item wording was clear and respondents were anonymous, and predictor and outcome constructs were separated in the questionnaire. Harman's single-factor approach was also employed as a first statistical test of common method bias to assess whether a single factor was responsible for the majority of covariance among the relevant data.

3.4. Data Analysis

The paper used the two-step structural equation modeling approach to evaluate the adequacy of the proposed research model. First, CFA has been performed to evaluate the adequacy of the measurement model and the reliability and validity of the model. Internal consistency has been assessed with Cronbach's alpha and CR, and convergent validity has been evaluated via the standardized factor loadings and AVE. Furthermore, the validity of the measurement model has been evaluated based on the model fit indices compared with that of the models. After validation of the measurement model, the structural model was estimated using maximum-likelihood estimation to examine the relationships between HAC, WB, ENG, and PROD. Employee engagement was also studied as a mediator between HAC and productivity and workplace well-being and productivity. We evaluated the indirect effects using bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals. An indirect effect was statistically significant if the confidence interval did not include zero.

4. Results

4.1. Descriptive Statistics and Normality

Table 1: Descriptive Statistics and Normality

Construct	Indicator	Mean	SD	Skewness	Kurtosis
Human–AI Collaboration	HAC1	3.66	0.82	−0.25	−0.42
	HAC2	3.70	0.79	−0.18	−0.21
	HAC3	3.72	0.76	−0.12	−0.05
	HAC4	3.68	0.81	−0.08	0.02
Workplace Well-Being	WB1	3.68	0.81	−0.18	−0.50
	WB2	3.73	0.77	−0.10	−0.24
	WB3	3.75	0.74	0.01	−0.06
	WB4	3.71	0.79	−0.06	−0.18
Employee Engagement	ENG1	3.70	0.84	−0.15	−0.38
	ENG2	3.76	0.75	0.05	0.08
	ENG3	3.73	0.78	−0.04	−0.12
Employee Productivity	PROD1	3.67	0.80	−0.21	−0.45
	PROD2	3.72	0.76	−0.14	−0.20
	PROD3	3.74	0.74	−0.02	0.04
	PROD4	3.70	0.78	−0.09	−0.16

Indicator means ranged from 3.66 to 3.76 ($SD = 0.74\text{--}0.84$) on the 1–5 scale, reflecting a mildly positive response tendency typical of workplace attitude surveys. Skewness (−0.25 to +0.05) and kurtosis (−0.50 to +0.08) values were well within the ± 2 range conventionally treated as acceptable for maximum-likelihood SEM estimation.

4.2. Measurement Model (CFA)

Table 2. Reliability and Convergent Validity of the Measurement Model

Construct	Items	α	CR	AVE	Loading Range
Human–AI Collaboration	4	.79	.79	.49	.65–.79
Workplace Well-Being	4	.74	.74	.42	.55–.70
Employee Engagement	3	.79	.79	.56	.63–.82
Employee Productivity	4	.80	.80	.51	.66–.75

All constructs met reliability thresholds (α and $CR \geq .70$). AVE for well-being (.42) fell marginally below the customary .50 benchmark; however, because CR exceeded .70, convergent validity is still considered adequate. Our guidance that AVE is a conservative index and CR alone can support convergent validity when AVE is only marginally low.

Table 2. Discriminant Validity: Fornell–Larcker Matrix

Construct	HAC	WB	ENG	PROD
HAC	.70			
WB	.31	.65		
ENG	.45	.48	.75	
PROD	.45	.44	.66	.71

The discriminant validity assessment indicates that the four constructs HAC, workplace well-being, employee engagement and employee productivity are different from each other. The diagonal values, i.e. the square root of the average variance extracted, are higher than the correlation with the other constructs. This is true for all the pairs of constructs as each has more variance with its own indicators than the other constructs in the model. While employee engagement and employee productivity are strongly positive ($r = 0.66$), the square root of AVE for engagement is (.71) and Production (.75) is higher than that of other constructs. Overall, these results are good enough to indicate that the four constructs are distinguishable and should be considered as distinct variables from the others in the next structural model.

Table 4. Measurement Model Fit Indices

Index	Value	Threshold
χ^2/df	0.78	< 3.00
CFI	1.00	$\geq .95$
TLI	1.00	$\geq .95$
RMSEA	.000	$\leq .06$
SRMR	.029	$\leq .08$

The measurement model demonstrated an excellent overall fit to the observed data. The chi-square statistic was non-significant ($\chi^2 = 62.37$, $df = 80$, $p = .928$), indicating no significant discrepancy between the hypothesized measurement model and the observed covariance structure. The CFI and TLI values were 1.00, while RMSEA was 0.000 and SRMR was 0.029, all of which fall within recommended thresholds for good model fit. These results indicate that the proposed four-factor measurement model adequately represents the relationships among the observed indicators and their respective latent constructs. The satisfactory model fit provides a basis for proceeding with the structural model and testing the hypothesized relationships among human–AI collaboration, workplace well-being, employee engagement, and employee productivity.

4.3. Common Method Bias Check

Harman's single-factor test showed that the first unrotated factor accounted for 32.9% of the total variance in the 15 indicators, well below the 50% threshold conventionally treated as indicative of a common-method-bias problem. Common method bias is therefore unlikely to account for the observed pattern of relationships.

4.4. Structural Model and Hypothesis Testing

Table 5. Standardized Structural Path Estimates

Path	β	SE	t	p	Hypothesis
HAC $\rightarrow$ ENG	.30	.049	6.10	< .001	H1 supported

WB → ENG	.29	.049	5.92	< .001	H2 supported
ENG → PROD	.41	.049	8.30	< .001	H3 supported
HAC → PROD (direct)	.17	.047	3.70	< .001	significant
WB → PROD (direct)	.15	.047	3.21	.001	significant

The structural model also supports all three of the hypothesized direct relationships. Human–AI collaboration ($\beta = .30, p < .001$) and workplace well-being ($\beta = .29, p < .001$) are positively associated with employee engagement and explain 21% of the variance ($R^2 = .21$). Employee engagement is also positively associated with employee productivity ($\beta = .41, p < .001$), and our model explains 33% of the variance in productivity ($R^2 = .33$). Hence, H1, H2 and H3 are supported, and we note that employee engagement is a key component of the relationship between AI-enabled work and workplace well-being and productivity.

4.5. Mediation Analysis

Table 6. Bootstrap Mediation Results

Indirect path	Point estimate	95% CI lower	95% CI upper	Conclusion
HAC → ENG → PROD	.121	.075	.174	Partial mediation
WB → ENG → PROD	.118	.069	.174	Partial mediation

Both HAC→PROD and WB→PROD direct effects remained significant alongside their indirect effects, indicating partial mediation. The indirect effect of HAC on PROD through engagement was .121, representing approximately 41% of the total effect (.296), with the 95% confidence interval excluding zero, supporting H4. Similarly, the indirect effect of WB on PROD was .118, accounting for about 44% of the total effect (.269), supporting H5. These findings indicate that employee engagement is an important, but not the only, pathway linking AI collaboration and workplace well-being with productivity.

5. Discussion

The study puts employee engagement as one of the major psychological mechanisms through which human-AI collaboration and workplace well-being are linked to employee productivity. All five hypotheses were verified. As in JD-R, both HAC and WB were found to be workplace resources that contribute to employee engagement and, later, productivity. The relative strength of the HAC with ENG and WB with ENG relationships suggest that good AI collaboration can contribute to employee engagement in a way similar to workplace well-being. The partial mediation results also confirm that HAC and WB contribute to productivity and efficiency as well as reduced errors, as well as other direct aspects. So, AI-enabled productivity should not be seen solely as a psychological outcome of employee engagement, but as a product of the motivational and task-related mechanisms.

5.1. Theoretical Implications

The study extends JD-R theory by situating human AI collaboration alongside a broader well-being resource within a single motivational pathway, rather than studying HAC in isolation as prior work has tended to do. It also contributes methodologically by demonstrating a full two-step SEM workflow, measurement model validation, structural estimation, and bootstrap mediation that mirrors the analytic standard expected in top-tier organizational-behavior and information-systems journals.

5.2. Practical Implications

The findings indicate that for practitioners, the return on investment in AI should be more about the way AI tools are created and deployed and not just on how efficient they are. AI implementations that make role clarity less clear, that escalate monitoring intensity or that create technostress will slow down the engagement pathway that is already robust to HAC. The parallel investment in general worker welfare (manageable workloads, psychological safety and work-life balance) seems to be a much more powerful resource too, and the two have complementary as opposed to direct pathways to engagement where they are equally useful.

5.3. Limitations and Future Research

The study is limited by its cross-sectional design and reliance on self-reported measures, which restrict causal interpretation and may introduce common method bias. Future research could use longitudinal or multi-source data across different industries to examine changes in human–AI collaboration, engagement, well-being, and productivity over time.

6. Conclusion

Human-AI collaboration and workplace well-being are key drivers for employee engagement and productivity as the study also found. The study indicates that employee engagement leads to the highest productivity and AI-enabled cooperation and workplace experiences. The partial mediation findings also suggest that productivity is driven by psychological as well as task-related factors. The study shows that organizations may benefit from AI, however, by harnessing the potential for AI with human-AI collaboration and a supportive work environment.

7. References

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